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Flood risk and vulnerability of populations' analysis in Southern, Burkina Faso

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Dedication

This work is dedicated to Allah the merciful,

my parents, brothers and sisters.

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List Of Abbreviations And Acronyms

AM : Arithmetic Mean method
ANAM: National Agency of Meteorological Services
BMBF: Federal Ministry of Education and Research
CC&DRM: Climate Change and Disaster Risk Management
CCW: Coefficient of Correlation Weighted method
CONASUR: Council for Emergency Relief and Rehabilitation
DGRE: General Directorate of Water Resources
EM-DAT: Emergency Event Disaster database
ENSO: EL Niño-Southern Oscillation
ETCCDI: Expert Team on Climate Change detection indices
GC : Geographical Coordinates method
GEV: Generalized Extreme Value distribution
GFZ : German Research Centre for Geosciences
GP: Generalized Pareto distribution
HFRI: Household Flood Risk Index
HFVI: Household Flood Vulnerability Index
IDW : Inverse Distance Weighting method
INSD: National Institute of Statistics and Demography
MA : Middle Atlantic
NA : North Atlantic
NCEI: National Centre for Environnemental Information
NOAA: National Oceanic and Atmospheric Administration
OR: Odds Ratio
POT: Peak-Over-Threshold
RMSE: Root Mean Square Error
SA : South Atlantic
SST: Sea Surface Temperature
UPB: Polytechnique University of Bobo-Dioulasso
WASCAL: West African Science Centre on Climate Change and Adapted Land Use

Author contributions

These papers represent the outcomes of the first and third specific objectives of the thesis, which were published in peer-reviewed academic journals. The majority of the work was carried out by the thesis author (M., S.). The co-authors of the two studies contributed to the research through discussions, comments, conceptualization, and manuscript review.

Sougué, M., Merz, B., Sogbedji, J. M., & Zougmoré, F. (2023). Extreme Rainfall in Southern Burkina Faso, West Africa: Trends and Links to Atlantic Sea Surface Temperature. *Atmosphere*, *14*(2), 284. https://doi.org/10.3390/atmos14020284

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Bassirou, H., Gnazou, M., D.-T., Seydou Sanda, I. ,Cheo, A., E., **Sougué, M.**, Pouye. I. (2023). Extreme Rainfall and Streamflow in Niamey City: Trends and Relationship Between Higher Streamflow and Rainfall. *Water Resources Engineering journal.*

Abstract

This Thesis seeks to understand the space-time variations of extreme rainfall events, and the assess flood risk and community vulnerability to floods in the southern Burkina Faso. To achieve this, the specific objectives include (i) analyzing the frequency and intensity of extreme rainfall for better insight of risks associated with flood disaster occurrences in communities, (ii) examining flood-related impacts as much as possible for better awareness and preparedness of flood disaster occurrences, (iii) analyzing flood risk, including perceptions of flood risk and their influencing factors, to increase the resilience of communities that may face flooding situation, and (iv) assessing flood vulnerability using various weighting methods under the definitions of IPCC 2007 and 2014 vulnerability frameworks. As far as the analytical process is concerned, various methods such as extreme value theory modelling, econometric modelling, indicator-based analysis, and statistical tests are performed, integrating both secondary data and household survey data. The results show substantial spatial heterogeneity in rainfall trends across the study area, with more downward than upward trends, particularly for indices representing extreme rainfall. This contrasts with national and supranational studies that primarily identified increasing trends in extreme rainfall. Furthermore, the findings demonstrate a strong spatial dependency in extreme rainfall, reaching up to 300 km away and decreasing as the distance between paired sites increases, potentially impacting thousands of people simultaneously. Regarding flood risk, our findings indicate that 12 out of the 14 villages in our sample group have experienced high levels of flood risk. Households pointed out the management of runoff from the nearest urban areas and poorly designed civil engineering infrastructure, such as roads, as significant factors contributing to their increased vulnerability. Furthermore, the results suggest that flood risk perception is largely influenced by informational and behavioural factors among households. The sensitivity analysis of vulnerability to different weighting methods shows that the vulnerability index is less sensitive to whichever equal and Principal Component Analysis weighting methods are considered for assigning weights to indicators. However, the equal weighting method is preferred when dealing with numerous indicators. This thesis could offer valuable insights for disaster risk management authorities, enabling them to allocate resources effectively, plan budgets, and coordinate their actions based on the priorities of areas.

Keywords: Extreme rainfall, extreme values theory, community vulnerability, flood risk, flood risk perception, indicator-based method, ordered logistic modelling, southern Burkina Faso.

Synthèse de la thèse

Résumé

Cette thèse porte sur l'analyse de la variation spatio-temporelle des précipitations extrêmes, l'évaluation de la vulnérabilité des populations face aux inondations, et l'évaluation du niveau de risque d'inondation auxquelles les populations rurales sont confrontées dans la partie sud du Burkina Faso. Pour ce faire, quatre objectifs spécifiques sont définis : (i) analyser la fréquence et l'intensité des précipitations extrêmes afin de mieux comprendre les risques associés aux inondations dans les communautés locales, (ii) déterminer les impacts des inondations sur ces communautés, avec un accent particulier sur les zones et les populations à risque d'inondation, (iii) évaluer les risques d'inondation et les facteurs influençant les perceptions de ces risques afin de renforcer la résilience des communautés face aux inondations, (iv) évaluer la sensibilité de l'indice de vulnérabilité selon le choix des méthodes de pondération des indicateurs et des définitions conceptuelles de la vulnérabilité fournies par le GIEC en 2007 et 2014. Les données utilisées dans cette thèse proviennent à la fois de sources secondaires et d'enquêtes effectuées auprès des ménages, constituant la base pour l'application de méthodes diversifiées, telles que la modélisation des valeurs extrêmes, la modélisation économétrique, l'analyse basée sur les indicateurs et les tests statistiques. Les résultats mettent en évidence une hétérogénéité spatiale substantielle dans les tendances pluviométriques à travers toute la zone d'étude, avec une prédominance de tendances à la baisse, en particulier pour les indices représentant les pluies extrêmes. Cette observation s'oppose à certaines études nationales et supranationales, qui ont principalement identifié des tendances à la hausse dans les précipitations extrêmes. De plus, les résultats révèlent une forte dépendance spatiale des pluies extrêmes, pouvant atteindre jusqu'à 300 km de distance entre les paires de sites, et cette dépendance diminue progressivement avec l'augmentation de la distance entre les paires de sites. Concernant les risques d'inondation, les résultats révèlent que 12 des 14 villages considérés dans cette étude ont été exposés à des niveaux élevés de risques d'inondation. Les ménages ont expliqué que la gestion des eaux de ruissellement provenant des zones urbaines proches, ainsi que la conception défectueuse des infrastructures de génie civil, notamment les routes et les ponts, sont des facteurs fondamentaux augmentant leur vulnérabilité. De plus, les résultats suggèrent que la perception du risque d'inondation est fortement influencée par des facteurs liés à l'information et au comportement au sein des ménages. L'analyse de la sensibilité de la vulnérabilité face aux différentes méthodes de pondération révèle que l'indice de vulnérabilité est moins sensible aux méthodes de pondération, telles que l'attribution de poids identique aux indicateurs et l'analyse en composantes principales (ACP), employées pour attribuer des poids aux indicateurs. Cependant, lorsqu'il s'agit d'évaluer la vulnérabilité en tenant compte de plusieurs indicateurs, la méthode consistant à attribuer un poids identique à tous les indicateurs se révèle être la plus appropriée. Cette thèse pourrait fournir des informations précieuses aux autorités chargées de la gestion des risques de catastrophes, les aidant à allouer efficacement les ressources, à planifier les budgets et à organiser leurs actions sur le terrain en fonction des priorités des zones concernées.

Mots-clés: Pluies extrêmes, théorie des valeurs extrêmes, vulnérabilité des communautés, risque d'inondation, perception du risque d'inondation, méthode basée sur les indicateurs, modèle logistique ordonné, sud du Burkina Faso.

Introduction

Le Burkina Faso est de plus en plus confronté à des inondations devenues plus fréquentes et intenses, à la suite d'une série de sécheresses et d'épidémies de méningites ayant affecté le pays vers la fin du XXe siècle. Depuis 2000, la fréquence et l'intensité des inondations ont augmenté dans plusieurs localités du pays, touchant toutes les régions du Burkina Faso. Plus de 50% des inondations enregistrées dans la base de données EM-DAT ont eu lieu à partir de 2000 (EM-DAT, 2023). Chaque région a été touchée par au moins une inondation entre 1900 et 2019. Selon Tazen et al. (2019), la fréquence des inondations a augmenté de manière significative pour atteindre cinq occurrences au cours de la période 2006-2016, par rapport aux décennies précédentes (1996-2005 et 1986-1995), affectant des millions de personnes, provoquant des déplacements internes et détruisant ou endommageant les propriétés des personnes. Cette situation devrait prendre de l'ampleur avec le réchauffement climatique déjà en cours. Dans ce contexte, les populations installées à proximité des infrastructures hydrauliques, comme les barrages, ainsi que celles qui s'installent le long des rivières, seront de plus en plus exposées à des risques élevés d'inondations. De même, ceux qui ont des résidences dans des zones difficilement inondables pourraient également être victimes de crues soudaines en raison de l'augmentation de la fréquence des pluies averses. En outre, depuis l'inondation sans précédent de septembre 2009 à Ouagadougou, les études concernant les inondations au Burkina Faso se sont principalement concentrées sur la région du centre, accordant peu d'attention aux autres régions, malgré leur grande vulnérabilité aux inondations. La région des Hauts-Bassins était la seconde la plus vulnérable après la région du centre.

Malgré son grand potentiel économique et agricole, la région soudanaise du Burkina Faso présente des défis importants pour sa population rurale vulnérable et pauvre, largement dépendante de l'agriculture pluviale. Ces communautés ont des capacités limitées pour faire face à la variabilité climatique. En outre, la gestion des risques d'inondation, bien que cruciale, est actuellement dominée par une approche réactive, plutôt que proactive. Alors que, Selon le Cadre de Sendai, tout développement et toute mise en œuvre de stratégies d'adaptation aux catastrophes doivent être basés sur la compréhension complète de toutes les composantes du risque. Ainsi, l'objectif de cette thèse est d'analyser les impacts et les risques associés aux inondations dans la partie sud du Burkina Faso. Spécifiquement, il s'agit de : (i) analyser la fréquence et l'intensité des précipitations extrêmes afin de mieux comprendre les risques associés aux inondations dans les communautés locales, (ii) déterminer les impacts des inondations sur ces communautés, avec un accent particulier sur les zones et les populations à risque d'inondation, (iii) évaluer les risques d'inondation et les facteurs influençant les perceptions de ces risques afin de renforcer la résilience des communautés face aux inondations, (iv) évaluer la sensibilité de l'indice de vulnérabilité selon le choix des méthodes de pondération des indicateurs et des définitions conceptuelles de la vulnérabilité fournies par le GIEC en 2007 et 2014.

Matériels et méthodes

Zone d'étude

La zone d'étude comprend presque entièrement la région soudanaise du Burkina Faso, exactement située entre les latitudes 9° 24' N et 12° 6' N, ainsi que les longitudes 5° 31' W et 0° 40' W. Elle couvre une superficie d'environ 45 526 km², ce qui constitue 16,6% du territoire national. Cette région est celle qui reçoit le plus de pluie au Burkina Faso, avec des précipitations annuelles fluctuant entre 612,8 mm et 1274,9 mm entre 1986 et 2017. Elle dispose d'un réseau hydrographique dense, caractérisé par la présence des fleuves Comoé et Mouhoun, dont les sources se trouvent dans cette zone, et qui se dirigent vers la Côte d'Ivoire et le Ghana. Le long de ces fleuves, plusieurs barrages ont été construits, dont le plus récemment est le barrage de Samandeni. Situé sur le fleuve Mouhoun, ce barrage est le troisième barrage hydroélectrique et agricole du pays. Avec une capacité de réservoir d'eau de 1,5 milliard de m³, il vise à générer environ 18 GWhs par an. En outre, il contribuera à l'irrigation d'environ 21 000 hectares de terres agricoles dans la vallée de Samandeni. Malgré ces ressources, les populations ont des capacités limitées pour répondre aux aléas climatiques qui se multiplient, entraînant des dommages et des pertes dans les cultures et les habitations, ainsi que des pertes humaines.

Données et méthodes

Précipitations les objectifs fixés, différentes données telles que celles concernant les précipitations, les débits, la topographie, les températures des surfaces de l'océan Atlantique, ainsi que les enquêtes auprès des ménages, et des méthodes économétriques et statistiques ont été utilisées. Quant aux données de débit, elles ont été utilisées pour caractériser la zone d'étude. Cette section présente les données et les méthodes employées pour chaque objectif spécifique.

Analyser la fréquence et l'intensité des précipitations extrêmes afin de mieux comprendre les risques associés aux inondations dans les communautés locales.

Les données de précipitations, de températures des surfaces de l'océan Atlantique et de topographiques ont été utilisées pour traiter ce l'objectif. Il est important de noter que les différentes régions de l'Atlantique pourraient avoir des impacts variés sur les précipitations extrêmes. Par conséquent, nous avons décidé de diviser la zone de l'Atlantique en trois sous-régions équivalentes : l'Atlantique Nord (AN), l'Atlantique Moyen (AM) et l'Atlantique Sud (AS). L'Atlantique Nord englobe la région située entre 20° N et 60° N. L'Atlantique Moyen abrite la région située entre 20° N et 20° S, tandis que l'Atlantique Sud couvre la région située entre 20° S et 60° S. Nous avons calculé la moyenne journalière des températures de l' Atlantique à partir de toutes les valeurs de la grille dans chaque sous-région, et cette valeur moyenne est considérée comme une covariable potentielle de la fréquence et de l'intensité des précipitations extrêmes. Analyser les séries chronologiques en météorologie et en hydrologie peut être particulièrement complexe en raison de problèmes liés aux données manquantes. Pour aborder ce défi, la méthode de la distance inverse, parmi d'autres méthodes testées, a été identifiée comme performante pour imputer les valeurs manquantes dans les séries temporelles de précipitations. Après le traitement des valeurs manquantes, les tendances de certains indices de précipitations ont été analysées par stations pluviométriques en utilisant le test de détection de tendance de Mann-Kendall. Une fois l'amplitude de la tendance déterminée, celle-ci est utilisée pour calculer l'amplitude par décennie avant d'être spatialement interpolée sur la zone d'étude en utilisant la méthode spatiale de distance inverse. Pour évaluer l'impact des températures des surfaces de l'océan Atlantique sur la fréquence et l'intensité des précipitations extrêmes, le modèle Peak-Over-Threshold (POT) a été utilisé dans le cadre non stationnaire, avec les paramètres de position et d'échelle dépendants des températures de l'Atlantique Nord (NA), de l'Atlantique Moyen (MA), et de l'Atlantique Sud (SA).

Déterminer les impacts des inondations sur ces communautés, avec un accent particulier sur les zones et les populations à risque d'inondation.

Pour cet objectif, les données utilisées comprennent les maxima mensuels des précipitations journalières et des cinq jours consécutifs de précipitations journalières, qui ont été extraites de la base de données des séries temporelles de précipitations pour les mois de juin à septembre sur la période de 1986 à 2017 ainsi que des données topographiques. Ces données ont été utilisées pour faire la modélisation spatiale des extreme pluvieux en utilisant le modèle Brown-Resnick appartenant à la famille des processus max-stables. Étant donné que les précipitations extrêmes dépendent de la topographie, le test d'AVONA a été utilisé pour identifier la meilleure équation de tendance surfacique à prendre en compte dans les modèles max-stables. Une fois les modèles max-stables estimés, le test relatif au Critère d'Information de Takeuchi (TIC) est utilisé pour sélectionner le modèle max-stable le mieux adapté aux données de précipitations. Le modèle choisi est utilisé pour analyser le degré de dépendance spatiale des extreme pluvieux en utilisant le coefficient extrémal. En août 2003, Sidéradougou a enregistré une pluie extrême de 232,3 mm, ce qui a conduit à l'estimation des niveaux de retour et des probabilités de contagion conditionnellement à cette station pluviométrique. De plus, les risques spatiaux relatifs aux populations et à la zone à risque ont été estimés.

Évaluer les risques d'inondation et les facteurs influençant les perceptions de ces risques afin de renforcer la résilience des communautés face aux inondations

Pour évaluer le niveau de risque d'inondation auquel chaque enquêté est confronté, une collecte de données au niveau ménage a été réalisée sur un échantillon de 376 ménages dans 14 villages des municipalités de Bama, Bobo-Dioulasso, Padéma et Satri. Les risques d'inondation des villages sont calculés en utilisant la méthode des indicateurs. Subséquemment, les cartes des différentes composantes telles que l'aléa, l'exposition, la susceptibilité et la résilience ainsi que de la vulnérabilité et du risque ont été produites. Ensuite, les scores de risques d'inondation calculés sont corrélés avec les risques d'inondation directs perçus par les ménages, et cela est fait en utilisant le test de corrélation Kendall. De plus, nous avons déterminé les facteurs qui influencent la perception du risque d'inondation des ménages en utilisant un modèle logistique ordonné.

Évaluer la sensibilité de l'indice de vulnérabilité selon le choix des méthodes de pondération des indicateurs et des définitions conceptuelles de la vulnérabilité fournies par le GIEC en 2007 et 2014.

Pour atteindre cet objectif, les données collectées lors d'une enquête ménage ont été utilisées pour évaluer la vulnérabilité des ménages aux inondations en utilisant la méthode basée sur les indicateurs. Cette évaluation a été réalisée en utilisant deux méthodes spécifiques pour pondérer les indicateurs de vulnérabilité et en s'appuyant sur deux cadres distincts pour définir la vulnérabilité. En outre, la susceptibilité des ménages à être touchés par des inondations a été évaluée grâce à des indicateurs reflétant les perceptions des ménages sur les dommages et pertes qu'ils ont subis. Les cartes de vulnérabilité ainsi que leurs composantes ont été produites. La sensibilité de l'indice de vulnérabilité par rapport au choix de la méthode de pondération a été évaluée en utilisant les tests de corrélation et Cramer-von Mises.

Résultats et discussion

Analyser la fréquence et l'intensité des précipitations extrêmes afin de mieux comprendre les risques associés aux inondations dans les communautés locales.

Les résultats mettent en évidence une hétérogénéité spatiale dans les tendances pluviométriques à travers toute la zone d'étude, avec une prédominance de tendances à la baisse, en particulier pour les indices représentant les pluies extrêmes. Quant aux indices représentant l'intensité des pluies extrêmes, c'est-à-dire le maximum annuel d'une journée de pluie (RX1day) et le maximum annuel de cinq jours consécutifs de pluies (RX5day), ils présentent une similitude, notamment au niveau de la station pluviométrique de Bobo-Dioulasso, qui montre une tendance à la hausse avec une amplitude de 4.38% pour RX1day et 4.34% pour RX5day par décennie. Cependant, il a été constaté que les indices de fréquence, c'est-à-dire le nombre annuel de jours avec des précipitations supérieures ou égales à 10 mm (R10), à 20 mm (R20) et au 95ème percentile des jours humides (R95p), n'ont présenté de tendances linéaires statistiquement significatives, à l'exception de R95p qui a montré une tendance à la baisse à Bobo-Dioulasso. De manière générale, la distribution spatiale des indices R10 et R20 est moins homogènes, avec certaines régions situées dans la partie nord montrant des tendances significatives à la hausse, tandis que toutes les stations météorologiques affichent des tendances significatives à la baisse pour l'indice R95P. Cela pourrait expliquer la recrudescence des inondations dans la ville de Bobo-Dioulasso et ses environs au cours des deux dernières décennies, mais cela ne peut être généralisé à toute la région soudanaise car d'autres localités ont également enregistré plusieurs inondations au fil des décennies passées, où les tendances dans les indices extrêmes sont à la baisse. De plus, il a été observé que les variations des températures de surface de l'Atlantique Nord ont tendance à avoir un impact plus significatif que les variations des températures de surface dans l'Atlantique Central et Sud. L'augmentation de la fréquence des précipitations extrêmes est multipliée par 3 à 9 lorsque la température de surface de l'Atlantique Nord augmente d'un degré Celsius. Il a été également constaté que l'intensité des précipitations extrêmes est significativement liée aux températures de surface de l'Atlantique Nord, de l'Atlantique Central et de l'Atlantique Sud, bien que le signe de cette corrélation ne soit pas homogène.

Déterminer les impacts des inondations sur ces communautés, avec un accent particulier sur les zones et les populations à risque d'inondation.

Les résultats de la modélisation spatiale des indices RX1day et RX5day révèlent que ces indices extrêmes présentent une forte dépendance spatiale, pouvant atteindre jusqu'à 300 km de distance entre paires de sites, et cette dépendance diminue progressivement avec l'augmentation de la distance entre les paires de sites. Cependant, la probabilité de contagion reste faible, variant de 0.14 à 0.18 pour RX1day et de 0.18 à 0.26 pour RX5day, lorsque les premières pluies extrêmes partent de la localité site de Sideradougou. De plus, peu importe la provenance des pluies extrêmes, le nombre de concurrences de RX1day est estimé entre 4 et 6 sites. De même, le nombre de concurrences de RX5day est estimé entre 5 et 8 sites, quelle que soit la provenance des pluies extrêmes. Il a été constaté que la quantité maximale de pluie tombée en une journée sur plusieurs localités de la zone d'étude pourrait provoquer des inondations graves sur une superficie de 3 km². Cette superficie pourrait augmenter jusqu'à 4,1 km² si les pluies extrêmes persistent pendant cinq jours consécutifs. Bien qu'ils soient potentiellement rares, ces événements entraînent des conséquences socio-économiques importantes, comme ce fut le cas à Ouagadougou en septembre 2009. Nous recommandons d'utiliser l'indice RX5day pour la modélisation des risques associés aux pluies extrêmes, notamment dans le domaine de l'assurance, car sa modélisation permet d'identifier le pire scénario afin de mieux se préparer face aux catastrophes d'inondations.

Évaluer les risques d'inondation et les facteurs influençant les perceptions de ces risques afin de renforcer la résilience des communautés face aux inondations

Les résultats concernant l'évaluation des risques d'inondation révèlent que 12 des 14 villages considérés dans cette étude ont été exposés à des niveaux élevés de risques d'inondation. Les ménages ont expliqué que la gestion des eaux de ruissellement provenant des zones urbaines proches, ainsi que la conception défectueuse des infrastructures de génie civil, notamment les routes et les ponts, sont des facteurs fondamentaux augmentant leur vulnérabilité. Les populations de Banakeledaga, Souroukoudougou et Banahorodougou ont même indiqué que les ruissellements provenant de la ville de Bobo-Dioulasso sont à l'origine de la sédimentation des terres arables par des terrains sablonneux. D'après ces populations, des centaines d'hectares de champs sont devenus inadaptés à la culture des céréales, et pour s'adapter, certaines personnes remplaçaient ces dernières par la culture des bananes. Ceci est confirmé par nos résultats, qui montrent que les ressources naturelles telles que les champs sont très sensibles aux inondations. En ce qui concerne les infrastructures de génie civil, les populations de Santidougou et Kadomba ont mentionné que le niveau de risque dans leurs villages a significativement augmenté après le bitumage de la route reliant les villes de Bobo-Dioulasso et Dédougou. Certains habitants, comme ceux de Nematoulaye, reconnaissent que leur village est situé dans une zone potentiellement inondable et n'excluent pas une rélocation assistée par les autorités. De plus, les résultats ont montré que la perception des ménages du risque d'inondation est fortement influencée par des facteurs liés à l'information et au comportement des chefs de ménages.

Évaluer la sensibilité de l'indice de vulnérabilité selon le choix des méthodes de pondération des indicateurs et des définitions conceptuelles de la vulnérabilité fournies par le GIEC en 2007 et 2014.

Les résultats montrent que la vulnérabilité aux inondations est modérée dans l'ensemble de la zone d'étude, à l'exception du village de Séguéré, où elle est nettement plus élevée. Les éléments clés vulnérables aux inondations englobent des facteurs naturels tels que les terres agricoles, les cultures en plein champ et la végétation. En outre, les biens matériels tels que les installations sanitaires, les sources d'eau, les biens ménagers, les infrastructures physiques et les stocks alimentaires sont également des éléments à risque, contribuant ainsi à l'augmentation de la vulnérabilité des ménages face aux inondations. Cependant, l'accès limité à l'information et la faible capacité des ménages à gérer les inondations ont considérablement augmenté leur vulnérabilité face à ces phénomènes. Ce qui est intéressant par rapport aux capacités d'adaptation des habitants, c'est qu'ils affichent des attitudes très positives envers les mesures actuelles et les attentes futures, et qu'ils ont manifesté des préférences appréciables pour les stratégies d'autoprotection. Ceci suggère également que les stratégies basées sur les ménages pour réduire la vulnérabilité aux inondations pourraient être efficaces pour améliorer la capacité d'adaptation aux inondations à l'avenir. Concernant la sensibilité, les résultats indiquent que la vulnérabilité n'est pas significativement influencée par les méthodes de pondération ACP, ni par l'attribution de poids identique aux divers indicateurs. Cependant, l'indice de vulnérabilité calculé en utilisant la définition du GIEC de 2007 s'est avéré plus sensible aux variations de poids attribués aux indicateurs que celle de la définition GIEC de 2014, car la composante « exposition » de la vulnérabilité est la composante la plus sensible aux variations des poids de indicateurs. Il est donc préférable d'utiliser le cadre conceptuel du GIEC de 2014 pour évaluer la vulnérabilité d'un système, car sa définition de la vulnérabilité ne tient plus compte de « l'exposition » comme une composante de la vulnérabilité, ce qui la rend moins sensible aux variations des poids attribués aux indicateurs.

Conclusion

Cette étude a montré qu'il existe une forte hétérogénéité spatiale dans les tendances des indices représentant les pluies extrêmes dans la zone soudanienne du Burkina Faso. Ces résultats obtenus à un niveau plus micro tendent à contredire certains résultats au niveau national ou régional qui indiquaient que les pluies extrêmes sont devenues beaucoup plus fréquentes et intenses au cours des dernières décennies. Malgré cette hétérogénéité spatiale dans les tendances des pluies extrêmes, les résultats révèlent aussi que les variations des températures de surface de l'Atlantique, surtout dans l'Atlantique Nord, ont tendance à avoir un impact significatif sur les variations de la fréquence et de l'intensité des pluies extrêmes. Concernant le comportement spatial des pluies extrêmes, celles-ci présentent une dépendance spatiale pouvant atteindre jusqu'à 300 km, mais avec une probabilité de contagion relativement faible. La contagion pourrait atteindre entre 4 et 6 localités, voire jusqu'à 8 localités, lorsque les pluies persistent sur cinq jours consécutifs. D’autre part, les résultats de l’analyse des risques d’ inondations dans les villages concernés par l’enquête ménage révèlent que 12 des 14 villages présentaient un niveau de risque élevé. Alors qu’ en se basant sur les ménages qui ont subi des dommages ou des pertes à cause des inondations au cours des derniers décennies, il ressort que le niveau de vulnérabilité aux inondations au niveau village est modéré dans la quasi-totalité des villages. Les éléments naturels, notamment les champs, sont particulièrement les plus vulnérables aux inondations, et une attention particulière doit être accordée aux agriculteurs dans le cadre de la gestion des risques d'inondations.

General Introduction

1.1. Background

Human-induced climate change is already affecting climate system in every region across the globe and the current state of many aspects of the climate system are unprecedented over many centuries to many thousands of years (Masson-Delmotte et al., 2022). Evidence of this changing climate is resulting in an increase in the frequency and intensity of extreme weather and climate events, including heatwaves and extreme rainfall. Globally, it is estimated that human activities have caused global warming of about 1.0°C above pre-industrial levels, with a likely range of 0.8°C to 1.2°C; Global warming is likely to reach 1.5°C between 2030 and 2052 if it continues to increase at the current rate (Masson-Delmotte et al., 2022). Unlike temperature, rainfall trends, including its extremes, are highly heterogeneous across space, from global to local levels. Only in Europe and North America is there certainty of an increasing trend in the frequency and intensity of extreme precipitation, the confidence in extreme rainfall trends is almost medium (Pachauri et al., 2014). Rainfall in Africa show high levels of variability across a range of spatial and temporal scales (Lumbroso, 2020). Increasingly, local studies in West Africa have pointed out that rainfall indices, including indices representing extreme rainfall, show more downward than upward trends (Klassou & Komi, 2021; Larbi et al., 2018). These changing, and variability of climate have become important factors that lead to many environmental disasters in vulnerable communities and ecosystems, with negative consequences on people and their properties.

Among climate-related disasters that have been occurred, floods have been the most common type of natural disaster over the past 20 years, accounting for 47% of all recorded natural disasters and affecting 2.3 billion people worldwide (Suhr & Steinert, 2022). At a global scale, annual flood occurrence showed an increasing trend from 1985 to 2019 (T. Liu et al., 2022). The same authors found that the increasing trend in flood occurrence was due to an increasing trend in floods that affected areas greater than 2.10^4 Km^2, while floods that affected areas less than 2.10^4 Km^2 showed a decreasing, but not significant trend. At continental level, Africa, South America, and Oceania are the nests of floods affecting areas greater than 2.10^4 Km^2, while Europe and North America are dominated by floods affecting areas smaller than 10^5 Km^2 (T. Liu et al., 2022). The number of floods per year increased to an average of 171 during 2005-2014, compared to an annual average of 127 during the previous decade of 1995-2005 (OCHA, 2023). Developing countries, particularly in Africa, South America, and Oceania, are the most vulnerable to flooding because of their limited capacity to cope with these disasters. But these climatic risks are not evenly distributed within populations, the communities, and countries because of the differences in the levels of development but the disadvantages in society are most vulnerable.

African countries in their effort to eradicate poverty within populations and to achieve economic growth with double digits have to cope with frequent and adverse disaster occurrences by the fact that Africa has been the third vulnerable continent after America and Asia. After East Africa, West Africa is a second part of Africa most vulnerable to disasters (Guha-Sapir et al., 2016) where in two last decades, floods have been one of climate extreme events frequently and affected many people in coastal as well as sahelian countries even though some drought spells were occurred in sahelian countries. The weakness of preparedness system associated with bad physical planning and urbanization in majority of West African countries have made to only increase in terms of frequent during last two decades but also the socio-economic and environmental effects and impacts attributed to these flood events have been very enormous. Most often, governments or local communities are not able to take care of disaster victims and so governments are often compelled to call for solidarity support, as was the case of September 1st, 2009, flooding in Burkina Faso. In order to cope with this situation many governments of west Africa work to develop structural and non-structural strategies in order to reduce vulnerability of people, to mitigate negative impacts of floods on environment and increase resilience of people. But many of them are confronted with financial and competence challenges to implement these strategies for a good mastering of flooding. Thus, Burkina Faso like other many West African countries have remained more vulnerable and exposed to disasters including floods in last two decades.

After a series of droughts and epidemics that have affected Burkina Faso towards the end of twentieth century, the country is nowadays confronted with frequent floods that increasingly become intense. Since 2000 flood occurrences have been in increase into be implemented in different communities to frequency and intensity and affecting all regions of Burkina Faso. More than fifty percent (50%) of flood occurrences recorded in EM-DAT data base have occurred since 2000 (EM-DAT, 2023). At least each region was a victim of flooding at least once from the years 1900 to 2019. But Hauts-Bassins is one of regions very vulnerable to flood disasters particularly the western part of Burkina Faso. The effects and impacts of these flood events on people, their economic activities as well as environment have been very considerable. Increasingly, rainy season delays to begin but often starts with extreme rainfalls accompanied of heavy winds that inflict tangible and intangible loss and damage attributed to public and private sectors and leads often to temporary migration within population. Thus, the poorest rural people are a part of population of Burkina Faso most vulnerable to climatic risks among which small crop farmers, women and young people pay the heaviest price (Sedogo, 2007).

Against this background, disaster risk management is an important aspect to consider in fighting against poverty and particular attention should be accorded to it. In order to cope with emergency situation like disasters and human crises, government of Burkina Faso has multiplied structural and non-structural measures. It is in this context that Council for Emergency Relief and Rehabilitation (CONASUR) was created and implemented in Burkina Faso in 2004 in order to adopt strategies for prevention, reduction disastrous effects of disasters and rescue people from disasters and human crises. To this end, institutional framework for the prevention and management of risks, humanitarian crises and disasters was adopted in 2014 as law n° 012-2014/AN. Although there have been varying efforts via contingency plans to reduce the effects of disasters in Burkina Faso, there is still the need to increase the level of proactive actions, including population preparedness, early warning system, and give special attention to flood-related studies to improve vulnerability assessment in order to identify comparatively, resilience measures that are efficient and efficacious as a response to disaster.

While global, regional, and national studies have argued that these existing climate risks, although unevenly distributed across all regions of Burkina Faso, are expected to increase, never types of climate risks are appearing and will affect human and natural system (Pachauri et al., 2014; Panthou et al., 2014a; Ta et al., 2016). The western part of Burkina Faso has been identified as being prone to extreme rainfall that may lead to flooding (Dayamba et al., 2019; B. Sawadogo et al., 2019). These climatic risks cannot be avoided or eradicated, so all stakeholders including researchers, communities and decision-makers have to work together for good preparedness planning so as to increase resilience of population and to improve adaptation capacities of communities.

1.2. Problem statement

The southwestern part of Burkina Faso represents the agriculture catchment of Burkina Faso because of its favourable climatic and land surface characteristics for agriculture known as garnary of Burkina Faso. Agriculture, livestock and forestry activities in Burkina Faso are the main sources of income, employ more than 90% of the working population and contribute about 40% to the Gross Domestic Product (Nana, 2019). In addition to the natural assets of this region, the development of the irrigated lowlands of the Kou Valley since the 1970s, whose irrigated perimeter continues to expand with the commissioning of the Samandeni hydroelectric and agricultural dam, has boosted rice production on a national scale. This has led many people from various parts of Burkina Faso to settle in this region, especially after the great droughts of the 1970s to looking for better conditions of life. The commissioning of the dam has also reduced power outages in the region by increasing the production capacity of the national electricity agency. Thus, all these potentialities contribute to improve the well-being of population by reducing the extreme poverty at local, regional, and national scale.

Despite this economic relevance, its vulnerable and poor rural population, which is largely dependent on rain-fed agriculture, has a limited capacity to respond to climate variability and change (Sultan & Gaetani, 2016). While climate-related disaster events have increasingly intensified and become more frequent in the western part of Burkina Faso, making it the second flood-prone area after the central region of the country. According to Tazen et al. (2019), the occurrence of floods increased dramatically to five occurrences during the period 2006-2016, compared to 1996-2005 and 1986-1995 decades, affecting millions of people, causing internal displacement, and destroying or damaging properties of people. This situation is expected to increase with ongoing global warming. In this context, peoples who live closely to the hydraulic structures like dams and those that settle along rivers would be increasingly exposed to high risks of floods. Even those who live in upstream areas could be victims of flash flood due the increase frequency of rain showers. In addition, since the unprecedented flood of September 2009 in Ouagadougou, studies about floods in Burkina Faso have focused on the central region and little attention was to other regions, although all regions are vulnerable to floods. All of these challenges, combined with poor land use management, constitute a barrier to any hope of sustainable development for the well-being of the population.

1.3. Research questions

Given that the frequency and intensity of flooding are increasing and are expected to be worse in the coming years in the southern Burkina Faso, question is to know how suitable adaptation measures could be implemented in order to increase the resilience of communities whether flood vulnerability and risks analysis remain a challenge to be heightened in these different communities. To this regard, four sub research questions will be in request as part of this work. These questions concern the flood risks, vulnerability, and resilience of communities, and are as follow:

i. What are the frequency and intensity of extreme rainfall with respect to risks to flooding?
ii. What will be the impacts of flood disasters on populations and the aggregated area at-risk in coming years?
iii. What specific factors of resilience are needed in each of the communities for them to cope better with flooding with respect to current flood risk level?
iv. Is the sensitivity of flood vulnerability assessments influenced by the application of different weighting methods under different vulnerability frameworks?

The answers to these questions aim to characterize the flood hazards, have insight on the vulnerability of households and significantly determine influencing factors that could contribute to reduce vulnerabilities of population.

1.4. Aim, hypothesises, and objectives.

1.4.1. Aim of the thesis

This thesis aims to determine factors that could significantly increase the resilience of communities to floods in Southern Burkina Faso.

1.4.2. Hypothesises

Most often, flood disasters occur in several areas at same time in Burkina Faso. It is further observed that most flood disasters occurred at the end of the rainy season. This seems to indicate that:

i. The communities are most vulnerable to flood occurrences at the end of the raining season as compared to its inception.
ii. There is a spatial dependence in flood occurrences in the research area.
iii. The social and economic factors are both significant in increasing resilience of communities.
iv. Flood vulnerability is sensitive to the application of different weighting methods under the old and new IPCC vulnerability framework.

1.4.3. General and specific objectives

The general objective of this research is to analyse the impacts and risks attributed to flood occurrences in southern Burkina Faso. Thus, the specific objectives of the thesis are the following:

i. Analyse frequency and intensity of extreme rainfall for better insight of risks associated with flood disaster occurrences in communities.
ii. Analyse flood-related impacts as much as possible for better awareness and preparedness of flood disaster occurrences.
iii. Analyse flood risk, flood risk perception and its influencing factors for increasing resilience of communities faced with an eventual flooding situation.
iv. Assess flood vulnerability applying different weighting methods under the definitions of IPCC 2007 and 2014 vulnerability frameworks.

1.5. Outline

We have presented this thesis in four main chapters with a general introduction and general conclusion. The general introduction contains background information, problem statement, research questions, hypothesises, and objectives. The first chapter addresses the literature review about extreme rainfall and flood vulnerability and risk assessment. The second chapter presents the study areas, the data used to address each specific objective and methods employed for data analysis. In the third, we discuss the filling of rainfall data, trend analysis in rainfall indices, and the relationship between extreme rainfall and Sea Surface temperature of Atlantic Ocean over the period 1986-2017. In fourth chapter, we address the spatial modelling of extreme rainfall and the spatial risk assessment. Our concern in this chapter is to characterize the spatial diversification of extreme rainfall, estimate the area and population likely to be affected by extreme rainfall that could lead to floods. Chapter five analyses flood risks and the factors that influence household flood risk perception. In chapter six, we address flood vulnerability assessment and analyze the sensitivity of vulnerability index to the variation of weights assigned to indicators under the old and new IPCC vulnerability frameworks. The general conclusion summarizes the whole thesis, gives recommendations for policy, provides limitations and shortcoming of the thesis and ends by perspectives.

Chapter 1: Literature Review

After the severe droughts of the 1970s in the West African Sahel, which led to famines in the region, many individuals migrated internationally, particularly to coastal countries like Côte d'Ivoire and Ghana. Additionally, Burkina Faso has been affected by various biological threats, notably meningitis, resulting in significant casualties and leaving some survivors with disabilities post-recovery. In recent decades, floods have become a common disaster in West African countries, with Burkina Faso experiencing numerous devastating floods that have impacted people, properties, and economic activities. Despite these challenges, the vulnerability and risk levels faced by different rural communities affected by climate-related hazards such as droughts and floods remain poorly understood. This is largely due to the notably low number of studies on climate-related hazards authored by local researchers, compared to other regions worldwide. Against this background, this chapter seeks to conduct a thorough literature review to understand what has been accomplished thus far, identify the challenges encountered, and highlight gaps in the study of extreme rainfall, flood risk assessment, and community vulnerability to floods. By doing so, it becomes possible to identify new avenues of research that could scientifically provide more details about extreme rainfall, flood risk management, and community vulnerability at the local level in Burkina Faso.

1.1. Frequency and Intensity of extreme rainfall

In recent decades, heavy rainfall has been the main driver of numerous flood disasters in the Sahelian countries of West Africa, with enormous consequences for people and their properties (Salack et al., 2018). In Burkina Faso the occurrence of (riverine and flash) floods has increased significantly to five flood events per year during the decade 2006-2016 compared to one event per year in the period 1986-2005 (Sultan & Gaetani, 2016; Tazen et al., 2019). For instance, from June to September 2009, flood events affected 512 031 and killed 22 people in the Sahelian countries of West Africa, including Burkina Faso (OCHA, 2022). During the same year, Burkina Faso experienced unprecedented flooding that affected the city of Ouagadougou and surrounding areas due to extreme rainfall of about 263 mm in just 10 hours (Panthou et al., 2014b), destroying private and public properties. In 2016, nine out of thirteen regions of Burkina Faso suffered from flooding as a result of heavy rainfall, affecting 27 826 people, causing 15 deaths and 35 injuries, while 7 032 people were left homeless (OCHA, 2022). In addition to direct consequences, flood disasters weaken the public health system, making people, particularly children, most vulnerable to water-borne diseases (Olanrewaju et al., 2019). Furthermore, climate and socio-economic changes are expected to lead to future flood risk hotspots in Africa (Alfieri et al., 2017; Merz et al., 2021). Against this background, the analysis of extreme rainfall becomes crucial for water resources management and water-related disaster risk reduction and climate adaptation.

Changes in extreme rainfall in the West African Sahel have attracted significant attention in the last two decades. Studies have pointed out that extreme rainfall has become more frequent and intense in the Central Sahel of West Africa (Ly Mouhamed et al., 2013; Panthou et al., 2014b; Sanogo et al., 2015; Ta et al., 2016). However, these studies were carried out on a national or even supranational scale, using a low density of climate stations, and thus provided large-scale results rather than local information. Such results are not detailed enough to develop risk management and climate adaptation measures at the municipal, household or farmer level (D. Liu & Li, 2016). As trends in rainfall characteristics have been found to vary substantially in space in West African Sahel (Sanogo et al., 2015), small-scale studies are necessary to understand the local changes in extreme rainfall behavior.

Precipitation results from complex atmospheric processes and can be highly variable in space and time. At the same time, it is influenced by regional and global climate conditions. For instance, the state of the El Niño–Southern Oscillation (ENSO) affects precipitation in many regions globally (Dai & Wigley, 2000). If substantial links between global or regional climate conditions and precipitation exist, such links can be used to understand past changes in precipitation, to forecast precipitation for the next season or to project precipitation under climate change (Conticello et al., 2018; Gerlitz et al., 2016; Steinschneider & Lall, 2015; Sun et al., 2014; White et al., 2017). Recently, a number of studies have explored the relation between extreme rainfall in West Africa and climate indices. For Ghana (Atiah et al., 2020) found that several rainfall indices, some of them representing heavy rainfall, were positively correlated with SST anomalies in the Atlantic Ocean and negatively correlated with SST anomalies in the Pacific and Indian Oceans. Further, extreme rainfall over the whole west African Sahel has been found to be mainly teleconnected with the state of the Eastern Mediterranean Sea, whereas extreme rainfall over West Sahel and Central Sahel has been observed to be associated with ENSO and the Madden Julian Oscillation (Diatta et al., 2020). Given these studies that identified climate-precipitation links for West Africa, we explore whether there are substantial relations between SST anomalies and heavy rainfall in our study area.

We focus on the southern part of Burkina Faso, which represents the garnary of Burkina Faso because of its favourable climatic and land surface characteristics for agriculture. Agriculture, livestock and forestery activities in Burkina Faso are the main sources of income, employ more than 90% of the working population and contribute about 40% to the Gross Domestic Product (Nana, 2019). Despite this economic relevance, its vulnerable and poor rural population, which is largely dependent on rain-fed agriculture, has a limited capacity to respond to climate variability and change (Sultan & Gaetani, 2016). Understanding changes in extreme rainfall at the local scale in this part of Burkina Faso is thus important to support local authorities, households, and farmers with more specific information about extreme rainfall variability. To the best of our knowledge, no local study about extreme rainfall has been carried out in southern Burkina Faso. Hence, this study aims to understand past changes in heavy rainfall. To this end, we investigate trends in rainfall characteristics and explore the relation between extreme rainfall and SST in the Atlantic Ocean.

1.2. Spatial modelling of extreme rainfall

Extreme rainfall, identified as the main trigger for floods in the West African Sahel over the past twenty years, has severely hit across multiple spatial and temporal scales in Burkina Faso. This severe weather event has resulted to catastrophic flooding, causing widespread devastation including the displacement of families, depletion of local food reserves, inundation of vast agricultural land, loss of small livestock, degradation of road infrastructure which hinders access to affected areas, and tragically, loss of lives (OCHA, 2005, 2009, 2013, 2016). The occurrence of a single weather event can affect multiple locations simultaneously, underscoring the necessity of comprehensive areal modelling to accurately capture the spatial dependencies inherent in extreme weather phenomena (Dombry et al., 2013; Zhang, Xiao, et al., 2014). This phenomenon is often referred to as compound extremes, characterized by the concurrent occurrence of extreme weather events across multiple locations, such as widespread flooding due to simultaneous heavy rainfall across a broad area (Hao et al., 2018). A notable example of such an event occurred in 2009, when Ouagadougou and its surrounding areas experienced an unprecedented level of extreme rainfall, leading to extensive flooding (Lafore et al., 2017; Miller et al., 2022). Despite their rarity, these events carry substantial socio-economic implications, necessitating precise assessment of their probabilities (Dombry et al., 2018). Against this background, it is vital for both governments and insurance companies to consider the spatial diversification of risk associated with the co-occurrence of extreme precipitation events. In the development of civil engineering structure design, it is crucial to consider spatial dependency as part of extreme precipitation modeling to minimize the impacts of compound flooding on these structures as much as possible. For insurance companies, understanding this spatial diversification is crucial for selecting their operational geographical areas and determining the size of their portfolios (Koch, 2017).

Traditionally, classical statistics of extremes, based on either block maxima or peak-over-threshold approaches, have been widely applied across various domains (Acero et al., 2011, 2014; Börner et al., 2023; Coles, 2001; Diamoutene et al., 2018) for modeling extreme events. The concepts of return level and return period derived from these pointwise approaches offer critical information for risk assessment and decision-making. The simplest way to extend this pointwise approach for analyzing extreme events to a spatial framework involves examining these extreme events individually at each site. Subsequently, a geostatistical method such as inverse distance weighting and similar methods can be used to spatially interpolate the return level or return period across the research area (Acero et al., 2014; B. Sawadogo et al., 2019; Zou et al., 2021).

However, this modelling approach for spatial extremes fails to account for spatial dependence between sites, thereby ignoring substantial impact of geographical features, such topography and other relevant covariables, on the occurrence of climate extremes. Max-stable processes, which extend generalized extreme value distributions to a spatial framework, are particularly well-suited for modelling extreme spatial events. This suitability stems from the fact that these models do not necessitate any further spatial interpolation during the estimation of model parameters. As computational capabilities advance, max-stable models are becoming increasingly prevalent across various disciplines. Ongoing research focuses on max-stable process modelling. Particularly, within meteorology and hydrology, numerous studies have leveraged max-stable models to simulate extreme rainfall events (Blanchet & Creutin, 2017; Davis et al., 2013; Thibaud et al., 2013; Westra & Sisson, 2011; Zheng et al., 2015), extreme temperature (Lee et al., 2013; Ribatet & Sedki, 2013) , streamflow (Albrecher et al., 2020) and wind dust (Ribatet, 2013). Among the families of max-stable processes, the Brown-Resnick max-stable process is commonly utilized for modeling spatial extreme rainfall events (Blanchet et al., 2018; Blanchet & Creutin, 2017).

Despite the strong spatial dependence of extreme rainfall, there has been insufficient attention paid to the occurrence of concurrent extreme rainfall events in the West African Sahel. To the best of our knowledge, only Blanchet et al.(2018) have conducted a regional study addressing the analysis of the co-occurrence of extreme rainfall in the West African Sahel. Our concern in this study is to improve the local understanding of the spatial dynamics governing extreme rainfall in the southern part of Burkina Faso. We specifically intend to explore the co-occurrence patterns of extreme precipitation events by analyzing their spatial organization, particularly focusing on the concept of co-experience within the research area. Understanding these co-occurrence dynamics is crucial for developing effective strategies in spatial risk analysis for extreme rainfall events, thereby facilitating better preparedness and mitigation efforts.

1.3. Rural household flood risk assessment

In the last two decades, floods have become increasingly frequent and intense in West African Sahel countries. Numerous floods have affected the West African Sahel region, making many people homeless, damaging important properties, and destroying farmlands (Li et al., 2016; Schraven et al., 2020; Teye, 2022). In addition to these direct consequences, floods have led to disease outbreaks (Ahern et al., 2005) and caused food security issues (Reed et al., 2022). In Burkina Faso, flood occurrences have increased significantly to five flood events per year during the decade 2006-2016 compared to one event per year in the period 1986-2005 (Tazen et al., 2019). In 2017, floods that were accompanied by strong winds caused the internal displacement of approximately 30,862 people in 12 out of 13 regions of Burkina Faso represented in this study (Teye, 2022). The Haut-Bassins region was the second most flood-affected region in Burkina Faso between 1986 and 2016. During this period, floods affected between 3,493 and 6,776 individuals, including between 619 and 1,300 who were left homeless and between 11 and 15 deaths (Tazen et al., 2019). In 2020, all regions in Burkina Faso were affected by several flood events, destroying properties and farmland in the Haut-Bassins region (IFRC, 2020). Human and economic losses associated with this increased upward trend in flood frequency are expected to increase significantly with global warming (Dottori et al., 2018). Economic damages from climate extremes have been detected in climate-exposed sectors, such as agriculture, forestry, fisheries, energy, and tourism (Howarth & Viner, 2022). Individual livelihoods have been affected through, for example, income, human health, and food security, with adverse effects on gender and social equity (Howarth & Viner, 2022). Against this background, it becomes necessary to pay particular attention to adaptation options, including disaster risk management, as despite progress, adaptation gaps exist across sectors and regions and there is increased evidence of maladaptation in various sectors and regions (Howarth & Viner, 2022).

In many African countries, the number of climate-related research publications authored by local researchers is notably low compared to other regions around the world. Studies conducted by external researchers may be less focused on local priorities due to data availability, disparities in funding, and research leadership (Trisos et al., 2022). Moreover, flood risk assessment is still a challenge in Burkina Faso as flood risk management is concentrated on the emergency response phase rather than on understanding flood characteristics and associated impacts as a basis for sustainable adaptation strategies. In addition, most studies that focused on flood hazards (Bouvier et al., 2018; Coulibaly et al., 2020; De Risi et al., 2018; Tazen et al., 2019b), flood vulnerability (Da et al., 2022; Karambiri et al., 2019), and coping capacity (Schlef et al., 2018) have been performed in Ouagadougou city and surrounding localities, as a direct consequence of the unprecedented flooding in 2009. Other regions have received little attention, despite all regions of Burkina Faso, including the Haut-Bassins, being highly vulnerable to floods (IFRC, 2020). Overall, flood risk assessment remains rudimentary at the national level and authorities and communities mostly select flood adaptation measures without a scientific basis. In contrast, according to the Sendai framework, any development and implementation of disaster adaptation strategies should be based on the understanding of all risk components (UNDRR, 2022).

Flood risk emerges from the interaction of hazard and vulnerability (Merz et al., 2010). This definition of risk was also used to assess the risk of multi-hazard events, including floods and droughts, in West Africa (Asare-Kyei et al., 2017). While there is a common understanding of the term hazard, vulnerability is one of the most ambiguous terms used in disaster risk management. There is currently no consensus on how to conceptualize and operationalize this term (Birkmann, 2006; Birkmann et al., 2013; Merz et al., 2010) and scientists tend to define and frame the term according to their area of expertise (Birkmann et al., 2013). Despite attempts to harmonize these different perspectives, diversity still persists, and it is crucial to specify the framework used in any study. In the context of this study, we adopted the vulnerability frameworks of UNESCO-IHE (Institute of Water Education, Netherlands (Balica & Wright, 2010)) and MOVE (Methods for the Improvement of Vulnerability Assessment in Europe (Birkmann et al., 2013)). Both frameworks describe vulnerability as the result of three components, namely exposure, susceptibility, and resilience (UNESCO-IHE) or lack of resilience (MOVE), respectively.

Fostering effective flood adaptation measures in African countries presents a set of common challenges. Structural measures are largely absent and the existing ones are not well maintained (Ouikotan et al., 2017). Non-structural measures, such as land use planning, early warning, and flood insurance, are impaired by misinterpretations and a lack of coordination among various stakeholders and decision-makers. These challenges hinder the governments and local authorities' ability to adequately support flood-prone communities. To ensure the successful implementation of flood adaptation measures, possible solutions have to be identified and accepted by all stakeholders. There is national as well as municipal governing bodies that are dedicated to disaster prevention and management. Despite this infrastructure, they are reactive instead of proactive. This is largely due to the challenges posed by quantifying flood risk, in particular due to limited data availability and the necessity of expertise in flood disaster management, which makes it difficult for decision-makers to make informed decisions. So far, only the study of (Guelbeogo & Ouedraogo, 2022), which focused on flood susceptibility mapping at the Kou Valley level, was carried out in the study area. However, local studies are crucial for identifying specific needs and implementing actions that consider local conditions, rather than solely relying on regional and national studies. Local studies provide a deeper understanding of flood risks and vulnerabilities associated with the local context, which can inform more targeted and effective disaster risk management strategies.

About three-quarters of the population of Burkina Faso lives in rural areas (INSD, 2023). Previous studies have mainly focused on flood disasters in urban areas of Burkina Faso (Bouvier et al., 2018; Coulibaly et al., 2020; Da et al., 2022; De Risi et al., 2018; Karambiri et al., 2019; Schlef et al., 2018; Tazen et al., 2019). Therefore, it is crucial to conduct studies in rural areas, as they are much more vulnerable to flood disasters due to the weakness of building structures and a lack of sufficient attention to disaster prevention and mitigation (Zhang, Zhang, et al., 2014). Studies conducted in rural areas of China (Zhang, Zhang, et al., 2014; Zhen et al., 2022) on flood risk aimed to guide the layout of rescue and relief goods. Similarly, studies carried out in rural areas of Zimbabwe (Mudavanhu et al., 2020) and in rural communities in the Oti River Basin, West Africa (Komi et al., 2016), addressed flood risk to help determine the level of flooding and identify the main factors contributing to flood risk. Research has been conducted in the context of rural flood risk to contribute to the development of a new comprehensive and systematic methodology for assessing flood risk in Nan Province, Thailand (Tingsanchali & Promping, 2022).

1.4. Household flood risk perception

The Protection Motivation Theory (PMT) is a widely used theory to explain the risk-reducing behaviour of people against natural disasters (Bubeck et al., 2018). PMT has two main components, namely the threat appraisal and coping appraisal, with the threat appraisal also referred to as risk perception (Bubeck et al., 2018). Risk perception can be understood as the risk a person envisages. It depends on the individual's subjective assessment of the risk sources (Rundmo, 1992). It results from how they assess the likelihood of a particular hazard occurring to them and how concerned they are about this hazard and its impacts (Rundmo, 1992). Risk perception is widely used to understand community responses to disaster risk (Rana et al., 2020). According to PMT, a higher risk perception, when combined with a high coping appraisal, may motivate people to take protective actions aimed at reducing their risk (Bubeck et al., 2018), such as by acting on flood early warnings, opting for insurance, undertaking precaution, adaptation or preparedness measures, and complying with emergency protocols (Rana et al., 2020). However, a higher risk perception when accompanied by a low coping appraisal, can lead people to avoid taking protective actions against the risk, which is referred to as fatalism (Bubeck et al., 2018). Many studies have been conducted in the context of flood perception risk elsewhere in different parts of the world (Adelekan & Asiyanbi, 2016; Lechowska, 2022a; D. Liu et al., 2018; Schlef et al., 2018; A. A. Shah et al., 2022; Thistlethwaite et al., 2018; Ullah et al., 2020a; Yaseen et al., 2023; Yin et al., 2021).

Our concern is the Haut-Bassins region, 1 of the 13 regions in Burkina Faso, with substantial potential for agricultural and livestock development. This potential is largely attributed to the abundance of water resources and the position of the region within the climatic zone known for the highest amount of rainfall in Burkina Faso. The plains account for 25% of the country's rice farms, contributing about 46% of the national rice production (Souleymane, 2015). In addition, the Haut-Bassins region accounts for 41% of the national cotton production (Herrera

& Ilboudo, 2012). Despite this economic relevance, the Haut-Bassins is considered as the second flood-prone region in Burkina Faso (Tazen et al., 2019b). Moreover, its rural poor population, heavily reliant on rain-fed agriculture, lacks the capacity to cope with climate variability (Sultan & Gaetani, 2016). To close the knowledge gap about flood risk in this region, this study presents a method that allows the assessment of flood risk from the microscale (household) to larger scales (such as the village scale). The method is particularly beneficial for developing countries where challenges exist due to limited data availability that is required for managing flood risk and vulnerability. This study demonstrates how data collected at the household level provide a comprehensive understanding of flood risk assessment at the village level. We further investigate the relation between flood risk and perceived risk and analyze the factors influencing flood risk perception at the household level. This study presents a framework that could serve as an alternative for monitoring flood vulnerability and risk across different administrative scales in Burkina Faso and other data-scarce regions.

1.5. Flood vulnerability assessment

Floods have inflicted devastating impacts on the lives of populations in West Africa over the past two decades (Wagner et al., 2021). The impacts of floods in the region span across various categories, including damage to buildings, health impacts, loss of livelihoods and income, environmental degradation, displacement, lack of food and drinking water, interruption of social activities, and constrained mobility (Wagner et al., 2022). Since 2000, Burkina Faso has experienced frequent flooding events. The Global Climate Risk Index ranks Burkina Faso as the 112th most climate-hazardous country and 78th in terms of recording the highest losses per unit of Gross Domestic Product in the world between 2000 and 2019 (Eckstein et al., 2021). Approximatively, the frequency of flood occurrences increased from one flood per year between 1986 and 2005 to five floods per year between 2006 and 2016, causing significant socioeconomic and environmental damage (Tazen et al., 2019). The spatiotemporal variability of extreme rainfall is the primary trigger for floods in the West African Sahel, resulting in significant socioeconomic and environmental impacts. Meanwhile, compound climate extremes, such as joint extreme events related to rainfall and wind (Rajeev & Mishra, 2023), or the occurrence of concurrent extreme rainfall events (Dombry et al., 2018), can cause widespread floods with more catastrophic effects on communities and their ecosystems than a single climate extreme event. Additionally, non-climatic factors that have exacerbated the flood problem include the expansion of settlements into flood risk zones and alterations in land use, such as the conversion of extensive forests and other natural areas into agricultural lands or urban developments (Wagner et al., 2022). Against this background, it is crucial to pay more attention to flood vulnerability assessment as flood risk cannot be stopped or completely eliminated (IPCC, 2012). However, flood vulnerability is manageable, indicating that assessing vulnerability may help prevent flood hazards from escalating into disasters.

In recent years, the focus has shifted from hazard control to vulnerability assessments (Mwalwimba et al., 2024), as it is increasingly recognized that natural hazard associated risk and threats to human security cannot be reduced by focusing solely on the hazards (Birkmann et al., 2014). Vulnerability assessment plays a crucial role in disaster risk reduction at both household and community levels. The Sendai Framework for Disaster Risk Reduction and the Sustainable Development Goals (SDGs) have underscored the importance of identifying assessing, and reducing vulnerability of people to hazards (Jamshed et al., 2019). In addition, flood vulnerability assessment provides metrics useful for decision-making processes (Mwalwimba et al., 2024). This type of assessment acts as a proactive measure in pre-hazard management and planning activities (Parvin et al., 2022). Moreover, assessing vulnerability helps in the allocation of resources to mitigate flood impacts and support all stakeholders in prioritizing their actions for flood risk reduction and climate change adaptation. Vulnerability assessments are essential to understand the conditions that either increase or decrease the likelihood that exposed elements will be affected by floods (Moreira et al., 2023). Given the importance of vulnerability assessment for reducing flood risk, it becomes particularly critical for rural areas in developing countries. This is due to the fact that rural areas have typically weak building structures and insufficient attention directed toward disaster prevention and mitigation.

Globally, approximately 3.4 billion of people live in rural areas (IPCC, 2023), and 90% of this population is concentrated in Asia and Africa (Jamshed et al., 2019), where many of them is highly vulnerable to climate change and natural disasters (IPCC, 2023). In Burkina Faso, approximately 75% of population resides in rural areas, where agriculture and livestock activities employ more than 80% of workforce, including residents from both rural and urban areas (INSD, 2023). The agriculture sector contributes over 30% to the country’s economic growth (Traore et al., 2022). The population density has increased over the years from 20.6 to 75.1 people per square kilometre between 1975 and 2019 in Burkina Faso (INSD, 2023). However, in Sub-Saharan countries, people have limited capacity to adapt climate change and to address hazard vulnerabilities (Van Niekerk & Nemakonde, 2017). Despite these challenges, the vulnerability and risk levels faced by different rural social-ecological systems affected by multiple hazards such as droughts and floods, are still poorly understood (Asare-Kyei et al., 2017). In Burkina Faso, very title research has been conducted on assessing flood vulnerability at the national level, and even less so at local level, including the Haut-Bassins region.

The Sahelian catchments studied in West Africa, including Burkina Faso, showed increasing trends in both frequency and magnitude (Nka et al., 2015). Population of Haut-Bassins region has experienced many floods with considerable impacts. Between 1986 and 2016, the Haut-Bassins region accounted for 14.26% of floods that occurred in Burkina Faso, impacting between 3498 and 6776 people, and recording between 11 between 15 deaths (Tazen et al., 2019). Furthermore, these flood events have led to the internal displacement of populations and have adversely impacted hundreds of agricultural lands. It has, therefore, become vital to assess vulnerability in flood-prone rural areas of Haut-Bassins, which may lead to decision-making and action for implementing coping and adaptation capacities measures against floods.

1.6. Theoretical and conceptual framework for vulnerability

The concept of vulnerability is defined differently by scientific from different disciplines. The concept of vulnerability has emerged as a key topic connecting researchers in fields such as sustainable development and poverty reduction, food security and livelihoods, hazard and disaster risk studies, and more recently, in the field of climate change science (Birkmann, 2006). Furthermore, the vulnerability is increasingly employed in healthcare science; however, there is notable heterogeneity in vulnerability definitions, as numerous researchers propose varying perspectives on what constitutes vulnerability (de Groot et al., 2019). This conceptual diversity complicates the comparison of research findings in this field and hinders the application of results from one clinical area to another. Consequently, practitioners across various disciplines employ different definitions, concepts, and frameworks of vulnerability, leading to a variety of methods for its measurement.

Due to the diversity of concepts and interpretations of vulnerability, numerous approaches and frameworks for addressing vulnerability have been developed based on various schools of thought. This study highlights some relevant frameworks in the domains of development and sustainable livelihoods, hazard and disaster risk reduction, and climate change adaptation. In the field of sustainable livelihoods, the vulnerability framework was introduced with the main aim of putting people at the centre of development and reducing poverty (Krantz, 2001). This framework analyses how people establish and sustain their livelihoods, where vulnerability is here partly referring to the hazard. However, this framework primarily focuses positive livelihood outcomes, overlooks the environmental impacts of these outcomes within the context of hazards, and fails to clearly demonstrate the interconvertibility of various forms of capital. Despite its limitations, sustainable livelihood framework has been cross-fertilized and inspired the development of hazard and disaster risk reduction frameworks.

The Turner framework, developed by Turner et al. (2003) within the field of hazard and disaster risk reduction, emphasizes that vulnerability is a consequence of interactions between human and environmental systems. According to this framework, vulnerability is composed of exposure, sensitivity, and resilience. However, the Turner framework remains difficult to be applied empirically, particularly in terms of capturing all cross-scale dynamics (Kloos et al., 2015). The Turner framework also does not establish any relationship with risk, nor does it shows how risk is linked to vulnerability (Damm, 2010). Additionally, the BBC framework is based on early frameworks. Its development is informed by the works of Bogardi, Birkmann and Cardona (Fekete et al., 2010). Vulnerability in this framework is defined as the interaction between exposure and susceptibility elements relative to coping capacities. Despite risk being a part of the BBC framework, the explicit link between risk and vulnerability is not highlighted, and it does not adequately address adaptation considerations. In 2010, Damm reproduced a modified version of the Turner framework, substituting the term resilience with capacities (coping and adaptive) to differentiate it from other resilience-related literature (Damm, 2010). Moreover, the MOVE framework offers a comprehensive approach that integrates concepts of vulnerability, resilience, coping, and adaptive capacities, building upon earlier frameworks like the BBC framework, and also incorporates elements of risk governance (Kloos et al., 2015). MOVE framework is addressed as a function of exposure, susceptibility and lack of resilience. Similarly, in the field of climate change, a concept and associated framework of vulnerability were introduced in the fourth assessment report (AR4) of the Intergovernmental Panel on Climate Change (IPCC, 2007).

In the fourth assessment report of the IPCC, the vulnerability to climate change is addressed as a function of exposure, sensitivity and adaptive capacity (IPCC, 2007). Recently, communities engaged in disaster risk reduction and climate change adaptation have converged on the concepts of vulnerability and risk, establishing a connection between these fields. The newly harmonized framework was developed as part of the Fifth Assessment Report. Unlike the AR4, the fifth assessment report does not consider vulnerability to depend on hazard and exposure. Instead, it views vulnerability as a function of sensitivity and the capacity to cope and adapt, moving away from the previous framework introduced in AR4, which emphasized exposure, sensitivity, and adaptive capacity (IPCC, 2014). Considering the multiple frameworks available for vulnerability assessments, it is crucial to conceptualize and precisely define the framework to be used in any vulnerability assessment.

This chapter demonstrates that few local studies have been conducted regarding the frequency, intensity, and spatial diversification of extreme rainfall in southern Burkina Faso. However, the studies carried out at the national or supranational level, with a low density of rainfall stations, do not provide detailed information at the local level. As far as flood risk and vulnerability assessments are concerned, previous studies have primarily focused on flood disasters in urban areas of Burkina Faso, as a consequence of unprecedented flooding in September 2009 in Ouagadougou and surrounding localities, with little attention paid to other regions, despite their vulnerability to floods. Therefore, there is a need for local studies focused on extreme rainfall, flood risk assessments, and community vulnerabilities to floods, particularly targeting communities that have frequently encountered flooding events. An extensive literature review was conducted on methods such as extreme value modelling, econometric modelling, and indicator-based approaches, which enables the achievement of the objectives.

Chapter 2: Study area, data, and methods

This chapter focuses on presenting the study area, encompassing aspects such as its geographical localization, relief, climate and climate variability, hydrography, vegetation, soil composition, population, and socio-economic activities. To fulfil the research objectives, both primary and secondary data were gathered within the study area. Among the secondary data collected there are rainfall, river discharges, digital elevation data, and sea surface temperatures. The analysis of these data employed a range of techniques, such as data processing, descriptive statistics, statistical tests, indicator-based assessments, and the application of extreme value statistics and econometric modelling frameworks.

2.1. Study area

2.1.1. Localization and relief

The study area (Figure 1) encompasses the southern portion of Burkina Faso, specifically situated between the latitudes of 9° 24' N and 12° 6' N, and longitudes of 5° 31' W and 0° 40' W. This region borders Côte d'Ivoire and Ghana to the south, the Republic of Mali to the west, and is enclosed by several administrative provinces and regions within Burkina Faso to the east and north. These include the Boucle du Mouhoun region, along with the provinces of Ziro and Sanguié in the northern part. Additionally, the eastern boundaries of this study area are defined by the provinces of Boulgou and Zoundwéogo. The geographical extent of this study area spans approximately 45,526 km^2, accounting for 16.6% of territory of Burkina Faso.

Relatively to relief, the elevation varies between 196 meters and 704 meters above sea level, with the highest elevations located in the western part of the study area. In this western region, there are the Sindou Peaks, also referred to as the needles of Sindou. These peaks, characterized by their steepness and high degree of erosion, are sandstone rock formations located in southwest Burkina Faso. They are recognized as the second-highest point in the country, they attract many tourists.

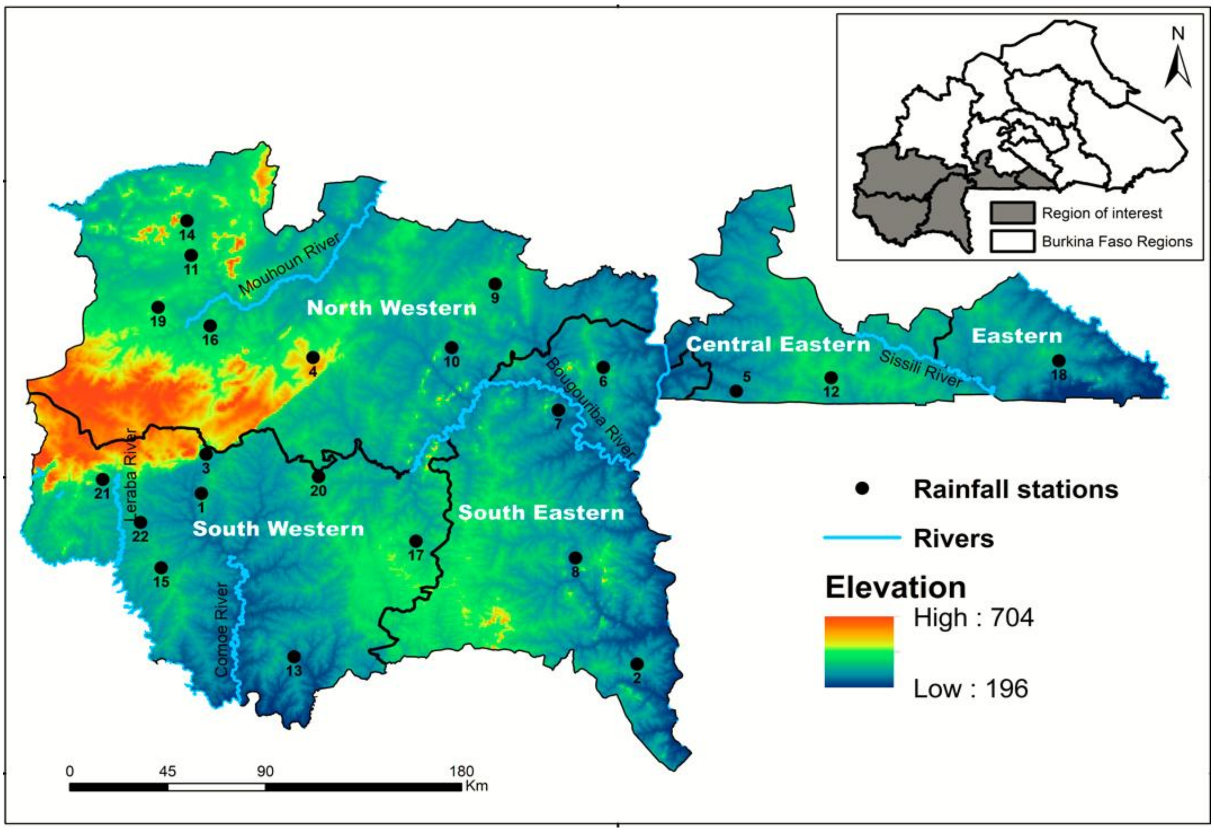


Figure 1: Topography, main rivers and rainfall stations of the study area located in the southern part of Burkina Faso. Eastern, Central Eastern, North Western, South Eastern and South Western are administrative areas of Burkina Faso corresponding to Nahouri, Sissili, Haut-Bassins, Sud-Ouest and Cascades.

In this study the flood vulnerability and risk were focussed on the Haut-Bassins located between the latitudes of 11°23' N and 11°24'N, and the longitudes of 4° 34'W and 4° 35'. It consists of 14 villages distributed across four municipalities in the Haut-Bassins region, which covers an area of 5,235 km^2. In these four municipalities, the altitude ranges from 258 meters to 573 meters, with the highest altitudes found in the district of Bobo-Dioulasso (Figure 2). Consequently, the topography surrounding the city of Bobo-Dioulasso naturally assists in channelling runoff water from heavy rainfall towards areas of lower elevation, thereby exposing neighbouring villages to flooding.

We selected this study area based on three considerations. Firstly, these villages have experienced several floods (Tazen et al., 2019) and have been identified as being susceptible to flooding (Guelbeogo & Ouedraogo, 2022). from the International Disaster Database EM-DAT confirms the occurrence of severe floods in the study area, affecting thousands of people and their livelihoods (EM-DAT, 2022). Secondly, extreme rainfall, the main driver of floods in Sahelian countries, is expected to increase in the future (Dayamba et al., 2019). Thirdly, after the commissioning of the Samandeni dam, the third largest hydroelectric and agricultural dam in the country, some households reported that their farmlands were increasingly flooded. As of the date of the survey used for the basis of our study, some communities close to the dam have not complied with the relocation process and have continued to live in flood-prone areas. This situation places these communities in a position of potentially severe exposure to flooding.

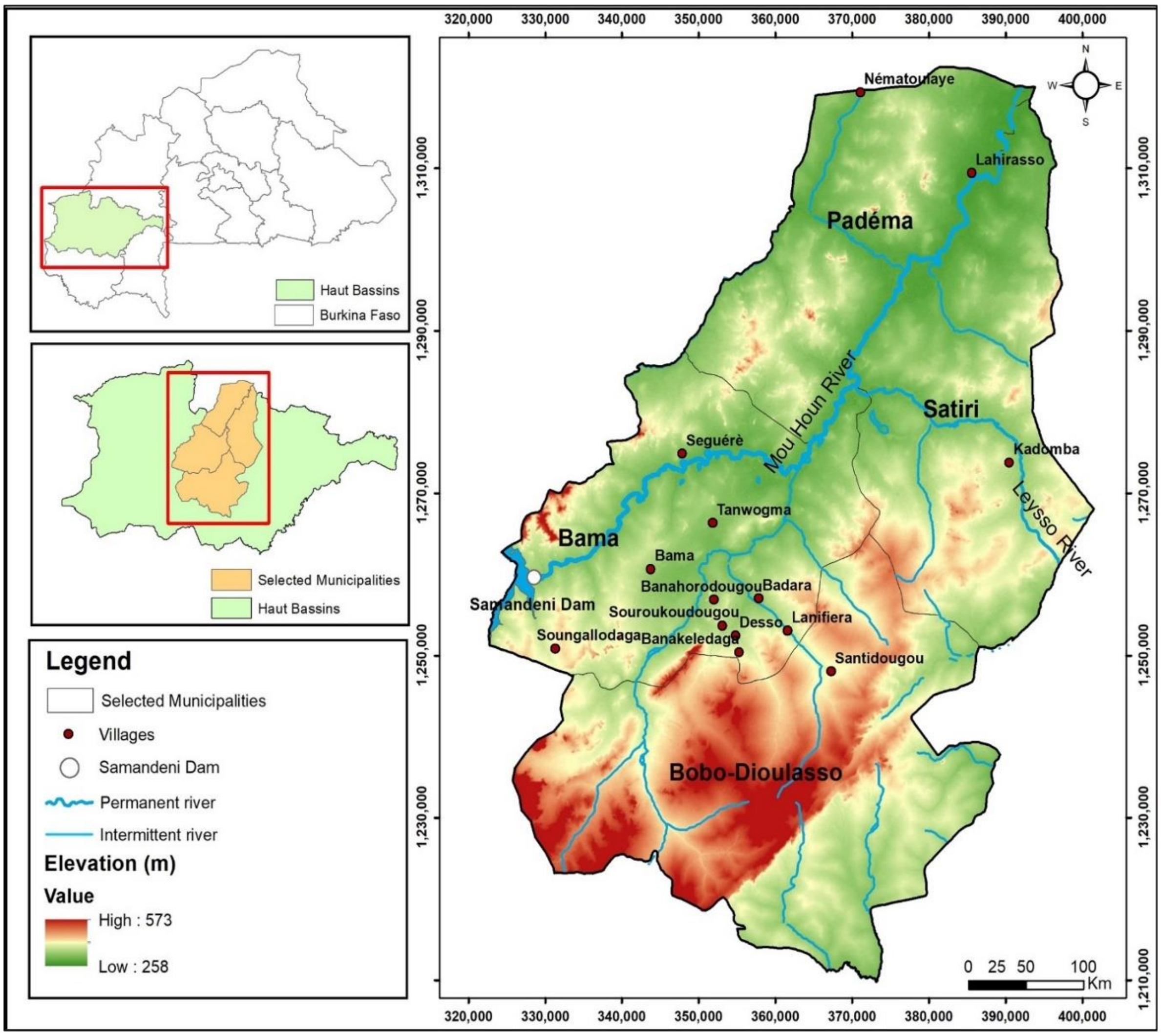


Figure 2: Topography and location of rivers, the Samandeni dam, and the 14 villages where the household survey was conducted in the four municipalities (Bama, Bobo-Dioulasso, Padema, and Satiri) of the Haut-Bassins region. Only villages were surveyed that experienced floods at least once between 2006 and 2020.

2.1.2. Climate and climate variability

In regions with a tropical climate, such as our study area, the climate is characterized by two distinct seasons. The dry season occurs from November to April, while the rainy season takes place from May to October. These seasonal changes lead to varying levels of precipitation throughout the year. On average, the study area receives between 900 and 1200 mm of rain annually. Floods are a common occurrence during the rainy season, particularly in August and September, when heavy rainfall is typical. However, it is important to note that the actual rainfall amounts can vary significantly. From 1986 to 2017, the recorded rainfall in the study area fluctuated, ranging from a low of 612.8 mm to a high of 1274.9 mm annually (Figure 3). Over the study period, the rainfall amounts recorded in May, June, and October varied between 0 and 200 mm. Conversely, in July, August, and September, rainfall increased significantly, averaging approximately between 150- and 500-mm. Regarding rainfall trends, no significant changes were noted in the rainfall patterns occurring in May, June, July, and October over the study area. However, in August, a subtle decrease in rainfall was observed in the regions of Banfora, Bobo-Dioulasso, and Gaoua, contrasting with a notable increase in rainfall in the area of Po. Additionally, Bobo-Dioulasso experienced a considerable rise in rainfall, while the rainfall trends appeared to follow a consistent pattern in September across the study area in Banfora, Gaoua, and Po.

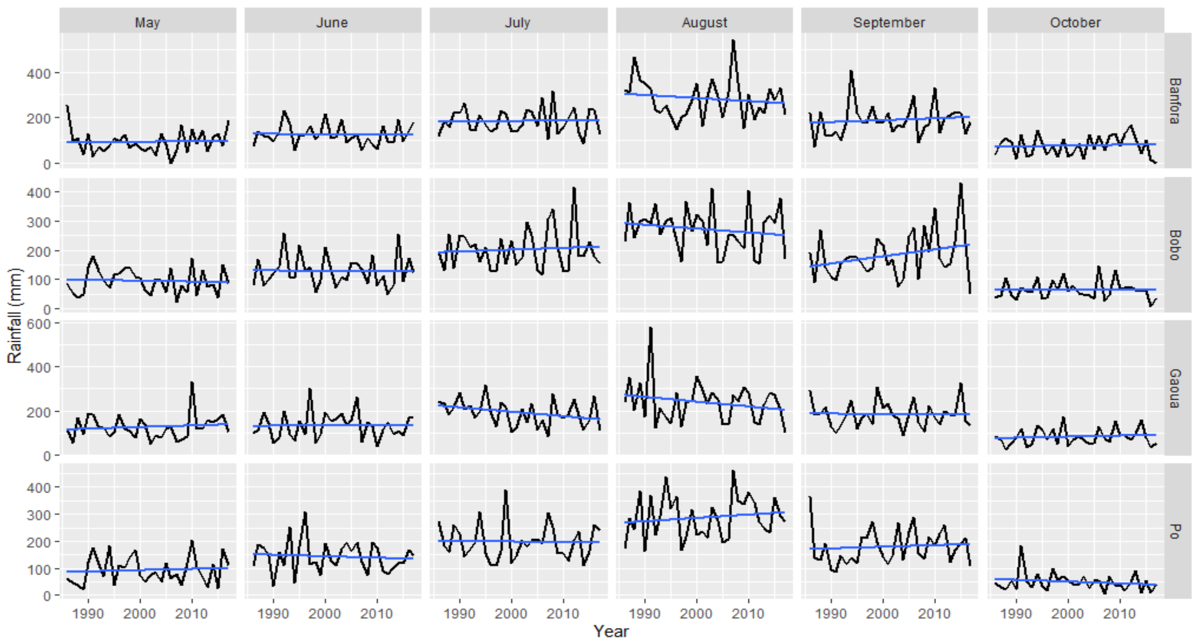


Figure 3: Monthly rainfall variability from 1986 to 2017 at specific stations - stations 1 (Banfora), 4 (Bobo-Dioulasso), 8 (Gaoua), and 18 (Po); Refer to Figure 1 for station locations.

From 1986 to 2001, within the areas of Banfora, the Standard Precipitation Index (SPI) values were consistently negative, indicating that rainfall was below the climatological average. During this period, a moderate drought was observed between 1986 and 1992. Following this, from 1992 until 2001, the rainfall conditions returned to near-normal levels. Starting from 2002, the rainfall began to exceed the normal precipitation levels, maintaining this trend until 2011. The most notable period of wetter-than-normal conditions occurred between 2012 and 2017 in Banfora. This rainfall regime led to a period of hydrological drought between 1986 and 1991, followed by wetter conditions between 2012 and 2017, which increased the risk of frequent flooding. The rainfall regime in Banfora seems to align with the idea that rainfall has transitioned towards a normal regime after the severe droughts of the 1970s in most Sahelian countries. As highlighted by De Longueville et al. (2016), most of the rainfall stations considered in their study have shown signs of rainfall recovery in the recent decade. However, it is crucial to note that the rainfall levels recorded in 2013 were still significantly lower than those before the severe droughts. Despite this recovery, the concept of a full return to pre-drought rainfall patterns remains contested, largely due to the significant geographical variability in rainfall across the West African Sahel (Nicholson et al., 2018).

Unlike in the areas of Banfora, where Standard Precipitation Index (SPI) values were consistently negative from 1986 to 2001 and turned positive between 2002 and 2017, in the study areas of Bobo-Dioulasso, Gaoua, and Po, the SPI values fluctuated, changing from positive to negative and vice versa throughout the study period. In the areas of Bobo-Dioulasso, there were instances of significantly wetter-than-normal rainfall in 1988, 1994, 2006, and 2008. In contrast, the years 1996, 2001, and 2009 experienced moderate dryer-than-normal conditions. Furthermore, in Gaoua, six years were identified as notably wetter than normal, occurring in 1992, 2000, 2010, 2014, 2015, and 2016. Conversely, the years 2002, 2004, 2011, and 2017 were characterized by dryer-than-normal conditions. It is noteworthy that rainfall exceeded normal levels in Gaoua only in 1991 and 1999, while dryer conditions were observed in 2005, 2007, 2011, and 2017. Despite experiencing several floods in recent decades due to intense and frequent extreme rainfall, drought conditions persisted until 2017 in the study area.

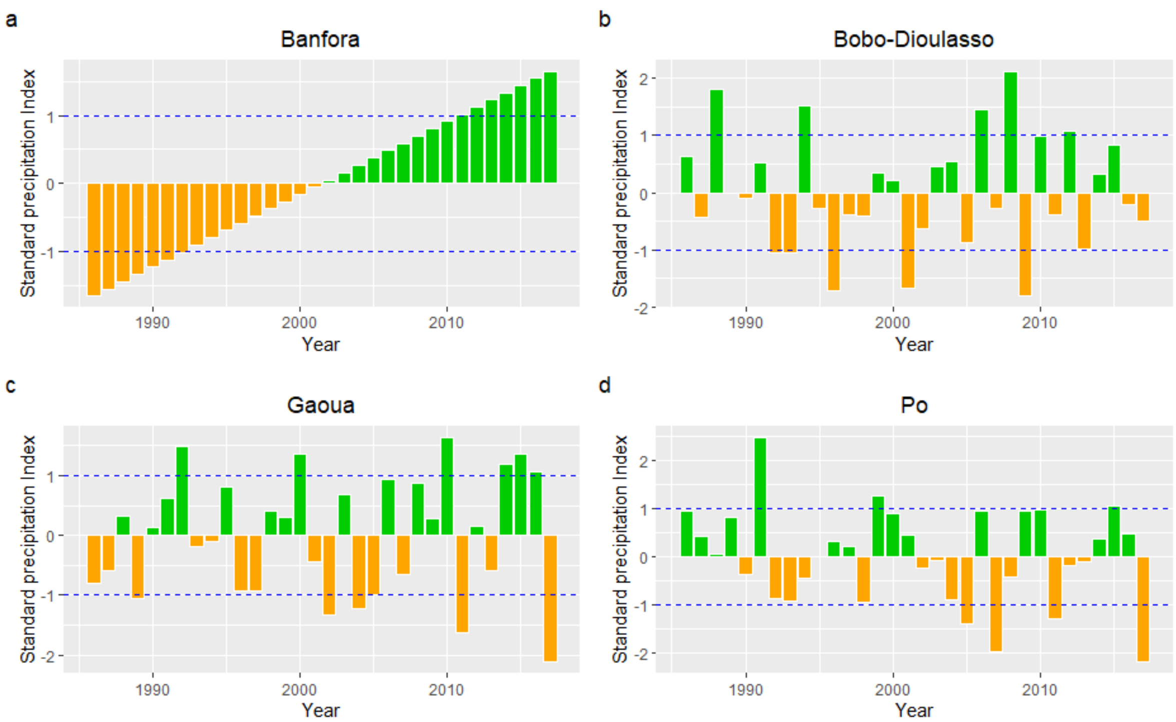


Figure 4: Standard precipitation index for rainfall stations located in Banfora, Bobo-Dioulasso, Gaoua, Po.

In southern Burkina Faso, the average monthly temperature ranges from 19°C to 38°C, with an approximate mean of 27°C. This temperature typically reaches its highest levels during the month of April. Trend analysis over West Africa indicates that the annual mean temperature indices have identified a statistically significant increase of 0.16 °C per decade for mean annual maximum temperature and 0.28 °C per decade for mean annual minimum temperature between 1950 and 2010 (Barry et al., 2018). According to projections under the SSP5–8.5 scenario, Burkina Faso is expected to experience a substantial temperature increase of more than 4.3 °C by the end of the century (W. Sawadogo et al., 2024).

2.1.3. Hydrography

Two primary rivers of Burkina Faso originate within the study area: the Comoé River and the Mouhoun River, also known as the Black Volta. The Comoé River takes its source between in Péni, locality situated between Banfora and Bobo-Dioulasso. It names one of the provinces in the Cascades region. It extends across the entire Côte d'Ivoire from north to south, covering a distance of 813 km, and terminates at the eastern edge of the Ebrié Lagoon in the Côte d'Ivoire. The portion of the Comoe River basin situated in Burkina Faso constitutes 18% of its overall basin, with the majority located in Côte d'Ivoire (Roncoli et al., 2016). Three reservoirs were constructed in the sub-basin of Burkina Faso at Moussodougou, Toussiana, and Lobi, with capacities of 38, 6, and 6 million cubic meters, respectively. However, the capacities of these reservoirs have been significantly diminished due to salinization (Roncoli et al., 2016). The Leraba and Iringou rivers are main tributaries of the Comoé River in Burkina Faso.

The Mouhoun River is the principal river in Burkina Faso, originating from Moussodougou municipality in the Cascades region near Mount Tenakourou, the highest peak in the country. The Mouhoun River flows approximately 1 000 km across Burkina Faso, serves as a border between Burkina Faso and Ghana, and then flows about 354 km as a border between Ghana and Côte d'Ivoire in northwest Ghana before joining the Nakambé River (also known as the White Volta). The Nakambé originates in northern Burkina Faso, and together with the Mouhoun, they form Lake Volta in Ghana, which then terminates its course in the ocean. About 15 tributaries of the Mouhoun River include the Kou, Plandi, Siou, Vouhoun, Sourou, Grand Balé, Bougouriba, Poené, Vranso, Boulkiemdé, Bolo, Sambayou, Kabouti, Bouguiguiri, and Kabarvaso, which serve as water resources to several localities within the Mouhoun Basin. The Samandeni Dam, constructed on the Mouhoun River, is the third hydropower and agricultural dam in Burkina Faso with a water capacity of 1.5 billion cubic meters. The energy capacity of the dam is estimated at 18 GWh annually, and it is expected to irrigate approximately 21 000 hectares of farmland in the Samandeni valley, thereby fostering the development of an agro-industrial growth centre.

Between 1990 and 2020, the annual average discharge of the Mouhoun River at Samandeni was approximately 21m^3/s, with the highest discharge values typically occurring in August. Throughout the study period, there was a wide variation in these highest discharge values, ranging from a minimum of 34.6 m^3/s to a maximum of 326 m^3/s. Most notably, the peak discharge of 326 m^3/s was recorded in August 2003. From 1990 to 2020, the annual average discharge of the Mouhoun River at Samandeni increased by 10.78%, whereas the annual maximum discharge experienced an increase of 5.08%. However, a monthly analysis of discharge provides more detail and highlights the variability in discharge throughout the year. Discharge recorded in December, January, and February showed a significant downward trend, whereas a significant upward trend was observed for April, May, September, and October over the 1990-2020 period (Figure 5). There is no significant trend in the discharge recorded in June, July, and August, which corresponds to the rainiest period in the study area (Figure 5).

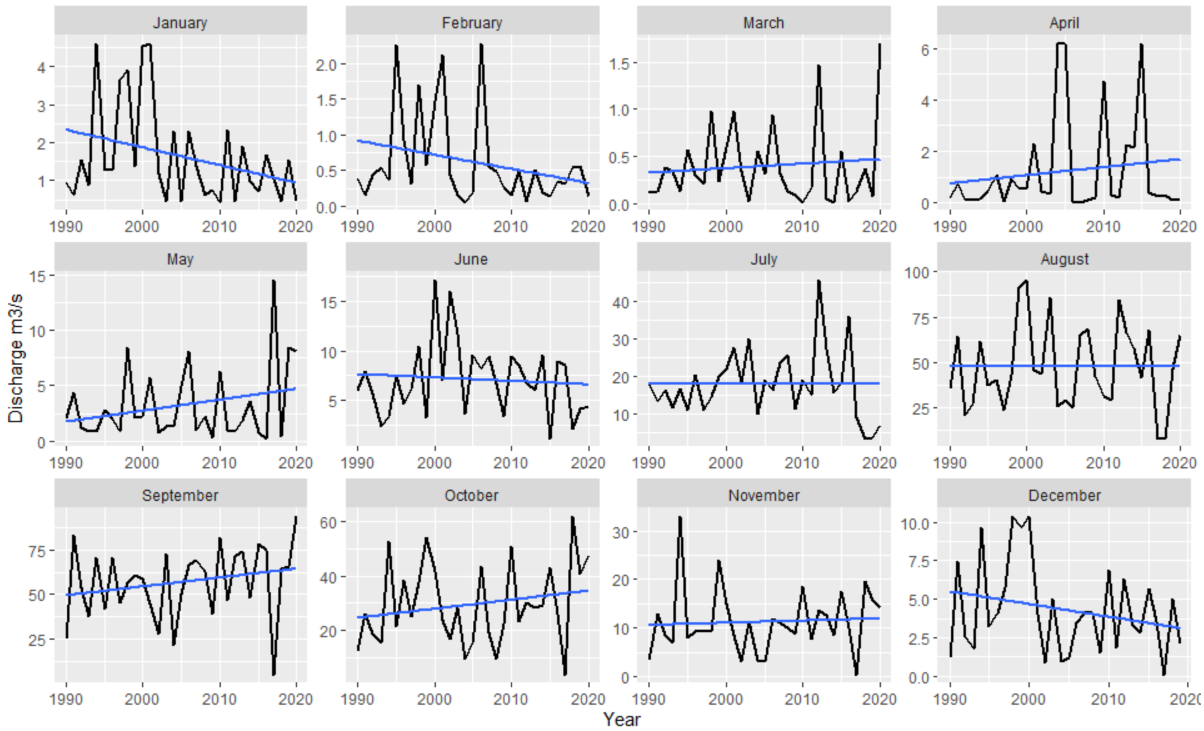


Figure 5: Monthly discharge variability of the Mouhoun river at Samandeni station (1990 – 2020).

2.1.4. Soil and vegetation

In the rainiest regions of Burkina Faso, the vegetation is predominantly characterized by Sudanese savannah, which comprises a mixture of shrubs, trees, and herbs (Idrissou et al., 2022). In the study area, the topsoil in most parts of the country primarily consists of erodible textures, including loam, sand-clay-loam, sandy-loam, clay, and clay loam (Nyamekye et al., 2018). Despite this, soil erosion by both water and wind poses significant challenges for farmers in Burkina Faso (Nyamekye et al., 2018).

2.1.5. Socio-economic conditions and occupation of populations

The population of Burkina Faso in 2019 was 20 505 155, with 51.7% being female. Nationally, the population of Burkina Faso has increased by 2.94% between 2006 and 2019, with an average density of 75.1 inhabitants per square kilometre (INSD, 2023). According to INSD, the population living in the study area in 2019 was estimated at 4 460 642, which represents 21.75% of the total population of Burkina Faso. This region of Burkina Faso is culturally rich, featuring numerous ethnic groups. Among the 11 ethnic groups present in Burkina Faso, predominantly 6 of them inhabit the study area, including the Bobo, Dagara, Gourounsi, Lobi, and Senoufo ethnic groups. Nowadays we have an integration of all the ethnic groups in the southern Burkina Faso due to internal migration and transhumance activities. Specifically, the population in the Hauts-Bassins region has experienced rapid growth since the 1970s, largely driven by internal migration from all regions of Burkina Faso to settle in the Kou Valley, which was developed to boost rice production. Additionally, another factor contributing to the rapid increase in population is the rural-to-urban migration of individuals towards the Bobo-Dioulasso city, which serves as a livelihood strategy. The internal migration rate in Burkina Faso stands at 13.4%. Among these internal movements, intra-province migration accounts for 49.1%, while inter-region migration constitutes 43%. Notably, inter-province mobility makes up just 7.9% of the total internal migration (INSD, 2023).

The results of Burkina Faso's latest general census indicate a predominantly rural economy, with approximately 63% of the population engaged in agriculture, livestock breeding, hunting, and related activities. With its dense hydrological network, the south of Burkina Faso is potentially ideal for agro-pastoral activities. In addition to these natural advantages, an integrated project involving the construction of the hydroelectric and agricultural dam at Samandeni aims to develop over 21 000 hectares of irrigated farmland in the Samandeni valley. This initiative, along with a similar project implemented in the Kou Valley in the 1970s, is designed to encourage agro-pastoral, fishing, and gardening activities during off-rainy periods, thereby contributing towards achieving food self-sufficiency.

Despite these potentialities, the populations have faced challenges related to climate hazards, biological hazards, and various types of conflicts, such as those involving agro-pastoralism, land-related issues, and terrorism attacks since 2016. Between 2006 and 2019, the CONASUR database recorded 48 flood events in the Haut-Bassins region (Figure **6a**), with approximatively 9 floods per year. These events significantly impacted the area, affecting approximately 22 334 individuals (Figure **6b**), leading to 16 injuries and causing 9 fatalities. The consequences of the flooding extended beyond human lives, impacting housing, agricultural lands, livestock, and both food and cash crops. Specifically, these floods caused damage or destruction to 2 604 houses, affected 92.8 hectares of farmland, and led to the loss of 896 animals (Figure **6c**). Furthermore, during this period, approximately 312 076 kilograms of food and cash crop stocks were destroyed due to these flooding incidents (Figure **6c**). Considering the same database, it recorded 662 flood events that had considerable impacts on people and their properties at the national level (Annex **A**).

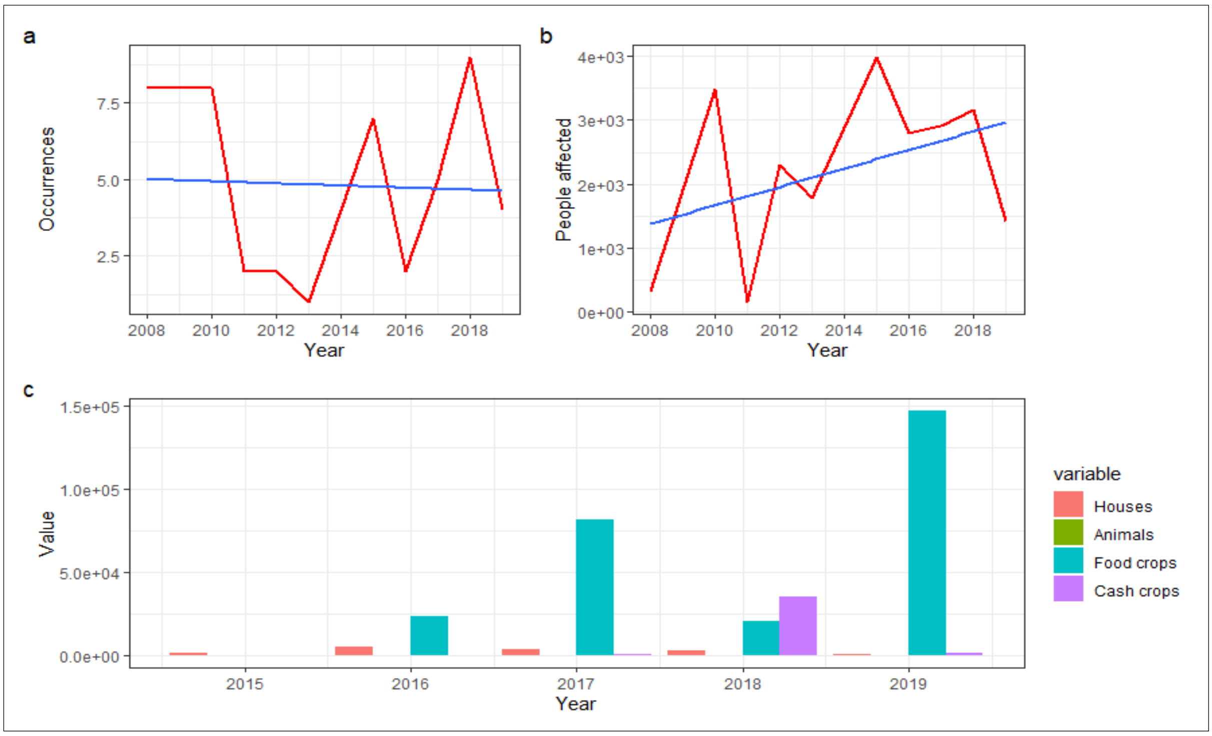


Figure 6: Flooding events and their impacts in the Haut-Bassins region from 2006 to 2019.

In addition to malaria, which is recognized as a significant public health issue, Burkina Faso has been dealing with dengue outbreaks since 2017. These outbreaks have notably intensified between 2022 and 2023, leading to a substantial number of deaths in Bobo-Dioulasso and Ouagadougou. Alongside conflicts between crop farmers and pastoralists and disputes over land, many regions of Burkina Faso have been impacted by armed conflicts related to terrorism since 2016. This has led to approximately 2 million people being displaced internally to other regions, particularly cities that are less affected by terrorism.

2.2. Data acquisition and sampling design

2.2.1. Secondary data acquisition

We use daily rainfall and sea surface temperature data in this study. The rainfall data for the rainy season, recorded between May and October over 32 years (1986-2017), were collected from the National Meteorological Service (ANAM) of Burkina Faso. Access to in-situ rainfall data was granted by a data request to ANAM. We obtained data from 22 stations, distributed rather equally across our study area (Figure **1**). We chose this study period for two main reasons. Firstly, because the rainfall data for the most recent five years are not accessible from ANAM, as the institution involves the quality control of the data before making it available to the public. Consequently, we could not access data beyond 2017. Secondly, we observed that some stations are newly operational, while others exhibit a high rate of missing values over long time series, exceeding 25%, which is not advisable for processing meteorological and hydrological data. Therefore, we selected the period from 1986 to 2017, representing at least a normal period in climatology, during which missing data from various rainfall stations could potentially be filled using imputation methods.

West African Sahel rainfall has been shown to be positively correlated with the Atlantic SST (Dieppois et al., 2015, Atiah et al., 2020), thus being a promising predictor for extreme rainfall in our study area. Atlantic SST data was downloaded from the NOAA National Centers for Environmental Information (NCEI) website (https://www.ncei.noaa.gov/products/avhrr-pathfinder-sst). The data is globally available twice a day (day and night) on a grid of 4 km resolution. We use the daily average of SST between May and October over 1986-2017. Because different regions of the Atlantic could have different links with extreme rainfall, we divide the Atlantic area in three equal subregions (North Atlantic, Middle Atlantic and South Atlantic). The North Atlantic (NA) covers the area between 20° N and 60° N. The Middle Atlantic (MA) is comprised of the region between 20° N and 20° S, and the region from 20° S to 60°S represents the South Atlantic (SA). We calculated the daily average of SST of all grid values within each subregion and use this average as potential predictors for the frequency and intensity of extreme rainfall.

To perform the spatial analysis of the frequency and intensity of rainfall, including extreme rainfall, topographic data was required. The Digital Elevation Model (DEM) was employed to extract topographic data for the study area, specifically, the topography data of the different stations. Firstly, topographic data was collected to be included in the interpolation model for determining the spatial distribution of rainfall, as the rainfall data was primarily analyzed at the site-level and then interpolated over the study area. Secondly, these data were also utilized as covariates for zonal modelling and spatial risk assessment of extreme rainfall.

Water discharges of the Mouhoun River were collected from the General Directorate of Water Resources (DGRE) to describe the study area and analyze flood trends. To gain insights into historical flood occurrences and their impacts within the study area, we gathered historical flood data from the Council for Emergency Relief and Rehabilitation (CONASUR). These historical flood data enabled the analysis of trends in flood occurrences and their impacts from 2006 to 2019, both at the national level and specifically within the Haut-Bassins region.

2.2.2 Identification of flood-prone households, sampling design, and data collection

To identify flood-prone households in the study area, we proceeded in several steps. We firstly selected villages that had experienced flooding between 2006 and 2020. Together with the regional authorities of CONASUR (National Council for Emergency Relief and Rehabilitation, national institution of Burkina Faso in charge of disaster and human crises, http://www.conasur.gov.bf/) in the Haut-Bassins we compiled a list of villages in the four municipalities that had experienced floods based on available historical data. We merged this list with the one obtained by discussing with the general secretaries of municipalities, as it was pointed out that not all past floods were recorded in the CONASUR database. The resulting list was used to select villages that had been flooded at least once in the last five years.

As next step we used Cohran's formula for a finite population (Cochran, 1977; Mondal et al., 2020) to estimate a sample size that ensures the representation of households affected by floods for a desired confidence level. Cohran's formula estimates the adequate sample size (*n*) for a given population *N* as (Mondal et al., 2020), as follows:

$$\mathrm{n} = \frac{(n_0)}{1 + \frac{(n_0 - 1)}{N}} \quad \textbf{(2.1)}$$

With

$$n_0 = \frac{Z^2 pq}{e^2} \quad \textbf{(2.2)}$$

Where Z is the Z value (e.g., Z=1.96 for 95% confidence interval), e is the desired level of precision, i.e., the margin of error, and p is the estimated proportion of the population with the attribute in question. When there is no literature on p and no pilot survey has been conducted to determine its value, p is set to 0.5, which ensures that the sample size is representative of the characteristic of interest for which the study is carried out and q corresponds to the opposite of p (q = 1-p).

Then, a stratified random sampling method was used to proportionally distribute the number of households to be interviewed to each village, according to its population size. All households in each village were considered a homogeneous group in the stratified random sampling process.

To facilitate data collection in the villages, we were assisted by the head of the Village Development Council (CVD) who introduced us to households with the support of the general secretaries of the municipalities and heads of the villages. With the agreement of village residents, the members of the CVD are selected and operate under the supervision of the municipal council to help prepare and implement communal development plans in the village (Burkina Faso, 2004). Members of the CVD are not part of the municipal staff and receive no remuneration or compensation. Despite the help of CVD heads, households in sector 3 of Soungallodaga refused to be interviewed due to their dissatisfaction with the relocation caused by the construction of the Samandeni dam. In addition, five households were not able to be interviewed in Bama due to time constraints that prevented the continuation of the interview. A total of 376 valid and complete questionnaires were collected out of 381 recorded. The survey was conducted between May and June 2021. The questionnaire was addressed to the head of the household proceeding to a face-to-face interview. The aim of the study was explained to the respondent of the household and his or her consent was obtained before interviewing. Respondents were at least 18 years old at the date of the survey.

2.3. Materials and methods

2.3.1. Rainfall missing data imputation

Missing data is one of the major challenges when processing data in climatology and hydrology. About 70% of climate stations obtained from ANAM contained missing data. The percentage of missing data per station ranges between 0.6% and 13.6%. We compare several gap-filling methods (Suhaila et al., 2008), namely the Arithmetic Mean (AM), Inverse Distance Weighting (IDW), Normal Ratio (NR), Geographical Coordinates (GC) and Coefficient of Correlation Weighted (CCW) in order to identify the most appropriate one to fill the rainfall data gaps in the study area. Due to the large number of stations, we evaluate the performance of the different methods for one station and use the best performing method to fill data gaps at all stations with missing data. The Kendall coefficient of correlation (τ) and root mean square error (RMSE) are used to quantify the performance of the candidate methods (Chen & Liu, 2012).

2.3.2. Rainfall trends analysis

Using the gap-filled rainfall time series, we analyze rainfall trends across the study area. To this end, we select eight rainfall indicators that are part of the 27 indices of rainfall and temperature indicators defined and recommended by the Expert Team on Climate Change Detection and Indices (ETCCDI; Sillmann et al., 2013). Our set of indices contains three metrics describing the mean behavior of rainfall and five metrics quantifying extreme rainfall (Table 1). Trends are quantified by Sen's slope and the Mann-Kendall test with a significance level of 5%. Both methods are non-parametric approaches that are widely used for analyzing gradual trends in climatological and hydrological time series (e.g., Hirsch & Slack, 1984; Yue & Pilon, 2004; Blöschl et al., 2019, Sa'adi et al., 2019). To obtain maps of rainfall trends, station trends are spatially interpolated by means of Inverse Distance Weighting (IDW), which is one of the recommanded methods for rainfall interpolation (Chen & Liu, 2012; Yang et al., 2015).

Table 1: Precipitation indices used in this study to characterize (extreme) rainfall behavior.

Index	Name	Unit	Description
R1day	Wet days	Days	Annual number of wet days (day with rainfall ≥ 1mm)
R10	Heavy precipitation days	Days	Annual number of days with rainfall ≥ 10 mm
R20	Very heavy precipitation days	Days	Annual number of days with rainfall ≥ 20 mm
R95p	Very wet days	Days	Annual number of days with rainfall ≥ 95^{th} percentile of the wet days
SDII	Simple daily intensity	mm/day	Mean rainfall on wet days
RX1day	Maximum 1-day precipitation	Mm	Annual maximum 1-day rainfall
RX5day	Maximum 5-day precipitation	Mm	Annual maximum of consecutive 5-days rainfall
PRCPTOT	Total wet-day precipitation	Mm	Annual total from wet days

2.3.3. Nonstationary modelling of the Peaks-Over-Threshold

In order to analyze the influence of the Atlantic SST on the frequency and intensity of extreme rainfall, we apply the Peak-Over-Threshold (POT) approach of Extreme Value Theory within a nonstationary framework (Acero et al., 2011, 2014; Coles, 2001). The POT approach is frequently preferred over the Block Maxima approach as it makes better use of extremes (Coles, 2001). When the threshold u is optimally selected, POT converges toward a Generalized Pareto (GP) distribution:

$$GP(z|\sigma_u(s), \gamma(s)) = 1 - \left(1 - \frac{z\gamma(s)}{\sigma_u(s)}\right)_+^{-1/\gamma(s)} \tag{2.3}$$

where $\sigma_u\ (s)$ and $\gamma(s)(\gamma(s) \neq 0)$ are the scale and shape parameter, respectively, at the site s to be estimated and z is a value of rainfall over the threshold u with z > 0. The shape parameter determines the type of distribution. Negative values of $\gamma(s)$ imply that the distribution GP is bounded, while the distribution GP has no upper bound for $\gamma(s) > 0$. Thus, for positive shape values, the distribution is heavy-tailed (Coles, 2001).

The main challenge of the POT approach is the selection of an optimal threshold that minimizes the bias in the parameter estimation; too high a threshold generates too few excesses leading to high variance, while too low a threshold likely violates the asymptotic basis of the model leading to bias (Coles, 2001). We use graphical methods of threshold stability and mean excess plots to select an optimal threshold. These methods consist of finding an appropriate threshold where the plots are approximately linear. Above the threshold, the excesses tend to form clusters, creating a form of dependency amongst elements of the same cluster, while Extreme Value Theory assumes that the data should be independent and identically distributed. A simple way to handle this dependence of exceedances above the threshold is to decluster them by determining clusters of excesses and replacing them with their maximum (Gilleland & Katz, 2016). The new dataset sampled from the maximum of each cluster is used to estimate the model parameters.

Given an optimal threshold, the excesses over the threshold u converge to the Poisson Process with rate parameter $\lambda(s)$ (Acero et al., 2014; Hamdi et al., 2021; Tramblay et al., 2013). The probability mass function of the Poisson Process is given as:

$$PP[\lambda(s)] = \frac{exp\,(-\lambda(s))\lambda(s)^n}{n!} \quad (2.4)$$

with *n=1, 2..., N*, where $\lambda(s) > 0$ is the rate parameter and N is the number of exceedances of daily rainfall above the threshold u.

The combination of both Poisson and GP distributions is known as the Poisson-GP model, and the probability that the cluster maximum of the Poisson-GP model is less than $z > u$ is expressed as (Smith, 2002):

$$Pr\{max_{1<i<N}\, Y_i \leq z\} = exp\left\{-\lambda(s)\left(1 + \gamma(s)\frac{z-u}{\sigma_u(s)}\right)^{-1/\gamma(s)}\right\} \quad (2.5)$$

where, $\sigma_u(s)$ and $\gamma(s)$ are the scale and shape parameter of the GP model, respectively, and $\lambda(s)$ is the rate parameter of the Poisson distribution. The Poisson-GP model allows to describe the intensity of extreme rainfall via the GP distribution and the frequency of extreme rainfall via the Poisson distribution.

To quantify the influence of the Atlantic SST on extreme rainfall in the study area, we define SST as covariate in the nonstationary POT approach. We thus consider the scale and rate parameters as functions depending on the daily average of SST of the Atlantic Ocean. For both dependencies we use an exponential function, ensuring positive values of these parameters (Coles, 2001) for all SST values. As the estimation of the shape parameter is highly uncertain, it is not recommended to express this parameter as a function depending on covariates in a nonstationary framework (Coles, 2001). The parameters of the nonstationary Poisson-GP model are thus expressed as:

$$\begin{cases} \sigma_u(s,T) = exp\,(\alpha_{0,s} + \alpha_{1,s}T_1 + \alpha_{2,s}T_2 + \alpha_{3,s}T_3) \\ \lambda(s,T) = exp\,(\beta_{0,s} + \beta_{1,s}T_1 + \beta_{2,s}T_2 + \beta_{3,s}T_3) \\ \gamma(s,T) = \gamma_{0,s} \end{cases} \quad (2.6)$$

where, σ_u, γ and λ are the scale, shape and rate parameters, and T_1, T_2 and T_3 denote the average daily SST of the NA, MA and SA. $\alpha_{i,s}$ and $\beta_{i,s}$ ($i = 0,1,2,3$) are parameters to be estimated for site s. The distribution of GP characterized by $\sigma_u(s, T)$ and $\gamma(s, T)$ is used to analyze the intensity of extreme rainfall, and $\lambda(s, T)$ characterizes the Poisson distribution for analyzing the frequency of extreme rainfall. The parameters $\alpha_{i,s}$ and $\beta_{i,s}$ are slopes of $\sigma_u(s, T)$ and $\lambda(s, T)$, respectively, which allow to evaluate the change of extreme rainfall intensity and frequency at each station s under the influence of Atlantic SST.

The likelihood ratio test at the 5% significance level is employed to determine which of the two Poisson-GP models (stationary and nonstationary) is preferred given the sample of extreme rainfall. We use the deviance statistic:

$$D = 2\{l(M) - l(M_0)\} \tag{2.7}$$

where $l(M)$ and $l(M_0)$ are the maximized log-likelihood functions of the nonstationary model M and the stationary model M_0, respectively. The deviance statistic D follows a Chi-square distribution of υ degree of freedom, where υ is the difference in the number of the parameters of M and M_0 (Coles, 2001). The model M_0 is nested within M with the parameters of M_0 being a subset of the parameters of M. In this case, if the P-value of the deviance statistic D is lower than 5%, then the hypothesis that the stationary model M_0 is preferred over the nonstationary model M is rejected. In that case, the nonstationary Poisson-GP model with parameters depending on Atlantic SST fits better the extreme rainfall than the stationary model with constant parameters.

Once the choice between the stationary and nonstationary model is done based on the deviance test, it is necessary to check whether the adopted model fits the data well. Thus, to assess model validity, quantile plot and probability plot are commonly used graphical methods to perform models diagnosis in the univariate framework of extreme value analysis (Coles, 2001). Considering $z_1(s) \leq z_2(s) \leq \cdots \leq z_n(s)$ as an ordered sample of the independent observations used to estimate the selected model, then a probability plot consists of the points

$$\left\{\left(\hat{F}(z_i(s)),\ \frac{i}{1+n}\right),\qquad i = 1,2,\ldots,n\right\} \tag{2.8}$$

and the quantile plot consists of the points

$$\left\{\left(\hat{F}^{-1}\left(\frac{i}{1+n}\right), z_i(s)\right), \qquad i = 1,2,\dots,n\right\} \tag{2.9}$$

where $\hat{F}$ and $\hat{F}^{-1}$ are respectively the estimated GP-Poisson model and its inverse function that was selected based on the deviance test (see eq. 5). Thus, the model is considered to fit the data well when both the probability plot and quantile plot are close to the unit diagonal (Coles, 2001).

2.3.4. Spatial modelling of extreme rainfall

2.3.4.1. Spatial extreme rainfall modelling using a max-stable process

As part of disaster risk management and emergency preparedness, it is thus crucial to estimate the probability that a given return levels of extreme rainfall occur simultaneously at multiple locations in the same season. The easiest way to address this concern within the framework of Extreme Value Theory is to estimate the return level at each station and interpolate them using an appropriate spatial interpolation method (Kriging, splines interpolation, Inverse Distance Weighted, etc.) to from the prediction map of extreme rainfall over the study area. However, this way to address the problem does not consider the spatial correlation between pairwise stations, whereas the precipitation variable has a strong spatial dependence.

To this regard, the univariate Extreme Value Theory was extended to spatial framework including max-stable. A max-stable process is an extent of Generalized Extreme Value Distribution to spatial domain widely used for modelling spatial extremes, as they appear like the pointwise maxima taken over an infinite number of stochastic processes. A stochastic process W is said to be max-stable if there exist continuous normalizing functions $\{a_n > 0\}$ and $\{b_n \epsilon \mathbb{R}\}$ such that (Ribatet, 2013)

$$W(s) = \max_{i=1,2,\dots,n} \frac{W_i(s) - b_n}{a_n}, \tag{2.10}$$

where $W_i(s)$ are independent copies of W(s) at site s of study area. The W(s) process belongs to the family of Generalized Extreme Value distributions named $GEV(\mu(s), \sigma(s), \varepsilon(s))$

$$GEV\big(x,\mu(s),\sigma(s),\varepsilon(s)\big)=\begin{cases} exp\left\{-\left[1+\ \varepsilon\left(\frac{x-\mu(s)}{\sigma(s)}\right)\right]^{-\frac{1}{\varepsilon}}\right\}, & for\ \varepsilon\neq 0 \\ exp\left\{exp\left[\frac{x-\mu(s)}{\sigma(s)}\right]\right\} & ,\ for\ \varepsilon=0 \end{cases} \quad \textbf{(2.11)}$$

where $\mu(s),\sigma(s)$ and $\varepsilon(s)$ are location, scale, and shape parameters at site s respectively. Three families of distributions can be distinguished according to the sign of the shape parameter ε. When shape parameter ε is equal to zero, GEV is said to belong to the Gumbel attraction domain. GEV belongs to the Fréchet attraction domain when the shape parameter is positive. A negative value of the shape parameter indicates that the GEV distribution belongs to the Weibull attraction domain. A max-stable process is an extension of GEV to the spatial framework. A max-stable process can be modelled either by transforming marginal distributions into unit Fréchet or by simultaneously estimating trend surfaces and spatial dependence parameters.

Theoretically, the construction of most max-stable processes is based on the unit Fréchet distribution, but in practice it is difficult to have real data to analyze that obey a unit Fréchet distribution without being transformed. Without loss of generality, it is convenient to transform any marginal distribution of $GEV\big(\mu(s),\sigma(s),\varepsilon(s)\big)$ at site s level to unit Fréchet distribution. Thus, any common GEV variable $W(s)$ can be transformed to unit Fréchet variable using the relation expressed as (Sebille et al., 2017)

$$Q(s)=\left[1+\ \varepsilon(s)\frac{W(s)\ -\ \mu(s)}{\sigma(s)}\right]^{\frac{1}{\varepsilon(s)}} \quad \textbf{(2.12)}$$

such that $W(s)$ is a random variable follows $GEV\big(\mu(s),\sigma(s),\varepsilon(s)\big)$ where $\mu(s),\sigma(s)$ and $\varepsilon(s)$ are location, scale, and shape parameters at site s respectively. $Q(s)$ is a simple max-stable process corresponding to unit Fréchet distribution, $GEV(1,1,1)$.

However, assuming that the marginal distributions of a max-stable process at different sites in a large domain are all Fréchet distributions is not realistic in practice, because for concrete applications, the variation of marginal (pointwise) distributions in space must be taken into consideration (Ribatet, 2013). This spatial variation of marginal distributions can be done by defining trend surfaces for the $GEV(\mu(s), \sigma(s), \varepsilon(s))$ parameters μ, σ and ε (see, Equation **2.11**). Usually, the trend surfaces are a system of $\mu(s), \sigma(s)$ and $\varepsilon(s)$ parameters as function of linear combination of covariables. In this work, we fit the pointwise $GEV(\mu(s), \sigma(s), \varepsilon(s))$ to each station by considering location $\mu(s)$, scale $\sigma(s)$ and shape $\varepsilon(s)$ parameters as function depending on the linear combination of longitude, latitude, and altitude covariables. The trend surface of shape parameter is preferable to be kept constant because its estimation has usually large uncertainties. The trend surfaces are fitted simultaneously with the spatial dependence parameters of the max-stable model. The most accurate and appropriate trend surfaces for extreme precipitation are selected from a few candidate trend surfaces. The selection of appropriate trend surfaces can be done using the Analysis of Variance (ANOVA) test at the 5% significance level. Five candidate trend surfaces are tested to select the appropriate one to model the monthly maximum of daily rainfall (RX1day) and the monthly maximum of consecutive five days rainfall (RX5day).

Table 2: Candidate trend surfaces for spatial precipitation extremes. These trend surfaces should be tested, and the appropriate trend surfaces are selected to transform the rainfall into max-stable process.

Model	**Trend surfaces**	
TRS0	$\sigma(s) = \sigma_0$; $\mu(s) = \mu_0$; $\varepsilon(s) = \varepsilon_0$	
TRS1	$\sigma(s) =$	$\sigma_0 + \sigma_1 \text{long}(s) + \sigma_2 \text{lat}(s) + \sigma_3 \text{alt}(s)$
	$\mu(s) =$	$\mu_0 + \mu_1 \text{long}(s) + \mu_2 \text{lat}(s) + \mu_4 \text{alt}(s)$
	$\varepsilon(s) =$	ε_0
TRS2	$\sigma(s) =$	$\sigma_0 + \sigma_1 \text{long}(s) + \sigma_2 \text{lat}(s) + \sigma_3 \text{alt}(s) + \sigma_4 \text{long}(s) \times \text{alt}(s)$
	$\mu(s) =$	$\mu_0 + \mu_1 \text{long}(s) + \mu_2 \text{lat}(s) + \mu_3 \text{alt}(s) + \mu_4 \text{long}(s) \times \text{alt}(s)$
	$\varepsilon(s) =$	ε_0
TRS3	$\sigma(s) =$	$\sigma_0 + \sigma_1 \text{long}(s) + \sigma_2 \text{lat}(s) + \sigma_3 \text{alt}(s) + \sigma_4 \text{long}(s) \times \text{alt}(s)$
	$\mu(s) =$	$\mu_0 + \mu_1 \text{lat}(s)$
	$\varepsilon(s) =$	ε_0
TRS4	$\sigma(s) =$	$\sigma_0 + \sigma_1 \text{lat}(s)$
	$\mu(s) =$	$\mu_0 + \mu_1 \text{long}(s) + \mu_2 \text{lat}(s) + \mu_3 \text{alt}(s) + \mu_4 \text{long}(s) \times \text{alt}(s)$
	$\varepsilon(s) =$	ε_0

Given the mathematical complexity of handling high dimensions of joint distribution of marginal distributions, the joint distribution is usually limited to two dimensions or bivariate case. when Q is a unit Fréchet distribution with probability function P set of sites $\{s_1, s_2, \dots, s_n\}$ belonging to the study area, the joint cumulative distribution function P of Q at sites is expressed as (Sebille et al., 2017):

$$P\{Q(s_1) \leq q, \dots, Q(s_n) \leq q\} = P\{Q(s_1) \leq q\}^{\theta(s_1,\dots,s_n)} \tag{2.13}$$

Such that $\theta(s_1, \dots, s_n)$ is the extremal coefficient over the study area. The relation between the probability function and the extremal coefficient function at sites s_1 and s_2 is such that:

$$P(Q(s_1) \leq q, Q(s_2) \leq q) = exp\left(-\frac{\theta(h)}{q}\right) \tag{2.14}$$

where $\theta(h)$ is the extremal coefficient and h is the Euclidean distance between s_1 and s_2. In bivariate case, the extremal coefficient takes its value within $1 \leq \theta\ (h) \leq 2$. If $\theta\ (h)$ =1, then the two marginal distributions $Q(s_1)$ and $Q(s_2)$ are completely dependence and they are absolute independence when $\theta\ (h) = 2$.

The pairwise model associated with Brown-Resnick process at sites s_1 and s_2 separated by distance h is expressed as (Sebille et al., 2017):

$$\mathrm{V}_{BR}(Q_1, Q_2) = \frac{1}{Q_1}\phi\left(\sqrt{\frac{\gamma(h)}{2}} + \frac{log(Q_2/Q_1)}{\sqrt{2\gamma(h)}}\right) + \frac{1}{Q_2}\phi\left(\sqrt{\frac{\gamma(h)}{2}} + \frac{log(Q_1/Q_2)}{\sqrt{2\gamma(h)}}\right) \tag{2.15}$$

and its extremal coefficient is given by.

$$\theta_{BR}(h) = 2\phi\left(\sqrt{\frac{\gamma(h)}{2}}\right) \tag{2.16}$$

Such that ϕ denotes the cumulative distribution of a gaussian process, h denotes the Euclidian distance between sites s_1 and s_2 and semivariogram $\gamma(h)$ is given by $\gamma(h) = \left(\frac{h}{\lambda}\right)^{\nu}$. λ and ν are the range and smoothness parameters, respectively. These parameters must be estimated to describe the spatial structure of RX1day and RX5day within the study area. Model diagnosis is performed using quantile-quantile plots. Once the Brown-Resnick model is properly calibrated, it is used to map the return levels associated with the 20, 50, and 100-months return periods.

2.3.4.2. Spatial risk assessment of extreme rainfall

Governments and insurance companies are paying increasing attention to the spatial diversification of natural disasters. There is growing interest in estimating the areas at risk and the people likely to be affected by compounds of a single hazard like extreme rainfall. Against this background, the normalized spatial aggregated loss function was introduced and is expressed as (Koch, 2017; Richards et al., 2022):

$$T_A = \frac{1}{|A|}\int_A Z(s)\, ds \tag{2.17}$$

Where A is the study area and $Z(s)$ is the marginal distribution of monthly RX1day and RX5day at site s. T_A is called normalized spatial aggregated loss of monthly RX1day and RX5day over the study area.

2.3.5. Flood risk assessment

2.3.5.1. Selection of household flood risk indicators

Flood risk analysis aims to quantitatively assess the flood risk (Merz et al., 2010). Typically, it evaluates the components of risk and the capacity to reduce risk and provides risk information to residents, municipalities, governments, and insurance companies (M. A. R. Shah et al., 2018).

We used a composite indicator-based method to estimate the household flood risk. This approach is flexible, transparent, and easy to understand and use by decision-makers (de Brito et al., 2017). Furthermore, it facilities mapping and comparing vulnerability and risk across regions; it enhances communication between the public and policymakers and it helps assess any progress achieved (Damm, 2010). It also facilitates monitoring and evaluation of flood risk, as well as the appropriate allocation of resources for risk reduction (Mondal et al., 2020).

A challenge of the indicator-based assessment is the selection of a minimum number of proper indicators to characterize the vulnerability of the system under study. We based our selection on earlier studies and used indicators that were shown to be informative for assessing household risk (Appendix **F** and Table **3**). In addition, we chose the indicators in such a way that multicollinearity was avoided (Hamidi et al., 2020). Based on this deductive approach, we selected indicators for the hazard, exposure, susceptibility, and resilience components of household flood risk.

Table 3: Indicators selected for assessing household flood risk, based on (Hamidi et al., 2020; Jamshed et al., 2017; Mondal et al., 2020; Rana & Routray, 2016)

Components and Subcomponents	**Indicator Name**	**Description**
Hazard		
Flood frequency	FF	Past flood events show that the area is flood-prone, and higher frequency of flooding implies higher risk.
Flood intensity	FI	Higher flood depth results in higher damages.
Exposure		
Local exposure	LE	Elevation and proximity to the river increase the household exposure.
Human exposure	HE	Family members injured or affected by communicable diseases by previous flooding implies that the household is exposed.
Assets exposure	AE	Damage to the house, loss of household goods, inundation of agricultural land and crops from previous floods indicates household exposure.
Susceptibility		
Socio-demographic factors	SD	Households with female or yound heads, dependent members (children and elders), women, low literacy or large household size are more vulnerable to flooding.
Health conditions	HC	Households with special needs have limited mobility in case of emergency; longer distance to health centre increases vulnerability.
Economic condition	EC	Households with low or unstable income, or households, which have taken loans and do not have access to financial institutions, are more vulnerable and recover worse from flooding.

Housing and amenities	HA	Earthen and wood houses, elderly houses, households without access to drinking water, sanitary toilet, tubewell and electricity are more vulnerable to floods.
Land ownership	LO	As households are mostly farmers, agricultural land supports the recovery process. Households living on rented land have fewer options or less willingness to fortify their house, thus increase vulnerability.
Natural resources degradation	LRD	Farmland degradation affects crop cultivation and productivity, and degradation of water quality affects human and crop health.
Resilience		
Knowledge	KN	Better knowledge of disaster risk and understanding of flood warnings increase the awareness and preparedness of households in case of flooding.
Emergency preparedness	EP	Households that have saved crops or other savings, households with portable, or households that have undertaken emergency planning, savings are better prepared and more capable of coping with floods.
Access to information	IN	Households that possess phones, TV sets, radios or transportation means, and households, that received an early warning the last time a flood occurred, are more aware and better able to receive early warning flood information and to respond during evacuation and recovery.
Mitigation measures	MM	Households, that have taken mitigation measures after the last flood, are better aware of flooding.
Livelihood diversification	LD	Households with members employed outside the community, multiple-earning members, non-agriculture income, and livestock tend to less be affected by flooding. Households that were able to recover from the last flood using their own resources are considered more capable to cope with flooding.
Social network	SN	Good cooperation from neighbors/the community helps household scope with floods. Households living in their community for a longer time will be aware of evacuation routes and the geography of their locality
Insurance	INS	Insurance increases the capacity to recover from flooding.
Land use adaptation	LUA	Afforestation and vegetation also increase over time to reduce the flow of flood water, but their use has remained limited. Also, cropping patterns may alter in

		response to pass flood events, which practices reduce household vulnerability to flooding.
Attitude	ATT	Households that perceive flooding as likely, and households that believe that flooding is God's will, tend to be less prepared for future floods. Households that tend to agree with government policies are inclined to follow flood initiatives, increasing their resilience.

2.3.5.2. Development of flood risk index

An indicator can be a single variable or a complex aggregate measure describing a system or process (Damm, 2010). Indicators can be formed from both quantitative and qualitative variables. In this study, most indicators were constructed from qualitative variables ranging from two to six classes. Data was gathered at the household level, but the indicators, the risk index and its components were calculated at the village level (Figure **7**).

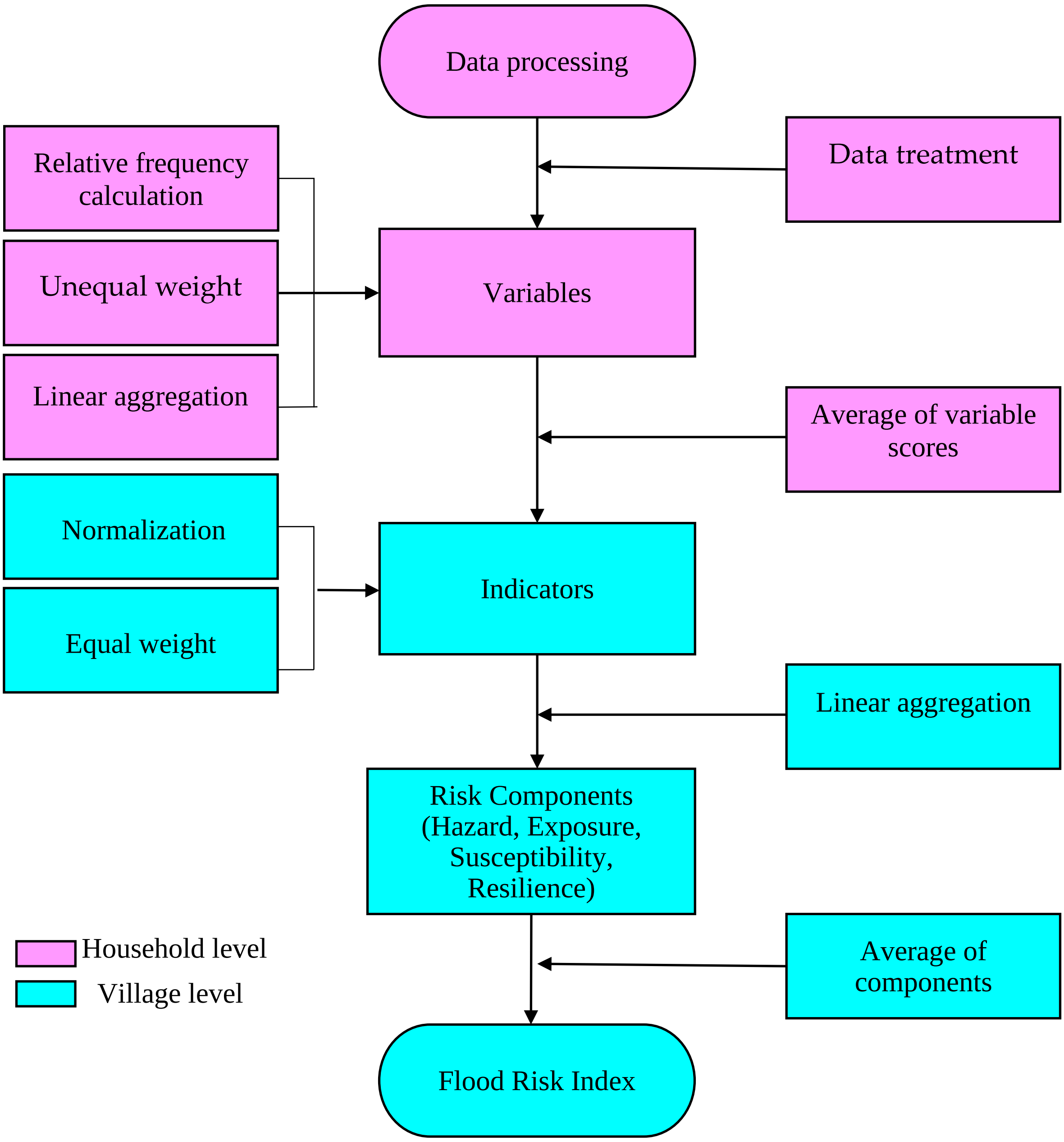


Figure 7: Flowchart of how the flood risk index at the village level was calculated from variables collected at the household level.

The first step involved processing the data to exclude incomplete questionnaires. Subsequently, we calculated the relative frequency of the variables used as input to the indicators at the village level. Variables were categorized into different classes, ranging from two (for instance, binary variables such as Yes or No) to six, based on their characteristics relating to household vulnerability to floods. We assigned unequal weights to each class of variables, depending on their vulnerability level. A value of one was assigned to the most vulnerable classes, while the value zero was assigned to the least vulnerable classes. For binary responses, the weights are zero (Yes) or one (No). For variables with three classes, the weights were assigned as 0.33, 0.67, and 1. Similarly, we assigned weights for variables with a higher number of classes. For instance, for variables with five classes, the weights are 0.2, 0.4, 0.6, 0.8, and 1 (Rana & Routray, 2018). Then, a linear aggregation was employed to combine all classes of variables into a single score. This linear aggregation can be expressed as follows:

$$V = \sum_{j=1}^{n} w_i K_i \tag{2.18}$$

where w_j represents the weight assigned to class j of the variable and K_j corresponds to the relative frequency of class j of the variable. *V* is the score of the variable, n is the number of classes for the variable, and the value score of each indicator is the arithmetic average of *V* for the variables that make up the indicator. The indicator score is expressed as

$$\mathrm{X} = \frac{1}{m}(V_1 + V_2 + \cdots + V_m) \tag{2.19}$$

Where *X* represents the indicator score and *m* denotes the number of variables included in the indicator. After constructing the indicators, they were normalized to a range of 0-1. This normalization process is essential because the indicators are measured in different units and on different scales. The normalization is expressed as

$$\mathrm{XN} = \frac{(\mathrm{X} - min(\mathrm{X}))}{max(\mathrm{X}) - min(X)} \tag{2.20}$$

where *X* refers to the original indicator and *XN* is the normalized indicator. After normalization, we applied the equal weighting method to assign weights to the indicators. The equal weighting method is straightforward, easy to reproduce, and eliminates any potential for subjective interpretation (Damm, 2010; Nazeer & Bork, 2021).

After weighing the indicators, four composite indicators representing the hazard, exposure, susceptibility, and resilience components were calculated using the arithmetic average as a linear aggregation method. Following this, the Flood Risk Index (*FRI*) (Maskrey, 1989; Mondal et al., 2020) and Flood Vulnerability Index (*FVI)* (Nazeer & Bork, 2021) were computed, as follows:

$$FRI = \frac{1}{4}\big(H + E + S + (1 - R)\big)\,, \tag{2.21}$$

and

$$FVI = \frac{1}{3}\big(E + S + (1 - R)\big) \tag{2.22}$$

Where *H, E, S*, and R denote the hazard, exposure, susceptibility, and resilience component, respectively. The term "1 - *R*" indicates "lack of Resilience". To represent the risk and the risk components of a certain village verbally, we transformed the numeric values, which range from 0 to 1, according to Table **4** (Mudavanhu et al., 2020).

Table 4: Transformation of numeric values of risk and its components (hazard, exposure, susceptibility, lack of resilience, and vulnerability) to five semi-quantitative levels from 'very low' to 'very high'.

Risk and its components	**Levels of measurement**				
	1-0.8	0.8-0.6	0.6-0.4	0.4-0.2	0.2-0
	Very high	High	Moderate	Low	Very low

2.3.5.3. Risk perception and flood risk perception index

Managing and communicating flood risks necessitates a strong understanding of how people perceive risk (A. A. Shah et al., 2022). Therefore, examining flood risk perception has become crucial for implementing effective measures against flood disasters.

Unlike the risk index, which was estimated using the indicator-based method, risk perception was collected directly during the survey. We asked the respondents how they assessed the risk of flooding in their household by assigning their risk to either "Not at all", "very low", "low", "medium", "high", or "very high". After processing the data, we observed that all the households surveyed perceived their flood risk level as either "medium", "high", or "very high". To enable comparisons at the village level between the flood risk estimated from indicators and the flood risk perception directly rated by households, we employed the flood risk perception index (D. Liu et al., 2018, 2022). This index was introduced to evaluate the flood risk perception of rural households in China, using four indicators: likelihood, fear, impact, and awareness (D. Liu et al., 2018, 2022). Researchers (Rana et al., 2020; Ullah et al., 2020b) in Pakistan have developed a flood risk perception index using more than four indicators. Hence, there is no consensus on how flood risk perception should be represented by an index.

In this study, the flood risk perception index at the village level was constructed directly using the single flood risk perception variable. The households rated the perception variable. The flood risk perception index was constructed in two steps. We first transformed the classes "medium", "high", and "very high" of the flood risk perception variable to 0.6, 0.8, and 1. Then, the Flood Risk Perception Index (FRPI) was calculated for each village, as follows:

$$FRPI = \frac{1}{n}\sum_{i=1}^{n} S_i \qquad \textbf{(2.23)}$$

where S_i corresponds to the different flood risk perceptions (0.6, 0.8, or 1.0) of the households and n denotes the number of households being interviewed in each village.

2.3.5.4. Determinants of household perception of flood risk

Flood risk perception varies between individuals and between communities (Rana et al., 2020). (Lechowska, 2018). The contextual factors include culture, history, government policy, religion, trust in government, and public protection measures (Lechowska, 2018).

To identify the determinants of the household flood risk perception, an ordered logistic model was used. The model establishes a relationship between the flood risk perception y, corresponding to one of the three states "medium", "high", or "very high", and the influencing factors. The model parameters were estimated applying the maximum likelihood statistic. The unobservable variable y^* is the latent variable corresponding to the dependent variable y, X is the set of influencing factors, β is the corresponding vector of parameters to be estimated, and ϵ is the term error of the logistic distribution:

$$y^* = \beta X + \epsilon \qquad \textbf{(2.24)}$$

Considering the critical values $\alpha_1 \leq \alpha_2 \leq \alpha_3$ to be estimated, the relationship between y^* and y depends on whether y^* is greater or smaller than the given critical value, that is, if $y^* \leq \alpha_1$, risk perception is low (y=1); if $\alpha_1 \leq y^* \leq \alpha_2$, risk perception is medium (y=2); and if $y^* > \alpha_2$, risk perception is high (y=3). The response probability of the dependent variable is given by (Ma et al., 2020), as follows:

$$\begin{cases} P(y=1) = P(y^* \leq \alpha_1) = P(\beta X + \epsilon \leq \alpha_1) = \Phi(\alpha_1 - \beta X) \\ P(y=2) = P(\alpha_1 < y^* \leq \alpha_2) = \Phi(\alpha_2 - \beta X) - \Phi(\alpha_1 - \beta X) \\ P(y=3) = P(y^* > \alpha_2) = 1 - \Phi(\alpha_3 - \beta X) \end{cases} \quad \textbf{(2.25)}$$

To ensure a good model fit and to test whether the model is meaningful, we applied the likelihood ratio test, which is a hypothesis test used to choose the best model out of several nested models (The Pennsylvania State University, n.d.). The multicollinearity test was also performed to avoid a high intercorrelation amongst the covariables. Finally, the Wald test was applied to determine the significance of individual regression coefficients (The Pennsylvania State University, n.d.), i.e., to access whether an independent variable has a significant effect on flood risk perception. We assumed a threshold of 0.1, i.e., variables with a probability lower than 0.1 are assumed to significantly influence risk perception.

Unlike the linear regression model, the interpretation of coefficients from a logistic regression is not straightforward because the coefficients cannot directly be used to quantify the relative effect or impact of the covariables on the dependent variable. Instead, the sign of the coefficients is used to evaluate whether the covariables impact negatively or positively the dependent variable. Thus, we used the odds ratio (*OR*) and the elasticity to quantify the effect of the covariables. An *Odds* is defined as the probability of an event occurring divided by the probability of that event not occurring:

$$Odds = \frac{P}{1-P} \quad \textbf{(2.26)}$$

Where P denotes the probability of an event to occur. The *OR* is defined as the ratio of two *Odds* values. In the logistic regression, the *OR* of a covariable X_i can be calculated as follows:

$$OR = \exp(\beta_i) \quad \textbf{(2.27)}$$

Here, β_i is the coefficient associated with X_i. When X_i is a categorial variable with m categories (from $X_{i,1}$ to $X_{i,m}$), assuming all other covariables remain constant, the OR compares the odds of an event occurring for each subsequent category (from X_{i+2} to X_{i+m}) relative to reference category $X_{i,1}$. A value of *OR* > 1 implies that the odds of the dependent variable occurring, given a unit increase in the independent X_i, are multiplied by the value of the *OR*. An *OR* smaller than 1 indicates that the odds of the dependent variable occurring, given a unit increase in the independent variable X_i , are reduced by the value of the *OR* (Ma et al., 2020).

In addition to the *OR*, we employed pseudo-elasticity to measure the impact of changes in independent variables on flood risk perception. For discrete variables, pseudo-elasticity $E_{X_{nk}}^{P_{nk}}$ is defined as (Kim et al., 2013; Ma et al., 2020; Ulfarsson & Mannering, 2004):

$$E_{X_{nk}}^{P_{nk}} = \frac{P[given\ X_{nk} = 1] - P[given\ X_{nk} = 0]}{P[given\ X_{nk} = 0]} \qquad (2.28)$$

Here, the pseudo-elasticity value $E_{X_{nk}}^{P_{nk}}$ represents the percentage change in the probability P_{nk} of flood risk perception of the nth household for the kth independent variable, from vector X of independent variables. The pseudo-elasticity is computed for each household individually. To estimate the pseudo-elasticity for all households, the average pseudo-elasticity is calculated (Kim et al., 2013).

2.3.6. Vulnerability assessment and sensitivity to weighting methods under different conceptualization of the vulnerability.

2.3.6.1. Vulnerability frameworks

The vulnerability assessment in this study integrates both the frameworks of the IPCC 2007 and IPCC 2014. The IPCC 2014 report introduced vulnerability as a pre-existing characteristic property of a system. Accordingly, vulnerability is addressed as a function of susceptibility and adaptive capacity, both of which are considered internal properties of a system. Comparatively, the IPCC 2007 report includes exposure, an external factor, as the third component of vulnerability. Contextually, susceptibility considered here refers to as damage or loss caused by floods to household assets. A comparative analysis of the vulnerability indices derived from both frameworks is performed.

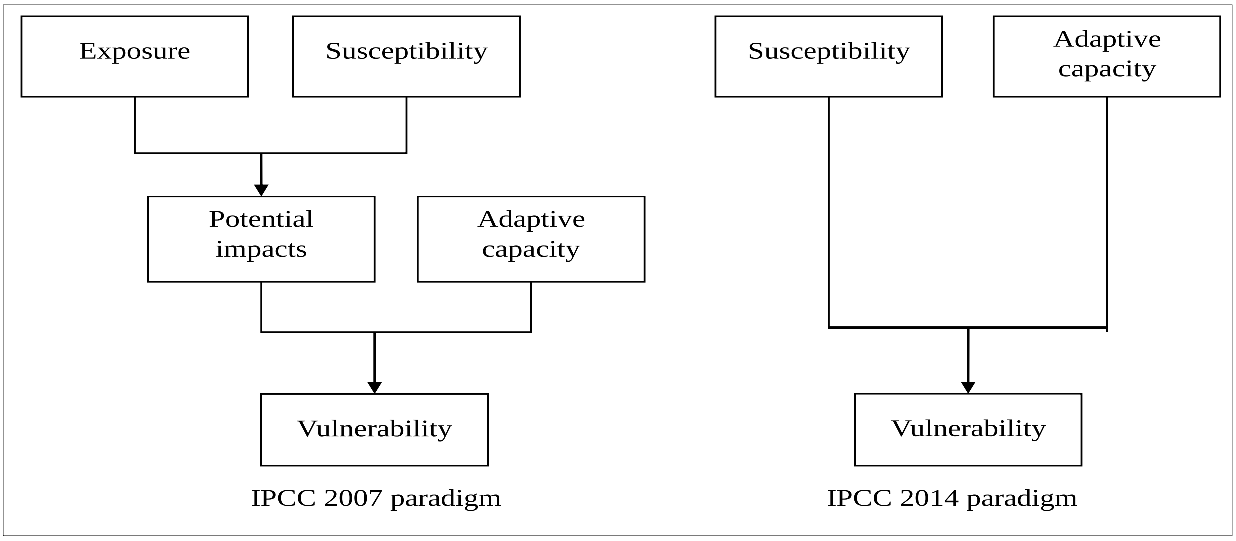


Figure 8: IPCC frameworks of vulnerability

2.3.6.2. Selection of flood vulnerability indicators

Vulnerability is multifaceted, varying among residents, municipalities, and regions, and also changes over time, which indicates that it cannot be accurately assessed with a single variable. Furthermore, the approaches used to assess vulnerability, and its elements present considerable challenges for researchers, especially in regions with limited available data. Against this background, compared to methods of curves and damage matrices, the indicator-based method was found to be the most appropriate method for assessing vulnerability due to its ability to capture the multiple dimensions of vulnerability (Kappes et al., 2012). The indicator-based approach is straightforward and effective for monitoring flood vulnerability and risks; It also provides information and simplifies the process of communicating vulnerability to all stakeholders engaged in efforts to reduce vulnerability. However, the challenge of this method resides in the selection a minimum number of relevant indicators that avoid multicollinearity issues and address the multifaceted nature to characterize the vulnerability of system being studied. Then, the selection of indicators in this study is based on earlier research, using those deemed appropriate for assessing vulnerability within the study area. Following this deductive approach, we selected indicators for components of vulnerability, including exposure, susceptibility, and adaptive capacity (Appendix **G** and Table **5**).

Table 5: Indicators selected for assessing flood vulnerability, based on.

Components and Subcomponents	Indicator Name	Description
Exposure		
Local exposure	LE	Elevation and proximity to the river increase the household exposure.
Human exposure	HE	Family members injured or affected by communicable diseases by previous flooding implies that the household is exposed.
Asset exposure	AE	Damage to the house, loss of household goods, inundation of agricultural land, and crops from previous floods indicates household exposure.
Susceptibility		
Human asset damage/loss	HA	Floods have affected household members, impacted water resources, damaged farmlands, destroyed crop harvests, compromised the primary needs of household members, affected household income sources, damaged public infrastructure, and hindered access to these facilities.
Natural asset damage/losss	NuA	
Physical asset damage/loss	PA	
Financial asset damage/loss	FA	
Social asset damage/loss	SA	
Adaptive Capacity		
Have acces to information	AI	Having access to information may increase increases household coping appraisal, leading to an interest in self-protection measures.
Capacities of residents	CR	Assessing the level of self-protection measures already implemented against flooding refers to assessing the coping capacity of households.
Attitude towards measures and future expectations	ATMFE	Understanding the expectations of households regarding the use of self-protection measures and their preferences for these measures may guide government and all stakeholders' actions involved in flood disaster risk reduction.
Preference for self-protection strategies	PSPS	
Attitude	ATT	Households that perceive flooding as likely, and households that believe that flooding is God's will, tend to be less prepared for future floods. Households that tend to agree with government policies are inclined to follow flood initiatives, increasing their resilience.

2.3.6.3. Development of flood vulnerability index

The data were collected at the household level, but the flood vulnerability index and its components were assessed at the village level. The indicators were constructed either through the combination of several variables or by using a single variable. Most of these indicators were developed from qualitative variables, which ranged from two to four classes.

The first step in developing the vulnerability index involved processing the data to exclude all incomplete questionnaires. Afterward, we calculated the relative frequencies of the variables, which serve as inputs for the indicators. Variables are classified into different categories, ranging from two (binary variables such as Yes or No) to four classes, based on household characteristics related to flood vulnerability. We assigned unequal weights to each category of variables, according to their vulnerability levels. A value of one was assigned to the most vulnerable classes, while the value zero was assigned to the least vulnerable classes. For binary responses, the weights are zero (No) and one (Yes). For variables with three classes, the weights were assigned as 0.33, 0.67, and 1. Relatively to variables with four classes, the weights are 0.25, 0.5, 0.75, and 1. Then, a linear aggregation method was employed to combine all classes of variables into a single score. The aggregation method is expressed as:

$$V = \sum_{\mathrm{i}=1}^{n} w_j K_j \qquad (2.29)$$

Where w_j is the weight attributed to class j of the variable and K_j corresponds to relative frequency of class j of the variable. V is the score of the variable and n represents the number of the classes of the variable. The value score of each indicator is the arithmetic average of V for the variables that compose the indicator. The indicator score is formulated as:

$$\mathrm{X} = \frac{1}{m}(V_1 + V_2 + \cdots + V_m) \qquad (2.30)$$

where X represents the indicator score and m denotes the number of variables included in the indicator. After constructing the indicators, they were normalized to a range of 0–1. The method of normalization is expressed as:

$$\mathrm{XN} = \frac{(\mathrm{X} - min(\mathrm{X}))}{max(\mathrm{X}) - min(X)} \tag{2.31}$$

where X refers to the original indicator and XN is the normalized indicator. Normalization involves transforming all indicators so that they are expressed without units, as these indicators are measured in various units and scales. After normalization, two non-subjective weighting methods were introduced for assigning weights to the indicators: the equal weighting method and the unequal weighting method using Principal Component Analysis (PCA). These two weighting methods were introduced to analyze the sensitivity of the vulnerability index and its components to different weights. The comparison involves calculating the vulnerability index based on equally weighted indicators versus calculating it based on unequally weighted indicators. The equal weighting method is straightforward, uncomplicated, and easily reproducible. Conversely, the PCA method for determining indicator weights is procedural, indicating that specific conditions for PCA application must be met before the weights can be calculated for each indicator. To calculate weights of indicators using PCA method involved five steps.

Initially, the correlation between indicators is analyzed, and those highly correlated (with a correlation coefficient greater than 0.8), are eliminated. Secondly, the Kaiser-Meyer-Olkin (KMO) test and Bartlett's test of sphericity are utilized to assess the suitability of the sample for PCA (Abdrabo et al., 2023). The KMO index ranges from 0 to 1; a KMO index greater than 0.7 indicates that PCA analysis is acceptable. Values of the KMO index between 0.6 and 0.5 suggest that the PCA analysis is mediocre but can still be performed, whereas a KMO value less than 0.5 indicates that PCA is not suitable (Abdrabo et al., 2023). Bartlett's test of sphericity assesses whether there is redundancy among indicators and determines if the chosen indicators are appropriate for PCA when the p-value is less than 0.01 (Abdrabo et al., 2023). Thirdly, calculate the initial eigenvalues of PCA, including the total initial eigenvalue, variance (%), and cumulative (%). Make sure that the cumulative (%) value is equal to or exceeds 80%. This indicates that the information captured by the extracted principal components represents the majority of the original variables (Liu & Li, 2016). Fourthly, compute the values of the rotated components matrix. Finally, determine the weights of each indicator. The weight of ith indicator (w_i), based on (Liu & Li, 2016), can be expressed as:

$$w_i = \frac{\sum_{j=1}^{k}\left(\frac{a_{ij}^2}{\lambda_j}\vartheta_j\right)}{\sum_{i=1}^{n}\left[\sum_{j=1}^{k}\left(\frac{a_{ij}^2}{\lambda_j}\vartheta_j\right)\right]} \tag{3.32}$$

Where a_{ij} is the value of the ith indicator at the jth rotated principe component. λ_j and ϑ_j are the values of total initial eigenvalue and variance (%) at the jth rotated principe component, respectively. Considering the equal or unequal weighting methods, the different steps involved in computing the flood vulnerability index were summarized in a flowchart represented below.

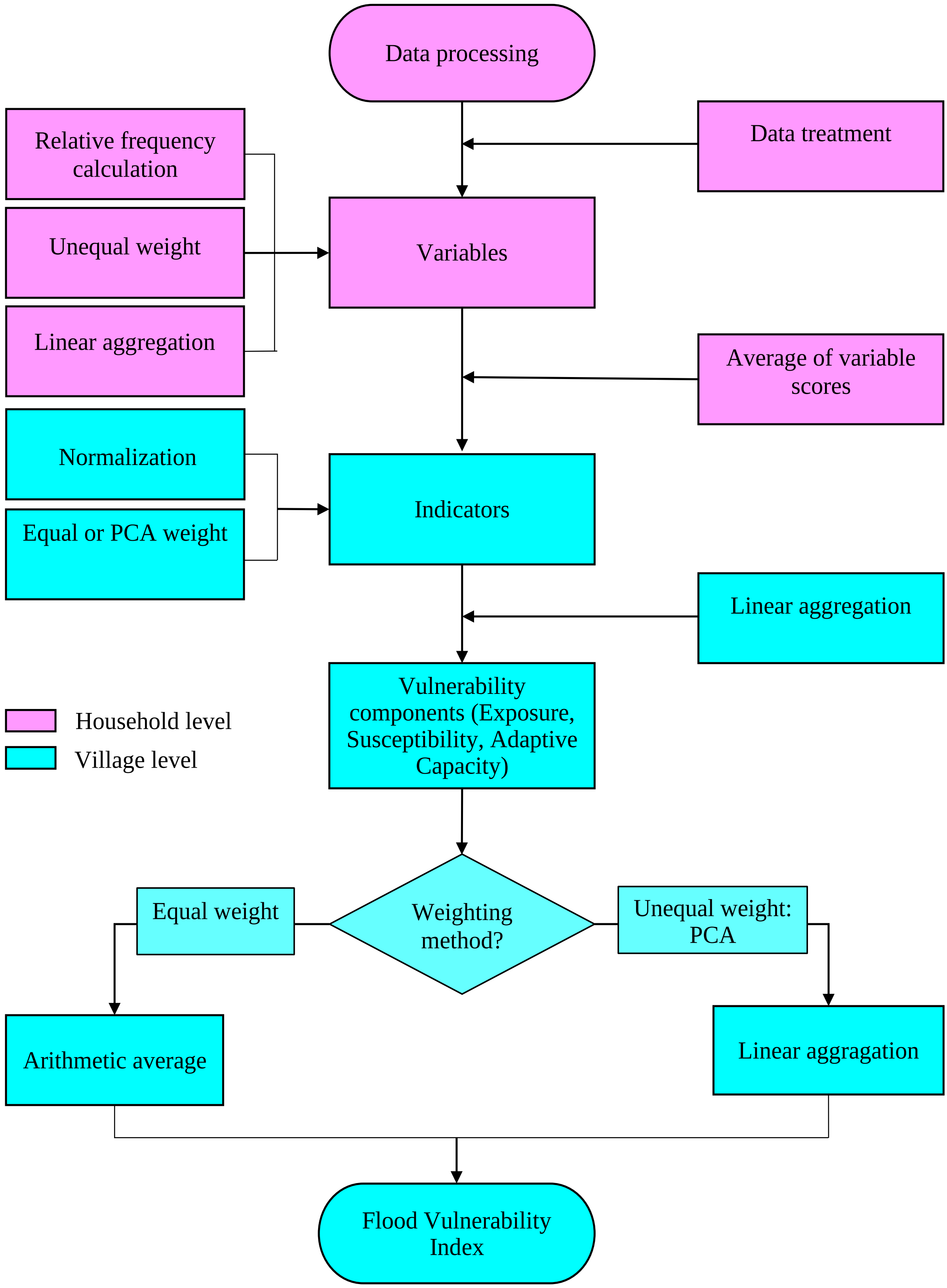


Figure 9: Flowchart of how the vulnerability index at village level was computed from variables collected at the household level, considering the chosen weighting method.

After weighting the indicators, vulnerability index and its components, including exposure, susceptibility, and adaptive capacity, were calculated using the arithmetic mean when the indicators were equally weighted. Linear aggregation was used to calculate the flood vulnerability index and its components when the indicators were unequally weighted. Following this, the flood vulnerability index (FVI), based on the IPCC 2007 was computed. When the indicators are equally weighted, FVI was expressed as:

$$FVI = \frac{1}{3}\big(E + S + (1 - AC)\big) \tag{2.33}$$

Where E, S, and AC denote the exposure, susceptibility, and adaptive capacity. The term "1-AC" indicates "lack of adaptive capacity". Then, when the FVI is computed from indicators that are unequally weighted, the FVI formula is expressed as:

$$FVI = \ a\left(\frac{\sum_{i=1}^{3} w_i E_i}{\sum_{i=1}^{3} w_i}\right) + b\left(\frac{\sum_{t=1}^{5} w_t S_t}{\sum_{t=1}^{5} w_t}\right) + c\left(1 - \frac{\sum_{j=1}^{5} w_j AC_j}{\sum_{j=1}^{5} w_j}\right) \tag{2.34}$$

Where E_i, S_t and AC_j represent exposure, susceptibility, and adaptive capacity indicators, respectively. w_i, w_t and w_j denote the weights assigned to the exposure, susceptibility, and adaptive capacity indicators. The parameters $a, b.$ and c are additional weights determined from w_i, w_t and w_j. The parameter a is defined as the sum of the weights of exposure indicators divided by the sum of the weights of exposure, susceptibility, and adaptive capacity indicators. Additionally, parameter b is determined as the sum of the weights of susceptibility indicators divided by the sum of the weights of exposure, susceptibility, and adaptive capacity indicators. Lastly, parameter c can be derived from a and b using equation $(c = 1 - a + b)$.

Unlike the IPCC 2007 framework, vulnerability in the IPCC 2014 framework depends solely on susceptibility and adaptive capacity, as exposure was not considered a component of vulnerability in this newly introduced framework. When the indicators are equally weighted, the FVI was computed as:

$$FVI = \frac{1}{2}\big(S + (1 - AC)\big) \tag{2.35}$$

Where S, and AC denote the susceptibility, and adaptive capacity. The term "1-AC" indicates "lack of adaptive capacity". Then, when the indictors were unequally weighted, FVI is expressed as:

$$FVI = p\left(\frac{\sum_{t=1}^{5} w_t S_t}{\sum_{t=1}^{5} w_t}\right) + q\left(1 - \frac{\sum_{j=1}^{5} w_j AC_j}{\sum_{j=1}^{5} w_j}\right) \tag{2.36}$$

S_t and AC_j represent susceptibility, and adaptive capacity indicators, respectively. w_t and w_j denote the weights assigned to susceptibility, and adaptive capacity indicators. The parameters p and q are additional weights determined from w_t and w_j. The parameter p is defined as the sum of the weights of susceptibility indicators divided by the sum of the weights of susceptibility, and adaptive capacity indicators. The weight q corresponds to the opposite of p ($q = 1 - p$). To represent the vulnerability and vulnerability components of a certain village verbally, we transformed the numeric values, which range from 0 to 1, according to Table 6.

Table 6: Transformation of numeric values of vulnerability and its components (exposure, susceptibility, lack of adaptive capacity, and vulnerability) to five semi-quantitative levels from 'very low' to 'very high'.

Vulnerability and its components	Levels of measurement				
	1-0.8	0.8-0.6	0.6-0.4	0.4-0.2	0.2-0
	Very high	High	Moderate	Low	Very low

2.3.6.4. Sensitivity analysis of flood vulnerability to weighting methods

In this study, the sensitivity analysis seeks to assess the reliability of the flood vulnerability score through the application of various methods for assigning weights to vulnerability indicators and by incorporating different vulnerability frameworks. This analysis aims to explore how the choice of a weighting technique and the adoption of a vulnerability framework impact the assessment of flood vulnerability. Several methods exist for conducting sensitivity analysis across various domains, including families of differential methods, one-at-a-time approaches, random sampling methods, and those involving segmented input distributions (Hamby, 1994). In our study, we performed a correlation analysis for sensitivity analysis, specifically comparing the effectiveness of equal weighting versus PCA weighting methods in assessing vulnerability and its components. To further analyze the distribution of vulnerability and its components, we employed the non-parametric Cramer-von Mises test (Hamby, 1994).

The Cramer-von Mises test is quite similar to the Kolmogorov-Smirnov test, which seeks to determine whether two distributions are statistically indistinguishable. However, there is a slight difference in the statistical power between the Cramer-von Mises test and the Smirnov statistic. Specifically, the Cramer-von Mises statistic, denoted as T, is calculated as the sum of the squares of the vertical distances between the empirical distributions $S_1(x)$ and $S_2(x)$. The statistic T of Cramer-von Mises test is expressed as:

$$T = \frac{m \times n}{(m+n)^2} \sum [S_1(x) - S_2(x)]^2 \tag{2.37}$$

Where the values of m and n are the number of samples used to estimate the empirical distributions $S_1(x)$ and $S_2(x)$. When the p-value associated with the Cramer-von Mises statistic (T) is less than the significance level of 0.05, it indicates that the distributions under consideration are significantly different from each other. Conversely, a p-value greater than 0.05 suggests that the two distributions are not significantly different.

2.3.4. Partial conclusion

The study area, located in southern Burkina Faso, comprises about 16% of the national territory, and approximately one-fifth of the total population of Burkina Faso resides here. The majority of residents are engaged in rain-fed agriculture and related activities. This region is characterized by Sudanese savannah ecosystems and a terrain with the highest elevations, and it is recognized as the rainiest area of the country, with a notably dense hydrographic network. Between 1986 and 2017, the annual average rainfall fluctuated between 612.8 mm and 1274.9 mm. From 1990 to 2020, the Mouhoun River in Samandeni witnessed an increase in both its average and peak discharge, with rates of 10.78% and 5.08% per decade, respectively. Despite these potential advantages, the communities in this region have limited capacity to cope with climate-related disasters, which they have experienced repeatedly, leading to significant impacts on both public and private properties. Against this background, in line with the objectives of this study, secondary data encompassing rainfall, Sea Surface Temperature (SST), and topographic information were gathered for analyzing the frequency, intensity, and spatial distribution of extreme rainfall. In addition to the secondary data, survey data were collected to evaluate flood risk, factors affecting flood risk perception, and community vulnerability to flooding. These datasets were analyzed through an indicator-based approach, extreme value modelling, and econometric modelling, which were executed across various software platforms. Data processing was conducted using Excel and SPSS, while the analysis of the frequency, intensity, and spatial patterns of extreme rainfall were performed using R software. Econometric modelling was carried out using STATA 16, aiming to identify factors influencing household flood risk perceptions for informed decision-making.

Chapter 3: Extreme Rainfall In Southern Burkina Faso, West Africa: Trends And Links To Atlantic Sea Surface Temperature

This chapter delves into the analysis of rainfall trends, including extreme rainfall, and examines how Sea Surface Temperature (SST) influences the frequency and intensity of these events. The initial segment discusses rainfall gap filling. Following this, the next section investigates rainfall trends, including extreme rainfall, using indicators proposed by the Expert Team on Climate Change Detection and Indices (ETCCDI). Additionally, the influence of SST on the frequency and intensity of extreme rainfall is explored through a Peaks-Over-Threshold approach within a non-stationary framework. The results of this chapter are presented in the subsequent section, concluding with a partial conclusion to wrap up the chapter.

3.1. Results

3.1.1. Rainfall gap filling

We generate artificially data gaps (5%, 10% and 15%) at a station with few data gaps, then we use all of the five candidate methods to fill the gaps and calculate τ and RMSE. The performance of the five candidate methods to fill data gaps is given in Table 2 for three fractions of missing data. IDW shows the best performance; it obtains the highest Kendall coefficient of correlation and the smallest RMSE. Its performance is substantially better than the performance of the other methods. This result agrees with other studies that found IDW to be a suitable method for rainfall data gap filling (Ismail et al., 2017; Suhaila et al., 2008). Hence, we use IDW to fill the data gaps in rainfall time series throughout the study area.

Table 7: Performance of gap-filling methods for station 1 (for location see Figure 1), which has with few data gaps, using the Kendall coefficient of correlation (τ) and root mean square error (RMSE).

	5% of missing data		10% of missing data		15% of missing data	
	τ	RMSE	τ	RMSE	τ	RMSE
AM	0.46	10.23	0.50	9.71	0.47	9.86
NR	0.46	10.21	0.50	9.73	0.47	9.84
IDW	0.96	2.29	0.92	2.93	0.88	3.71
CC	0.47	9.96	0.49	9.12	0.48	9.71
GC	0.47	10.11	0.47	9.12	0.48	3.91

3.1.2. Preliminary statistics of climatology rainfall

Table 8: Climatology (normal) precipitation characteristics given by minimum (Min), average (Mean), standard deviation (SD) and maximum (Max). Min, Mean, SD and Max of a given index provide a climatological precipitation of the corresponding index at the study area level.

Indices	**Min**	**Mean (± SD)**	$\boldsymbol{Max}$
R1day	48	58.2 ± 4.8	66
PRCPTOT	803.7	927.5 ± 57.6	1029.8
R10	28.3	31.1 ± 1.6	34.1
R20	14.3	16.6 ± 1.2	19.1
R95p	2.5	3.0 ± 0.3	3.5
SDII	14.4	16.2 ± 1.2	19.6
RX1day	61.8	74.5 ± 5.1	83.0
RX5day	92.8	106.7 ± 6.2	118.2

The climatological average of the number of wet days (R1day), the total wet-day precipitation (PRCPTOT), the annual maximum 1-day rainfall (RX1day), the annual number of days with rainfall ≥ 10 mm (R10), ≥ 20 mm (R20) and ≥ 95th percentile (R95p) show some similarities in term of distribution (Figure **10a-e, g, h**). The higher values of these indices with respect to their average (see Mean, Table **8**) are observed in the southwest part of the study area, while the eastern part has recorded values relatively lower than their average. The climatological distribution of annual maximum precipitation over 5 consecutive days (RX5days) differs from the distribution of previous rainfall indices. The higher values of RX5days with respect to its average are observed in the western and eastern parts, whereas its lower values are mostly found in the central part of the study area. As for SDII (mean rainfall on wet days), it is almost uniformly distributed over the study area (Figure **10f**) with values more or less close to the average of 16.2 mm/day. Except for SDII and RX5day rainfall indices, most of the stations with rainfall index values lower than their average are in the northern part of the study area, implying that the rainfall indices have decreased climatologically from northeast to west-south over the study area.

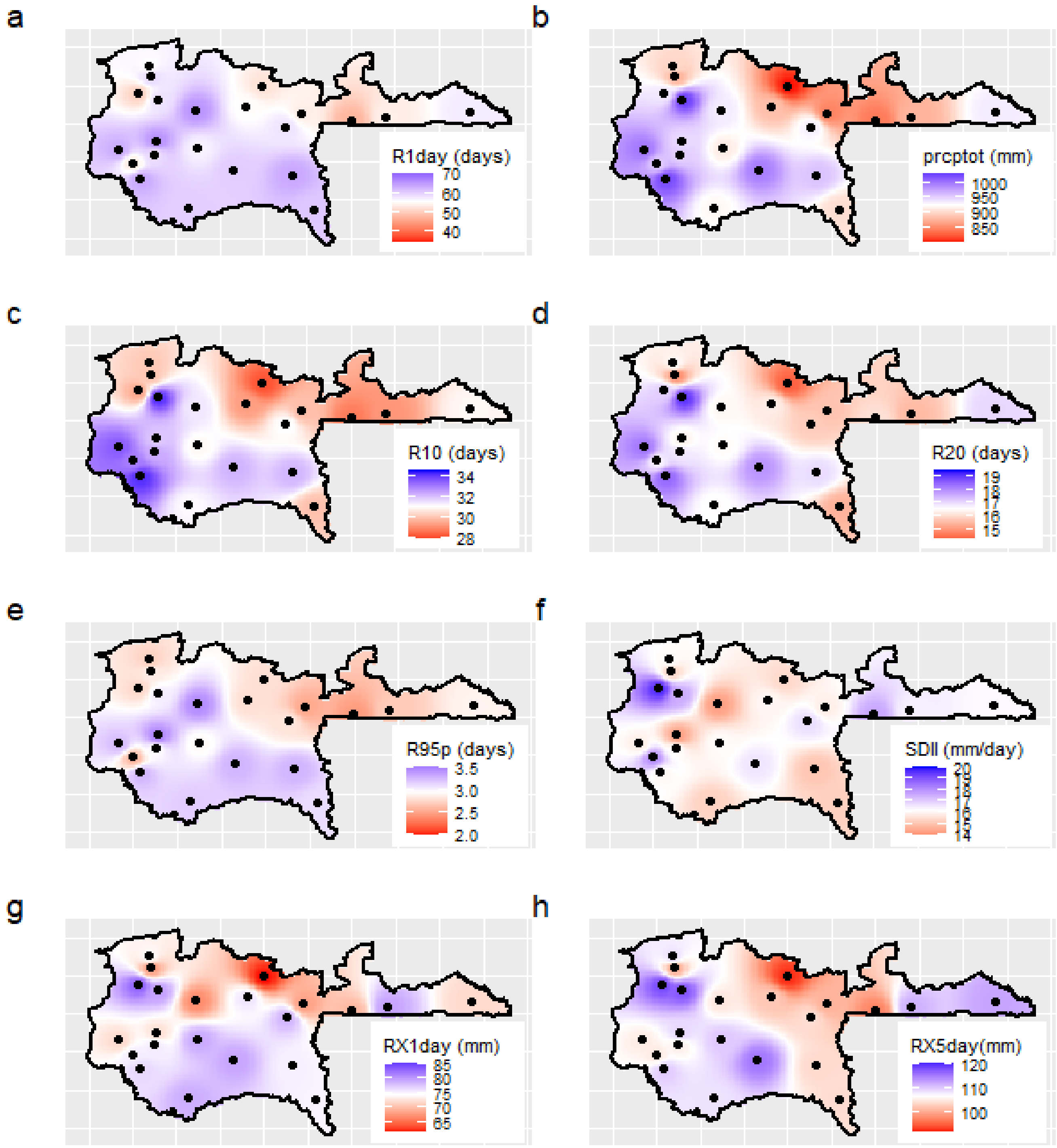


Figure 10: Distribution rainfall indices given as climatological average of rainfall index (see Table **1**). Circles denote climate stations. The blue (respectively red color) represents the areas with the index value higher (respectively lower) than its normal average of the study area and the white color corresponds to value close to the normal average.

3.1.3. Rainfall trends

Changes in the number of wet days (R1day) show increases and decreases between -9.9% and 4.4% per decade (Figure **11a**). The three eastern regions show only decreasing trends (some of them not significant), while the two western zones show a mixture of upward and downward changes. For total wet-day precipitation (PRCPTOT) we also detect a mixture of changes (Figure **11b**) with 27% (41%) of stations showing significant upward (downward) trends. The spatial pattern of changes shows a tendency towards decreasing (increasing) precipitation in the southern (northern) parts. Trends at single stations range from - 6.8% to 4.6% per decade. Overall, we find different patterns for changes in R1day and PRCPTOT, and the direction of change in total precipitation is not at all stations aligned with the direction of change in the number of wet days. The effect of the superposition of both indicators is seen in SDII (mean rainfall on wet days, Figure **11f**). Mean daily rainfall intensity has changed significantly at 73% of stations with values between -9.6% and 7.6% per decade. There is a tendency towards decreases in the south, while the north shows a mixture of areas with increasing and decreasing trends.

The spatial patterns for the annual maximum 1-day rainfall (RX1day) and annual maximum of consecutive 5-days rainfall (RX5days) show some similarities (Figure **11g, h**). The south (South Western and South Eastern) tends to show downward trends, while the western part of the North Western region shows upward trends (up to 14.2% per decade) or nonsignificant changes. Overall, we detect a tendency towards less intensive 1-day and 5-day rainfall maxima. As far the frequency indices of heavy rainfall as concerned, i.e., the annual number of days with rainfall $\geq$ 10 mm (R10), $\geq$ 20 mm (R20) and $\geq$ 95th percentile of the wet days (R95p), respectively, we find mostly downward trends (Figure **11c-f**). All climate stations show significant downward trends for R95P with values between -13.5% and -1.6% per decade. The spatial patterns for R10 and R20 are less homogeneous with some areas in the northern part with significant upward trends.

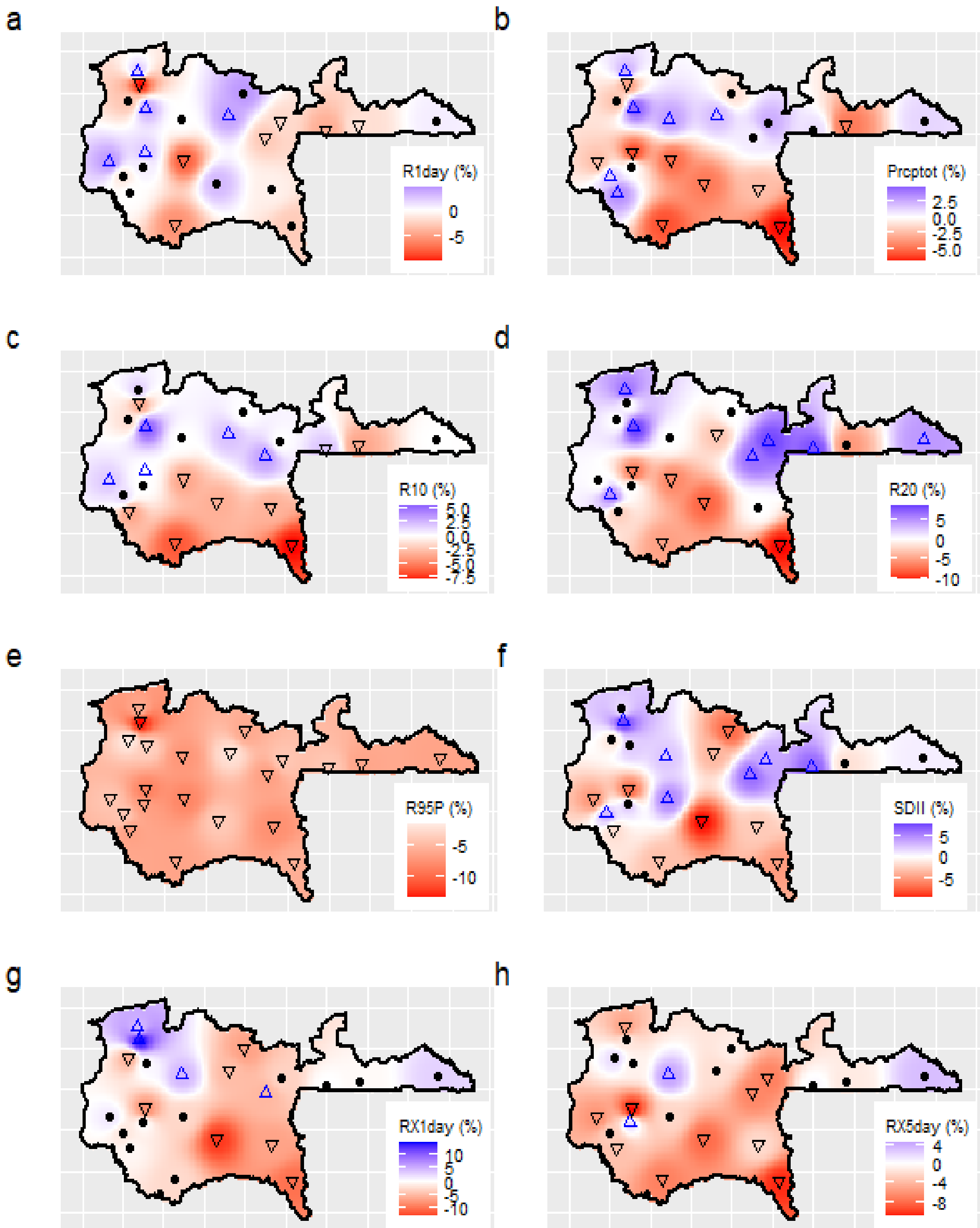


Figure 11 Trends in rainfall indices given as change per decade in % for the different rainfall index. Upward/downward triangles denote stations with statistically significant upward/downward trends at the 5% significance level. Circles show stations with non-significant changes.

3.1.4. Link between Atlantic SST and heavy rainfall

Using threshold stability and mean excess graphical methods, we select an optimal threshold beyond which daily rainfall is considered as extreme rainfall. The optimal threshold to ensure the stability of Poisson-GP parameters ranges from 30 to 53 mm with an average value of 41.6 mm across all stations. With these thresholds, an average of 2.4% of daily rainfall is considered as extreme rainfall with a range from 1.1% to 4.5%. After the threshold selection and the decluttering of excess values, we fit the stationary and the nonstationary Poisson-GP models using the maximum likelihood method. Based on the deviance statistic we find that the nonstationary Poisson-GP model with parameters depending to the daily SST of NA, MA and SA is preferred over the stationary model to represent the extreme rainfall at all stations.

Table 9 shows the deviance and the p-value associated with the deviance test for each station (see Figure **1** for station locations). At the 5% significance level, the deviance test at all stations is statistically significant, meaning that the non-stationary model SST as covariable outperforms the stationary model (see Table **9**).

Table 9: Performance of the deviance test at a 5% significance level for all the climate stations using the p-values associated with deviance value (see figure 1 for station localization).

Station	**1**	**2**	**3**	**4**	**5**
Deviance	85.07	148.58	42.76	60.49	38.99
p-value	3.19×10^{-16}	2.20×10^{-16}	1.30×10^{-7}	3.58×10^{-11}	7.18×10^{-7}
Station	**6**	**7**	**8**	**9**	**10**
Deviance	27.61	48.54	33.08	42.45	45.20
p-value	1.11×10^{-4}	9.03×10^{-9}	1.01×10^{-5}	1.50×10^{-7}	4.28×10^{-8}
Station	**11**	**12**	**13**	**14**	**15**
Deviance	60.56	45.39	40.16	69.31	36.51
p-value	3.47×10^{-11}	3.92×10^{-8}	4.24×10^{-7}	5.66×10^{-13}	2.20×10^{-6}
Station	**16**	**17**	**18**	**19**	**20**
Deviance	83.93	49.67	51.28	65.77	19.34
p-value	5.51×10^{-16}	5.47×10^{-9}	2.60×10^{-9}	3.00×10^{-12}	3.63×10^{-4}
Station	**21**	**22**			
Deviance	56.20	52.93			
p-value	2.66×10^{-10}	1.22×10^{-9}			

Table **9** shows that the nonstationary models with SST as covariables significantly outperforms the stationary models for all the stations. Thus, the validation of the nonstationary model at the station level was done using the probability and quantile plot methods. The results pointed out that the nonstationary models are well fitted to the rainfall data. Figure **12** shows the quantile and probability plot results for stations 4, 13 and 18. We found that the quantile and probability plots of these models are close to the unit diagonal. The left column is the quantile plots, and the right column denotes the model probability plots.

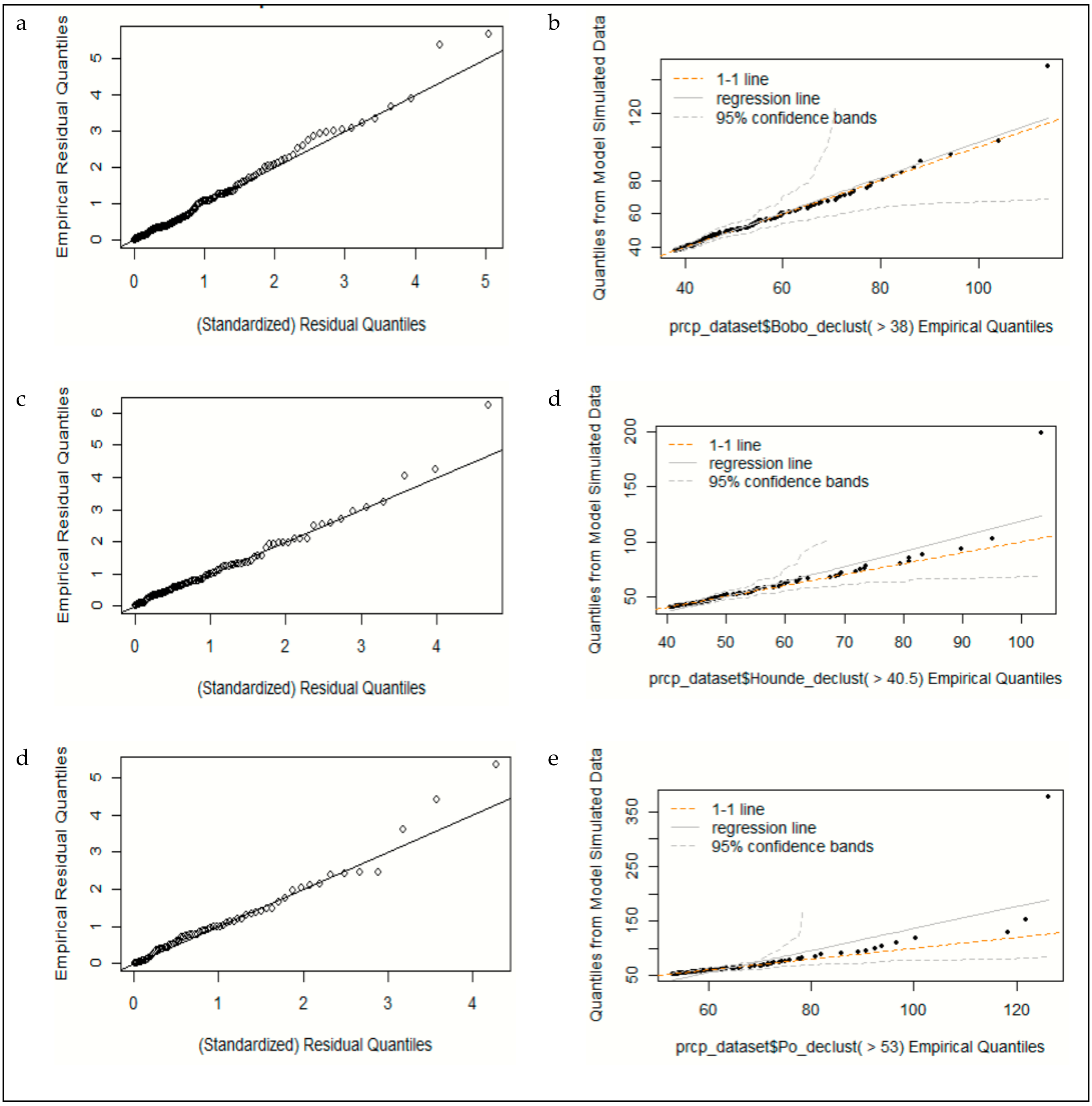


Figure 12: Quantile and probability plots of the nonstationary GP-Poisson model for stations 4, 13 and 18. The left and right columns represent the quantile and the probability plots of the nonstationary models for station 14, 13 and 18, respectively.

Figure **13** shows maps of the slope values ($\alpha_{1,s}, \alpha_{2,s}, \alpha_{3,s}$, $\beta_{1,s}$, $\beta_{2,s}$ *and* $\beta_{3,s}$; eq. 4) of the nonstationary models. The frequency of extreme rainfall is positively associated with NA SST throughout the study area with comparatively high slope values in the range of 3.1-9.5 (Figure

13a). That means that the frequency of extreme rainfall increases by a factor of 3 to 9 when SST of NA increases by one degree Celsius. The influence of MA and SA SST varies in the study area (Figure **13c, e**); extreme rainfall frequency is positively affected by higher SST values in some areas, while other areas are negatively affected. The slope values of MA and SA are somewhat lower compared to the slope values slopes of NA. The average of the absolute slopes is 6, 0.6 and 2.6 for NA, MA and SA, respectively. Hence, changes in SST of NA tend to have a stronger effect compared to changes in SST in MA and SA. For the Eastern region we find large positive associations between the frequency of extreme rainfall and SST in all three parts of the Atlantic.

The intensity of extreme rainfall is significantly linked to the SST of NA, MA and SA, but the sign of this correlation is not homogeneous over the study area (Figure **13b, d, f**). SST of NA is positively associated with the intensity of heavy rainfall for most stations. The slope values vary between 3.9% and 20.1% per °C. SST of MA only locally influences the intensity of extreme rainfall in rather small areas in the central, southern, and eastern parts. SA SST tends to increase extreme precipitation in the north and south, and to decrease extreme precipitation in central parts. For the Eastern region we find a strong positive association for all three parts of the Atlantic Ocean. Here we find the highest slope values. The intensity of extreme precipitation increases by 20.1%, 40.1% and 39.9% per °C increase in SST of NA, MA and SA, respectively.

We have also compared the frequency and the intensity of extreme rainfall between the two mid rainy seasons of May-July and August-October. We note that Atlantic SST between August and October had a greater impact on the frequency and the intensity of extreme than from May to July, with most of the impacts being caused by North Atlantic SST variability (Figures **14-15**). However, we noted that the risk of extreme precipitation between May and July under the influence of Atlantic SST is stochastically higher in some areas of the research zone than between August and July (Appendix **B**).

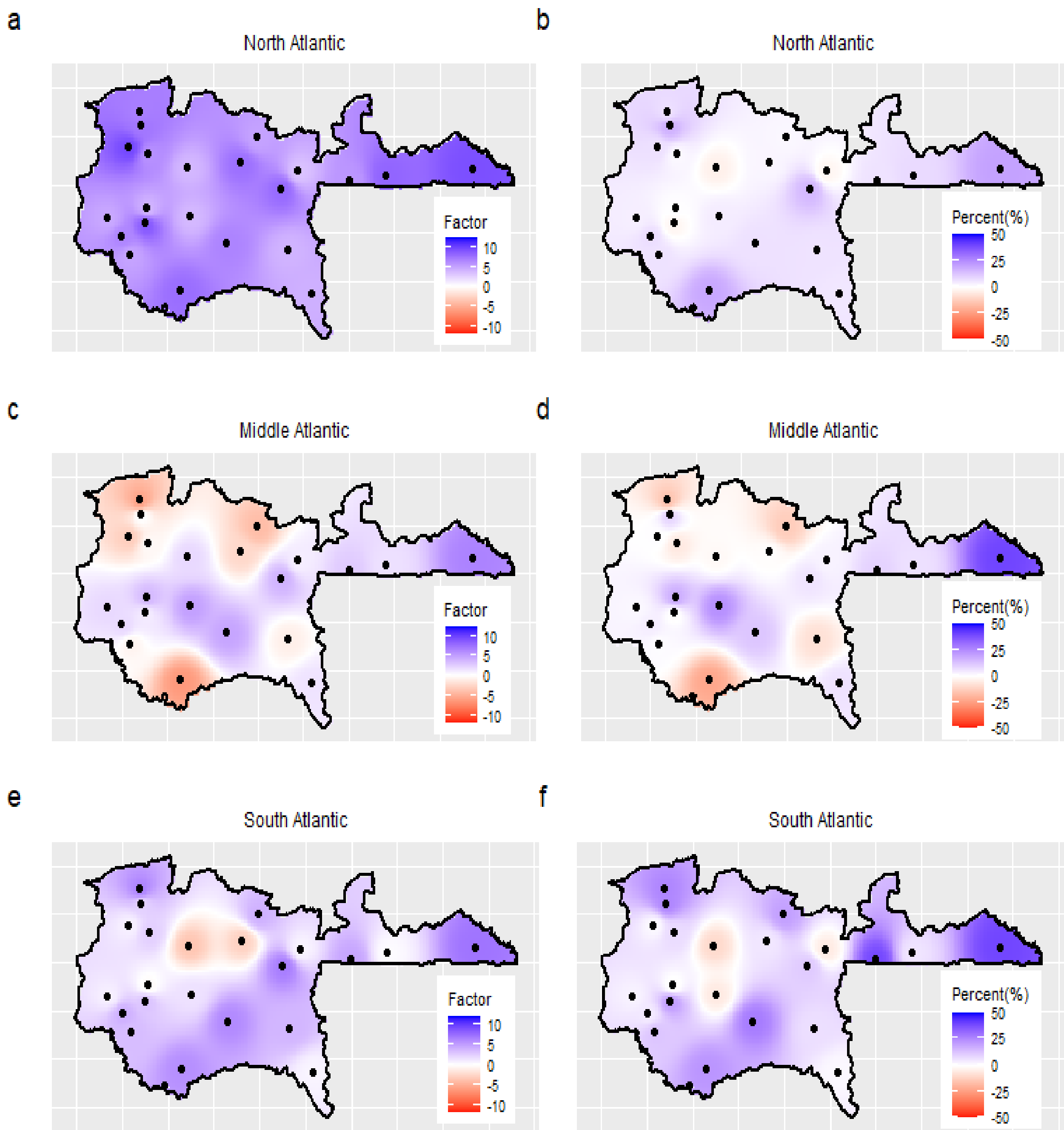


Figure 13: Slope values of the linear relations between SST and extreme rainfall. The left column represents the impact of SST on the frequency of extreme rainfall, and a value of n means an n-fold increase in the frequency of extreme precipitation per °C increase in SST. The right column denotes the impacts of SST on the intensity of extreme rainfall, a value of n means an n% increase in the intensity of extreme precipitation per °C increase in SST.

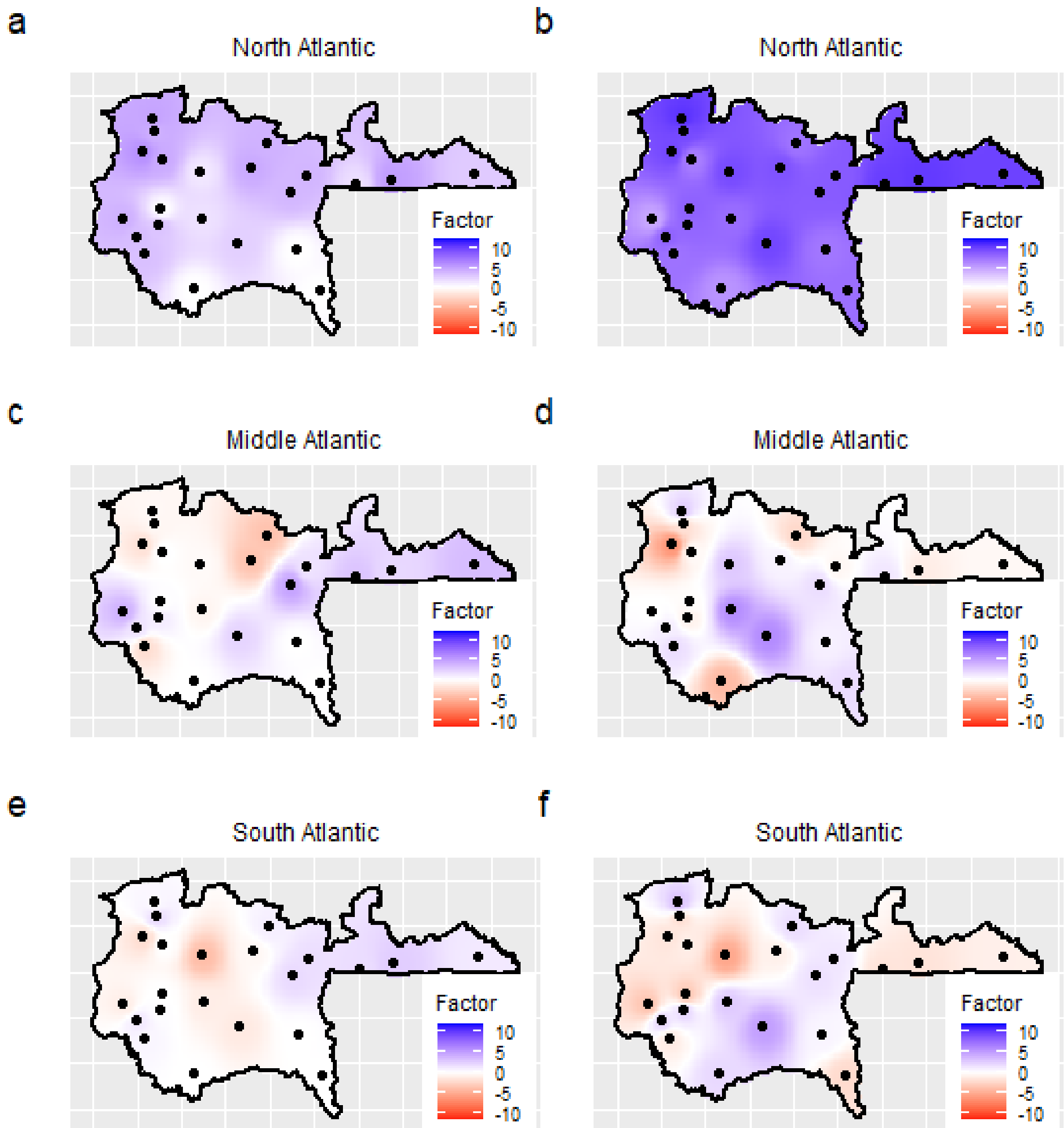


Figure 14: Slope values of the linear relations between SST and extreme rainfall frequency. The left column shows the impact of SST on extreme rainfall frequency from May to July, while the right column represents the same relationship for the period from August to October.

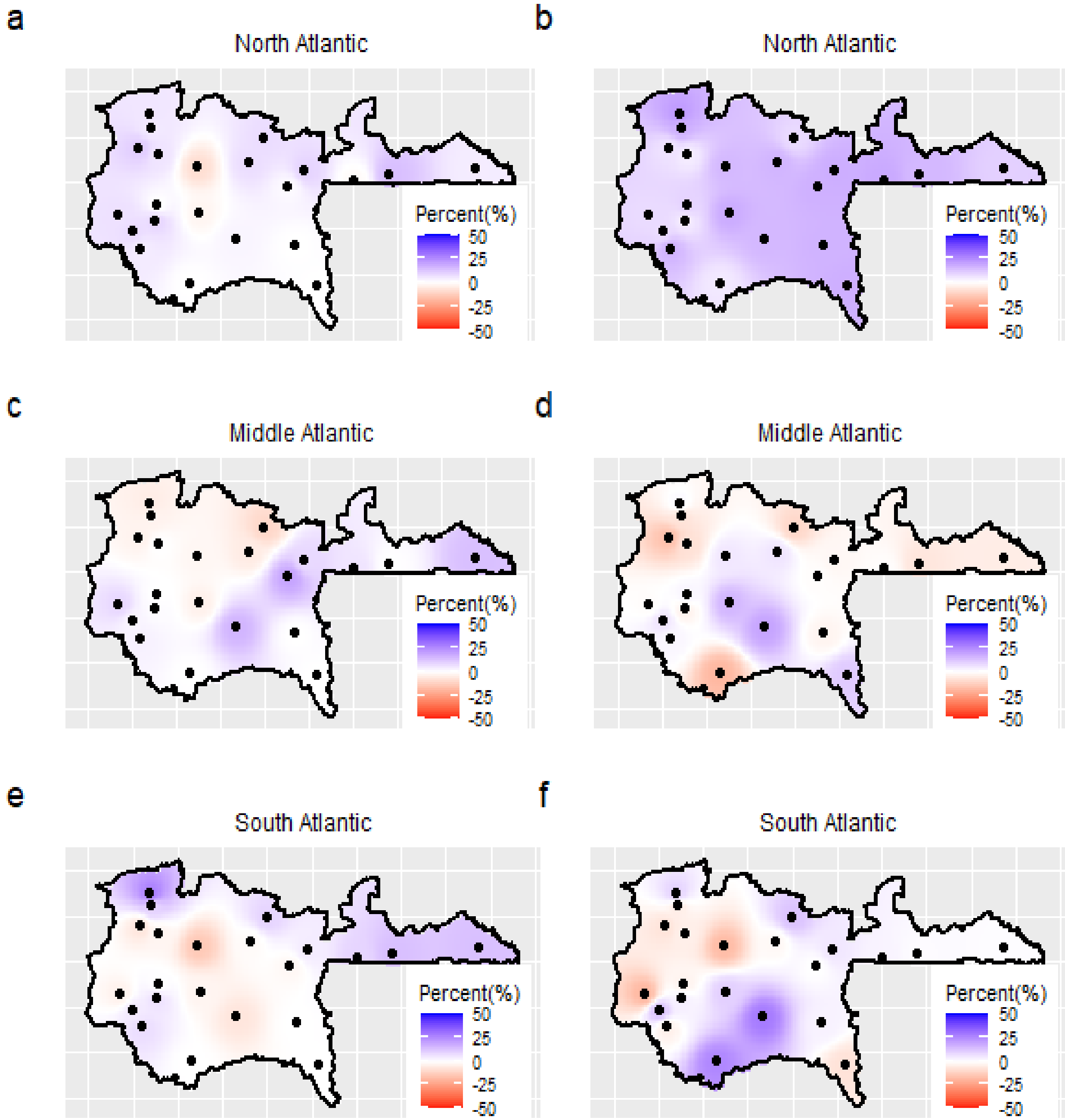


Figure 15: : Slope values of the linear relations between SST and extreme rainfall intensity. The left column represents the impact of SST on extreme rainfall intensity from May to July, while the right column represents the same relationship for the period from August to October.

3.2. Discussion

To inform disaster risk reduction and climate adaptation at the local scale in West Africa, it is important to understand the space-time behavior of rainfall. Understanding of space-time variation in precipitation is necessary for the identification and monitoring of flash flood hotspots, which facilitates the appropriate allocation of resources to flood risk projects for a more effective emergency response to floods. Our study shows that rainfall trends are spatially heterogeneous in southern Burkina Faso. Large-scale trend studies at the national or supranational scale have concluded that extreme rainfall has become more frequent and intense in West Africa (Ly Mouhamed et al., 2013; Panthou et al., 2014b; Sanogo et al., 2015; Ta et al., 2016). We find not only a much more nuanced behavior, based on the much higher density of stations in our study, but also some opposite effects. For most rainfall indices, we find decreasing trends at a majority of stations. Similar results have been found by other local studies in the Oti Bassin in Togo (Klassou & Komi, 2021) and in the Vea catchment in Ghana, where more than 78% of stations showed downward trends in the intensity and frequency of extreme rainfall (Larbi et al., 2018). This discrepancy between the large-scale studies and local studies suggests that national or supranational studies may misinterpret rainfall trends when they are based on scarce data.

Besides the overall tendency towards decreasing trends, we also find areas with increasing trends. Most stations with upward trends are located in the northern part of our study area. As this part is drier than the southern part, the standard catchphrase 'dry gets drier, wet gets wetter' does not hold in our study area. It needs to be mentioned, however, that the evidence for this catchphrase is rather weak (Greve et al., 2014; see Figure **16**).

Our nonstationary Poisson-GP model suggests that the frequency and intensity of extreme rainfall are linked to SST in the Atlantic Ocean. The northern part of the Atlantic plays a larger role, in particular for the frequency of extreme rainfall. Given the observed and expected warming of the Atlantic as consequence of anthropogenic climate change (Masson-Delmotte et al., 2021), our modelling approach suggests that the hypothesis of stationary is no longer suitable for extreme rainfall analysis in the study area.

The impact of the Atlantic SST on the frequency and intensity of extreme rainfall was estimated at the station level and spatially interpolated using the inverse distance weighted method. This approach has the advantage of simplicity but does not consider the spatial dependence structure. An alternative, more sophisticated approach would be the generalized pareto process modelling (Palacios-Rodríguez et al., 2020) which is able to capture the spatial correlation directly in the modelling framework. Further, we considered only the SST of the Atlantic. A more comprehensive analysis including SST of other regions and/or other atmospheric variables could result in more skillful covariates in the statistical modelling of extreme rainfall.

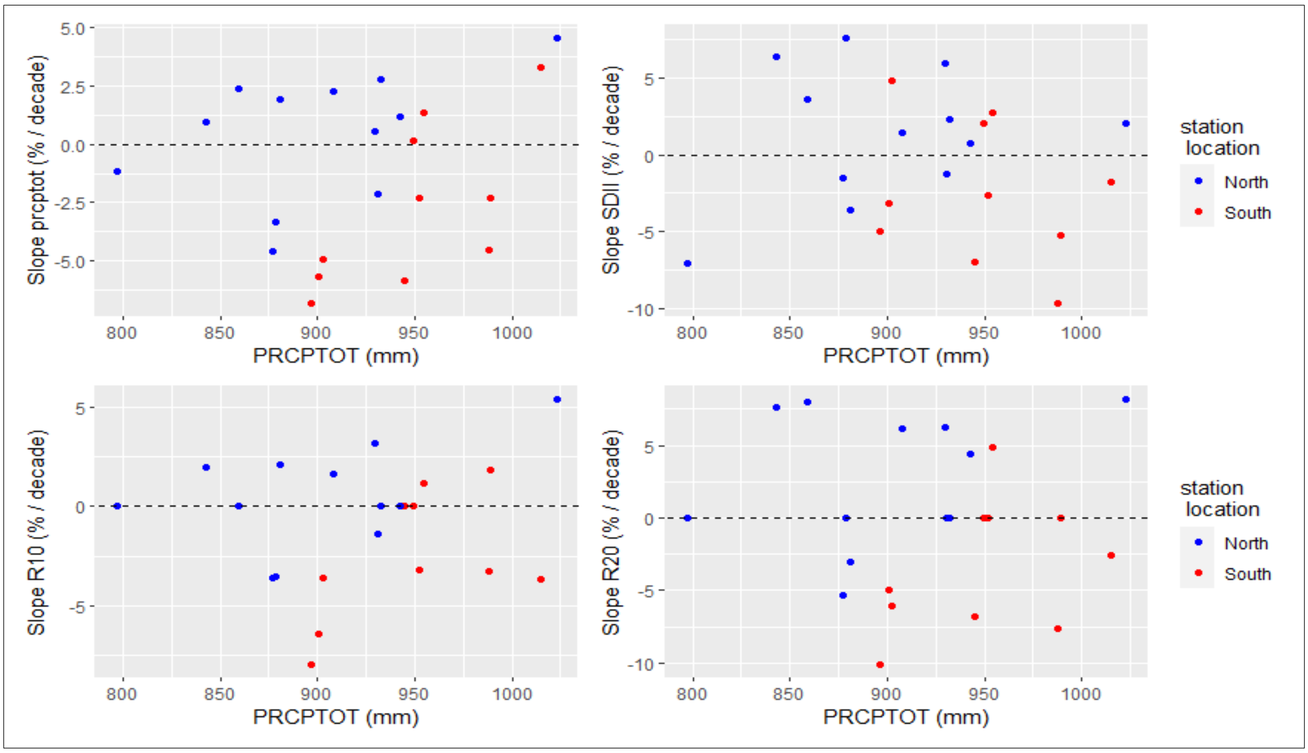


Figure 16: Relationship between PRCPTOT and slopes for PRCPTOT, SDII, R10, and R20 by station. This relationship consists of testing whether the dry areas get wetter, versus wet areas get drier.

Our trend results, i.e., more downward trends than upward trends, seem to contradict the general evolution of increasing flood events in Burkina Faso and adjacent countries. We cannot attribute the increasing number of flood events and of affected people to increasing rainfall extremes. Only in the northwestern part of our study area, we find increasing trends, particularly in RX1day. This area is the second frequently flooded region in Burkina Faso in 1986-2016, affecting many people and their properties, only surpassed by the central region of Burkina Faso (Tazen et al., 2019). Upward trends in extreme rainfall may have contributed to this flood hotspot. This is in line with study conducted in Mali by (Fofana et al., 2022) who found that flash floods are extremely related to extreme rainfall. Otherwise our analysis supports the explanation that has been concluded for the increasing flood risk in Ouagadougou north of our study area; namely that land use and land cover changes, population and urban growth, accompanied by low investments in flood-resilient infrastructure and management, have been the main drivers of flood risk (Aich et al., 2015; Tazen et al., 2019b). The similar results were found in Mali, country that borders the study area, where (Fofana et al., 2022) pointed out that about 58% of floods occurrence were caused by normal rainfall. According to the same authors, these floods could be due to changes in land use and land cover and the increase in impervious areas.

3.3. Partial conclusion

This chapter has investigated the spatiotemporal variability of rainfall characteristics and the impact of SST of different areas of the Atlantic Ocean upon the frequency and intensity of extreme rainfall for the period 1986-2017 in the southern part of Burkina Faso. In contrast to large-scale, data-scarce trend studies that concluded that extreme rainfall has become more frequent and intense in West Africa, our results show a more nuanced picture. Although trends vary with rainfall characteristics and in space, we find more downward trends across the study area, particularly for indices representing extreme rainfall. We also show that a nonstationary Poisson-GP model with SSTs as covariables outperforms the stationary Poisson-GP model, which implies that the assumption of stationary has to be considered with care when modelling the frequency and intensity of extreme rainfall. Future work should explore whether the linkage between Atlantic SST variations and extreme rainfall are strong enough to be used in water resources management, for instance, for seasonal rainfall forecasting. Our results suggest that the recent increase in flood disasters is rather caused by population and urban growth than by increasing rainfall extremes in the southern part of Burkina Faso.

Chapter 4: Likelihood Co-occurrence And Spatial Risk Of Extreme Rainfall In Southern Burkina Faso.

This chapter focuses on the spatial modelling and spatial risk assessment of both the monthly maximum of 1-day rainfall and the monthly maximum of 5-days consecutive rainfall, collected from June to September over the span from 1986 to 2017. The analytical process comprises describing extreme rainfall events, estimating and diagnosing models for both extreme rainfall indices, investigating the spatial dependency of extreme rainfall, computing conditional return periods based on stations that recorded the highest rainfall values during the study period, and assessing the spatially aggregated losses related to extreme rainfall. The subsequent section discusses the results, which ultimately leads to a preliminary conclusion to wrap up the chapter.

4.1. Results

4.1.1. Preliminary analysis of extreme rainfall

The box plots indicate that the variability of RX1day and RX5day monthly values is quite large, with values that deviate significantly from the average. The black dots appearing above the box plots represent values that are considered excessively extreme relative to the average (see Figure **17**).

On August 17, 2003, an extreme rainfall event occurred, with Sideradougou in the southwestern part of the study area experiencing 232.3 mm of rain. Concurrently, neighbouring localities such as Ouo, Banfora, Beregadougou, and Sindou reported varying amounts of extreme rainfall, ranging from 115.4 mm to 57.5 mm. The coefficient of variation for RX1day ranges from 46.1% to 64.9%, averaging at 52.1%, while for RX5day, it spans from 47.6% to 64.4%, with an average of 54.7%. Analysis of the coefficient of variation indicates a high risk of RX1day and RX5day values being excessively extreme throughout the study area, attributed to their significant spatial variability (Appendix **C**).

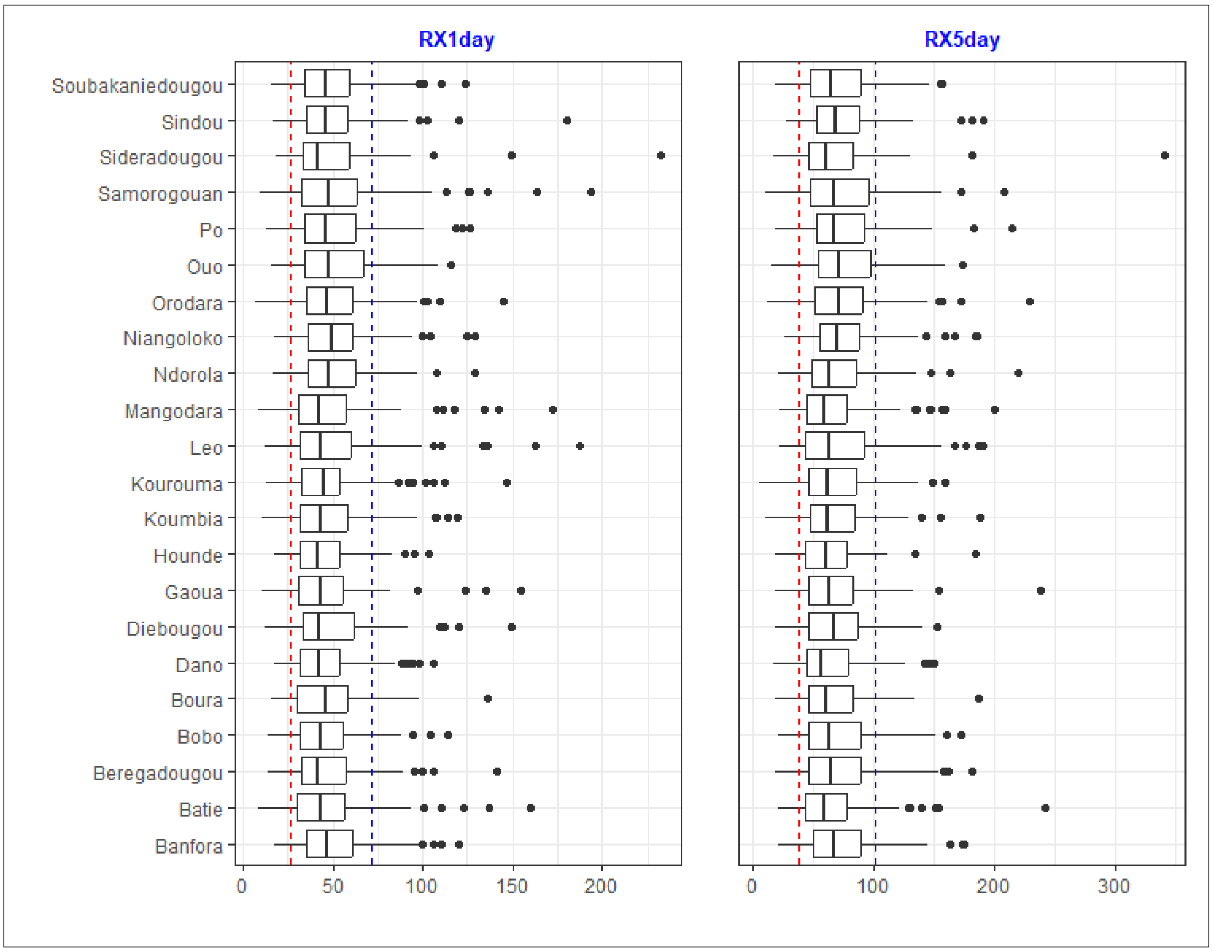


Figure 17: The left and right plots of monthly RX1day and RX5day of rainfall stations. The zone between the red and blue dot lines represents the normal distribution of extreme rainfall.

4.1.2. Spatial GEV and trend surfaces Estimation

A multivariate Mann-Kendall (MMK) test analysis on the monthly daily maximum extreme rainfall (RX1day) and monthly maximum of consecutive 5-days extreme rainfall (RX5day) shows no significant regional trend in the time series. The MMK test results show that the p-values associated with the regional trends for both RX1day and RX5day correspond to 0.6804 and 0.4821, respectively. This test implies that there is no significant temporal trend in the monthly RX1day and RX5day over the study area. Therefore, it will not be essential to consider time as a covariate in the development of trend surfaces for RX1day and RX5day spatial GEV and max-stable models. Additionally, as SST in the North Atlantic (NA), Middle Atlantic (MA), and South Atlantic (SA) have influenced the frequency and intensity of extreme rainfall, the monthly averages of SST in each subregion of the Atlantic will be explored as covariates in the development of spatial GEV and max-stable models.

To select the best candidate trend surface that fits the spatial GEV of monthly maximum of RX1day and RX5day over the study area, we used an ANOVA test at the 5% significance level. The analysis reveals that the trend surface model named **TRS2** (Table **2**) outperforms other candidate models, suggesting its suitability as a trend surface for converting point distributions into max-stable distributions. The chosen trend surfaces demonstrate that the parameters $\mu(s), \sigma(s)$ and $\varepsilon(s)$ of the marginal distributions GEV are influenced by longitude, latitude, and topography (altitude), including an interaction effect between longitude and altitude. Additionally, the NA, MA, and SA SSTs were assessed as additional covariables to trend surfaces to determine whether they were necessary to be included in the models. For both monthly RX1day and RX5day indices, the ANOVA test showed that trend surfaces with the SSTs outperformed trend surfaces without the SSTs (Table **10**). For the RX1day spatial GEV model, it was found that when the monthly average of NA SST changed by 1°C, the location and scale parameters increased by 3.9 and 1.2, respectively (Table **10**). While NA and MA SSTs influenced only the scale parameter of the max-stable model during five consecutive days of rainfall (RX5day). This suggests that NA and MA SSTs primarily influenced the dispersion of RX5day with respect to the average extreme rainfall value over the research area. However, the results revealed that a change in the monthly average of MA SST led to decreases in both RX1day and RX5day across the study area. Consequently, an increase of 1°C in MA SST resulted in decreases of 1.48 and 0.56 in dispersion for RX1day and RX5day, respectively.

Table 10: Estimated parameters of preferred trend surfaces using spatial GEV.

Rainfall variable	Model	Estimated parameters	
RX1day	Trend surfaces	σ(s) =	71.2 -1.7 lat(s) + 6.7 lon(s) – 79.5 alt -20 (lon(s) × alt(s)) + 1.2 NA – 1.48 MA
		μ(s) =	61.3 – 1.6 lat(s) + 7.1 lon(s) – 86.2 alt -21.9 (lon(s) × alt(s)) + 3.9 NA – 1.55 MA
		ε(s) =	5.7×10^{-2}
RX5day	Trend surfaces	σ(s) =	29.5 + 0.2 lat(s) + 3.4 lon(s) – 16.6 alt -10.1 (lon(s) × alt(s)) + 0.59 NA – 0.56 MA
		μ(s) =	55.5 -0.8 lat(s) + 0.03 lon(s) + 24.1 alt – 0.3 (lon(s) × alt(s))
		ε(s) =	1.1×10^{-2}

It is crucial to assess the occurrence of extreme rainfall magnitudes between climate stations over the study area after selecting appropriate trend surfaces for both RX1day and RX5day pointwise spatial Generalized Extreme Value (GEV) models. The incorporation SST influences in the spatial GEV models for both RX1day and RX5day revealed significant differences compared to models that do not account for SST effects (Figure **18-19**). The R50 and 100-year return level figures for RX1day (Figure **18**) and RX5day (Figure **19**) showed that increasing North Atlantic (NA) and Middle Atlantic (MA) SSTs resulted in greater amounts of extreme precipitation in the northeast to west-southern directions of the study area, compared with scenarios without SST integration. Without integrating SSTs into the RX1day spatial GEV model, the ranges for the 50-year return period were between 79 and 136 mm, while for the 100-year return period, they were between 89 and 156 mm over the entire study area. When SSTs were integrated into the RX1day spatial GEV model, extreme rainfall became more intense, with ranges between 46 and 206 mm for both 50- and 100-year return periods. The western part of the study area was most affected by daily maximum monthly extreme rainfall, regardless of whether SST influences were considered or not.

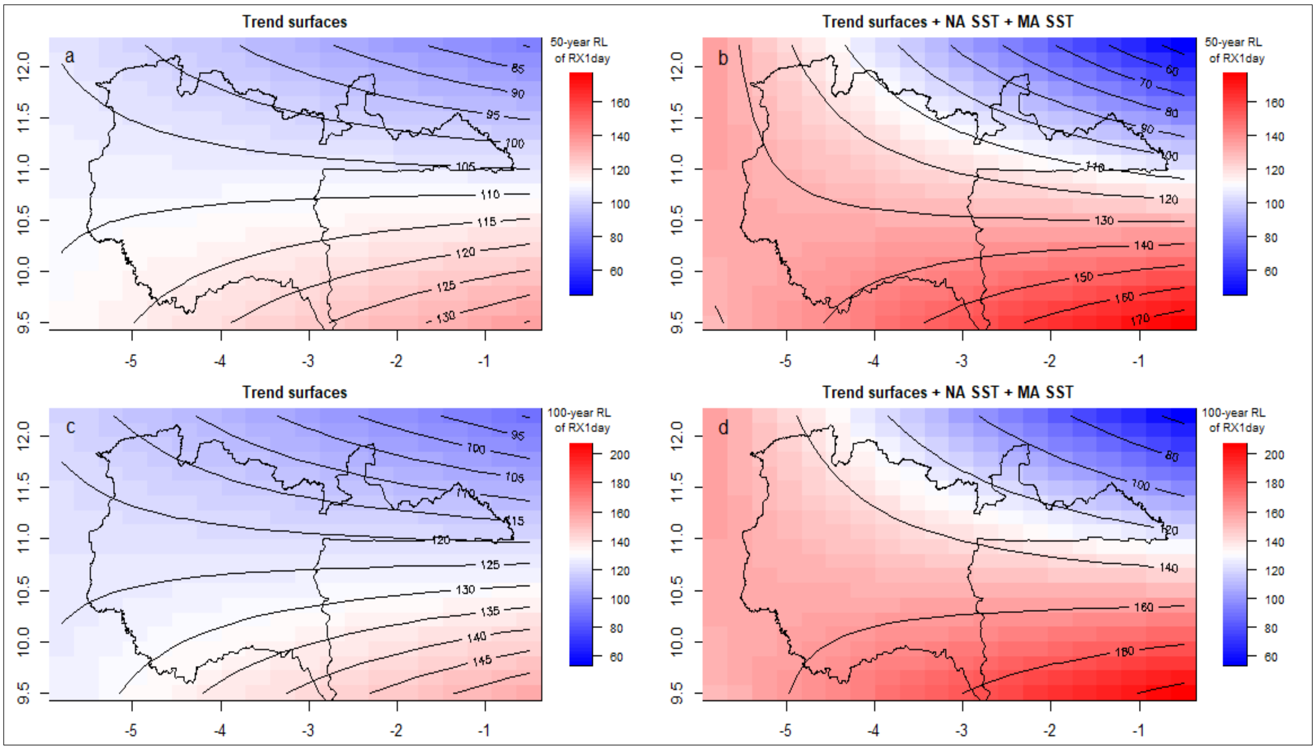


Figure 18: Spatial variation of RX1day pointwise 50- and 100-year return levels estimated from spatial GEV models influenced by North Atlantic (NA) SST and Middle Atlantic (MA) SST over the study area.

Relative to RX5day, we found similarities with RX1day concerning the influence of SST on the 50- and 100-year return periods of RX5day over the study area (Figure **19**). Without integrating SSTs in the RX5day spatial GEV model, the extreme rainfall range was between 145 and 189 mm for a 50-year return period, while for a 100-year return period, the range of extreme rainfall was between 164 and 213 mm over the study area. However, under the influence of SSTs, the monthly maximum of consecutive five-day extreme rainfall (RX5day) ranges between 149 and 195 mm for a 50-year return period and between 166 and 220 mm for a 100-year return period. Unlike RX1day, it is interesting to note that RX5day return levels for 50- and 100-year return periods evolved from northwestern to southeastern directions, with the southeastern part of the study area being most affected by the monthly maximum of consecutive five-day extreme rainfall.

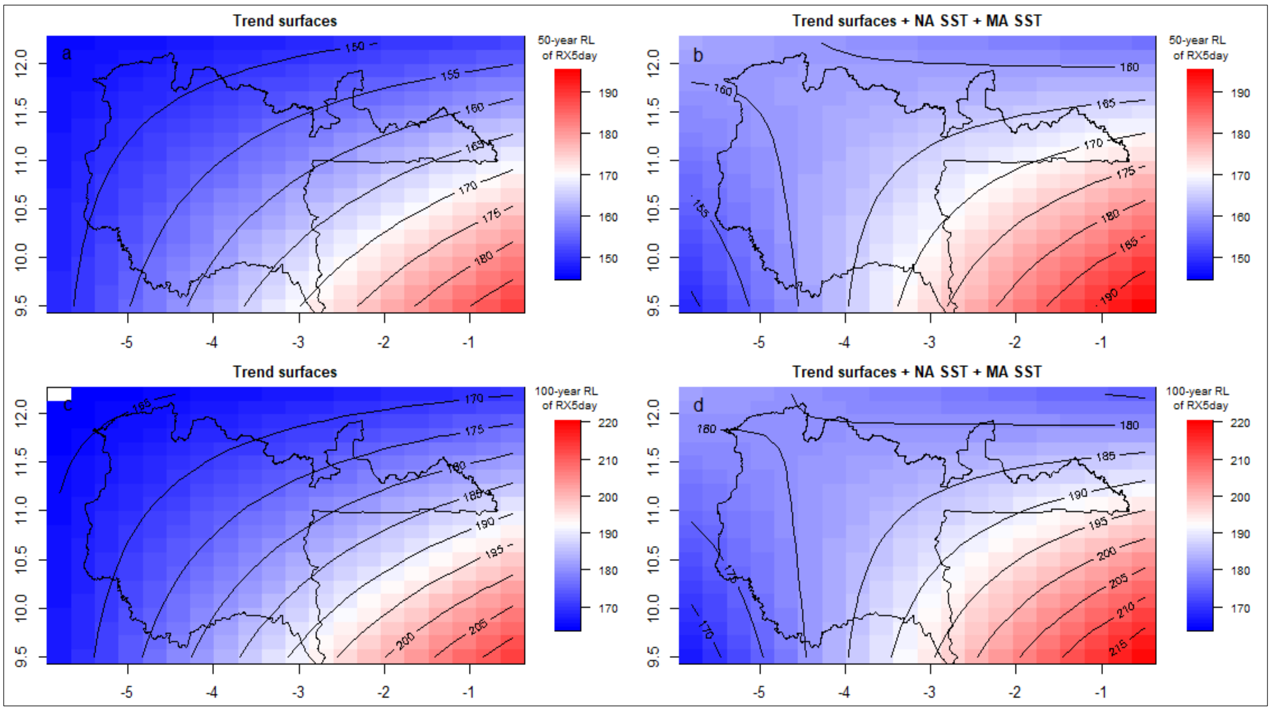


Figure 19: Spatial variation of RX5day pointwise 50-, and 100-year return levels estimated from spatial GEV influenced by North Atlantic (NA) SST and Middle Atlantic (MA) SST over the study area.

The southern part of Burkina Faso could potentially become more prone to flooding if there is warming in the Middle and North Atlantic, leading to flood-prone areas with considerable impacts on people and their properties due to extreme rainfall. However, this spatial GEV modelling was based on a pointwise approach and did not consider the spatial dependence amongst the climate stations. Therefore, the max-stable modelling considering the spatial dependence will be introduced in the next section.

4.1.3. Spatial dependence of Brown-Resnick max-stable process in modelling extreme precipitation.

To consider the spatial dependence among climate stations in the modelling of both extreme rainfall indices, we used Brown-Resnick max-stable models. Table **11** shows the results of estimation of both RX1day and RX5day max-stable models. We found that when spatial dependence was considered in zonal modelling (Table **11**), the variability effects of SSTs in the north and middle Atlantic on both RX1day and RX5day extreme rainfall indices were relatively smoother compared to pointwise modelling (Table **10**). An increase in North Atlantic SST by 1°C has increased the dispersion of RX1day and RX5day with respect to the average magnitude of the centre of their distributions by 0.9 and 0.22, respectively. While the upward increase in middle Atlantic SSTs led to the dispersion of RX1day and RX5day shifting downward with respect to the average magnitude of the centre of their distributions (Table **11**). As far as the location parameter of RX1day is concerned, when the North Atlantic SST increases by 1°C, extreme rainfall shifts upward with respect to the baseline magnitude of the centre of the RX1day distribution. While extreme rainfall shifts downward when an upward increase in middle Atlantic SSTs is observed over the study period. Additionally, we found that topography increases RX5day severity with respect to the average magnitude of the centre of its distribution, while it affects negatively RX1day with respect to the average magnitude of the centre of its distribution. It is crucial to note that topography in this study has decreased the dispersion of both RX1day and RX5day with regard to the average magnitude of the centre of their distributions over southern Burkina Faso. Relative to spatial dependence, it was noticed that RX1day has higher range parameter values compared to RX5day, which implies that the spatial dependence between pairs of stations was stronger for RX1day than for RX5day over the study area. This suggests that RX1day was correlated over longer distances than RX5day, and this correlation decays more slowly with increasing distance between pairs of climate stations. In contrast, RX5day spatial dependence decays more quickly with increasing distance between pairs of stations. The smooth parameter of RX1day has a much higher value than the smooth parameter of RX5day in the max-stable model, suggesting that RX1day tends to vary more predictably and gradually across space, while RX5day rainfall extremes show more abrupt changes.

Table 11: Estimation of Brown-Resnick max-stable models of both RX1day and RX5day extreme rainfall indices

Rainfall index	Model	Estimated parameters	
RX1day	Trend surfaces	$\sigma(s) =$	51.7 – 2.5 lat(s) + 1.7 lon(s) – 35.5alt –17.1 (lon(s) × alt(s)) + 0.9× (NA SST) – 6.0 × (MA SST)
		$\mu(s) =$	75.9 +1.5 lat(s) + 5.6 lon(s) – 69.3 alt -17.1 (lon(s) × alt(s)) + 1.8× (NA SST) – 3.0× (MA SST)
		$\varepsilon(s) =$	2.85×10^{-2}
	Spatial dependence	$\lambda =$	9.31×10^{-2}
		$\nu =$	1.44
RX5day	Trend surfaces	$\sigma(s) =$	35.7 – 0.9 lat(s) + 2.2 lon(s) – 4.6 alt -6.6 (lon(s) × alt(s)) + 0.22 (NA SST) – 0.22(MA SST)
		$\mu(s) =$	53.6 -0.6 lat(s) – 0.6 lon(s) + 20.3 alt + 0.6 (lon(s) × alt(s))
		$\varepsilon(s) =$	5.12×10^{-2}
	Spatial dependence	$\lambda =$	3.82×10^{-3}
		$\nu =$	1.8×10^{-1}

Please note: λ and ν are the range and smoothness spatial parameters of the models, respectively.

4.1.4. Diagnostic of Brown-Resnick max-stable models

The left and right panels of Figure **20** independently assess the quality of the RX1day and RX5day models. The plots indicate that observations at each simple location are well modelled, as evidenced by the proximity of the return level plots to the unit diagonal. Additionally, the spatial dependence, as measured by the extremal coefficient, is also effectively captured. Given that the plots are very close to the unit diagonal, this suggests that the RX1day and RX5day models accurately represent conditions at each simple site. Moreover, the fitted extremal coefficients closely match those observed, demonstrating effective modelling of spatial dependence. Notably, the calibration of the spatial dependence measure for the RX5day model appears superior to that of the RX1day model (Figure **20**). This implies that the RX5day model may offer a more accurate representation of spatial dependence across the study area compared to the RX1day model.

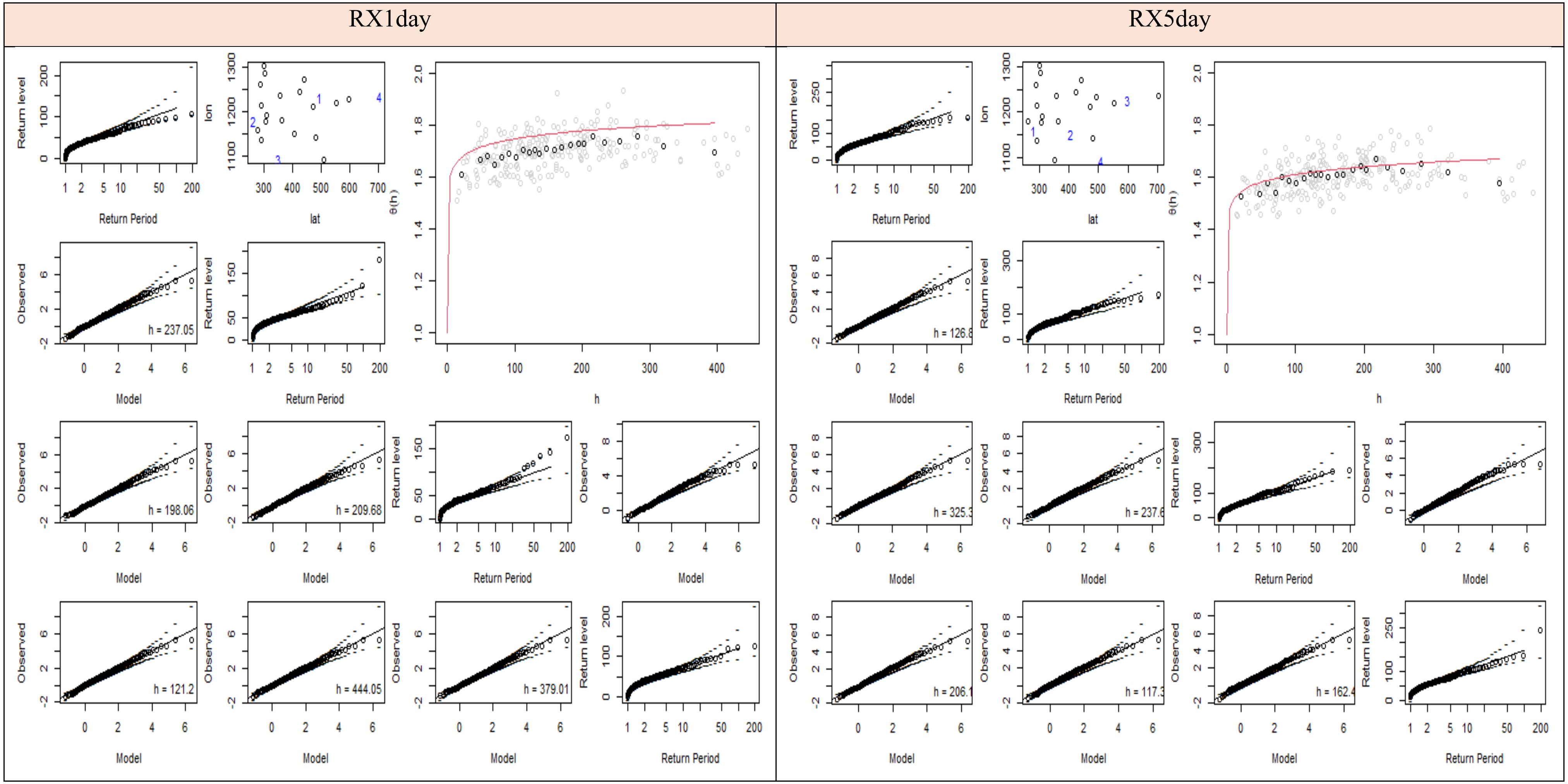


Figure 20: Calibration of max-stable models to extreme rainfall (RX1day and RX5day)

4.1.5. The concurrence of extreme rainfall.

We found that the value maximum of fitted extremal coefficient of RX1day index is about $\theta_{BR}(h) = 1.8$ whereas the maximum value of fitted extremal coefficient of RX5day is about $\theta_{BR}(h) = 1.67$. In addition, it was observed that the probability of concurrence of RX1day and RX5day is less than 0.5 over the study area (Figure **21**).

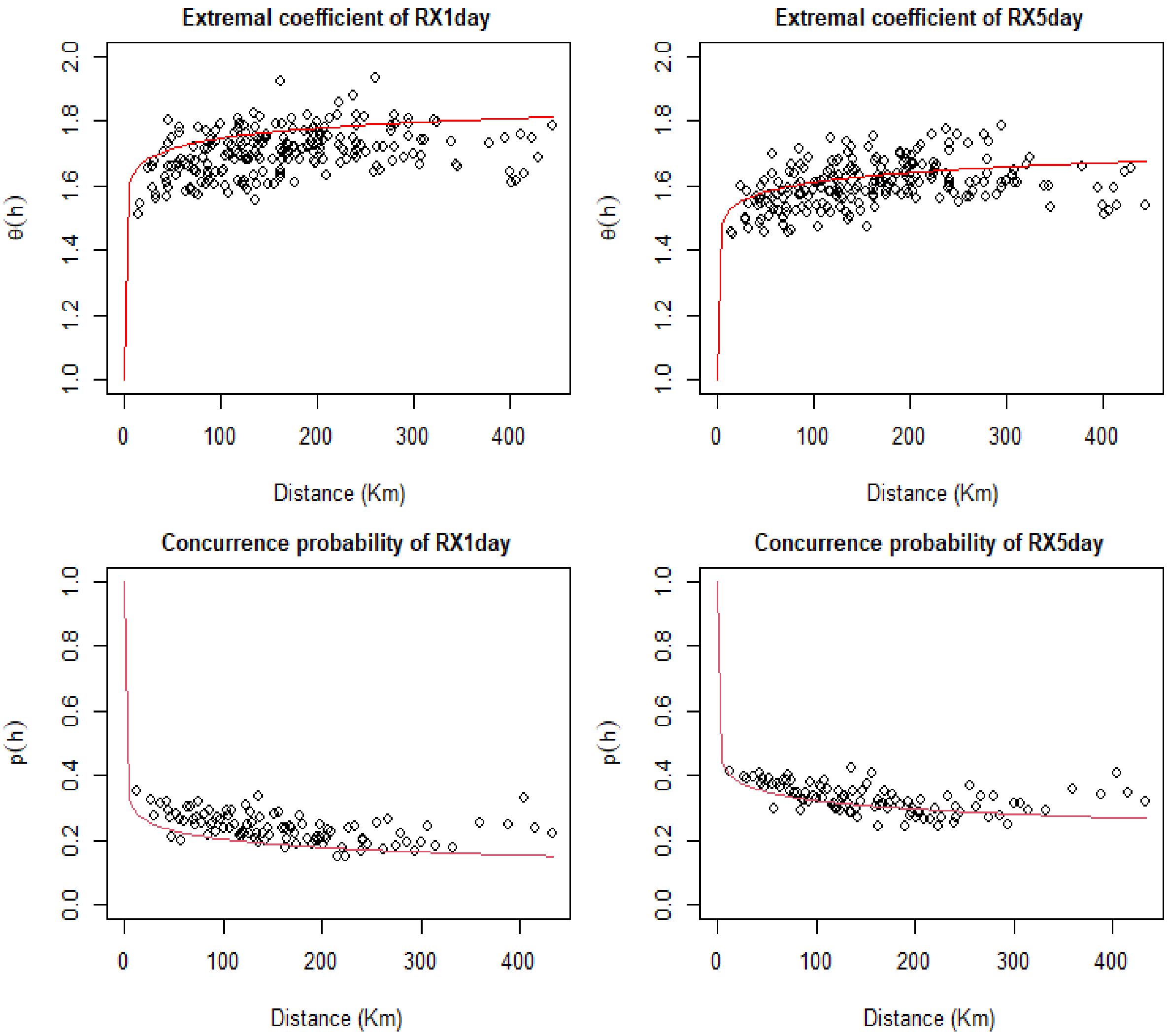


Figure 21: First row: we have extremal coefficients of Brown-Resnick model fitted using RX1day and RX5day, respectively.

From the analysis extremal coefficient of RX1day, we found that the distances h such that $\theta_{BR}(h) = 1.77$ and $\theta_{BR}(h) = 1.79$ are equal to 230 km and 300km, respectively. For distances of 200 km and 300 km the extremal coefficient of RX5day is $\theta_{BR}(200\ km) = 1.65$ and $\theta_{BR}(300\ km)$ =1.67. This indicates that extreme precipitation exhibits spatial dependency within a radius of 300 km. Within a radius of 200 km, this spatial dependence of extreme precipitation is particularly strong, gradually diminishing until around 300 km, where it becomes less likely to observe dependent extreme rainfall in our study area. Beyond this distance, the spatial dependence further decreases, rendering the co-occurrence of extreme precipitation increasingly improbable.

There are similarities between RX1day and RX5day in terms of the probability of occurrence when the extreme event originates from the locality of Sideradougou, which recorded the highest values of rainfall over the study period. The concurrence probabilities of extreme rainfall remain relatively low when the extreme rainfall events (RX1day and RX5day) originate from Sideradougou. The concurrence probability of both RX1day and RX5day ranges within specific intervals: between 0.16 and 0.22 for RX1day, and between 0.2 and 0.3 for RX5day, showing an increase from east to west across the study area (Figure **22-a,b**). Additionally, when extreme rainfall originates from Gaoua, the concurrence probabilities range between 0.1 and 0.25 for RX1day and between 0.18 and 0.28 for RX5day, with the highest concurrence probability occurring in the southeastern part of the study area (Appendix **E-a,b**). However, we noted that extreme rainfall originating from Koumbia exhibited a strong concurrence probability across the study area. Specifically, the concurrence probability ranged between 0.2 and 0.6 for daily rainfall and increased up to 0.8 for rainfall persisting over five consecutive days. The highest concurrence probabilities were observed in the northern part of the study area (Appendix **E-c,d**).

To determine the number of sites that could be concurrently affected by extreme rainfall from a randomly selected site in the study area, we introduced the concept of extremal concurrence cell areas. The results indicate that the expected number of RX1day concurrence cell areas ranges between 4 and 5, with a homogeneous spatial distribution across the study area. Conversely, the spatial distribution of expected RX5day concurrence cell areas is less uniform. Specifically, the expected RX5day concurrence cell areas span between 6 and 7 in the eastern part of the study area, and between 5 and 6 in the western part. This suggests that RX1day could concurrently occur at between 4 and 5 locations, and when the rainfall persists for five consecutive days (RX5day), the number of affected sites could increase up to 7, regardless of where the extreme rainfall has originated in the study area.

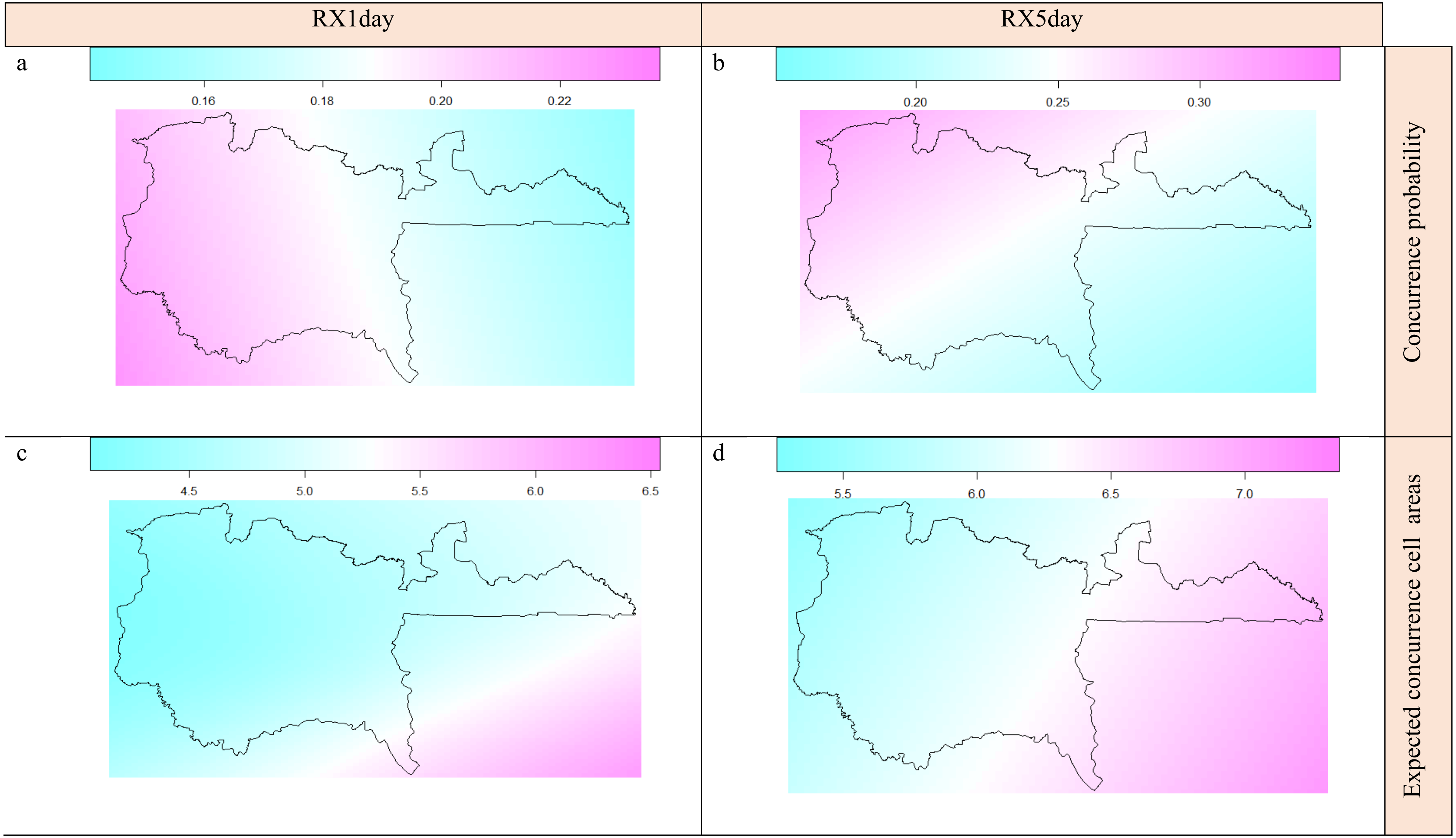


Figure 22: Maps of the extremal concurrence probability and spatial distribution of expected extremal concurrence cell areas of extreme rainfall

4.1.6. Spatial variation of predicted extreme rainfall using Brown-Resnick max-stable models

4.1.6.1. Spatial variation of 50-, and 100-year of return level of extreme precipitation

Using a max-stable process to model spatial patterns of extreme rainfall under the influence of North and Middle Atlantic Sea Surface Temperatures (SSTs), we found that the 50-year return level was estimated to range between 74 and 161 mm for RX1day and between 153 and 199 mm for RX5day over the study area. Similarly, for long-term predictions, we found that the 100-year return level of RX1day was estimated to range from 77 to 177 mm, and for the same return period, RX5day was estimated to range between 174 and 227 mm. It is crucial to note that RX1day and RX5day had different directions over the study area. Therefore, RX1day had a direction from northeast to southwest, while RX5day had a direction from northwest to southeast (Figure **23**). This suggests that these extreme rainfall indices tend to develop and become more severe according to their respective directions.

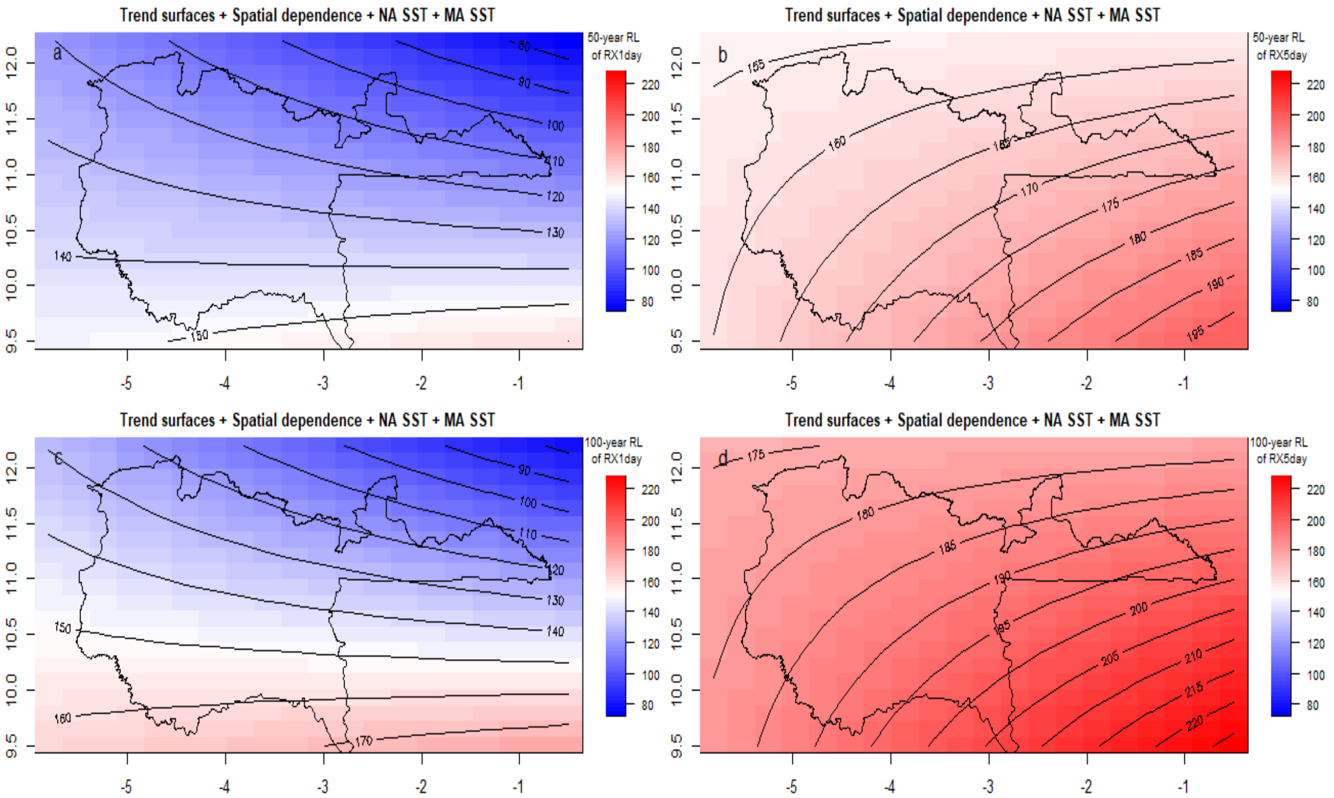


Figure 23: Spatial variation of 50-, and 100-year return level of RX1day and RX5day using max-stable models which were influenced by North Atlantic (NA) SST and Middle Atlantic (MA) SST over the study area.

4.1.6.2. Spatial variation of conditional 20-, 50-, and 100-year return level of extreme precipitation

Data processing has shown that on August 17, 2003, an extreme rainfall event of 232.3 mm impacted Sideradougou, with surrounding localities also recording substantial rainfall amounts. Remarkably, approximately 341.2 mm of rain fell over just five consecutive days, equivalent to about a quarter of the annual precipitation for the study area. The station situated near the centre of the study area recorded the highest values of RX1day and RX5day throughout the study period.

Consequently, we calculated the conditional return levels for RX1day and RX5day for 20-, 50-, and 100-year return periods at this central station. Figure **24** illustrates that the northwestern part of the study area is projected to experience the greatest impact for the 20-, 50-, and 100-year return periods, based on the 20-year return level observed at the Sideradougou site. This study further confirms the shift in extreme precipitation patterns towards an east-west direction. Specifically, we discovered that the 20-year conditional return level for RX1day ranges between 180 and 320 mm, and for RX5day, it falls between 320 and 450 mm. We also discovered that the 20-year conditional return level for RX1day ranges between 220 and 340 mm, and for RX5day, it varies between 360 and 500 mm. For the 100-year return period, the return levels for RX1day and RX5day fluctuate between 220 and 380 mm and between 400 and 560 mm, respectively.

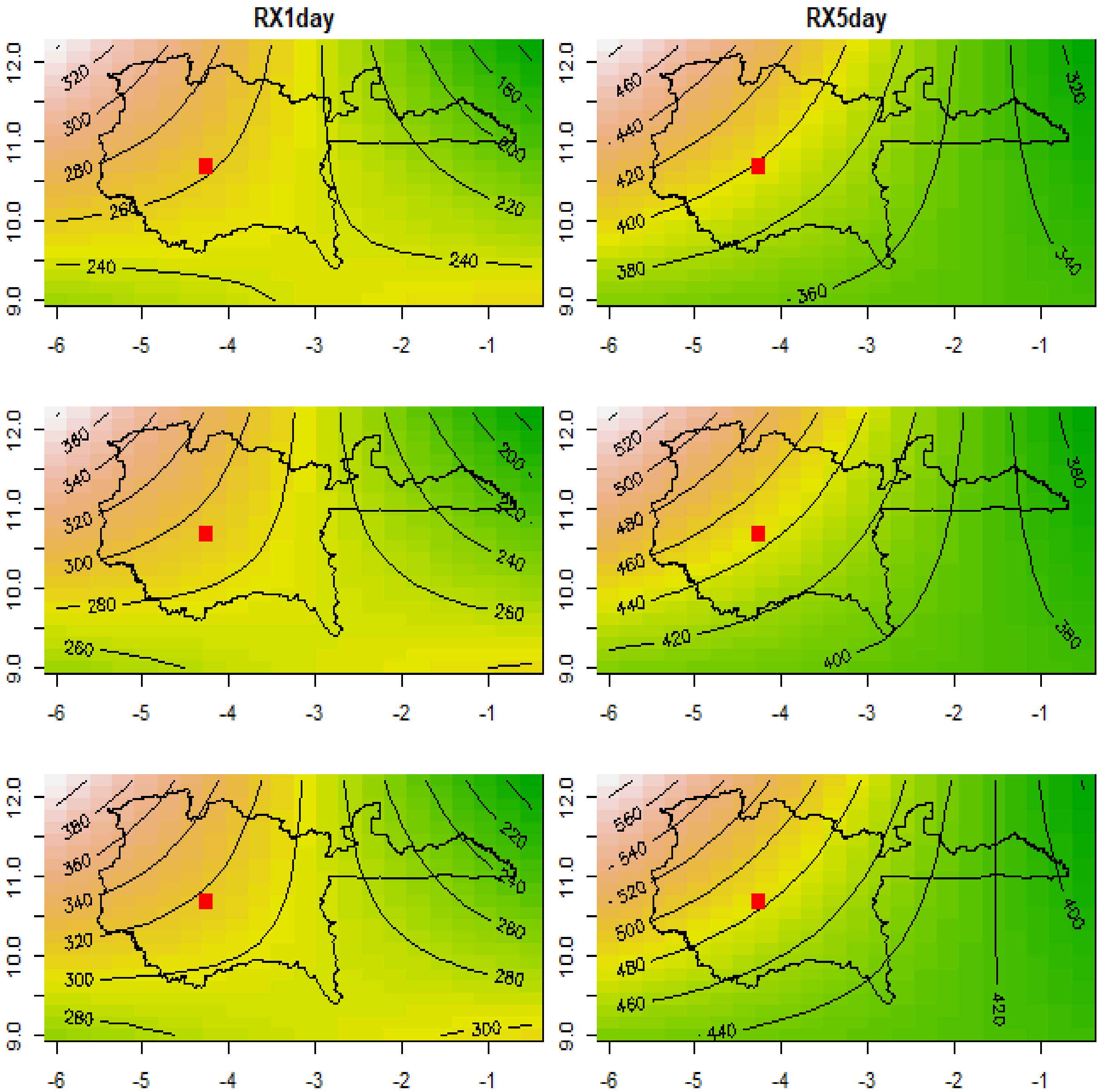


Figure 24: Return levels for 20-, 50-, and 100-year periods for rx1day and rx5day, conditioned on a 20-year return period at the Sideradougou station (indicated by the red square), which recorded the highest values for both rx1day and rx5day during the study period.

4.1.7. Spatial risk assessment and normalized spatial aggregated loss due to extreme rainfall.

The average area of the study area likely to be affected by the normalized aggregated rainfall amount T_A for monthly maximum of 1-day rainfall is such that

$$T_A = \frac{1}{|A|}\int_A Z(s)\,ds = 5.5 \times 10^{-4} \qquad \textbf{(2.9)}$$

T_A also represents approximately 0.055% of the study area, indicating that the total rainfall amount of monthly RX1day could potentially affect around 0.055% of the study area. This 0.055% equates to roughly 3 km^2, which is the estimated area likely to be impacted by monthly RX1day during the occurrence of extreme rain events. The population density of the study area, derived from the most recent 2019 census data compiled by the National Institute of Statistics and Demography (INSD, 2023), is approximately 852 people per km^2. Given this recent population density, it is estimated that an average of 2,556 people could be affected by a monthly RX1day events. Furthermore, we found that the probabilities of the aggregated rainfall amount of monthly RX1day exceeding the capacity of water reservoirs of volumes 900,000 m^3 and 10^6 m^3 are 0.054 and 0.044, respectively (Figure **25**-top left and right).

Similarly, the average surface of the study area likely to be affected by the normalized aggregated rainfall amount T_A for monthly RX5day is such that

$$T_A = \frac{1}{|A|}\int_A Z(s)\,ds = 7.8 \times 10^{-4} \qquad \textbf{(2.10)}$$

Which corresponds to 0.078% of the study area. The average area of localities likely to be affected by monthly RX5day is therefore estimated at 4.1 km^2 with an estimated population at risk of 3 493 people. We determined that the probabilities for an aggregated rainfall amount, corresponding to the monthly RX5day event, overflowing water reservoirs with volumes of 900,000 m^3 and 10^6 m^3 are 0.272 and 0.21, respectively (Figure **25**-bottom left and right)

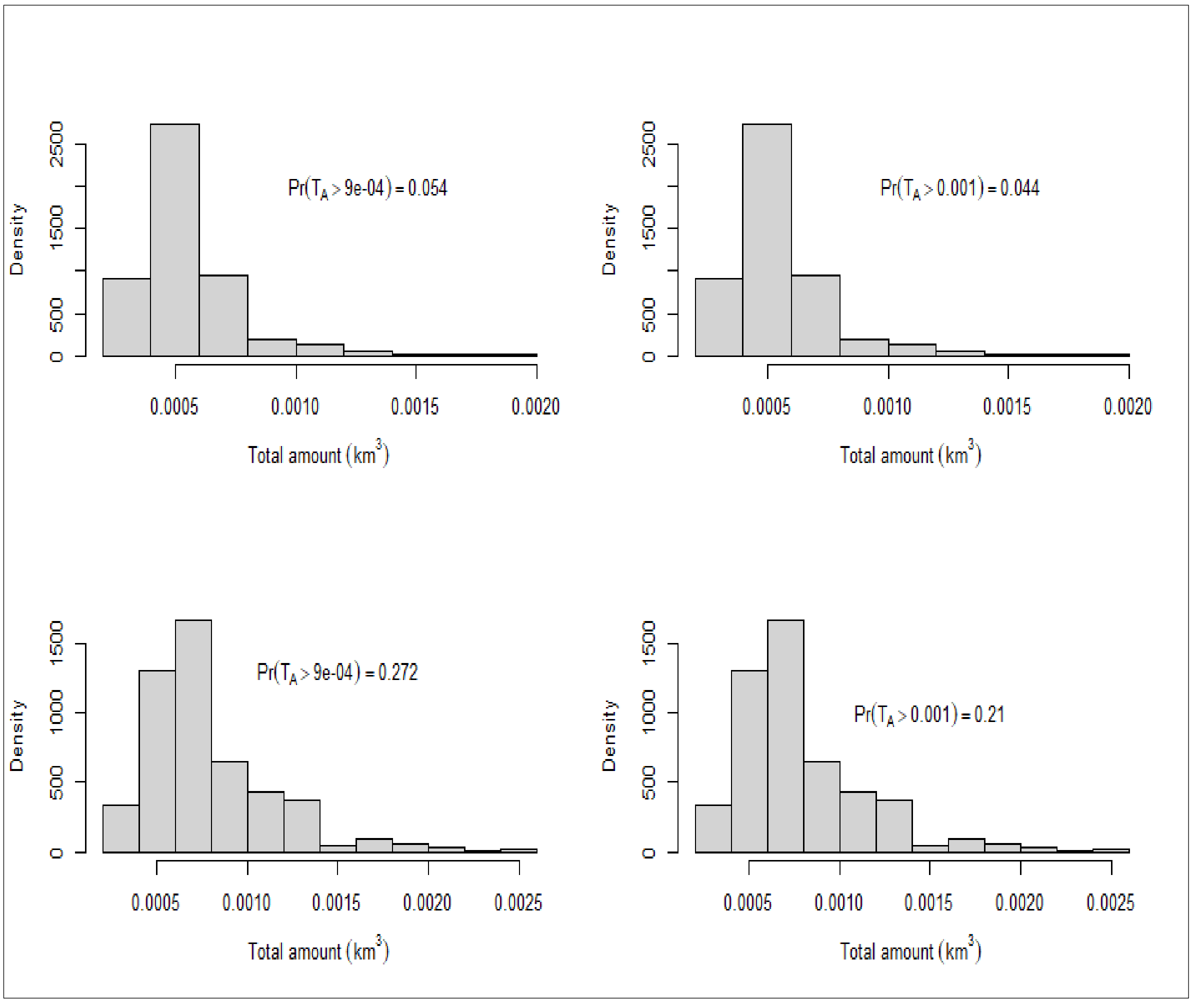


Figure 25 : Probability of total amount of monthly RX1day and RX5day to overflowing a reservoir with a volume of 900 000 m^3 and 1 000 000 m^3 are shown from left to right, respectively.

4.2. Discussion

Identifying hotspots of simultaneous extreme precipitation probability may be of interest to the government in determining risk areas for allocation of emergency flood response resources and to insurance companies seeking to operationalize disaster insurance, given that this region receives significant amounts of daily precipitation over the past two decades. In terms of concurrence probabilities, significant similarities were observed between RX1-day and RX5-day, despite minor differences in their concurrence probabilities. Analyzing both precipitation variables, considering spatial dependence structures, is crucial for characterizing their spatial behaviour in southern Burkina Faso.

The larger ranges and higher smoothness values of the RX1day max-stable model indicate that these events are influenced by mesoscale processes such as regional convective systems or atmospheric patterns with smoother, more widespread effects. This suggests that RX1day events are more predictable spatially and tend to affect larger regions, making RX1day models potentially more suitable for assessing risks from large-scale events for infrastructure planning or risk assessment purposes. In contrast, the smaller ranges and lower smoothness values of the RX5day max-stable model reflect the dominance of localized effects in these extreme rainfall events, likely due to multiple independent storms or spatially variable rainfall accumulation. This leads to patterns that are less predictable and more heterogeneous over space, resulting in more localized and harder to predict RX5day events due to rapid spatial decorrelation. Consequently, RX5day models may be better suited for localized flooding risk assessments, as they capture the heterogeneity in extreme rainfall accumulation over time.

Geographical coordinates, topography, and Atlantic sea surface temperatures were used as potential covariates to understand the factors influencing spatial extreme rainfall over the study area. However, time variable as a potential covariable was not considered in the spatial modelling of extreme rainfall because the results of a regional Mann-Kendall test revealed no significant trend in both RX1day and RX5day rainfall variables. Similarly, a trend analysis of RX1day and RX5day in the same study area (Sougué et al., 2023) found more downward and non-significant trends than upward trends in both RX1day and RX5day rainfall indices at the station level. Relatively to the topography, it was influenced by both extreme RX1day and RX5day events over the study area. Indeed, RX1day events were less dispersed and closer to the average magnitude of the centre of their distribution when elevations are higher compared to lower elevations. This influence of high elevation to decrease the uncertainty of RX1day could be a reason why this rainfall variable is more appropriate for large-scale studies than RX5day. Similarly, a study carried out in the Nelson Churchill River basin of North America found that topography had less of an effect on RX1day amounts compared to their average magnitude of distribution with higher elevations (Boluwade, 2023). Unlike RX1day events, topography influences RX5day events differently across the study area. Topography was negatively correlated with the scale parameter of RX5day max-stable model, indicating that RX5day events were less dispersed at higher elevations. While there was a positive correlation between topography and the location parameter of its max-stable model, suggesting that the amount of RX5day event increased relative to the baseline magnitude of its distribution at higher elevations. Thus, these opposite effects of topography on the dispersion of RX5day compared to its baseline magnitude come to further strengthen the idea that the RX5day variable should be used for local-scale studies rather than large-scale studies. This different behaviour of topography on rainfall indices was also found in Cape Verde, where the interaction between topography and rainfall is complex and variable. It creates rainfall patterns that are not repeated from one season to the next, reflecting the erratic behaviour of rainfall (Sanchez-Moreno et al., 2014). Additionally, the South Atlantic SST, as a covariate in the spatial extreme rainfall modelling using max-stable processes, was not statistically significant. However, pointwise modelling of daily extreme rainfall events conducted in the same research area indicated that North, Middle, and South Atlantic SSTs influenced daily extreme rainfall (Sougué et al., 2023). The similarities between both pointwise and zonal modelling approaches are that when North Atlantic SST increased, it also increased the severity of extreme rainfall. In the context of climate change, global temperatures, including land and ocean temperatures, are expected to significantly increase climate extremes as global greenhouse gas emissions have continued to rise (IPCC, 2023).

To spatial distribution of concurrence case of monthly RX1day and monthly RX5day, we found that the risk of concurrence probability of both extreme rainfall indices was moderate over the study area when these extreme rainfalls were originated from Sideradougou and Gaoua, except when they are originated from Koumbia where the risk of concurrence probability was notably high. The western part of the was also found to be hotspot area of extreme rainfall (Sougué et al., 2023) and has recorded several floods between 1986 and 2017, making it one of the most flood-prone areas in Burkina Faso (Tazen et al., 2019). Furthermore, Guelbeogo & Ouedraogo (2022) found that 76% of the Kou Valley in the southwestern part of the study area has a moderate to very high susceptibility to flooding. However, the number of RX5day concurrence cell areas is higher in the eastern part of the study area compared to the western part, regardless of the specific sites within the study area where the RX5day events originated. This indicates that the eastern region tends to be a hotspot for extreme rainfall events lasting five consecutive days. The research conducted by Sougué et al.(2023) found that areas experience more frequent and intense extreme rainfall, especially when thy were influenced by the variability of Atlantic sea surface temperatures.

In this study, we identified a slight spatial heterogeneity with respect to the concurrence of both monthly RX1day and RX5day. This spatial heterogeneity of the study area shows that the risk of extreme rainfall in the study area violates the risk property of spatial invariance under translation, which implies that the risk score should be the same at any site covered by an insurance company (Koch, 2017). The sustainability of disaster insurance, as a complement to other coping and adaptive strategies, also depends on the diversification of disaster risks. Governments and insurance companies should therefore better consider the issue of disaster risk diversification in risk management policies. In addition to risk diversification, the scarcity and poor quality of historical data about natural disasters has been made it difficult for insurance companies to assess medium- and long-term risk of disasters. A pilot of index-based insurance program introduced in some developing countries over the past ten years was found to be not sustainable (Tiepolo et al., 2017). The same authors support the results were below expectations. They also supported the idea that this pilot study did not lead to long-term results.

This study offers unconditional and conditional return levels that consider the spatial dependence of extreme precipitation, providing valuable insights for the design of future hydrological infrastructures. The concurrence of extreme rainfall analysis must be increasingly considered in flood hazard mapping, as flood hazard mapping has long and widely been carried out using the pointwise extreme quantile method, whereas extreme precipitation has a spatial dependence. We also analyze the spatial dependence of extreme precipitation and found that the monthly RX1day and RX5day were moderately dependent within about 300 km. Similar results were found in a national scale study using generalized pareto process modelling, that showed that extreme precipitation is spatially correlated within 200 km and gradually decreases with increasing distance (Béwentaoré & Barro, 2022). Such information is useful for climate weather modelers and hydrologists in monitoring and generating of extreme rainfall.

Public and private entities involved in disaster risk management are increasingly interested in identifying the spatial risk and estimating the average number of people likely to be affected by extreme events. In this work, we were able to determine the total area of the study area likely to be affected by flooding due to monthly RX1day or RX5day events. In addition to the estimating the aggregated area at risk, we estimated the number of people likely to be affected by monthly RX1day and RX5day events. Our results indicate that the estimates of the number of people likely to be affected by flooding from extreme precipitation events closely match the observed data for individuals impacted by floods between 2006 and 2019 (Appendix **D**). These statistics regarding the area and population at risk offer valuable insights that could assist governments and private partners engaged in disaster risk management in effectively planning budgets and allocating emergency resources during flood events. This study has contributed to the practical application of spatial extremes models, which, until now, have seen limited use ranging from national to local studies across West Africa.

4.3. Partial conclusion

The study investigates the small-scale diversification of concurrence probability for monthly RX1day and RX5day events over the period from 1986 to 2017 in southern Burkina Faso. We applied the max-stable model of Brown-Resnick to monthly RX1day and RX5day data on a small-scale area representing approximately 16% of Burkina Faso. Our analysis revealed similarities between the monthly RX1day and RX5day variables, suggesting that these should be preferred for modelling the concurrence of extreme rainfall in flood hazard management. This approach is advantageous because the rainfall index presents a worst-case scenario of extreme rainfall risk, thereby bolstering preparedness efforts, particularly for insurance companies. We found a significant spatial dependence between rainfall extremes, resulting in 100-year conditional return levels for monthly RX1day and RX5day events reaching 30% and 45% of annual rainfall, respectively. Furthermore, our findings indicate that the probability of concurrence probability of extreme rainfall is higher in the western, whereas the number of expected monthly RX5day concurrence cell areas is greater in the eastern part of the study area. In this study, we calculated the average area and population likely to be affected by flooding from monthly RX1day and RX5day events. The notable spatial dependence of rainfall extremes highlights the significance of using spatial extremes models instead of pointwise models for mapping flood risks linked to extreme rainfall.

Chapter 5: Assessment Of Rural Flood Risk And Factors Influencing Household Flood Risk Perception In The Haut-Bassin Region Of Burkina Faso

In this chapter, the section of data analysis concentrates on flood risk assessment and the determinants of household flood risk perception. The results of the data analysis involve processing of survey data gathered at the household level, assessing flood risk and the identifying the drivers of flood risk. Additionally, the relationship between flood risk and flood risk perception is investigated, and the correlation between flood risk perception and its influencing factors is analyzed to select potential covariates for the regression model. Furthermore, the flood risk perception model is estimated, and the key influencing factors are identified. Following this, the flood risk perception model is estimated, and the influential factors are pinpointed. The subsequent section discusses these results, and the chapter concludes with a partial conclusion.

5.1. Results

5.1.1. Socio-demographical characteristics of households

The average size of households surveyed was large, with an average size of 12 people per household. At the time of the survey, 83% of these households had men as a head of the household. The household heads without schooling represented 63.6% of the sample against only 36.5% of the households that attend least primary school. About 55.1% and 22.1% of the heads of household reported having people with chronic diseases and people's disabilities, respectively. Most households (81% of households) reported having an income below the national average, although 39.4% of households said having a non-farm income. Given the progressive degradation of land and the vulnerability of the agricultural sector to climate variability (rainfall and temperature), few households (25%) have access to financial institutions to help them in their daily activities. Households living in earthen and wooden houses represent about 64% of the surveyed households, which are likely to be homeless during intense floods. Because 74.5% of the households reported that their houses were older than 10 years. Against this background, 78.5% of households were revealed to have taken mitigation measures. But only 13.3% of households have adopted an emergency plan, as the majority, 86.7% of households, believe that the floods are due to the willingness of God. Few households reported having health or farm insurance in the study area. Amongst the households surveyed, only 2 out of 100 households reported having health or agricultural insurance. About half of the households surveyed (48%) said that they no longer had confidence in government disaster risk management programs, especially for implementation of flood mitigation and reduction measures.

5.1.2. Assessment of household flood risk components

Out of the 14 villages in the study area, 13 are characterized by high to very high hazard of flooding (Figure **26-a**), apart from a village in the northern part where the flood hazard is moderate. The villages most exposed to flooding are located in the west-central region Figure **26-b**). Lahirasso (village 11), with an exposure score of 0.56, exhibits the lowest flood exposure due to the lowest human exposure among all villages as well as low assets exposure. Tanwogma (village 7) and Seguere (village 10) have the highest exposure scores (> 0.8), as both residents and their assets are strongly exposed to floods. However, the local exposure in Tanwogma is not as high as local exposure in Seguere. Food susceptibility is moderate with values of the susceptibility indicator ranging from 0.47 to 0.58 across all villages (Figure **26-d**). This small variation indicates that susceptibility to flooding is not statistically different from one village to another. In all villages, except for Lahirasso (village 11) and Nematoulaye (village 12) in the northern area, households show a moderate lack of resilience (Figure **26-e**). Lack of resilience ranges from 0.48 to 0.66, with the highest values for Lahirasso (0.66) and Nematoulaye (0.63). In both villages, none of the residents have subscribed to health or agricultural insurance and a small proportion of residents have knowledge about flooding and warning systems.

Flood vulnerability, composed of exposure, susceptibility, and lack of resilience, scores from 0.56 to 0.66 (Figure **26-c**) from moderately to highly vulnerable. Overall, 50% of the villages are classified as moderately vulnerable and the other 50% are classified as highly vulnerable to floods. Again, the variation across the villages is small. Combining the hazard and vulnerability indicators shows that flood risk is high throughout the study area (Figure **26-f**), except for Lahirasso (village 11) and Banakeledaga (village 9). These two villages show moderate risk, mainly due to low values of hazard and susceptibility for Lahirasso, and low values of susceptibility and lack of resilience for Banakeledaga. About 93% of the surveyed households live in the 12 villages with high flood risk. High risk is mainly a consequence of high values of hazard and exposure, whereas susceptibility and lack of resilience are predominately moderate throughout the study area. Overall, the variation in the flood risk index is rather small, ranging from 0.55 to 0.68.

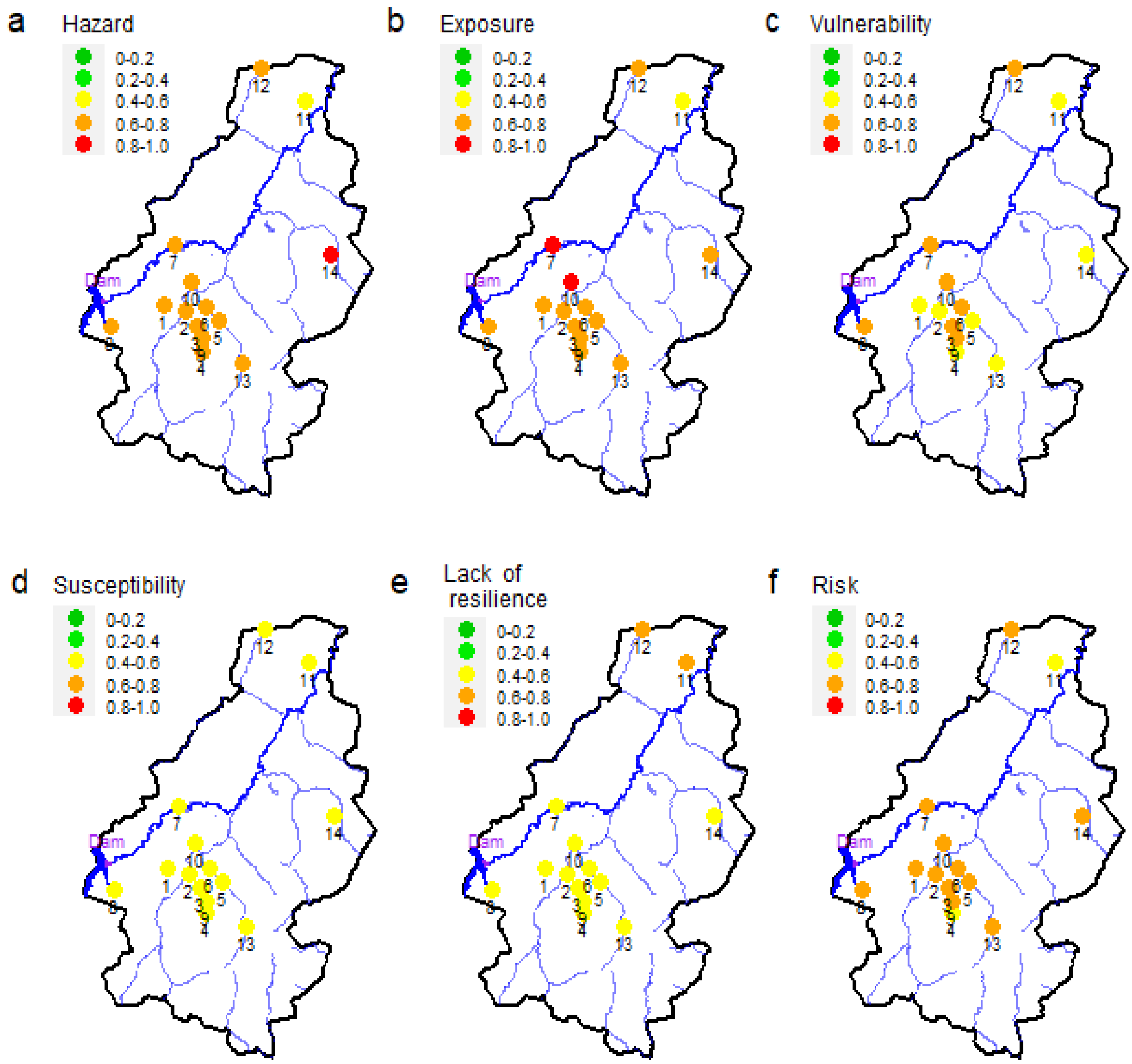


Figure 26: Scores of flood risk and its components for the flood-prone villages in the study area. The **red** (1-0.8), **orange** (0.8-0.6), **yellow** (0.6-0.4), **light green** (0.4-0.2) and **green** (0.2-0) colour denotes **very high**, **high**, **moderate**, **low**, and **very low** score, respectively. Numbers denote villages: **1**: Bama, **2**: Badara, **3:** Banahorodougou, **4:** Banakeledaga, **5:** Desso, **6:** Lanifiera, **7:** Seguere, **8:** Soungallodaga, **9:** Souroukoudougou, **10:** Tanwogma, **11:** Lahirasso, **12**: Nematoulaye, **13**: Santidougou, **14:** Kadomba. The purple dot shows the location of the dam of Samandeni.

5.1.3. Contribution of indicators to flood risk components

Figure 18 shows that flood frequency indicator contributed around twice as much to flood risk as the flood intensity indicator in the study area. It was found that exposure indicators were contributed almost equally to flood exposure. Relatively to susceptibility, we found that social network, economic condition, and natural resources degradation were found to contribute more to flood susceptibility, while the housing and amenities indicator was the one that contributes less to flood susceptibility. We found that indicators relating to information, mitigation measures and land-use adaptation contributed most to flood resilience, while the contribution of insurance indicators was not insignificant. All other indicators contribute equally to flood capacity. As mentioned, households are aware that their natural resources, social network, and economic condition are highly sensitive to flooding. Against this background, mitigation measures, land-use adaptation and information have been the most widely adopted measures to improve flood resilience.

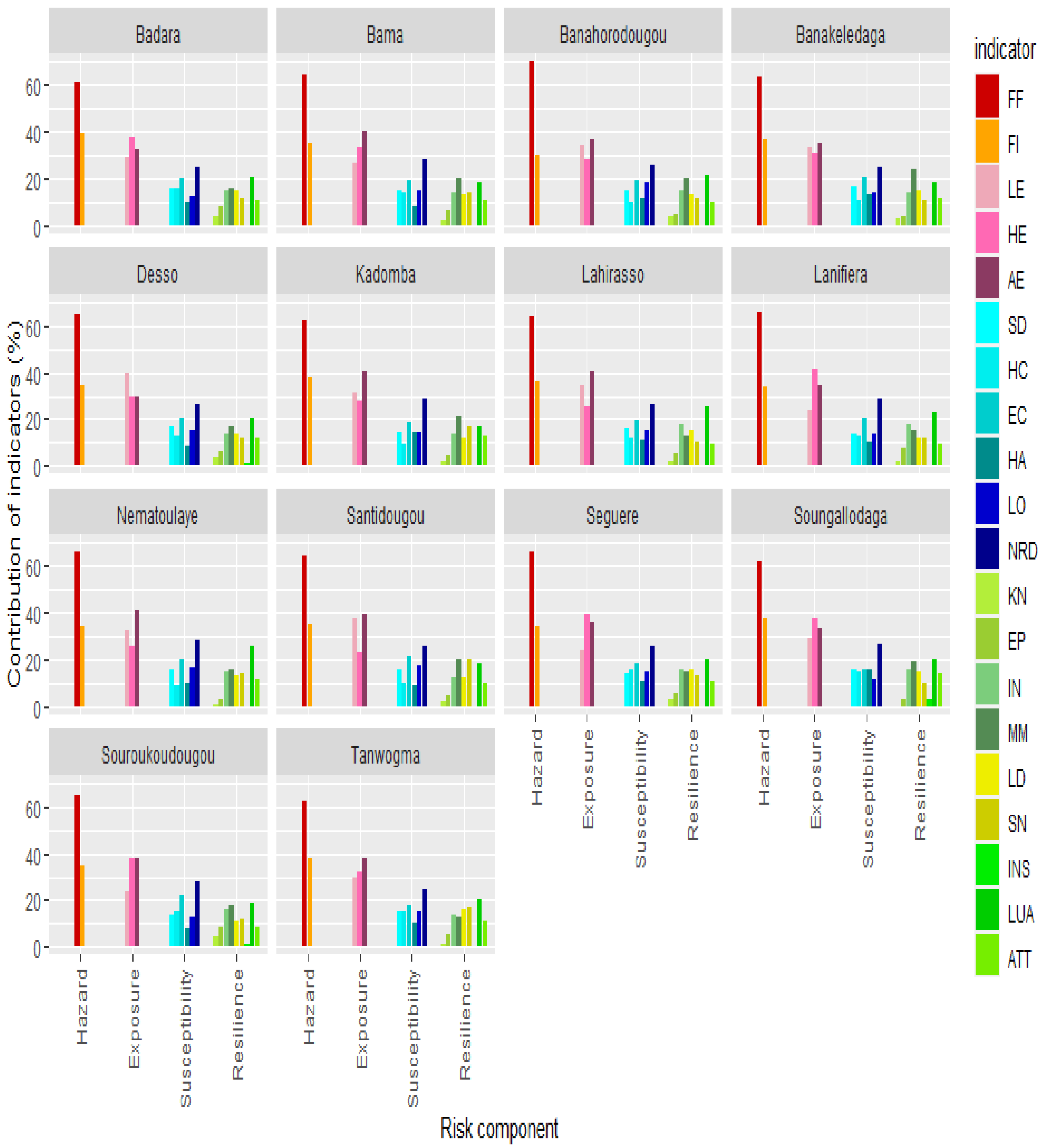


Figure 27: Contribution of indicators (Table **3**) to the flood components hazard, exposure, susceptibility and capacity.

5.1.4. Flood risk perception, flood risk perception index and link with flood perception index

5.1.4.1. Flood risk perception by households

Unlike flood risk assessed using the indicator-based method, the head of household was asked directly about his or her perception of flood risk. This perception of flood risk was considered a dependent variable in this modelling section. On the survey date, we found that 14.4%, 26.6%, and 59% of households perceived flood risk as medium, high, and very high, respectively (Figure **28**). We found that in all the villages studied, most households perceived the risk of flooding as very high. In the villages of Badara, Banakeledaga, Kadomba, and Tanwogma, all households surveyed perceived the risk of flooding as high or very high (Figure **28**).

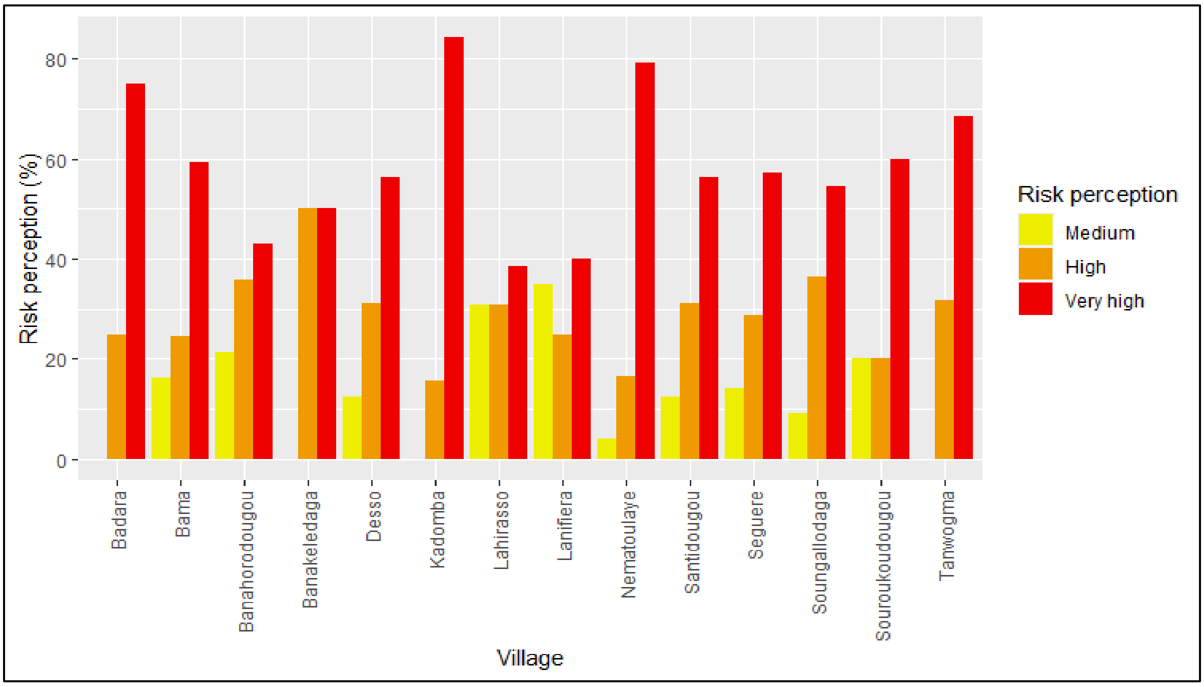


Figure 28: Household perception of flood risk in their respective villages

5.1.4.2. Link between the flood risk perception index and the estimated flood risk index

The flood risk perception index at the level of the villages, directly calculated from the risk perception of the households, consistently exceeds the risk index derived from various indicators (Figure **29**). FRPI ranges from 0.81 to 0.97, while FRI does not reach 0.8 in any village. An explanation for the much higher values of FRPI is that the households believed that they would get assistance from government and non-governmental organizations when they rated flood risk as high. During the survey interview, some households inquired about the likelihood of receiving support from national authorities. FRI and FRPI are correlated (Pearson correlation coefficient: 0.38), although this correlation is not statistically significant (p-value = 0.18). The R-squared value, which indicates the proportion of the variance of FRI that is explained by FRPI is low with a value of 0.14.

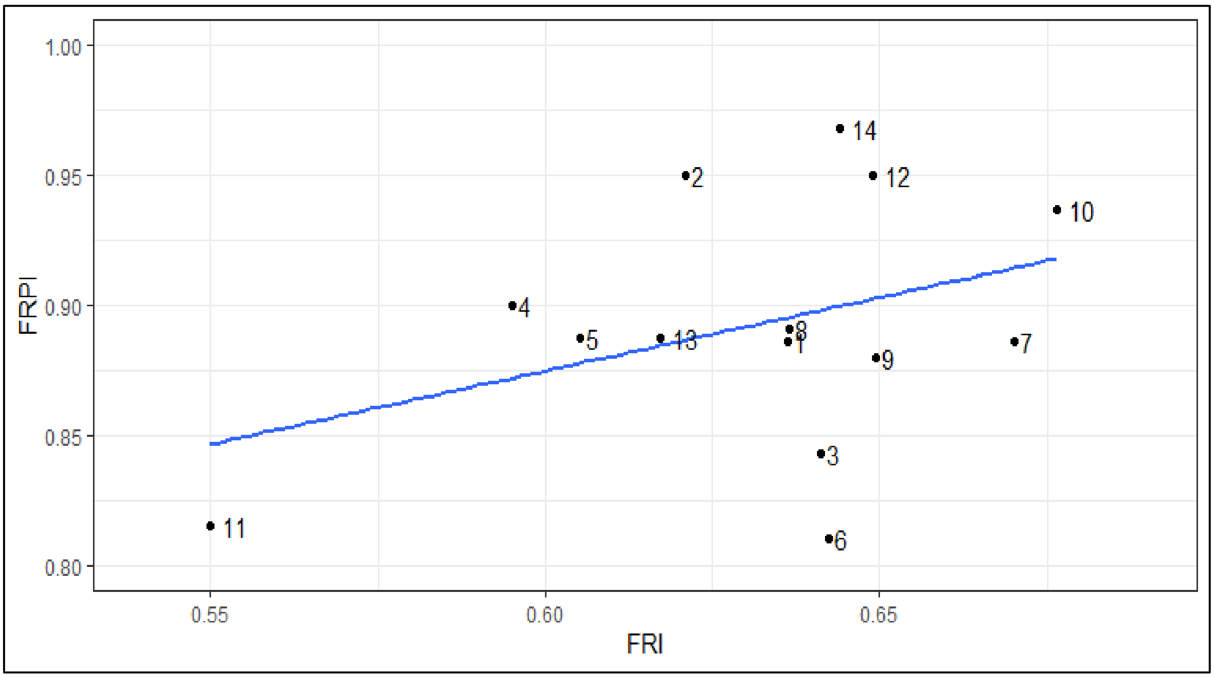


Figure 29: Relationship between the flood risk index (FRI) and the flood risk perception index (FRPI) for the 14 villages. Numbers denote villages.

5.1.5. Exploring the bivariate relationships between factors and flood risk perception

Before performing the ordered logistic regression analysis, one-factor analysis was used to determine if the selected possible influencing factors had significant differences in the mean on household flood risk perception. The chi-square test is used to perform the one-factor analysis for the fourteen factors. Factors that may affect the flood risk were analyzed using the Chi-square test and the results of the data analysis are shown in Table **12.** The results of the analysis showed that there were statistically significant differences in the severity competition of the 14 factors influencing household flood risk. ($p < 0.1$). Therefore, it can be considered that 14 influencing factors selected can be used for logistic regression analysis of the household flood risk.

Table 12: relation between dependent variable and covariables

Variable	Medium	High	Very high	Chi-Square	*P* Value
Gender of the household's head	---	---	---	5.6	0.061
1.Male	49 (15.7%)	87 (27.9%)	176(56.4%)		
2.Female	5 (7.8%)	13(20.3%)	46 (71.9%)		
Household head schooling	---	---	---	4.72	0.580
1.No schooling	33(13.8%)	57(23.8%)	149(62.3%)		
2.Primary	18(16.1%)	34(30.4%)	60(53.6%)		
3.Secondary	3(12.5%)	34(30.4%)	60(53.6%)		
4.University	0	0	1 (100%)		
Household head occupation	---	---	----	4.78	0.333
1.Commerce and trade	3(30%)	4(40%)	3(30%)		
2.Agriculture and husbandry	51(14%)	96(26.3%)	218(59.7%)		
3.Daily wage	0	0	1 (100%)		
Monthly income of the household head less national average	---	---	---	0.25	0.880
1.No	9(12.7%)	20(28.2%)	42(59.2%)		
2.Yes	45(14.*%)	80()26.2%	180(59%)		
Having experienced flooding	--	---	---	9.741	0.045
1.No	8(25%)	6(18.8%)	18(56.2%)		
2.Yes, once	5(21.7%)	10(43.5%)	8(34.8%)		
3.Yes, more than once	41(12.8%)	84(26.2%)	196(61.1%)		
Residing in a flood-prone area	---	---	---	7.27	0.026
1. No	12(10.7%)	40(35.7%)	60(53.6%)		
2. Yes	42(15.9%)	60(22.7%)	162(61.4%)		
Well-informed by local authorities about flood occurrences and its prevention measures	---	---	----	9.07	0.011
1. No	31(11.2%)	78(28.1%)	169(60.8%)		
2. Yes	23(23.5%)	22(22.4%)	53(54.1%)		
Learn self-protection against floods by your own.	---	---	---	5.163	0.076
1.No	8(25.8%)	10(32.3%)	13(41.9%)		
2. Yes	46(13.3%)	90(26.1%)	209(60.6%)		
Learn self-protection against floods by taking from others affected by floods	---	---	---	25.876	2.405×10^{-6}
1. No	35(26.3%)	36(27.1%)	62(46.6%)		
2. Yes	19(7.8%)	64(26.3%)	160(65.8%)		
Being informed by the media about self-protection	---	---	---	5.820	0.054
1. No	47(13.3%)	95(26.8%)	212(59.9%)		
2. Yes	7(31.8%)	5(22.7%)	10(45.5%)		

knowledge of self-protection adoption	---	---	---	14.537	6.973×10^{-4}
1. No	48(13.2%)	95(26.2%)	220(60.6%)		
2. Yes	6(46.1%)	5(38.5%)	2(15.4%)		
Having applied self-protection measures	---	----	---	12.004	2.474×10^{-3}
1. No	36(19%)	57(30.2%)	96(50.8%)		
2. Yes	18(9.6%)	43(23%)	126(67.4%)		
Believing in self-protection measures	---	---	---	9.380	0.052
1. No	9(8%)	34(30.1%)	70(61.9%)		
2. Yes	43(17.6%)	64(26.2%)	137(56.1%)		
3. Do not know	2(10.5%)	2(10.5%)	15(78.9%)		
Unnecessary need of self-protection against floods	---	----	-----	11.726	0.068
1. I fully agree	20(18.2%)	30(27.3%)	60(54.5%)		
2. I rather agree	20(19.2%)	29(27.9%)	55(52.9%)		
3. I rather no agree	6(17.1%)	8(22.9%)	21(60%)		
4. I do not agree at all	8(6.3%)	33(26%)	86(67.7%)		
Intention to migrate	---	---	---	8.409	0.015
1. Still live here	28(11.4%)	60(24.5%)	157(64.1%)		
2. Migrate to less exposed areas	26(19.8%)	40(30.5%)	65(49.6%)		
Flood training frequency	---	----	---	26.175	2.065×10^{-4}
1.Once event every month	12(8.6%)	31(22.1%)	97(69.3)		
2.Once event every three months	25(14.5%)	60(29.1%)	97(56.4%)		
3. One event every six months	9(21.4%)	11(26.2%)	22(52.4%)		
4. One event a year	6(50%)	5(41.7%)	1(8.3%)		
Insurance (health and agriculture)	---	---	----	8.724	0.068
1. No	7(25.9%)	11(40.7%)	9(33.3%)		
2. Yes	44(13.9%)	80(25.3%)	192(60.8%)		
3. Do not know	3(9.1%)	9(27.3%)	21(63.6%)		
Preference for adopting self-protection measures	-----	-----	-----	34.326	5.818×10^{-6}
1. Dike heightening	17(11%)	28(18.2%)	109(70.8%)		
2. Better flood barriers	15(9.8%)	53(34.6%)	85(55.6%)		
3.Adaptation of land use in flood-prone area	17(30.9%)	16(29.1%)	22(40%)		
4. Better self-protection, scientific findings, early warning	5(35.7%)	3(21.4%)	6(42.9%)		

5.1.6. Model parameter calibration and Odds Ratio analysis.

At the 1% significance level, the univariate analysis showed that 14 variables are likely to have a significant influence on household flood risk perception. These 14 variables are therefore used as covariates in an ordered logit model to establish the effects that exist between these variables and household flood risk perception. The results revealed that the likelihood ratio test of the model was statistically significant at the 1% significance level (X^2 =85.30, $p < 0.0001$), implying that the ordered logit regression was meaningful. The collinearity test was also applied. Variables with higher autocorrelation were automatically removed from the regression process. The bootstrap method on the model coefficients was applied and the results showed that the level of stability of the coefficients was acceptable. The model results are shown in the Table **13**.

Table 13: Results of ordered logistic regression. B, S.E., Wald X2, denotes the coefficients, Standard Error and Wald statistic associated with each coefficient of the regression, respectively. OR and 95% CI of OR represents Odds Ratio and its confidence interval at 95% of significant.

Influencing factors	**B**	**S.E.**	**Wald X^2**	**OR**	**95% CI of OR**	***P* Value**
Gender of the household's head						
1.Male (control)						
2.Female	0.633	0.326	1.94	1.883	0.937-3.784	0.075
Having experienced flood						
1.No (control)						
2.Yes, once	-0.385	0.643	-0.600	0.680	0.217-2.129	0.549
3.Yes, more than once	0.265	0.466	0.570	1.304	0.571-2.976	0.569
Residing in a flood-prone area						
1. No (control)						
2. Yes	0.630	0.305	2.070	1.877	1.049-3.358	0.039
Well-informed by local authorities about flood occurrences and its prevention measures						
1. No (control)						
2. Yes	-0.254	0.319	-0.800	0.776	0.435-1.383	0.425
Learn self-protection against floods by your own.						
1.No (control)						
2. Yes	-0.318	0.488	-0.650	0.728	0.269-1.967	0.515

Learn self-protection against floods by taking from others affected by floods						
1. No (control)						
2. Yes	0.439	0.302	1.460	1.552	0.900-2.675	0.145
Being informed by the media about self-protection						
1. No (control)						
2. Yes	-0.816	0.487	-1.680	0.442	0.168-1.165	0.094
No knowledge of self-protection adoption						
1. No (control)						
2. Yes	-1.227	0.640	-1.920	0.293	0.070-1.223	0.050
Having applied self-protection measures						
1. No (control)						
2. Yes	0.355	0.266	1.330	1.426	0.869-2.341	0.182
Believing in Self-protection measures						
1. No (control)						
2. Yes	-0.535	0.259	-2.060	0.585	0.333-1.029	0.039
3. Do not know	0.807	0.852	0.950	2.241	0.442-11.368	0.344
Unnecessary need of self-protection against floods						
1. I fully agree (control)						
2. I rather agree	-0.043	0.331	-0.130	0.958	0.519-1.768	0.897
3. I rather no agree	0.458	0.435	1.050	1.581	0.697-3.587	0.292
4. I do not agree at all	0.470	0.294	1.600	1.599	0.874-2.925	0.110
Intention to migrate						
1. Still live here (control)						
2. Migrate to less exposed areas	-0.639	0.252	-2.530	0.528	0.322-0.864	0.011
Flood training frequency						
1. One event every six months (control)						
2. Once event every three months	0.50	0.348	1.44	1.65	0.855-3.185	0.150
3. Once event every month	0.625	0.389	1.68	1.868	0.92-3.793	0.093
Insurance (health and agriculture)						
1. No (control)						
2. Yes	0.676	0.405	1.670	1.967	0.857-4.514	0.095
3. Do not know	0.902	0.497	1.820	2.465	0.767-7.918	0.069
Preference for adopting self-protection measures						
1. Dike heightening (control)						
2. Better flood barriers	-0.623	0.306	-2.04	0.536	0.304-0.945	0.041

3.Adaptation of land use, . Better self-protection, scientific findings, early warning	-0.972	0.373	-2.61	0.378	0.187-0.766	0.009

The regression results show that 8 independent variables have a significant influence on flood risk perception. These significant factors include living in a flood-prone area, being informed by the media about self-protection against flooding, self-protection to reduce the impact of flooding, adoption of self-protection strategies to cope with future increase in flooding, time required to learn about self-protection, insurance as a strategy against flooding, and effective measures to reduce flood impacts. These influencing factors could be grouped into attributes to facilitate interpretation of the results. The results of the elasticity analysis for 8 significant influencing factors with a p-value less than 0.1 in the regression analysis of the ordered logit model are presented in Table **14**.

Table 14: Pseudo-elastic analysis of factors that significantly influence household flood risk perception.

Variable	Pseudo-elasticity		
	Medium	**High**	**Very high**
Gender (female)	-6.0%	-6.3%	12.6%
Residing in a flood-prone	-8.5%	-5.6%	12.4%
Being informed by the media about self-protection	8.1%	4.8%	-16.1%
Believing in self-protection measures	3.7%	5.6%	-10.6%
Intention to migrate	6.3%	5.1%	-12.6%
Flood training frequency	-7.4%	-5.5%	12.6%
Preference for adopting self-protection measures			
Better flood barriers	6.3%	6.4%	-12.5%
Adaptation of land use, better self-protection measure, scientific findings, early warning	10.9%	9.1%	-19.5%

5.1.7. Analyzing factors influencing household flood risk perception

We used the ordered logistic model to determine the influence of various factors on the households' perception of flood risk.

The results of the regression revealed that being female as the head of the household positively influences the household's perception of flood risk (OR= 1.98, pseudo-elasticity = 12.6%). It implies that a female household head is approximately twice as likely to perceive a very high flood risk compared to a male household head. Elasticity analysis indicates that when the household head changes from a man to a woman, the probability of perceiving flood risk as very high increases by 12.6% on average.

We found that households that perceived themselves as being located in a flood-prone area had a higher perception of flood risk (OR = 1.88). Households in flood-prone areas were approximatively twice as likely to perceive a very high flood risk compared to those living outside flood-prone areas. The elasticity analysis also showed that living in a flood-prone area or moving from a safe location to a flood-prone location influenced their perception of risk, increasing the probability of perceiving flood risk as very high by 12.4% on average. For instance, some of the households in Soungallodaga (village 8, Figure **26**) reported in the interview that they were relocated to a flood-prone area compared to their original location because there was no drainage system for runoff in the village. Similarly, some households in Bama (village 1, Figure **26**) reported that the drainage system was not maintained, so their residences became flood-prone.

Conversely, being informed by the media about self-protection against flooding reduced the household flood risk perception (OR = 0.44 and pseudo-elasticity = -16.1%). This suggests that households informed by the media may learn how to implement preparedness measures, thus reducing their concern about flood impacts. Having applied self-protection measures against flooding decreases the probability of households perceiving flood risk as very high (OR = 0.24 and pseudo elasticity = -24.2%). This indicates that these households tend to believe in the efficacy of these measures.

Believing that self-protection can diminish flood impacts reduced flood risk perception. Households that believed in self-protection as an efficient measure against floods perceived lower flood risk (OR = 0.61). Similarly, the elasticity analysis revealed that believing in self-protection reduced the probability of perceiving flood risk as very high by 10.6% on average. These results indicate that households may believe in the efficacy of self-protection measures, which is an important factor in motivating people to adopt protective behaviors.

The intention to migrate to less flood-prone areas due to anticipated increases in flood risk is negatively correlated to household flood risk perception (OR = 0.54). The elasticity analysis also reveals that households intending to migrate were associated with a lower likelihood of perceiving flood risk as very high by 12.6% on average. From these results, we conclude that, even though households fully understand the level of flood risk they face, it is hard for them to accept a decision to move as a self-protection option. However, despite the expectation of increasing flood risk, about 65.2% of the households did not show interest in migrating. This may be explained by a lack of knowledge about suitable places to move to. Additionally, they might have heard negative reports about the relocated villages prior to the construction of the Samandeni dam, leading them to avoid situations similar to those experienced by the relocated households. Moreover, a decision to migrate could significantly affect the traditions and culture of communities, which are a heritage passed down from generation to generation that some households are not prepared to lose.

Households expressed a need to increase their capacity for self-protection measures. The effectiveness of the training diminished as the frequency of these sessions reduced. Households receiving monthly training showed a higher perception of flood risk, compared to those who received training bi-annually (OR = 1.89). Similarly, households who received monthly training experienced a 12.6% increase in the likelihood of perceiving flood risk as very high, compared to those with bi-annual training. This indicates that households receiving bi-annual training in self-protection measures tend to underestimate flood risk compared to those receiving monthly training.

Households that preferred flood barriers as self-protection measures had a lower likelihood of perceiving flood risk as very high, compared to those who preferred dikes (OR = 0.54 and elasticity = -12.5%). Additionally, households that preferred adapting land use in flood-prone areas, adopting better self-protection measures, and receiving early warnings from authorities had a lower (OR = 0.36 and elasticity = -19.5%) likelihood to perceive flood risk as very high, compared to those who preferred dikes.

Our data showed a positive correlation (OR = 1.88 and elasticity = 13%) between the preference for subscribing to health or agriculture insurance and flood risk perception. However, this influence is small and not statistically significant. Moreover, having experienced floods more than once is positively correlated with flood risk perception (OR=1.14, elasticity=2.8%) but this correlation is not statistically significant. These factors can be classified into various categories.

Social factors include gender, while geographical factors include residence in a flood-prone area. Informational factors encompass being informed by the media about self-protection and having applied self-protection measures. Contextual factors include believing in self-protection measures. Behavioral factors include intention to migrate, flood training frequency, preference for flood barriers, adapting land use, better self-protection, and early warnings. Cognitive factors include insurance and having experienced a flood. Figure **30** summarizes the impact of the factors influencing household flood risk perception.

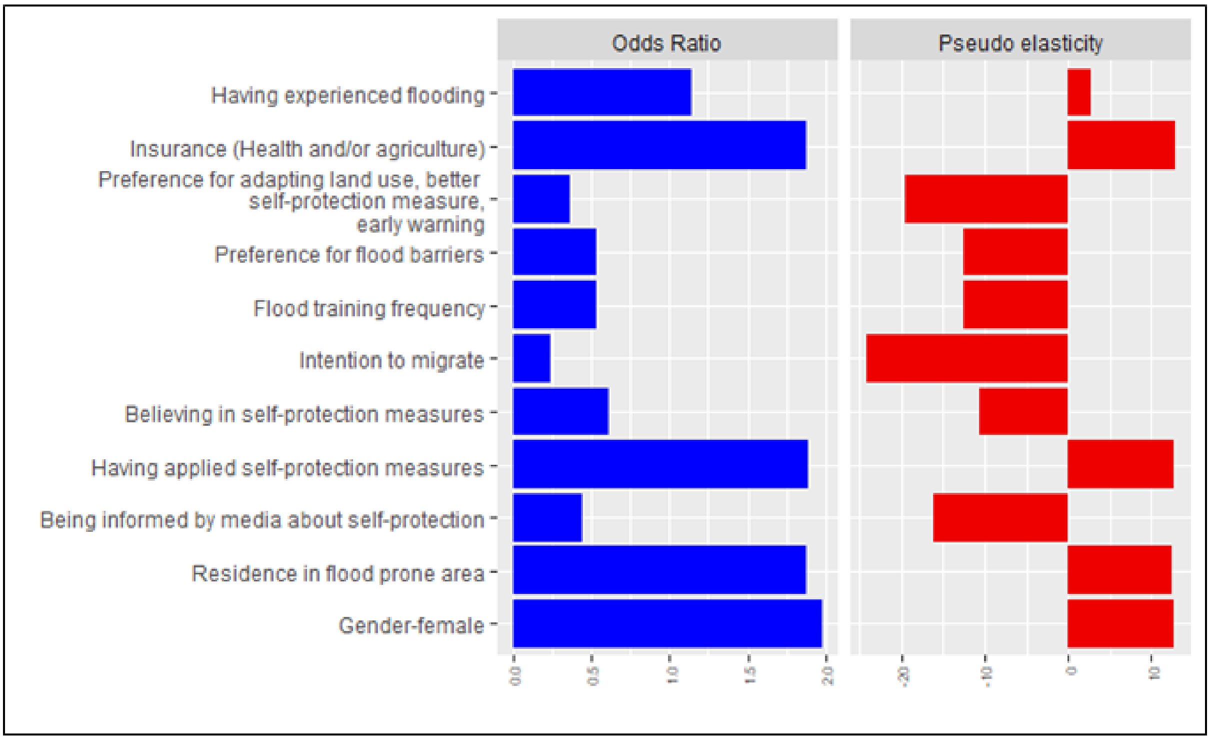


Figure 30: Odds ratio (blue) and pseudo elasticity (red) of the factors influencing household flood risk perception.

5.1.7. Discussion

This study evaluated the flood risk faced by the rural households in flood-prone villages within four municipalities in the Haut-Bassins region, Burkina Faso. Results indicate a spatial variation in household flood risk within the study area, with levels ranging from moderate to high levels. Furthermore, the study analyzed the factors influencing food risk perception using an ordered logit model

5.1.7.1. Household flood risk assessment

The level of flood hazard is uniform (high) across the villages, with the exception of the two villages Lahirasso (village 11, medium) and Kadomba (village 14, very high). This uniformity is attributed to the fact that the villages are rather close to each other and located within the same valley. Households in Lahirasso reported that flooding primarily occurred around the periphery of the village and occasionally reached residential areas. Residents of Kadomba and Santidougou (village 13) reported that the flood hazard increased significantly after asphalting the national road through the village linking Bobo-Dioulasso and Dédougou cities. They attributed this increase to the narrow bridge spanning the river, which they believe directs runoff water from heavy rainfall toward the village, possibly causing inundation. Many households mentioned that their properties were located at a lower elevation than the newly asphalted road. The elevated road disrupts the natural runoff system, leading to water stagnation, which in turn exacerbates the risk of flooding within the village.

Flood exposure is high in 11 villages, very high in two villages (Seguere, village 7; Tanwogma, village 10), and medium in Bama (village 1). Distance to the river is one of the commonly used determinants in assessing flood exposure and risk (Samanta et al., 2016; Tehrany et al., 2015). However, there is not a distinct distance from which exposure to floods is low (Roy et al., 2021). We observed that there was not a single factor that dominated the level of household exposure, given the different indicators (local, human, and assets exposure) that contribute to flood exposure. The Government of Burkina Faso has listed Seguere as one of the villages scheduled for relocation, due to the expansion of agricultural development, particularly for rice cultivation, facilitated by the construction of the Samandeni dam.

Flood susceptibility is medium across the entire study area. Housing amenities and natural resource degradation were particularly important in affecting susceptibility. Key indicators, which included residences, their farmland, and the quality of their water resources, significantly influenced flood susceptibility, accounting for roughly 47% of the total indicators. As old houses built from mud bricks are more susceptible to flooding (Hamidi et al., 2020), it becomes evident that housing conditions and access to basic amenities significantly influence flood susceptibility. In particular, households without access to clean water and sanitary facilities were more susceptible to floods. Specific instances were highlighted in Banahorodougou, Desso, and Souroukoudou (villages 3, 5, and 9), located near the city of Bobo Dioulasso. These villages have experienced frequent floods over the years, leading to the erosion of sediment from city areas onto farmlands. This process has rendered several hundred hectares unsuitable for agriculture. Furthermore, households that rely on wells for their drinking water reported a decrease in water quality following floods. This deterioration escalates the risk of communicable diseases, posing a serious public health concern.

Most villages showed a moderate lack of resilience, apart from Lahirasso and Nematoulaye (villages 11 and 12), with a high lack of resilience. Nematoulaye, located in a rice-growing lowland area, is particularly vulnerable to flooding. The head of the village communicated that the community had agreed to move to less flood-prone areas with government support once the survey was completed. However, the ability of households to cope with floods can be diminished by a lack of disaster knowledge, emergency preparedness, and/or low insurance coverage. Particular attention should be paid to these aspects to improve the ability of households to cope with floods.

Flood vulnerability is medium in 50% of villages and high in the other 50%. The most vulnerable households are typically located in rice-growing lowlands where flood hazards are expected to be high. However, households in Banahorodougou, Banakeledaga, Desso, and Souroukoudougou (villages 3, 4, 5, and 9; Figure **26**) have indicated that in recent years, floods in their villages were primarily caused by the management of runoff from the urban area of Bobo-Dioulasso. Furthermore, households in these villages reported that hundreds of hectares of farmland have become unsuitable for agriculture due to the sedimentation caused by runoff from the drainage systems of Bobo-Dioulasso. Therefore, the vulnerability assessment of these villages depends on the management of the urban areas of Bobo-Dioulasso. These findings align with another study (Jamshed et al., 2020), which proposed a theoretical and conceptual framework that considers urban–rural linkages in rural vulnerability assessments. This conceptual framework suggests that the flood vulnerability of rural areas should not be assessed independently but should be connected with the nearest urban areas, which is key to reducing the vulnerability of these villages (Jamshed et al., 2020). Furthermore, poorly designed civil engineering infrastructures, such as roads, were highlighted by households as a significant factor increasing the vulnerability of households in Santidougou and Kadomba (villages 13 and 14, Figure **26**) traversed by a national road connecting Bobo-Dioulasso and Dédougou.

Most of the villages experienced high levels of flood risk, except for Banakeledaga and Lahirasso (villages 4, 11) with moderate flood risk. Flood hazard and exposure were key components contributing to high risk levels. The lower scores for susceptibility and lack of resilience that we find in our study area suggest that households have increasingly adapted to floods. The degree of flood risk was considered moderate due to the elevated location of the village.

We found a positive, but insignificant correlation ($p = 0.38$) between the flood risk index and the flood risk perception index. The study of (Rana & Routray, 2016) found a significant positive correlation for urban communities. More studies are needed to understand whether these different results are linked to the different environments (urban versus rural area).

5.1.7.2. Factors influencing households' flood risk perception

Our results show that the flood experiences of households and their implementation of self-protection measures played a significant role in reducing the perception of flood risk. Their flood experience amplified their perception of flood risk. To mitigate this risk, they took measures to reduce flood risk. Learning self-protection practices from the media can effectively decrease household flood risk.

Many households believed that self-protection measures could minimize flood risk. With a growing skepticism toward national disaster risk management, households increasingly turned to self-management of flood events. As the rainy season drew near, residents began to organize and clean the drainage system of the community. Self-protection measures had proven to be the most effective mitigation strategy up to the 100-year return period (Garrote et al., 2019). Beyond this point, its effectiveness declines significantly (Arnall, 2019). These findings suggest that coordinating self-protection efforts by authorities could substantially improve flood risk mitigation.

Households perceived relocation as an effective flood mitigation measure. However, the implementation of relocation measures should be carefully considered, as several African countries have encountered many difficulties in its implementation (Arnall, 2019). For instance, after the unprecedented floods of 2009 in Ouagadougou, the relocation program of the government turned into a challenge for the government and not into a solution. Renters, who were a portion of the victims, were excluded from a resettlement site at Yagma, located about 20 kilometers from Ouagadougou (McLeman et al., 2016). This site, chosen without considering amenities and livelihood opportunities, lacked essential services such as water and electricity; health clinics and secondary schools were too far, transportation was scarce, and economic opportunities were limited (McLeman et al., 2016). Thus, any relocation program must carefully ensure that it does not become a source of injustice. This is in line with a study in Africa and Asia (Arnall, 2019) reporting that relocation typically generates winners and losers. The new site could offer opportunities for some new settlers, whereas others could lose their customers, businesses, or employment. It also argued that governments and aid agencies should be better informed about flooding, its characteristics and impacts, and the degree of people resisting shocks before proceeding to any flood relocation.

We found that women perceived a higher flood risk compared to men. Our finding agrees with (Kellens et al., 2011), which also stated that women perceived higher levels of flood risk. Gender inequality is higher in countries where both legal and cultural differences between genders are strong (Ardaya et al., 2017), as is the case in Burkina Faso. In Burkina Faso, gender inequality is mainly attributed to the socio-cultural weights of tradition rather than to legal factors (Helmfrid, 2004). Men and women have the same rights in both the private and public sectors. However, it remains challenging for women to be leaders in their communities, especially in their roles as guardians of tradition and lands. Before performing regression analysis, we conducted a correlation analysis of each factor with flood risk perception. The results showed no significant link between socio-economic factors, including household head schooling ($p = 0.58$), household occupation ($p = 0.33$), household income ($p = 0.88$), and flood risk perception. Therefore, we concluded that these factors should not be considered in the ordered logit regression. Other studies also found only insignificant effects of socioeconomic factors, including education, occupation, and income, on flood risk perception (Kellens et al., 2011; Lechowska, 2022; O'Neill et al., 2016; A. A. Shah et al., 2022).

We acknowledge the limitations of this section from our study. While the indicator-based approach is simple and effective for monitoring flood risks, it fails to estimate flood losses and lacks insight into vulnerability dynamics. Specifically, it cannot provide estimates of building and contents losses nor address future human–flood interactions, including potential changes in vulnerability. Furthermore, the analysis of factors influencing the perception of flood risk could be improved. The concepts of threat appraisal, referred to as risk perception, and coping appraisal are two factors of the Protection Motivation Theory, but this research does not consider coping appraisal. Given the relationship between flood risk perception and flood coping appraisal (Bubeck et al., 2018), understanding how households might respond based on their coping appraisal in relation to their flood risk perception is essential. Therefore, the Structural Equation Modeling framework is a suitable choice, as it is particularly useful for testing complex relationships simultaneously in a single model, rather than employing multiple models (Christ et al., 2014; Faruk & Maharjan, 2022; Kurata et al., 2023).

5.3. Partial conclusion

To our knowledge, this work is the first study in the Hauts-Bassins region to provide detailed insights into actual and perceived flood risk using household-level data. The national disaster risk management agency lacks data about the risk of flooding. Therefore, our approach to household surveys is considered a viable option to fill this knowledge gap.

Our study provided essential knowledge about the flood risks faced by households at the village level and determined the factors that influenced household flood risk perception. Our findings revealed that the drainage system in certain areas of Bobo-Dioulasso city directly impacted the flood risk levels in nearby villages and the vulnerability of their inhabitants. Additionally, the construction of road infrastructures, particularly during the asphalting phase of the road connecting Bobo-Dioulasso and Dédougou, was identified as a potential driver that may have contributed to increased flooding in some villages. We found a positive but weak correlation between the estimated flood risk and the perceived flood risk. Our results suggest that households may overestimate flood risk compared to the more objective approach of using an indicator-based method. Informational factors, such as being informed by media about self-protection and having applied self-protection measures, along with behavioral factors like the intention to migrate, flood training frequency, preference for flood barriers, adapting land use, better self-protection, and early warnings, have been found to strongly influence perceptions of household flood risk.

Very little research on natural hazards has been conducted in Burkina Faso and even less has been conducted in our study area. Our findings can serve as a starting point for developing effective risk reduction and climate adaptation strategies. Future work should consider exploring multi-variable flood loss models for residential buildings and contents (Chinh et al., 2015, 2017), as well as paying attention to how floods interact with and affect vulnerability using the socio-hydrological modelling approach (Schoppa et al., 2024). This may help to overcome the reactive approach of the national disaster risk management agency in Burkina Faso and foster a more proactive flood risk management.

Chapter 6: Flood Vulnerability Assessment Using Various Weighting Methods Under Both The Old and New IPCC Vulnerability Frameworks

The concern of this chapter is to evaluate flood vulnerability using the definitions of both the old and new IPCC vulnerability frameworks. As part of this assessment, we examine the sensitivity of the vulnerability index when applying various weighting methods. this chapter introduces the susceptibility element of vulnerability, which focuses on the perception of indirect impacts, particularly the damages and losses recorded by households. The analytical process involves the computation of weights obtained from the PCA method for assigning weights to indicators, and it compares flood vulnerability components under both equal and PCA weighting schemes. Furthermore, we also compare flood vulnerability maps produced using both equal and PCA weighting techniques when adopting the old and new IPCC vulnerability frameworks. Additionally, we investigate the sensitivity of flood vulnerability to various weighting methods. Following the presentation of results, we discuss the implications of these findings, leading to a partial conclusion to wrap up this chapter.

6.1. Results

6.1.1. Employing Principal Component Analysis for determining the weights of indicators

The multicollinearity among indicators is overall acceptable; however, the correlation between physical asset damage or loss (PA) and asset exposure, as well as between PA and human asset damage or loss, has reached a threshold of 0.8. Despite this high correlation, since the correlation coefficients do not exceed 0.8, PA remains suitable for further analysis. Indicators such as household preference for self-protection strategies (PSPS), attitudes towards measures and future expectations (ATMFE), and the accessibility of households to information (AI), alongside resident attitudes (ATT) and the capacities of residents (CR), considered as adaptive capacity indicators, show a negative correlation with local exposure (LE), asset exposure (AE), human asset damage or loss (HA), physical asset damage or loss (PA), social asset damage or loss (SA), natural asset damage or loss (NuA), and financial asset damage or loss (FA). This negative correlation indicates that the selected indicators for assessing flood vulnerability in this study effectively reduce household exposure and susceptibility to flooding.

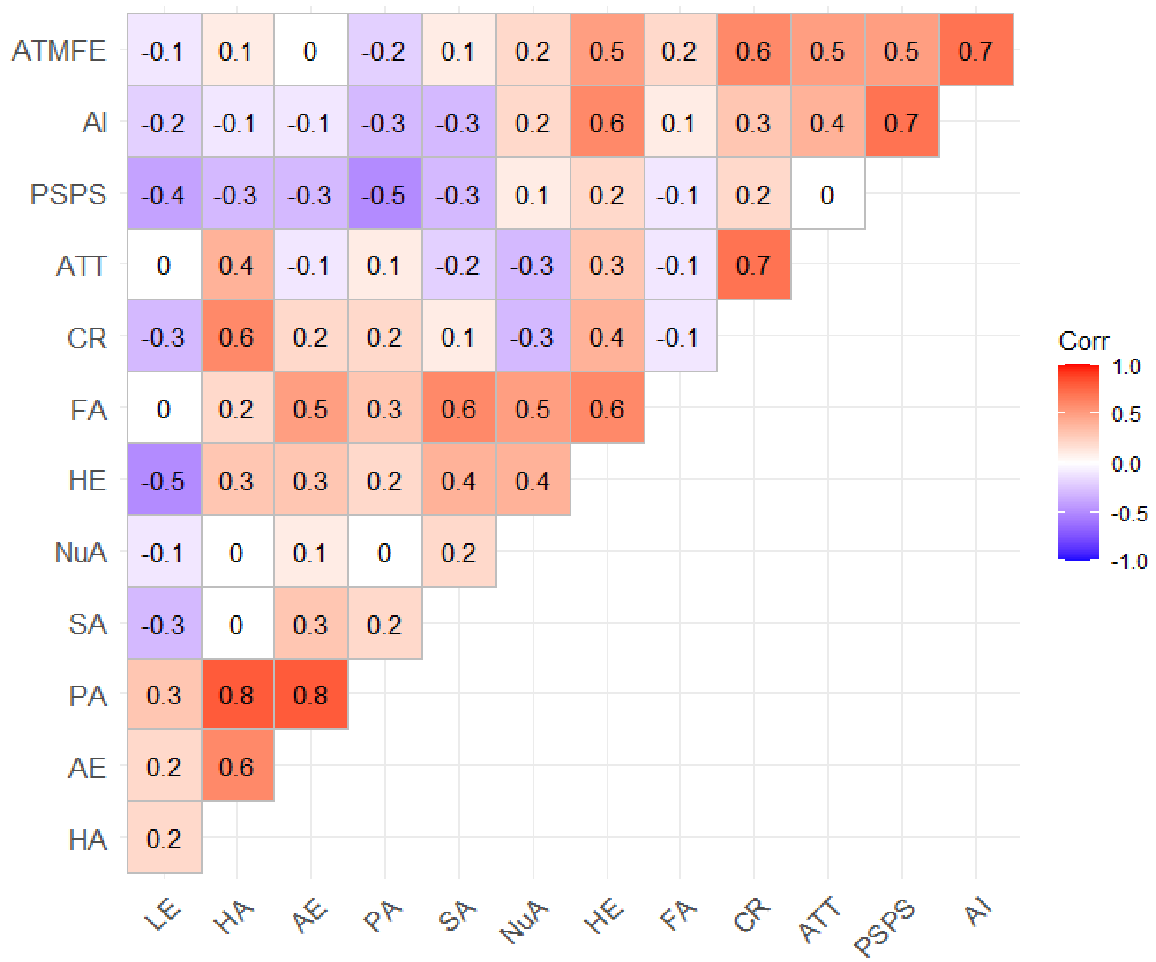


Figure 31: Correlation plot of vulnerability indicators

After analyzing the multicollinearity among indicators, tests for Kaiser-Meyer-Olkin (KMO) and Bartlett's sphere were conducted to assess the adequacy and sphericity of the indicators for performing principal component analysis. The Kaiser-Meyer-Olkin (KMO) values were 0.6 and 0.61, respectively, for the indicators utilized in assessing vulnerability according to the IPCC 2007 and IPCC 2014 frameworks. These values suggest that it is appropriate to proceed with PCA for both sets of indicators. Additionally, the Bartlett test results indicated that the p-values associated with the indicators evaluated under each framework were statistically significant at the 1% significance level (IPCC 2007, p-value = 0.000; IPCC 2014, p-value = 0.000), further confirming the suitability of these indicators for performing PCA. With satisfactory results from both tests, PCA was performed, and the weights of the indicators were computed based on the PCA results. Considering the IPCC 2007 framework, PCA results revealed that approximately 81.6% of the variance in the indicators could be explained by four proxy components. These proxies were then used to compute the weights of the indicators. Under the IPCC 2014 framework, it was found that 86.9% of the variance in the indicators could also be explained by four proxy components. Table **15** lists the weights calculated using PCA methods, considering both the IPCC 2007 and 2014 frameworks.

Table 15: Weights of indicators computed based on PCA method.

Vulnerability components and its indictors	IPCC 2007 framework		IPCC 2014 framework	
	Indicator weight	Component weight	Indicator weight	Component weight
Exposure		**0.223**		
Local exposure	0.075			
Human exposure	0.080			
Asset exposure	0.068			
Susceptibility		**0.391**		**0.511**
Human asset damage/loss	0.080		0.107	
Natural asset damage/loss	0.069		0.097	
Physical asset damage/loss	0.085		0.100	
Financial asset damage/loss	0.079		0.098	
Social asset damage/loss	0.078		0.110	
Adaptive capacity		**0.385**		**0.489**
Have acces to information	0.084		0.101	
Capacities of residents	0.090		0.108	
Attitude towards measures and future expectations	0.070		0.102	
Preference for self-protection measures	0.070		0.091	
Attitude	0.071		0.088	

1.1.2. Assessment of flood vulnerability components using diverse weighting methods

The vulnerability components were assessed using indicators with equal weighting and indicators with unequal weighting. When equal weights are assigned to the indicators, it is observed that 13 out of 14 villages show a high to very high exposure to flooding (Figure **32-a**), except for Lahirasso with a moderate exposure to flooding (village 11). Among the villages with high exposure to flooding, Seguere (village 7) and Tanwogma (villages 10) are particularly notable, as they have the highest exposure scores, exceeding 0.8 (Figure **32-a**). However, when unequal weights are assigned, the pattern changes slightly, with 12 out of 14 villages still showing a high to very high level of exposure to flooding (Figure **32-e**). Interestingly, both Desso (village 5) and Lahirasso (village 11) show moderate exposure scores, which are notably lower than the threshold of 0.6 set for high exposure. It is observed that among the 12 villages with high exposure scores, 4 stand out with very high exposure scores, surpassing 0.8 (Figure **32-e**). These villages are Bama (village 1), Banahorodougou (village 3), Seguere (village 7), and Tanwogma (village 10). However, we need to proceed with a sensitivity analysis on the exposure if the difference between equal-weighted exposure and PCA-weighted exposure is statistically significant.

Regardless of the equal and PCA weighting methods employed, it was found that the susceptibility and adaptive capacity scores show no variation in the research area. As for susceptibility, its score ranges from 0.46 to 0.74 (Figure **32-b,e**), indicating moderate to high levels of susceptibility to floods. Among the 14 villages, 9 exhibited high susceptibility to flooding, and 5 showed moderate susceptibility. As concerns the lack of adaptive capacity, its scores range from 0.35 to 0.57 (Figure **32-c,f**), indicating a low to moderate level of adaptive capacity. Most villages exhibited moderate lack of adaptive capacity, except for Lanifiera (village 6) and Souroukoudougou (village 9), which showed a low level of lack of adaptive capacity. These results suggest that susceptibility and lack of adaptive capacity are not sensitive to either equal weighting methods or PCA in this study area; however, further sensitivity analysis is needed for deeper understanding.

The key factors contributing to flood susceptibility and flood adaptive capacity are essential for selecting appropriate measures to reduce the vulnerability of residents in the most vulnerable villages. Natural and physical assets are the primary drivers that make residents within the study area highly susceptible to flooding. Natural assets, such as farmlands, groundwater, village vegetation, and standing crops, significantly increase flood susceptibility in the study area. However, in Kadomba, these natural assets showed only moderate susceptibility to flooding. As for physical assets, they include sanitation facilities, water sources, modes of transportation, physical infrastructures, and harvesting facilities. These significantly increased flood susceptibility in the research area, except for the villages of Desso, Banakeledaga, Lanifiera, and Lahirasso, where the increase in flood susceptibility due to these physical assets was only moderate.

The adaptive capacity factors that enhance residents' abilities to cope with flooding include their attitudes toward preventive measures, their future expectations, and their preferences for adopting self-protection strategies. However, access to information was found to contribute less to household flood adaptive capacity. Despite households adapting their houses construction methods, the overall coping capacity to withstand floods remained moderate within the study area. Furthermore, approximately 60% of households reported not trusting in government disaster risk reduction programs and policies. This lack of trust could complicate collaboration between communities and disaster reduction workers.

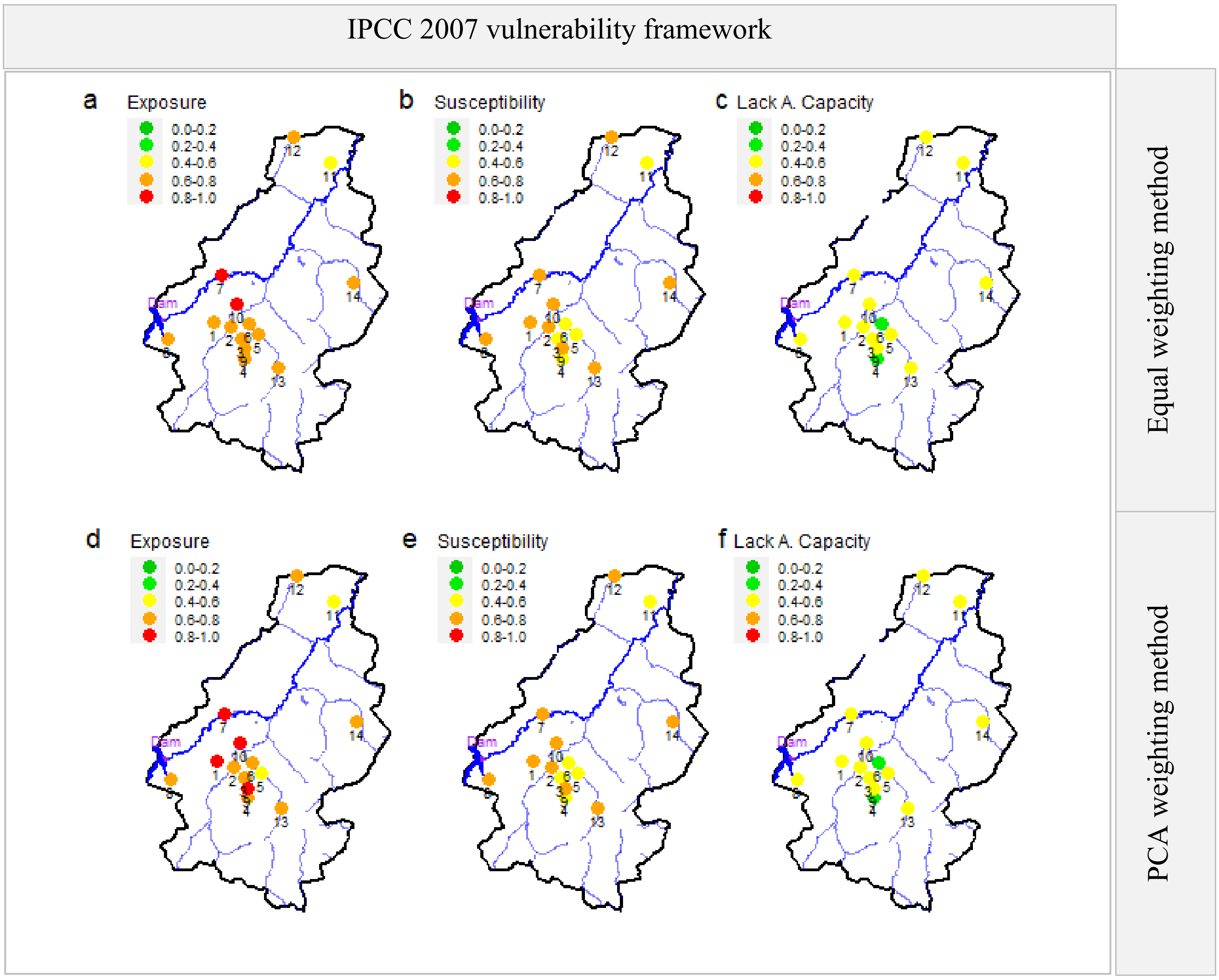


Figure 32: Assessment flood vulnerability components. Numbers denote villages: **1**: Bama, **2**: Badara, **3:** Banahorodougou, **4:** Banakeledaga, **5:** Desso, **6**: Lanifiera, **7**: Seguere, **8**: Soungallodaga, **9:** Souroukoudougou, **10:** Tanwogma, **11:** Lahirasso, **12**: Nematoulaye, **13**: Santidougou, **14:** Kadomba. The purple dot shows the location of the dam of Samandeni.

1.1.3. Comparative assessment of flood vulnerability using various weighting methods and frameworks

Under the IPCC 2007 framework, the vulnerability score calculated from indicators using equal weights is not identical to the score obtained when these indicators are weighted using the PCA weighting method across the study area. With equal weighting, only Seguere (village 7) out of 14 villages exhibited a high vulnerability to flooding, scoring 0.61, while the other 13 villages showed a moderate score of vulnerability, with scores ranging from 0.45 to 0.58 (Figure **33-a**). Conversely, when the indicators were unequally weighted, five out of 14 villages had higher vulnerability scores, ranging from 0.61 to 0.66, while nine villages were moderately vulnerable to flooding, with scores ranging from 0.47 to 0.59.

When vulnerability was assessed according to the IPCC 2014 framework, it was observed that there were no differences whether the equal or PCA methods were used for weighting indicators. Regardless of the weighting method employed, only one out of 14 villages displayed a significantly higher level of vulnerability, scoring 0.61, whereas the rest exhibited moderate vulnerability to flooding, scoring from 0.45 to 0.58 (Figure **33-c,d**). Moreover, it was found that vulnerability maps generated under the IPCC 2014 framework are identical to those generated under the IPCC 2007 framework, especially when equal weights were assigned to indicators.

As previously noted, natural and physical factors have worsened flood vulnerability. Nonetheless, the attitudes of households towards these measures, combined with their future expectations and preferences for self-protection measures, significantly enhance the adaptive capacity of households against flooding. Moreover, it is imperative to bolster coping capacity factors, such as access to information and the capabilities of households to endure floods, to minimize losses and damages associated with floods.

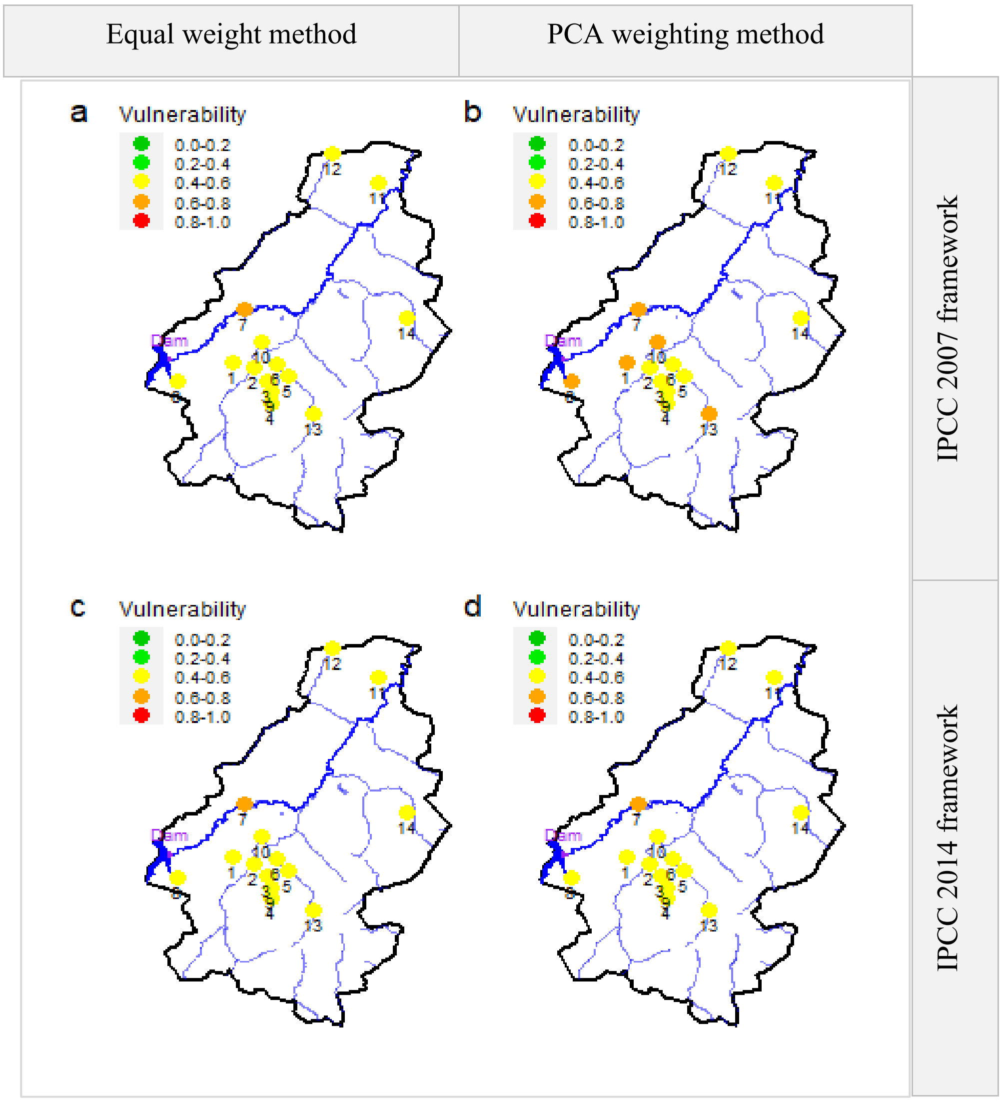


Figure 33: Flood vulnerability index computed based on equal and PCA weights under IPCC frameworks. Numbers denote villages: **1**: Bama, **2**: Badara, **3:** Banahorodougou, **4:** Banakeledaga, **5:** Desso, **6**: Lanifiera, **7**: Seguere, **8**: Soungallodaga, **9:** Souroukoudougou, **10:** Tanwogma, **11:** Lahirasso, **12**: Nematoulaye, **13**: Santidougou, **14:** Kadomba. The purple dot shows the location of the dam of Samandeni.

6.1.4. Sensitivity analysis of flood vulnerability and its components

It was found that the correlation between vulnerability and its components, when assessed using equally weighted indicators and compared to their values obtained through the PCA weighting method, exceeded 0.96. Specifically, the correlations for exposure, susceptibility, and lack of adaptive capacity were 0.96, 0.99, and 0.99, respectively. Moreover, the correlation between vulnerability, when assessed by assigning equal weights to indicators versus when indicators were weighted using the PCA method, was 0.99 for both the IPCC 2007 and 2014 frameworks. The correlation between vulnerability scores computed based on the IPCC 2007 framework and those assessed using the IPCC 2014 framework was found to be 0.91 (Table **16**).

The R-squared values, which indicate the proportion of variance explained by vulnerability and its components when evaluated using equally weighted indicators, show remarkable consistency when compared to their values obtained using indicators weighted according to the PCA method. These values exceed 0.80 for all vulnerability components and the overall vulnerability index (Table **16**). Therefore, the correlation and linearity analysis suggest that vulnerability and its components show almost no sensitivity to different methods for weighting indicators.

Table 16: Correlation and R-squared values for vulnerability and its components, evaluated with equal weights assigned to indicators versus their scores obtained using the PCA method for indicator weighting, within the context of the IPCC frameworks.

	Exposure	**Susceptibility**	**Lack of adaptive capacity**
Correlation	0.96	0.98	0.99
R-squared	0.93	0.97	0.99
		Vulnerability	
	IPCC 2007	IPCC 2014	IPCC 2007 vs 2014
Correlation	0.99	0.99	0.91
R-squared	0.98	0.99	0.84

The results of the Cramer-von Mises test, which compares vulnerability and its components when evaluated using equally weighted indicators versus the PCA method for weighting indicators, indicate that vulnerability and each of its components can be fitted to the same distribution, with p-values less than 0.05. Additionally, these results confirm that vulnerability and its components exhibit minimal sensitivity to the methods employed for weighting indicators. However, the test reveals that vulnerability assessed based on the IPCC framework has an empirical distribution significantly different from that of vulnerability assessed using the IPCC 2017 framework (p-value < 0.05). Figure **34** illustrates the spatial distribution of these vulnerabilities and their components.

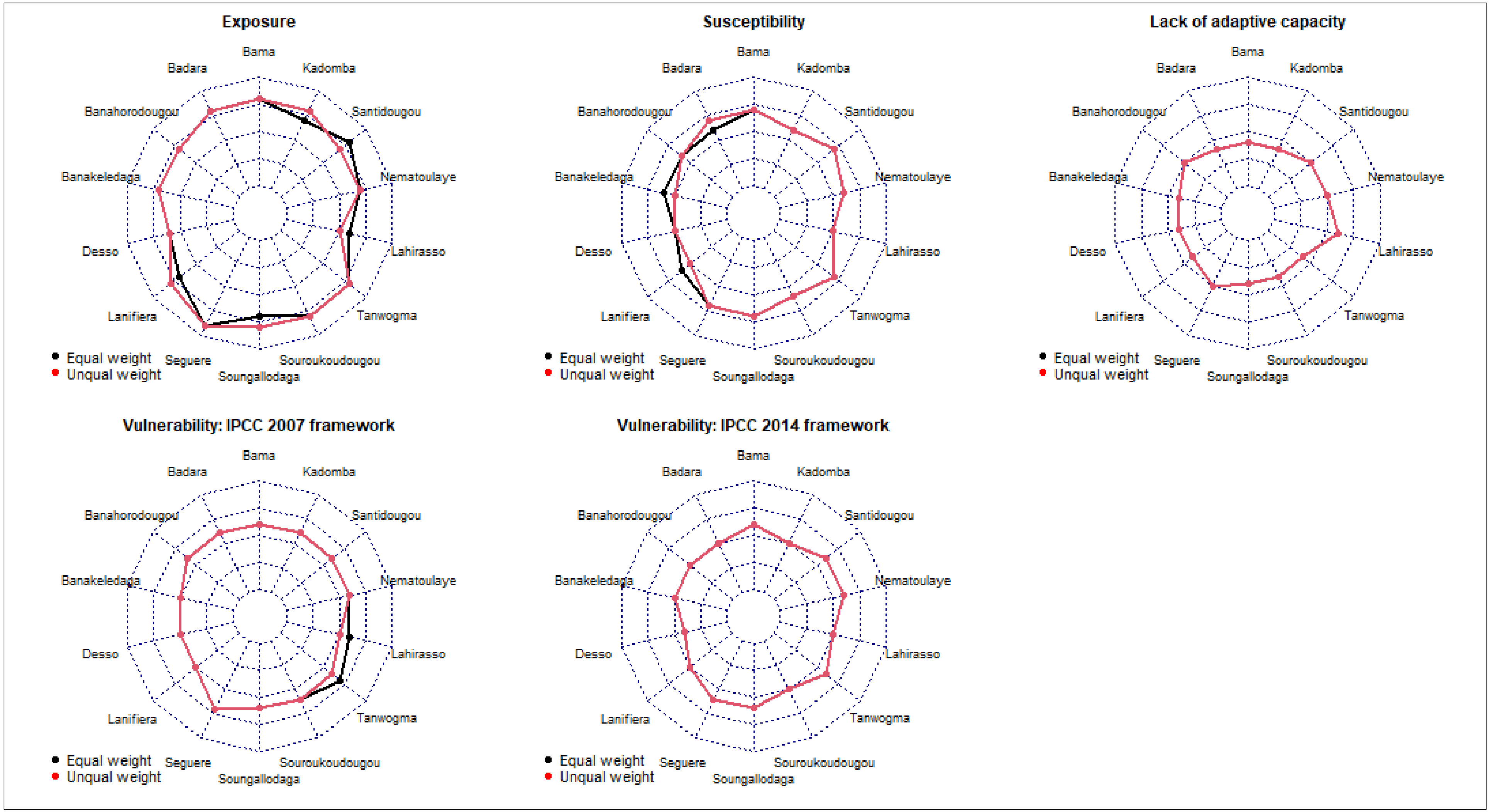


Figure 34: Comparison of vulnerability and its components assessing from equal and PCA methods for weighting indicators.

1.2. Discussion

An understanding of procedures and various measurement methodologies of vulnerability and outcomes of vulnerability assessment can assist planners and emergency managers in prioritizing measures to reduce vulnerability and minimize disaster damages (Yoon, 2012). In this study, the assessment of flood vulnerability examined various vulnerability frameworks and methods for assigning weights to indicators.

This study found that the residents of Bama (village 1), Soungallodaga (village 6), Seguere (village 7), and Santidougou (village 13) were highly vulnerable to flood (Figure **33**). However, the residents provided varied explanations for their village's high flood vulnerability. Those interviewed in Bama highlighted that their vulnerability has increased due to the deficiency in both monitoring and maintenance of the drainage network in rice-irrigated areas. The irrigation system is linked to the Mouhoun River; consequently, an increase in river flow leads to flooding in rice farmlands and impacts nearby households in flood-prone areas. In Seguere and Soungallodaga, the residents in both villages were impacted by the construction of the Samadeni dam. The development and expansion of agricultural areas, enabled by the construction of the Samadeni dam, have led national authorities to plan the relocation of the village of Seguere due to potential vulnerability from Mouhoun river overflowing and the risk of disastrous flooding caused by the spillage of excess water from the Samandeni dam. Conversely, some residents who were displaced due to the construction of dam were resettled in Soungallodaga, where they found the new location to be flood-prone due to the inadequate preparation and limited support during the relocation process.

To effectively manage flood risk, it is essential to understand elements that contribute to flood vulnerability (Smits et al., 2024). The key elements that contribute to flood vulnerability include natural assets such as farmlands, standing crops, groundwater, and village vegetation. Some residents reported that floods have had a greater impact on their farmlands than on their residences. Additionally, residents of Soungallodaga noted an increase in flooding of the farmlands since the Samandeni dam was constructed. Residents of Banahorodougou (village 3), Banakeledaga (village 4), Desso (village 5), and Souroukoudougou (village 9) have observed that runoff water from the drainage system of Bobo-Dioulasso city has deposited sandy sediments over hundreds of hectares of their farmland, rendering it unsuitable for crop cultivation (Figure **33**). Consequently, certain cereals like millet, maize and sorghum are now being replaced with plantain crops due to the altered soil conditions. The physical assets, including sanitation facilities, water sources, household items, physical infrastructures, food storage, and transportation means, have increased household vulnerability to floods. In rural areas, infrastructures such as houses and sanitation facilities are frequently constructed using earthen and wooden materials, sometimes lacking iron or cement. These infrastructures are notably more susceptible to floods, especially those caused by prolonged or successive rainfall events. Additionally, these infrastructures become excessively vulnerable to floods when they experience prolonged inundation.

Limited access to information and a low level of household capacity to handle floods have significantly increased their vulnerability to such events. Increasingly, the inhabitants of many villages are replacing their traditional earth and wood houses with ones constructed from cement bricks and reinforced with iron. Moreover, some families have built small dikes in front of their homes to keep water out, and in certain villages, communities are working together to excavate canals for draining runoff water away from the village. Despite these efforts to cope with floods, households coping capacities remained weak in the study are due to the varied perceptions of communities about disasters and different initiatives they employ to cope with floods. It should be noted that behaviors of rural households and the development of coping mechanisms, if properly understood, can guide local authorities and communities in developing collaborative measures to reduce flood vulnerability and enhance their ability to manage floods (Adedeji et al., 2012). However, lack of proper understanding of the dynamics of coping capacity under the present and future circumstances may lead to false sense of security (Radhakrishnan et al., 2018). The early warning systems in many West African countries are either absent or operate partially. According to a survey conducted in 2014, among the 17 countries in West Africa, only Ghana had an early warning system that was considered moderately effective in mitigating humanitarian effects (Chahinian et al., 2023). In 2019, Mali developed a partially operational early warning system demonstrator, which, however, did not operate in real-time during the event. Overall, in sub-Saharan Africa countries, early warning systems often do not communicate hazards well to vulnerable communities or reduce their impacts at a local level. The early warning systems in many sub-Saharan countries encounter substantial funding difficulties, necessitate a solid scientific and technical basis, and must prioritize populations at risk (Lumbroso, 2018). Despite considerable advances in flood forecasting during recent decades in Europe, operational flood early warning system need to be equipped with near-real-time inundation and impact forecasts and their associated uncertainties (Najafi et al., 2024). What is reassuring about the adaptive capacities of residents in the study area is that they displayed very positive attitudes toward measures and future expectations and demonstrated appreciable preferences for self-protection strategies. This suggests that central involvement of these residents in flood vulnerability reduction strategies could lead to achieving satisfactory outcomes in terms of their capacity to adapt to flooding in the future. To achieve this, flood risk management should integrate both reactive and proactive strategies and ensure coordination across all levels, from national to local.

Flood vulnerability assessment is a complex task that involves numerous uncertainties (Moreira et al., 2023), especially those arising from weighting methods or vulnerability frameworks utilized in assessment. The sensitivity analysis showed that the choice of weighting methods did not substantially alter the spatial distribution of flood vulnerability, regardless of the definition of the IPCC 2007 IPCC 2014 vulnerability frameworks applied in the assessment. Likely, when an equal weighting method is used to assign weights to indicators in the vulnerability assessment, the spatial distribution of the vulnerability index and the vulnerability map remain practically the same, regardless of whether the IPCC 2007 or IPCC 2014 vulnerability frameworks are applied. These finding aligns with those of Moreira et al. (2023), which indicate that the choice of weights does not influence the spatial variability of the flood vulnerability index. However, the vulnerability index calculated using the IPCC 2007 definition was found to be more sensitive than the vulnerability index derived from the IPCC 2014 vulnerability framework, as the exposure component of vulnerability is more affected by variations in weighting methods compared to the susceptibility and adapt components. Therefore, it is preferable to use the conceptual framework of the IPCC 2014 for assessing the vulnerability of a system because it is less sensitive to the choice of weighting methods applied in flood vulnerability assessments. Furthermore, the IPCC vulnerability framework offers more comprehensive treatment of vulnerability, providing practical utility. It facilitates the analysis of vulnerability assessment results and the selected indicators to identify the drivers of vulnerability (Sharma & Ravindranath, 2019). Despite the advantages of the IPCC 2014 framework for assessing vulnerability, its adoption has been limited, likely due to researcher preferences, potential misinterpretations, confusion, and lack of awareness (Estoque et al., 2023). These factors may represent the technical and practical challenges encountered in adopting the novel vulnerability framework proposed by the IPCC.

The vulnerability assessment carried out in this study acknowledges its limitations. The weighting methods commonly used to assign weights to indicators in studies employing an indicator-based approach for computing indices include equal weighting methods, Principal Component Analysis (PCA) methods, and Analytic Hierarchy Process (AHP) weighting methods. The sensitivity of flood vulnerability to the Analytic Hierarchy Process (AHP) weighting method was not considered; it could be interesting to also explore the sensitivity of flood vulnerability to this weighting method (Abdrabo et al., 2023; Dandapat & Panda, 2017). Furthermore, expanding the vulnerability assessment to large flood-prone areas could improve the sensitivity analysis of vulnerability to various weighting methods.

1.3. Partial conclusion

This chapter discusses flood vulnerability assessments at the village level and explores how flood vulnerability is sensitive to different weighting methods considering both old and new IPCC vulnerability frameworks. Flood vulnerability assessment was conducted using an indicator-based approach.

The results indicate that using the equal weighting method to allocate weights to indicators showed a moderate level of flood vulnerability across the study area, with the exception of the village of Seguere, where vulnerability was notably higher, regardless of the application of either the old or new IPCC vulnerability frameworks. Interestingly, when the PCA weighting method was utilized to assign weights to indicators based on the new IPCC vulnerability framework, the findings remained consistent with those obtained using the equal weighting method. However, a significant discrepancy emerged when the PCA method was applied for weighting indicators under the old IPCC vulnerability framework. In this scenario, the number of villages deemed highly vulnerable to floods escalated from one to five, representing an increase from 7.1% to 35.7% of the total villages assessed. Despite the discrepancies noted in vulnerability maps when different weighting methods were applied, the sensitivity analysis, focusing on spatial distribution, indicated that flood vulnerability did not exhibit significant sensitivity to the equal and PCA methods employed as weighting techniques. The new IPCC vulnerability framework offers more benefits compared to the old one, as vulnerability maps were maintained consistency across different weighting methods, and the spatial distribution of flood vulnerability was not substantially affected by varying weighting methods. The factors driving flood vulnerability were identified as the natural and physical assets of households, along with the deficiency in information dissemination about floods and their capacity to withstand them. However, it is crucial to acknowledge that households' attitudes towards measures, future expectations, and their preferences for self-protection have yielded valuable insights that could benefit all stakeholders involved in flood risk management in the development of flood mitigation measures. Future research should concentrate on understanding the dynamics of flood vulnerability, particularly among farmers, and explore their adaptation strategies to these climate hazards.

General Conclusion

Flooding has become more frequent and more intense due to the extreme rainfall that triggers most of flood events in Burkina Faso, with considerable consequences for people and their properties. The aim of this thesis was to determine the factors that could significantly increase the resilience of communities to floods, with the main objective of analysing the impacts and risks attributed to flood occurrences in the Southern Burkina Faso. The first and second specific objectives were addressed by applying the one-dimensional model and the spatial model of extreme value theory to rainfall data over the period 1986-2017, respectively. The third and fourth specific objectives were addressed using index-based method and ordered logistic model applied on household survey data.

1. Summary of the thesis

We found that there was a mismatch between local and large-scale studies, as we found that there were more downward than upward trends in precipitation indices characterizing the intensity and frequency of extreme precipitation. We also found that surface temperatures in the Atlantic Ocean, particularly in its northern part, had a significant impact on the frequency and intensity of extreme precipitation events. In addition, the stationary approach should be used with caution when modelling the intensity and frequency of extreme precipitation events in the study area. Relatively to hypothesis that the communities are most vulnerable to floods occurrences at the end of raining season as compared to its interception is verified, as the risk of extreme rainfall under the influence of North Atlantic SST is greater between August and October than between May and July.

The results of our study revealed that there is a strong spatial diversification of extreme precipitation in the research area, with a strong dependence on extreme precipitation that decreases with increasing distances around 300 km. The concomitant extreme precipitation is strongly observed in the south-west, while its expectation is more pronounced in the eastern part of the research area. The monthly maximum of 1-day and consecutive 5-days rainfall could trigger floods over approximatively 3 km^2 and 4.1 km^2 of the study area, affecting over two thousand people, respectively. In most Sahelian countries, floods are mainly triggered by extreme precipitation events, implying a strong spatial dependence on extreme precipitation, in turn leading to a strong spatial dependence on floods in the study area. Consequently, the hypothesis that there is spatial dependence in the occurrence of floods in the research area is verified.

Flood risk assessment using an index-based approach reveals that nine out of ten villages considered in this study present a high risk of floods. Flood hazard and exposure are household flood risk components that contribute considerably to flood risk. Derived from flood risk, household vulnerability to flooding was used to divide the households surveyed into different groups. We found that runoff from drainage systems in the city of Bobo-Dioulasso has a significant impact on the vulnerability of households living in villages close to the city of Bobo-Dioulasso. This situation has sedimented several hectares of farmlands in some neighboring villages of Bobo-Dioulasso. We have found that the factors that have a significant influence on increasing community resilience are essentially social and environmental. Insurance factors were found to be not significant. Then the hypothesis that social economic factors significant in increasing resilience communities is not verified in our study area because insurance factors have a moral effect on resilience of communities to flood risk.

Relatively to vulnerability assessments, we evaluate flood vulnerability by considering susceptibility indicators based on household perceptions of damage and loss (indirect impacts) experienced over the past six years, with the survey date acting as a reference point. The results indicate that flood vulnerability was typically moderate across the villages, with the notable exception of one village (Seguere), which showed high vulnerability to floods. It was also found that the vulnerability index is less sensitive to changes in the weights assigned to various indicators. However, the vulnerability framework proposed by the IPCC in 2014 provides clearer insights compared to its earlier 2007 framework. When dealing with numerous indicators in system assessments, the equal weighting method for attributing weights to indicators should be preferred. Consequently, the hypothesis that vulnerability is sensitive to variations in weights cannot be confirmed.

2. Recommendations for policy

i. Researchers should be encouraged to pay more attention to local studies of extreme precipitation using dense station, which help to assess the trends and variability of extreme precipitation, rather than considering national and supranational studies sometimes with sparse data. These local studies could lead to an efficient and effective allocation of flood risk management resources.

ii. The government and insurance companies should consider the spatial diversification of risks associated with extreme rainfall when implementing flood risk insurance in southern Burkina Faso. Considering the diversification of risks associated with extreme rainfall could help for test the sustainability of disaster insurance.

iii. The vulnerability of villages located not far from the city of Bobo-Dioulasso could be considerably reduced by considering their interconnection with the city in the drainage system. Because runoff from city of Bobo-Dioulasso affects considerably the flood vulnerability of households living in the adjacent villages.

iv. The authorities need to pay more attention to civil engineering infrastructures such as bridges and roads, which are increasingly becoming flood triggers in some villages. Impact studies for civil engineering infrastructures must therefore consider trends and variations in climatic parameters.

3. Limitations of the thesis

Due to resource and time constraints, some questions remained unanswered in this research. The limits/weaknesses of the study are presented below:

i. The analysis of trends in the frequency and intensity of extreme precipitation events is focused on historical data and this kind of analysis does not inform about future variation of the frequency and intensity of extreme rainfall. Historical and future datasets could be gathered to extend the trend analysis of extreme rainfall frequency and intensity in the future. Skillful variables such as atmosphere variables could be considered in the nonstationary Poisson-GP model to predict the intensity and the frequency of extreme precipitation events.

ii. The assessment of household flood risk considered in this thesis concerns perceived risk and vulnerability of households. The actual flood risk and vulnerability of households were not considered which could be important for a rational allocation of water management resources and implementation of further appropriate management decisions and actions against floods. Perceived risk assessment is mainly required for project monitoring and decision-making purposes. Thus, the assessment of actual risk is necessary for predicting the risk and vulnerability of households to floods.

iii. In this thesis, we have not explored the frequency and intensity of streamflow data, which should allow us to analyze trends in flood frequency and intensity at the local level. Researchers disagree on the main factor behind the upward trend in flood in the Sahelian countries over the two last decades. On the one hand, we have those who point to environmental and socio-economics factors as the main driver of flooding and, on the other, those who point to extreme precipitation as the cause of floods. In such a context, a complex modelling framework is needed to determine the factor or set of factors that exacerbate floods in Sahelian countries.

4. Perspectives

For future research we are going to approach the aspects below:

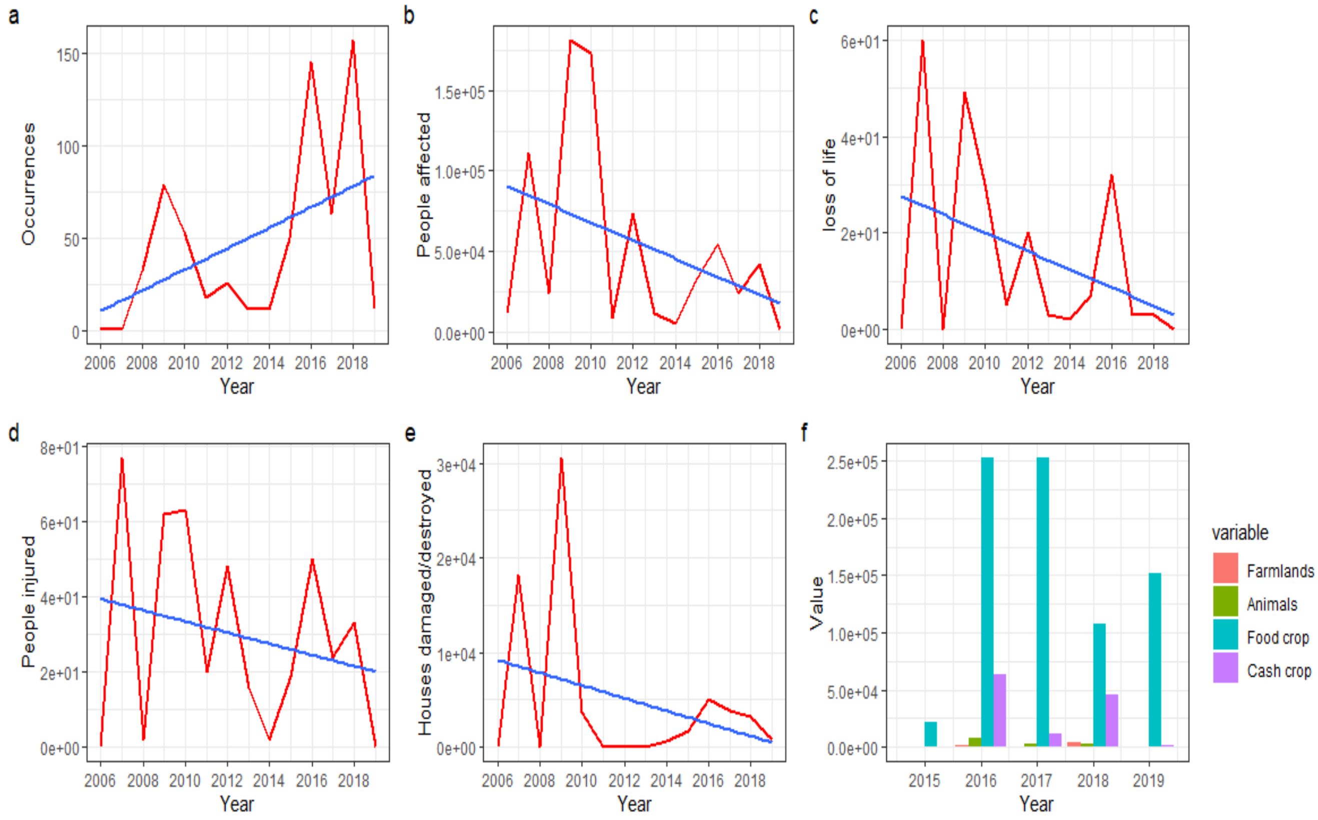
i. Future research should consider a more complex framework for modelling the frequency and intensity of extreme precipitation as a function of SST and other relevant atmospheric variables, considering the spatial dependence of extreme precipitation.

ii. Further research should consider flood loss and risk for building and contents in households. This study could be extended to urban areas of Burkina Faso, which are the most affected by flooding.

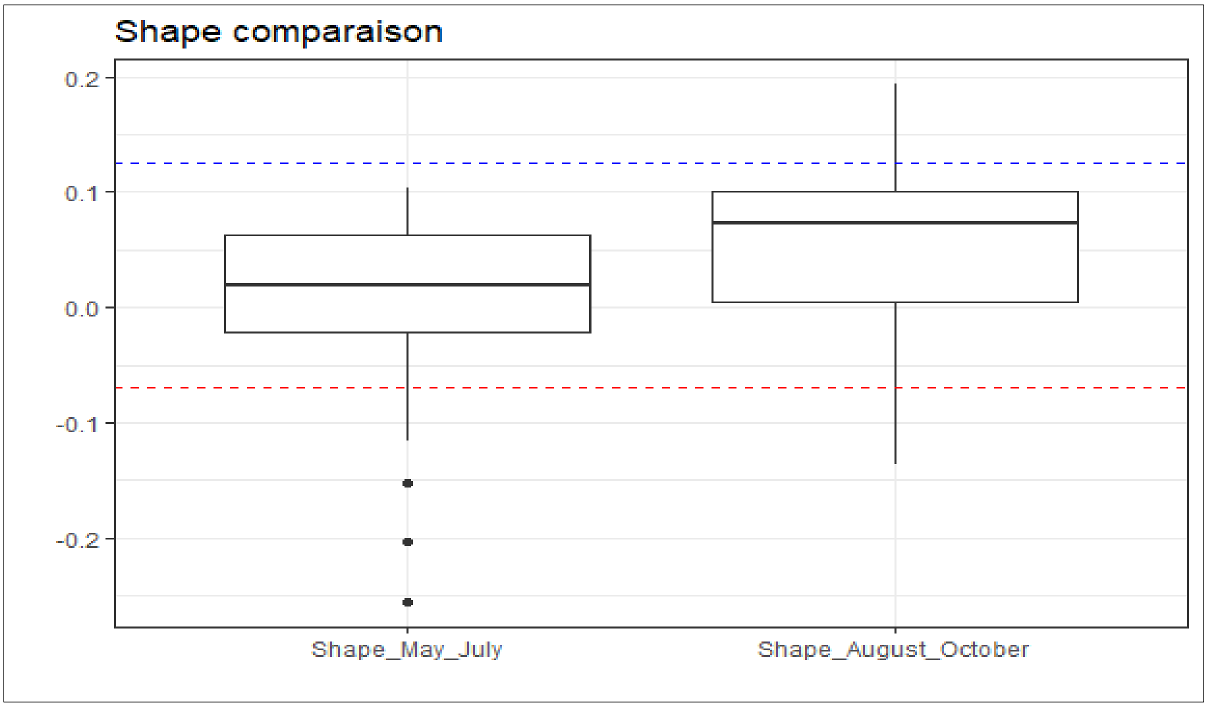
iii. Further research should explore the variability of flow in the Mouhoun River and analyze the strength of correlation between flows, extreme precipitation and changes in land use and land cover. In addition, studying the correlation between streamflow and teleconnection indices should give us a better understanding of streamflow variability.

Appendices

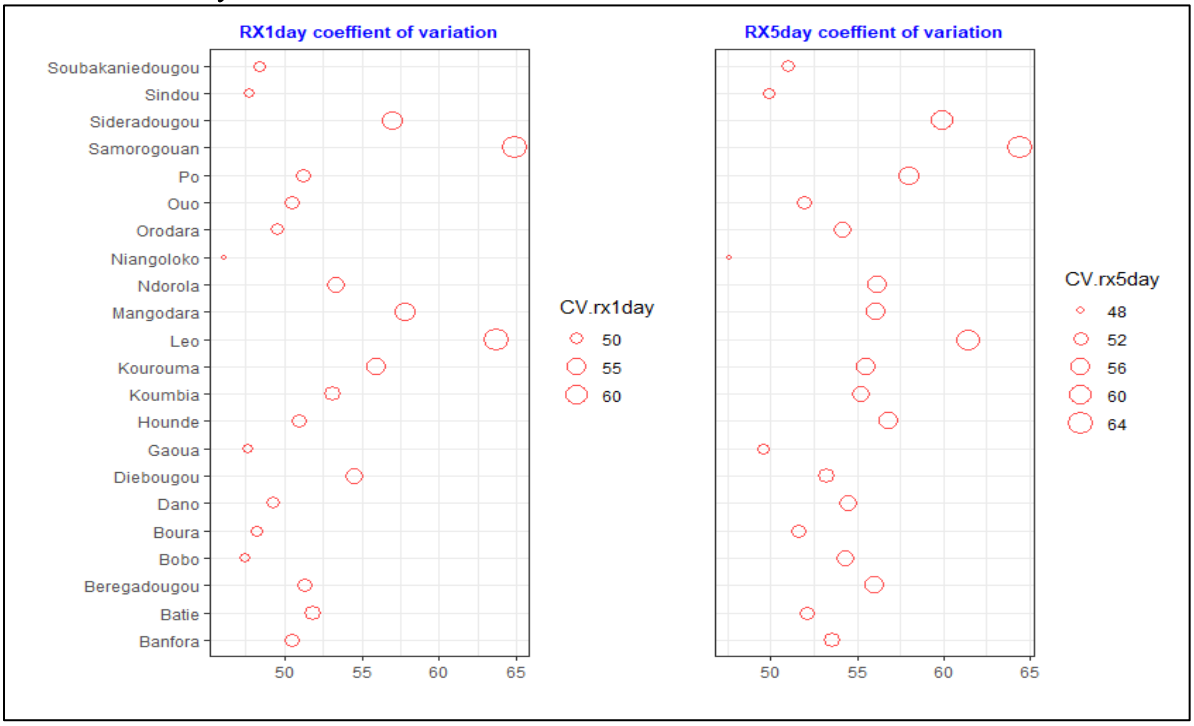
Appendix A: Flood occurrences and impacts in Burkina Faso from 2006 to 2019 obtained from CONASUR



Appendix B: Here, box plots consist of comparing the tail of the extreme precipitation distribution over the May-July period to that of August-October to detect the period with the most extreme occurrences. We note that the tail of extreme rainfall distribution over August-October is heavier than over the May-July period in general. However, very heavy rainfall could occur in certain areas of the study area between May and July.



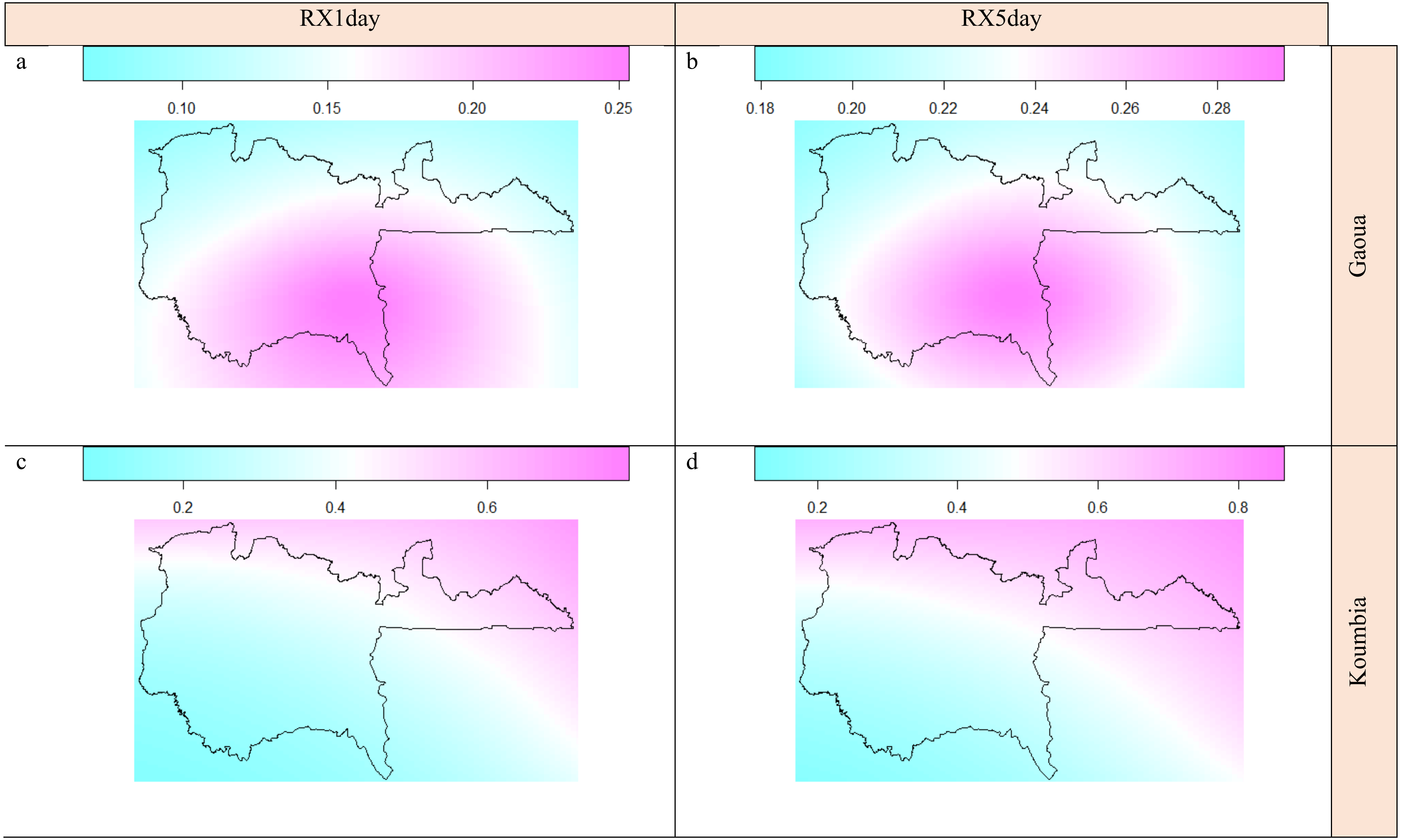
Appendix C: These plots represent the coefficient of variation associated with RX1day and RX5day. These plots allow to observe the strong variability of monthly maximum of 1-day and consecutive 5-days rainfall in the southern Burkina Faso.



Appendix D: Historical data of floods of Burkina Faso provided by National Emergency Relief and Rehabilitation Council called CONASUR. These data were only used to test the results of the max-stable models concerning the normalized spatial aggregated area et risk.

Year	occurrences	Deaths	Victims	Injured people	Destroyed house
2006	1	-	11,170	-	-
2007	1	60	111,356	77	18,150
2008	33	-	24,090	2	-
2009	79	49	181,320	62	30,562
2010	53	30	173,234	63	3,635
2011	18	5	8,854	20	-
2012	26	20	73,726	48	-
2013	12	3	11,290	16	-
2014	12	2	5,586	2	627
2015	50	7	31,739	19	1,747
2016	145	32	54,689	50	5,128
2017	63	3	23,946	24	3,779
2018	157	3	41,964	33	3,292
2019	12	-	1,583	-	751
Total	662	214	754,547	416	67,671

Appendix E: Concurrence probability maps of RX1day and RX5day originate from Gaoua and Koumbia.



Appendix F: The table shows how the indicators of risk were constructed from the variables.

Risk component	Indicator/variable	Villages													
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**
Hazard															
	How many times has flood been affected inside this household in last 15 years?	0.96	0.84	1.00	0.81	1.00	0.93	0.96	0.91	1.00	0.89	0.52	0.92	0.97	1.00
	How many times has flood been affected outside the household in last 15 years?	0.98	0.84	1.00	0.88	0.94	1.00	0.96	0.91	1.00	1.00	0.69	0.98	0.97	1.00
	Frequency of flood	**0.97**	**0.84**	**1.00**	**0.84**	**0.97**	**0.96**	**0.96**	**0.91**	**1.00**	**0.95**	**0.61**	**0.95**	**0.97**	**1.00**
	What was the height of floodwater inside the home that affected you the most?	0.36	0.39	0.27	0.28	0.26	0.33	0.33	0.31	0.28	0.36	0.18	0.32	0.44	0.48
	What was the height of floodwater outside the home from local roads that affected you the most?	0.55	0.59	0.44	0.63	0.65	0.54	0.53	0.56	0.63	0.55	0.34	0.43	0.63	0.69
	What was duration of floodwater that affected the household (hours)?	0.69	0.66	0.57	0.56	0.66	0.63	0.64	0.77	0.70	0.82	0.50	0.73	0.53	0.63
	Intensity of flood	**0.53**	**0.54**	**0.43**	**0.49**	**0.52**	**0.50**	**0.50**	**0.55**	**0.54**	**0.57**	**0.34**	**0.49**	**0.53**	**0.60**
Exposure															
	What is the location of residence of the household?	0.68	0.66	0.66	0.62	0.72	0.64	0.64	0.69	0.66	0.68	0.60	0.65	0.77	0.70
	How far is the residence from the river?	0.56	0.71	0.88	0.71	0.77	0.40	0.62	0.60	0.44	0.79	0.56	0.80	0.94	0.72
	Local exposure	**0.62**	**0.68**	**0.77**	**0.66**	**0.75**	**0.52**	**0.63**	**0.65**	**0.55**	**0.73**	**0.58**	**0.72**	**0.85**	**0.71**
	Have family members been affected by communicable diseases, injured or died in the 15 last years due to flood?	0.78	0.88	0.64	0.63	0.56	0.90	1.00	0.82	0.87	0.79	0.42	0.58	0.53	0.63
	Human exposure	**0.78**	**0.88**	**0.64**	**0.63**	**0.56**	**0.90**	**1.00**	**0.82**	**0.87**	**0.79**	**0.42**	**0.58**	**0.53**	**0.63**
	Has the Household been recorded damage of home in the last 15 years due to flood?	0.94	0.75	0.86	0.88	0.63	0.75	0.93	0.91	0.80	0.95	0.58	0.92	0.94	1.00
	Has the Household been recorded loss of goods in the last 15 years due to flood?	0.89	0.75	0.71	0.50	0.56	0.75	0.93	0.55	0.87	0.89	0.62	0.92	0.91	1.00
	Has the Household been recorded loss of standing crops in the last 15 years due to flood?	0.95	0.75	0.93	0.75	0.50	0.75	0.93	0.73	0.93	1.00	0.85	0.92	0.84	0.74
	Assets exposure	**0.93**	**0.75**	**0.83**	**0.71**	**0.56**	**0.75**	**0.93**	**0.73**	**0.87**	**0.95**	**0.68**	**0.92**	**0.90**	**0.91**
Susceptibility															
	What was the gender of household's head in the last 15 years? (women)	0.20	0.19	0.21	0.25	0.25	0.10	0.07	0.09	0.00	0.32	0.23	0.17	0.09	0.00
	ratio of women population in the house	0.54	0.57	0.54	0.54	0.58	0.59	0.47	0.52	0.59	0.48	0.52	0.56	0.44	0.51
	Age dependency ratio	0.08	0.14	0.10	0.13	0.22	0.07	0.15	0.15	0.08	0.15	0.09	0.08	0.16	0.13
	What is the level of education of the Household Head?	0.87	0.86	0.89	0.88	0.94	0.94	0.84	0.95	0.88	0.92	0.86	0.94	0.91	0.95
	How old is the household head?	0.72	0.75	0.66	0.70	0.70	0.71	0.71	0.72	0.71	0.77	0.70	0.70	0.68	0.70
	Socio-demography	**0.48**	**0.50**	**0.48**	**0.50**	**0.54**	**0.48**	**0.45**	**0.49**	**0.45**	**0.53**	**0.48**	**0.49**	**0.46**	**0.46**
	There are chronically ill people in the household?	0.61	0.56	0.57	0.38	0.44	0.55	0.86	0.55	0.87	0.53	0.46	0.38	0.44	0.37
	There are disability people in the household?	0.30	0.25	0.07	0.13	0.31	0.15	0.29		0.20	0.32	0.12	0.08	0.16	0.21
	How far is the house from health facility?	0.45	0.68	0.34	0.45	0.46	0.65	0.39	0.36	0.51	0.76	0.53	0.39	0.23	0.31
	Health condition	**0.45**	**0.50**	**0.33**	**0.32**	**0.40**	**0.45**	**0.51**	**0.45**	**0.52**	**0.53**	**0.37**	**0.28**	**0.28**	**0.29**
	What is the primary occupation of the household?	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.58	0.58	0.61	0.57

	Is the household monthly income less than national average (90 000 CFA for men and 60 000 CFA women)?	0.79	0.88	0.79	0.75	0.88	1.00	0.86	0.55	0.93	0.63	0.77	0.88	0.84	0.84
	Does the household have debt to pay back?	0.34	0.50	0.50	0.38	0.50	0.30	0.14	0.09	0.40	0.32	0.23	0.08	0.19	0.26
	Does the household have access to any form of financial institution?	0.70	0.50	0.57	0.75	0.63	0.90	0.71	0.73	1.00	0.89	0.77	0.92	0.81	0.68
	Economic condition	**0.61**	**0.62**	**0.61**	**0.62**	**0.65**	**0.70**	**0.58**	**0.49**	**0.73**	**0.61**	**0.59**	**0.61**	**0.61**	**0.59**
	What building construction materials have you used?	0.59	0.92	0.91	0.81	0.67	0.84	0.79	0.77	0.80	0.74	0.83	1.00	0.54	0.78
	What is the age of household building?	0.55	0.55	0.61	0.72	0.63	0.56	0.57	0.36	0.57	0.62	0.40	0.59	0.55	0.46
	Does the household have access to drinking water?	0.08	0.00	0.00	0.00	0.13		0.29	0.73	0.00	0.11	0.38	0.13	0.00	0.53
	Does the household have tubewell?	0.24	0.25	0.36	0.75	0.13		0.36	0.73	0.20	0.47	0.04	0.04	0.38	0.42
	Does the household have sanitary toilet?	0.11	0.06	0.07	0.00	0.00	0.00	0.07	0.09	0.07	0.05	0.00	0.00	0.06	0.37
	Does the household have any form of electricity?	0.03	0.06	0.29	0.13	0.13	0.00	0.00	0.18	0.00	0.05		0.04	0.03	0.16
	Housing and amenities	**0.27**	**0.31**	**0.37**	**0.40**	**0.28**	**0.35**	**0.35**	**0.48**	**0.27**	**0.34**	**0.33**	**0.30**	**0.26**	**0.45**
	Does the household have agriculture land?	0.90	0.69	1.00	0.75	0.81	0.85	0.86	0.55	0.80	0.95	0.92	1.00	1.00	0.89
	Does the household live in rented house?	0.08	0.06	0.14	0.13	0.19	0.10	0.07	0.18	0.07	0.11	0.00	0.00	0.00	0.00
	Land ownership	**0.49**	**0.38**	**0.57**	**0.44**	**0.50**	**0.48**	**0.46**	**0.36**	**0.43**	**0.53**	**0.46**	**0.50**	**0.50**	**0.45**
	Has the farmland belonging to household been degraded?	0.92	0.94	0.86	0.75	0.88	1.00	1.00	0.91	0.93	1.00	0.81	0.88	0.91	1.00
	Has water quality to which household has access been degraded?	0.92	0.63	0.79	0.75	0.81	1.00	0.64	0.73	0.93	0.68	0.81	0.83	0.53	0.84
	Natural resources degradation	**0.92**	**0.78**	**0.82**	**0.75**	**0.84**	**1.00**	**0.82**	**0.82**	**0.93**	**0.84**	**0.81**	**0.85**	**0.72**	**0.92**
Resilience															
	Does the household have at least one member who received training on flood disaster management?	0.11	0.00	0.14	0.00	0.13	0.00	0.14	0.00	0.07	0.00	0.00	0.04		0.05
	Do all adult family members know how to swim?	0.01	0.00	0.00	0.00	0.00	0.00	0.07	0.00	0.07	0.05	0.00	0.00	0.00	0.00
	Does the household have a good understanding of flood disaster warning?	0.25	0.50	0.29	0.38	0.31	0.20	0.14	0.00	0.47	0.11	0.19	0.00	0.34	0.26
	Knowledge	**0.12**	**0.17**	**0.14**	**0.13**	**0.15**	**0.07**	**0.12**	**0.00**	**0.20**	**0.05**	**0.06**	**0.01**	**0.11**	**0.11**
	Does the household have precautionary crop savings?	0.62	0.69	0.50	0.38	0.56	0.55	0.50	0.18	0.87	0.53	0.50	0.33	0.50	0.53
	Does the household have emergency planning?	0.16	0.25	0.14	0.25	0.19	0.25	0.14	0.00	0.20	0.16	0.00	0.00	0.03	0.11
	Does the household have a portable cooking stove?	0.25	0.25	0.00	0.00	0.06	0.30	0.14	0.09	0.07	0.00	0.15	0.04	0.19	0.05
	Does the household have precautionary money savings?	0.22	0.31	0.14		0.25	0.25	0.07	0.18	0.40	0.16	0.04	0.04	0.19	0.16
	Emergency Preparedness	**0.31**	**0.38**	**0.20**	**0.16**	**0.27**	**0.34**	**0.21**	**0.11**	**0.38**	**0.21**	**0.17**	**0.10**	**0.23**	**0.21**
	Has the household received last flood disaster warning?	0.20	0.19	0.14	0.00	0.25	0.45	0.21	0.18	0.33	0.00	0.12	0.00	0.03	0.05
	Do you know what to do when you received the flood warning?	0.42	0.50	0.36	0.38	0.38	0.50	0.29	0.36	0.53	0.26	0.08	0.08	0.41	0.42
	Does the household have mobile phone/TV set/radio at home?	1.00	1.00	0.93	1.00	0.88	1.00	1.00	1.00	0.93	0.95	1.00	1.00	0.97	1.00

Does the household have at least one transportation means (chariot, tricycle bike, motorbike)?	0.99	1.00	0.93	0.88	0.94	1.00	1.00	0.91	1.00	1.00	1.00	0.96	0.84	1.00
Informational	**0.65**	**0.67**	**0.59**	**0.56**	**0.61**	**0.74**	**0.63**	**0.61**	**0.70**	**0.55**	**0.55**	**0.51**	**0.56**	**0.62**
Has the household taken at least one structural mitigation measure to prevent a flood disaster?	0.92	0.69	0.79	1.00	0.75	0.65	0.57	0.73	0.80	0.53	0.38	0.54	0.94	0.95
Mitigation measures	**0.92**	**0.69**	**0.79**	**1.00**	**0.75**	**0.65**	**0.57**	**0.73**	**0.80**	**0.53**	**0.38**	**0.54**	**0.94**	**0.95**
Does the household have their family member (s) working outside of the flood prone area and sending remittance?	0.70	0.88	0.50	0.63	0.56	0.60	0.64	0.73	0.47	0.63	0.50	0.42	0.56	0.42
Does the household have a non-farm income?	0.50	0.50	0.36	0.38	0.50	0.20	0.29	0.27	0.27	0.47	0.19	0.29	0.34	0.32
Does the household have more than one earning member?	0.48	0.56	0.29	0.50	0.44	0.30	0.43	0.36	0.20	0.32	0.15	0.21	0.44	0.32
Does the household have a livestock?	0.53	0.56	0.50	0.63	0.63	0.40	0.71	0.64	0.60	0.84	0.73	0.50	0.50	0.68
Did the household be able to recover from last flood disaster using their own resources?	0.92	0.81	0.86	0.88	0.88	0.95	1.00	0.82	1.00	0.95	0.77	0.88	0.97	0.95
Livelihood diversification	**0.63**	**0.66**	**0.50**	**0.60**	**0.60**	**0.49**	**0.61**	**0.56**	**0.51**	**0.64**	**0.47**	**0.46**	**0.56**	**0.54**
Has the household lived in the village for more than 15 years?	0.95	1.00	1.00	0.88	0.94	1.00	1.00	0.55	0.93	1.00	0.96	0.96	1.00	1.00
Has the household received help from their community during a flood disaster response?	0.51	0.19	0.14	0.13	0.25	0.20	0.21	0.36	0.13	0.74	0.19	0.38	1.00	0.95
Did the household exchange goods or services with their neighbour in the last year?	0.85	0.81	0.57	0.75	0.75	0.85	0.86	0.55	0.93	0.89	0.15	0.54	1.00	0.95
Is the household affiliated with any organization?	0.27		0.07		0.13			0.09	0.13	0.11			0.63	0.16
Social network	**0.65**	**0.50**	**0.45**	**0.44**	**0.52**	**0.51**	**0.52**	**0.39**	**0.53**	**0.68**	**0.33**	**0.47**	**0.91**	**0.76**
Does household have life/health insurance?	0.01	0.00	0.00	0.00	0.13	0.00	0.00	0.00	0.07	0.00	0.00	0.00	0.00	0.00
Does the household have agricultural insurance?	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.27	0.07	0.05	0.04	0.00	0.00	0.00
Insurance	**0.01**	**0.00**	**0.00**	**0.00**	**0.06**	**0.00**	**0.00**	**0.14**	**0.07**	**0.03**	**0.02**	**0.00**	**0.00**	**0.00**
Has the household been changed the cropping pattern?	0.75	0.88	0.71	0.63	0.88	0.90	0.64	0.64	0.73	0.68	0.62	0.83	0.72	0.53
Does the Household use bio-fertilizers for soil improvement?	0.97	0.94	0.93	0.88	0.88	1.00	0.93	0.91	0.93	0.95	0.96	0.92	0.97	1.00
Land use adaptation	**0.86**	**0.91**	**0.82**	**0.75**	**0.88**	**0.95**	**0.79**	**0.77**	**0.83**	**0.82**	**0.79**	**0.88**	**0.84**	**0.76**
Do you believe in possibility of the future occurrence?	0.80	0.81	0.71	0.75	0.81	0.70	0.71	0.73	0.67	0.95	0.46	0.58	0.69	0.79
Do you believe that flood occurrences are due to God willing?	0.16	0.13	0.14	0.25	0.31	0.00	0.00	0.27	0.00	0.00	0.04	0.08	0.16	0.26
Has the household kept trusting in government disaster risk reduction program and policies?	0.58	0.44	0.29	0.38	0.50	0.50	0.57	0.64	0.47	0.42	0.38	0.50	0.50	0.68
Attitudinal	**0.51**	**0.46**	**0.38**	**0.46**	**0.54**	**0.40**	**0.43**	**0.55**	**0.38**	**0.46**	**0.29**	**0.39**	**0.45**	**0.58**

Appendix G: The table shows how the indicators of vulnerability were constructed from the variables

Vulnerability components	Variables// Indicators	Village													
		1	2	3	4	5	6	7	8	9	10	11	12	13	14
Exposure															
	What is the location of residence of the household?	0.68	0.66	0.66	0.62	0.72	0.64	0.64	0.69	0.66	0.68	0.60	0.65	0.77	0.70
	How far is the residence from the river?	0.56	0.71	0.88	0.71	0.77	0.40	0.62	0.60	0.44	0.79	0.56	0.80	0.94	0.72
	Local exposure	**0.62**	**0.68**	**0.77**	**0.66**	**0.75**	**0.52**	**0.63**	**0.65**	**0.55**	**0.73**	**0.58**	**0.72**	**0.85**	**0.71**
	Have family members been affected by communicable diseases, injured or died in the 15 last years due to flood?	0.78	0.88	0.64	0.63	0.56	0.90	1.00	0.82	0.87	0.79	0.42	0.58	0.53	0.63
	Human exposure	**0.78**	**0.88**	**0.64**	**0.63**	**0.56**	**0.90**	**1.00**	**0.82**	**0.87**	**0.79**	**0.42**	**0.58**	**0.53**	**0.63**
	Has the Household been recorded damage of home in the last 15 years due to flood?	0.94	0.75	0.86	0.88	0.63	0.75	0.93	0.91	0.80	0.95	0.58	0.92	0.94	1.00
	Has the Household been recorded loss of goods in the last 15 years due to flood?	0.89	0.75	0.71	0.50	0.56	0.75	0.93	0.55	0.87	0.89	0.62	0.92	0.91	1.00
	Has the Household been recorded loss of standing crops in the last 15 years due to flood?	0.95	0.75	0.93	0.75	0.50	0.75	0.93	0.73	0.93	1.00	0.85	0.92	0.84	0.74
	Assets exposure	**0.93**	**0.75**	**0.83**	**0.71**	**0.56**	**0.75**	**0.93**	**0.73**	**0.87**	**0.95**	**0.68**	**0.92**	**0.90**	**0.91**
Susceptibility															
	Have family members been affected by communicable diseases, injured or died in the last 6 years due to flood occurrences?	0.69	0.69	0.36	0.38	0.44	0.50	0.86	0.73	0.67	0.79	0.31	0.25	0.75	0.74
	Did the household have vulnerable groups (person upper 60 years old, children under 18 years, women and disability person) in the last 6 years due to flood occurrences?	0.56	0.25	0.29		0.06	0.10	0.43	0.55	0.20	0.47	0.04	0.25	0.75	0.63
	Has flood occurrences affected ground water in the last 6 years?	0.93	0.75	0.79	0.75	0.69	0.80	0.57	0.91	0.93	0.63	0.54	0.75	0.84	0.95
	Damage or loss associated with human assets	**0.73**	**0.56**	**0.48**	**0.56**	**0.40**	**0.47**	**0.62**	**0.73**	**0.60**	**0.63**	**0.29**	**0.42**	**0.78**	**0.77**
	Has flood occurrences affected ground water in the last 6 years?	0.93	0.75	0.79	0.75	0.69	0.80	0.57	0.91	0.93	0.63	0.54	0.75	0.84	0.95
	Has the household been recorded damage/loss of the standing crop due to flood occurrences in the last 6 years?	0.90	0.94	0.86	0.75	0.81	0.75	0.86	0.91	0.93	1.00	0.81	0.79	0.81	0.37
	Have you noticed that the natural vegetation was affected by flooding in the last 6 years?	0.95	1.00	0.93	0.75	0.88	0.80	0.93	1.00	0.93	0.95	0.88	0.96	0.91	0.53
	Has your farmland damaged by flooding in the last 6 years?	0.91	0.94	0.86	0.75	0.75	0.80	0.93	1.00	0.80	1.00	0.92	0.92	0.81	0.37
	Damage or loss associated with natural assets	**0.92**	**0.91**	**0.86**	**0.75**	**0.78**	**0.79**	**0.82**	**0.95**	**0.90**	**0.89**	**0.79**	**0.85**	**0.84**	**0.55**
	Has the household recorded house damage/loss due to flood occurrences in the last 6 years?	0.66	0.75	0.64	0.50	0.50	0.70	0.86	1.00	0.47	0.68	0.46	0.67	0.91	0.89

	Has flooding caused damage/ loss to household items and personal belongings (bed, clothing, food items) in the last 6 years?	0.61	0.38	0.36	0.13	0.19	0.35	0.71	0.45	0.33	0.47	0.50	0.38	0.97	0.89
	Has the flood occurrences caused damage/loss to sanitation facilities (latrine, bath) in the last 6 years?	0.83	0.69	0.57	0.50	0.38	0.50	0.79	0.55	0.60	0.84	0.50	0.58	0.91	0.79
	Has the household recorded loss/damage of food storage places caused by flood occurrences in the last 6 years?	0.60	0.50	0.36	0.25	0.19	0.40	0.71	0.45	0.40	0.68	0.50	0.67	0.94	0.84
	Have flood occurrences caused the loss/damage of tube wells/ water pumps in the last 6 years?	0.83	0.63	0.86	0.63	0.50	0.65	0.64	0.55	0.93	0.63	0.54	0.71	0.84	0.84
	Has the village been recorded loss/damage physical infrastructures (roads, electricity, drains) due flood occurrences in the last 6 years?	0.94	0.88	0.86	0.75	0.75	0.75	0.93	0.91	0.87	0.95	0.65	0.92	1.00	1.00
	Has the household recorded loss/damage of transport mode (Motor cycle, motor bike, chariots, and bicycle) due to flood occurrences in the last 6 years?	0.77	0.81	0.71	0.63	0.50	0.70	0.93	0.73	0.87	0.84	0.62	0.88	0.75	0.74
	Damage or loss related to physical assets	**0.75**	**0.66**	**0.62**	**0.48**	**0.43**	**0.58**	**0.80**	**0.66**	**0.64**	**0.73**	**0.54**	**0.68**	**0.90**	**0.86**
	Has the household recorded damage/loss of harvest crop due to flood occurrences in the last 6 years?	0.86	0.94	0.86	0.88	0.75	0.70	0.86	0.82	0.87	1.00	0.85	0.88	0.75	0.42
	Has the household recorded loss/damage of livestock related to flood occurrences in the last 6 years?	0.27	0.50	0.36	0.13	0.06	0.15	0.64	0.36	0.27	0.32	0.46	0.21	0.22	0.58
	Has at least one of household members loosed his employment due to flood occurrences in the last 6 years?	0.41	0.63	0.29	0.25	0.25	0.25	0.50	0.55	0.33	0.42	0.08		0.25	0.37
	Has the household noticed an increase of cereals, seed for crop price by the fact of flood occurrences in the last 6 years?	0.90	0.88	0.86	0.88	0.81	0.95	0.93	0.91	0.87	0.95	0.54	1.00	0.75	0.68
	Damage or loss associated with financial assets	**0.61**	**0.73**	**0.59**	**0.53**	**0.47**	**0.51**	**0.73**	**0.66**	**0.58**	**0.67**	**0.48**	**0.69**	**0.49**	**0.51**
	Has the village recorded the loss/damage of public infrastructure and/or institution (health center, school, mosque) in the last 6 year	0.68	0.50	0.57	0.50	0.38	0.65	0.93	0.73	0.67	0.84	0.65	0.67	0.50	0.53
	Has the household stooped to have access to public institution (education, health, income) in the last 6 years?	0.28	0.25	0.07	0.38	0.19	0.20	0.57	0.45	0.07	0.58	0.46	0.50	0.06	0.21
	Damage/loss associated with social assets	**0.48**	**0.38**	**0.32**	**0.44**	**0.28**	**0.43**	**0.75**	**0.59**	**0.37**	**0.71**	**0.56**	**0.58**	**0.28**	**0.37**
Adaptive Capacity															
	Do feel sufficiently informed by the local authorities on occurrences of flooding and possible prevention measures?	0.30	0.31	0.43	0.25	0.31	0.35	0.36	0.27	0.40	0.32	0.08	0.25	0.09	0.00
	Did you learn how to protect yourself against lood event from your own experiences with flooding event	0.97	1.00	0.71	1.00	0.88	1.00	1.00	0.82	1.00	0.84	0.62	0.83	0.94	1.00
	Did you learn how to protect yourself against flood event by taking others affected by flooding	0.63	0.75	0.64	0.63	0.69	0.90	0.64	0.55	0.80	0.58	0.38	0.75	0.69	0.58
	Did you learn how to protect yourself against flood event by media coverage	0.04	0.06	0.00	0.00	0.06	0.20	0.00	0.00	0.07	0.05	0.15	0.13	0.03	0.00
	Did you learn how to protect yourself against flood event by public informative	0.00	0.00	0.07	0.25	0.06	0.05	0.00	0.27	0.00	0.00	0.00	0.00	0.00	0.11
	Did not you know how to protect yourself against flood event	0.01	0.00	0.29	0.00	0.19	0.00	0.00	0.00	0.00	0.05	0.08	0.04	0.03	0.00

Access to information	**0.32**	**0.35**	**0.36**	**0.35**	**0.36**	**0.42**	**0.33**	**0.32**	**0.38**	**0.31**	**0.22**	**0.33**	**0.30**	**0.28**
Have you personally taken measures against flooding	0.88	0.81	0.64	0.88	0.75	0.95	0.86	0.82	0.80	0.84	0.46	0.58	0.84	1.00
Have you personally applied a structural measure (House is built with materials allowing it to resist flooding)	0.89	0.81	0.64	1.00	0.69	0.90	0.71	0.82	0.73	0.89	0.50	0.75	0.84	1.00
Have you personally applied a behavioral measures (I have taken preparation for flooding event and what has been to be done)	0.51	0.38	0.36	0.63	0.50	0.65	0.57	0.55	0.60	0.53	0.46	0.46	0.31	0.58
Have you personally applied a financial risk transfer (I hold an insurance policy)	0.01	0.00	0.00	0.00	0.06	0.05	0.00	0.00	0.07	0.05	0.08	0.04	0.00	0.00
Have you personally applied any measures	0.92	0.81	0.64	1.00	0.75	0.95	0.86	0.91	0.80	0.84	0.81	0.79	0.84	1.00
Capacities of residents	**0.65**	**0.56**	**0.46**	**0.70**	**0.55**	**0.70**	**0.60**	**0.62**	**0.60**	**0.63**	**0.46**	**0.53**	**0.57**	**0.72**
Do you think that you can personally diminish the impacts of flooding by self-protection measures?	0.69	0.63	0.50	0.88	0.50	0.80	0.57	0.64	0.60	0.74	0.42	0.50	0.75	0.68
Do you think that losses due flooding will increase in the future for you personally?	0.82	0.94	0.71	1.00	1.00	0.95	0.86	0.91	0.93	0.84	0.81	0.92	0.53	0.84
Further self-protection measures are necessary additional to actions taken by government	0.61	0.63	0.79	0.63	0.59	0.64	0.64	0.61	0.57	0.74	0.44	0.74	0.70	0.43
Attitude towards measures and future expectations	**0.71**	**0.73**	**0.67**	**0.83**	**0.70**	**0.80**	**0.69**	**0.72**	**0.70**	**0.77**	**0.56**	**0.72**	**0.66**	**0.65**
Intention to migrate to less exposed areas	0.37	0.38	0.36	0.63	0.56	0.55	0.21	0.36	0.60	0.11	0.12	0.21	0.47	0.05
Are you interested in events that inform you about self-protection measures?	0.97	1.00	0.93	1.00	1.00	1.00	1.00	0.91	1.00	1.00	1.00	1.00	0.97	0.84
Frequency of self-protection measures training	0.82	0.77	0.83	0.78	0.77	0.74	0.80	0.75	0.82	0.79	0.69	0.85	0.83	0.86
Assuming that the risk of flooding increases in the future, would you choose to be insured against flood losses?	0.82	0.94	0.71	0.88	0.88	0.95	0.79	0.73	1.00	0.95	0.92	1.00	0.56	0.84
Assuming that the risk of flooding increases in the future, would you implement measures if incentives/subsidies were given by government?	0.94	1.00	0.86	1.00	1.00	1.00	1.00	0.91	1.00	0.84	1.00	1.00	0.94	1.00
Measures considered to be effective for reducing flood impacts	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.20	0.17	0.17	0.17	0.17	0.17
Preferences for self-protection strategies	**0.68**	**0.71**	**0.64**	**0.74**	**0.73**	**0.73**	**0.66**	**0.64**	**0.77**	**0.64**	**0.65**	**0.70**	**0.66**	**0.63**
Do you believe in possibility of future occurrence?	0.80	0.81	0.71	0.75	0.81	0.70	0.71	0.73	0.67	0.95	0.46	0.58	0.69	0.79
Do you believe that flood occurrences are due to God willing?	0.16	0.13	0.14	0.25	0.31		0.00	0.27	0.00	0.00	0.04	0.08	0.16	0.26
Has the household kept trusting in government disaster risk reduction program and policies?	0.58	0.44	0.29	0.38	0.50	0.50	0.57	0.64	0.47	0.42	0.38	0.50	0.50	0.68
Attitude	**0.51**	**0.46**	**0.38**	**0.46**	**0.54**	**0.60**	**0.43**	**0.55**	**0.38**	**0.46**	**0.29**	**0.39**	**0.45**	**0.58**

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App i: Recommendation letter for data collection

TPZ/GD

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Unité – Progrès - Justice

Ouagadougou, le 06 APR 2021

N° 2021 ...[illegible]..../MESRSI/SG/UJKZ/ED-ICC/D

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Le Directeur

A

Monsieur le Représentant
du CORESUR/Hauts-Bassins
BOBO-DIOULASSO

Objet *: Recommandation*

Monsieur le Représentant,

Dans le cadre de la préparation de leurs travaux de thèse de doctorat, les étudiants du réseau WASCAL s'adressent à des structures techniques en vue de la collecte des données nécessaires à l'exercice académique.

Monsieur SOUGUE Madou, étudiant inscrit en thèse à l'École Doctorale Changement Climatique et Gestion de Risques des Catastrophes de WASCAL-Togo à l'Université de Lomé, est en séjour de recherche terrain. Il est actuellement en stage au sein de notre structure et travaille sur les risques d'inondation et vulnérabilité des populations.

Aussi voudrais-je vous demander de bien vouloir lui accorder des facilités d'accès aux données en rapport avec son thème de recherche. L'utilisation de ces données sera exclusivement académique.

En vous exprimant par avance ma profonde gratitude pour votre compréhension et votre collaboration, je vous prie d'agréer, **Monsieur le Directeur,** mes salutations distinguées.

Ecole Doctorale Informatique et Changements Climatiques
Le Directeur
ED-ICC
Université Joseph KI ZERBO

Pr Tanga Pierre ZOUNGRANA
Officier de l'Ordre national

App ii: Questionnaire

This survey aims to analyse household flood risk in Hauts-Bassins region and deem the trajectory of household flood vulnerability in the future so as to determine factors which could significantly increase their resilience to flooding. This questionnaire will be informed in a face-to-face interview addressed to head of household.

1. Questionnaire Identification

Subcomponent	Names of variables	Questions (Label of variables)	Modalities of variables (sub-factors)	Description of factors
Questionnaire identification	**VID1**	Questionnaire Identifier	/---/----/----/----/	This item will allow to avoid the duplicated observation in dataset
	VID2	It is municipality of	1. Bama 2. Padma 3. Satri 4. Banzon 5. Karagasso-sambla	These can help us to go back to respondent of questionnaire when a mistake was done during the data collecting. They can be used for data quality.
	VID3	The village name is		
	VID6	Your phone number is		

2. Household flood vulnerability and risk indicators

Subcomponents	Names of indicators	Indicators	Scales	Description of indicators
		1. Hazard indicators		
Frequency of flood	**VFH1**	How many times has flood been affected inside this household in last 15 years?	1. Yes, once 2. Yes, more than once 3. None	Past flood events show that the area is prone to hazards. Higher incidence of flood implies higher risk.
	VFH2	How many times has flood been affected outside the household in last 15 years?	1. Yes, once 2. Yes, more than once 3. None	
Intensity of flood	**VFH3**	What was the height of floodwater inside the home that affected you the most?	1. 0m 2. 0-0.5 m 3. 0.5-1 m 4. 1-1.5 m 5. 1.5-2 m 6. More than 2 m	Higher the flood height means more severity, and resultant damages.
	VFH4	What was the height of floodwater outside the home from local roads that affected you the most?	1. 0 2. 0-0.5 m 3. 0.5-1 m 4. 1-1.5 m 5. 1.5-2 m 6. More than 2 m	
	VFH5	What was duration of floodwater that affected the household (hours)?	1. No flood 2. 1-24 H 3. More than 24 H	Long duration shows the severity and exposure of flood hazard in neighborhood.
		2. Exposure indicators		
	VHE1	What is the location of residence of the household?	1. Upland 2. Floodplain 3. Between Levee and riverbank	

Local exposure	**VHE2**	How far is the residence from the river?	1. 0-1 km 2. 1-2 km 3. More than 2 km	Elevation and proximity to river make the household more exposure to flooding.
Human exposure	**VHE3**	Have family members been affected by communicable diseases, injured or died in the 15 last years due to flood?	1. No 2. Yes	Family member injured or affected by communicable diseases due to previous flood implies that household is exposed.
Assets Exposure	**VHE4**	Has the Household been recorded damage of home in the last 15 years due to flood?	1. No 2. Yes	Damages of house from previous flood indicates exposure of household.
	VHE5	Has the Household been recorded loss of goods in the last 15 years due to flood?	1. No 2. Yes	Loss of household goods from previous flood indicates the exposure of household.
	VHE6	Has the Household been recorded loss of standing crops in the last 15 years due to flood?	1. No 2. Yes	Inundation of agriculture lands and loss crops of previous flood indicates exposure of household.
3. Sensitivity Indicators				
Socio-demography	**VHS1**	What was the gender of household's head in the last 15 years?	1. Male 2. Female	Female-headed household are more vulnerable than male-head.
	VHS2	How many people do you have in the household (including head of household)?		Larger the household size, larger the number of people exposed in the neighbourhood.
	VHS3	How many men is the number of men in the house?		Women are more vulnerable than male because of their limited mobility, physical strength and other social norms.
	VHS4	How many women do you have in the household?		
	VHS5	How many children under 15 year do you have in the household?		Higher dependency indicates higher vulnerability of household. It is the ratio of the members below 10 years and above 60 years to the members 11-59 years.
	VHS6	How many elderly (+60) people do you have in the household?		
	VHS7	What is the level of education of the Household Head?	1. No schooling 2. Primary 3. Secondary 4. University	Low literacy with increase the vulnerability of households' access to information.
	VHS8	How old is the household head?	1. Less than 18 years 2. 18-60 years 3. More than 60 years	Elderly household head could handle the flood disaster than young household head.
Health condition	**VHS9**	There are chronically ill people in the household?	1. No 2. Yes	Households with special needs will hinder mobility in case of emergency.
	VHS10	There are disability people in the household?	1. No 2. Yes	
	VHS11	How far is the house from health facility?	1. Less than 1 km 2. 1-3 km 3. 3-5 km 4. 5-7 km 5. More than 7 km	The longer distance of health center for residence, higher will be vulnerability.
			1. Government work	

Economic condition	**VHS12**	What is the primary occupation of the household?	2. Commerce and trade 3. Agriculture and husbandry 4. Daily wage 5. Unemployed	Unstable source of income from particular occupation will increase the vulnerability.
	VHS13	Is the household monthly income less than national average (90 000 CFA for men and 60 000 CFA women)?	1. No 2. Yes	Low-income results in higher vulnerability and more time to recover from flood.
	VHS14	Does the household have debt to pay back?	1. No 2. Yes	Households have taken loan are economically challenged, and thus at more risk.
	VHS15	Does the household have access to any form financial institution?	1. No 2. Yes	Households can recover quickly if it has access to financial institutions
Housing and amenities	**VHS16**	What building construction materials have you used?	1. Earthen and wood 2. Bricks, no cement and thatched 3. Bricks with cement and thatched 4. Bricks + cement with Iron sheets	Earthen and wood houses are more vulnerable to floods.
	V_HS17	What is the age of household building?	1. Less than 10 2. 10-20 3. 20-30 4. More than 30	The elderly houses are more vulnerable to flood disasters.
	VHS18	Does the household have access to drinking water?	1. No 2. Yes	Vulnerability of household increases without access to drinking water.
	VHS19	Does the household have tubewell?	3. No 4. Yes	Vulnerability of household increases without a tubewell.
	VHS20	Does the household have sanitary toilet?	1. No 2. Yes	Vulnerability of household increases without access to a sanitary toilet.
	VHS21	Does the household have any form of electricity?	1. No 2. Yes	Vulnerability of household increases without access to electricity.
Land ownership	**VHS22**	Does the household have agriculture land?	1. No 2. Yes	Agricultural land supports the recovery process.
	VHS23	Does the household live in rented house?	1. No 2. Yes	Households living in rented land have fewer options options or less willingness to fortify their house, thus increase vulnerability.
Natural resources degradation	**VHS24**	Has the farmland belonging to household been degraded?	1. No 2. Yes	Farmland degradation affects crop cultivation and productivity.
	VHS25	Has water quality to which household has access been degraded?	1. No 2. Yes	Degradation of water quality affects human and crop health.
		4. Resilience indicators		
	VHC1	Does the household have at least one member who received training on flood disaster management?	1. No 2. Yes	Knowledge and attitude towards disaster risk will be enhanced by receiving training from experts.

Knowledge	**VHC2**	Do all adult family members know how to swim?	1. No 2. Yes	Swimming will increase capacity as it will help save lives and household items during a flooding.
	VHC3	Does the household have a good understanding of flood disaster warning?	1. No 2. Yes	Good understanding of flood warning systems will increase the awareness of households about the onset of a flood
Emergency Preparedness	**VHC4**	Does the household have precautionary crop savings?	1. No 2. Yes	Households who have save crops are more capable of absorbing flood disaster shocks.
	VHC5	Does the household have emergency planning?	1. No 2. Yes	Household with emergency planning are considered to be better prepared than those without.
	VHC6	Does the household have a portable cooking stove?	1. No 2. Yes	Portable stoves are very useful when a house is underwater or for taking shelter outside the house.
	VHC7	Does the household have precautionary money savings?	1. No 2. Yes	Savings will increase capacity to cope with a flood and thus help in recovery.
Informational	**VHC8**	Has the household received last flood disaster warning?	1. No 2. Yes	If a household received an early warning the last time a flood occurred, it means that they are more aware of floods hazard.
	VHC9	Do you know what to do when you received the flood warning?	1. No 2. Yes	
	VHC10	Does the household have mobile phone/TV set/radio at home?	1. No 2. Yes	Household with phone/TV set/radio are more able to get early warning flood information.
	VHC11	Does the household have at least one transportation means (chariot, tricycle bike, motorbike)?	1. No 2. Yes	Household with transportation means are more able to get mobilize during evacuation and recovery.
Mitigation measures	**VHC12**	Has the household taken at least one structural mitigation measure to prevent a flood disaster?	1. No 2. Yes	Households who take risk mitigation measures after the last flood have more risk perception.
Livelihood diversification	**VHC13**	Does the household have their family member (s) working outside of the flood prone area and sending remittance?	1. No 2. Yes	Households with family member employed outside the community will not be affected by flood.
	VHC14	Does the household have a non-farm income?	1. No 2. Yes	Agriculture seems to be more affected by flooding than non-agricultural income.
	VHC15	Does the household have more than one earning member?	1. No 2. Yes	Household with multiple earning members can increase capacity, since

				even if one income is cut off due to a flood, these household can survive on another.
	VHC16	Does the household have a livestock?	1. No 2. Yes	Owning livestock may help in the recovery process by selling them, selling milk, or using them for agriculture purposes.
	V_HC17	Did the household be able to recover from last flood disaster using their own resources?	1. No 2. Yes	Households who were able to recover from the last flood using their own resources are considered more capable.
Social network	**VHC18**	Has the household lived in the village for more than 15 years?	1. No 2. Yes	Households living in their community for a long time will be aware of evacuation routes and the geography of their locality, and also have a strong network with neighbours.
	VHC19	Has the household received help from their community during a flood disaster response?	1. No 2. Yes	Good cooperation with neighbours/community help households cope with floods.
	V_HC20	Did the household exchange goods or services with their neighbour in the last year?	1. No 2. Yes	Household who gives more support to neighbours are more capable.
	VHC21	Is the household affiliated with any organization?	1. No 2. Yes	Affiliation with any organization gives more confidence in building a network.
Insurance	**VHC22**	Does household have life/health insurance?	1. No 2. Yes	Insurance will increase coping capacity and help household in recovery after floods.
	VHC23	Does the household have agricultural insurance?	1. No 2. Yes	
Land use adaptation	**VHC24**	Has the household been changed the cropping pattern?	1. No 2. Yes	Changing cropping pattern reduces the chance of future losses of crops
	VHC25	Does the Household use bio-fertilizers for soil improvement?	1. No 2. Yes	Use of bio-fertilizers reduces expenses of chemical fertilizers to improve degraded soil and hence adds to the capacity.
Attitudinal	**VHC26**	Do you believe in possibility of future occurrence?	1. No 2. Yes	Household who believes in flood likelihood might be less vulnerable.
	VHC27	Do you believe that flood occurrences are due to God willing?	1. No 2. Yes	Households who do not believe that flooding occurs by Good willing's will fear potential destruction of their assets then they will seek preparedness measures against future flooding, what will make them less vulnerable.

	VHC28	Has the household kept trusting in government disaster risk reduction program and policies?	1. No 2. Yes	Households who are agree with government initiatives will follow them increase their resilience to flooding.
3. Household flood loss/damage-related vulnerability				
Loss/ Damage related to human assets	**VHLD1**	Have family members been affected by communicable diseases, injured, or died in the last 6 years due to flood occurrences?	1. No 2. Yes	Flood disasters have been affected people in the different regions of Burkina Faso including Hauts-Bassins. Flood loss/damage related to human assets are ones of indicators assessed by agencies responsible to disaster risk management.
	VHLD2	Did the household have vulnerable groups (person upper 60 years old, children under 18 years, women, and disability person) in the last 6 years due to flood occurrences?	1. No 2. Yes	
	VHLD3	Has flooding caused heath issues (illness, disability, disease) in the last 6 years in this household?	1. No 2. Yes	
Damage/Loss related to Natural assets	**VHLD4**	Has flood occurrences affected ground water in the last 6 years?	1. No 2. Yes	Flood disasters have affected water resources, farmland and in turn affect crop harvest.
	VHLD5	Has the household been recorded damage/loss of the standing crop due to flood occurrences in the last 6 years?	1. No 2. Yes	
	VHLD6	Have you noticed that the natural vegetation was affected by flooding in the last 6 years?	1. No 2. Yes	
	VHLD7	Has your farmland damaged by flooding in the last 6 years?	1. No 2. Yes	
	VHLD8	Has the household recorded house damage/loss due to flood occurrences in the last 6 years?	1. No 2. Yes	Most often flooding damages or carries away physical assets of people and leaves them with primary needs. In this case people need emergency evacuation support to survive.
	VHLD9	Has flooding caused damage/ loss to household items and personal belongings (bed, clothing, food items) in the last 6 years?	1. No 2. Yes	
	VHLD10	Has the flood occurrences caused damage/loss to sanitation facilities (latrine, bath) in the last 6 years?	1. No 2. Yes	
	VHLD11	Has the household recorded loss/damage of food storage places caused by flood occurrences in the last 6 years?	1. No 2. Yes	
	VHLD12	Have flood occurrences caused the loss/damage of	1. No 2. Yes	

Loss/Damage related to Physical Assets		tube wells/ water pumps in the last 6 years?		
	VHLD13	Has the village been recorded loss/damage physical infrastructures (roads, electricity, drains) due flood occurrences in the last 6 years?	1. No 2. Yes	
	VHLD14	Has the household recorded loss/damage of transport mode (Motor cycle, motor bike, chariots, and bicycle) due to flood occurrences in the last 6 years?	1. No 2. Yes	
Loss/ Damage related to financial assets	**VHLD15**	Has the household recorded damage/loss of harvest crop due to flood occurrences in the last 6 years?	1. No 2. Yes	Flooding affect indirectly the income sources either by stopping people to get their working places trade or by destroying working places.
	VHLD16	Has the household recorded loss/damage of livestock related to flood occurrences in the last 6 years?	1. No 2. Yes	
	VHLD17	Has at least one of household members lost his employment due to flood occurrences in the last 6 years?	1. No 2. Yes	
	VHLD18	Has the household noticed an increase of cereals, seed for crop price by the fact of flood occurrences in the last 6 years?	1. No 2. Yes	
Loss/damage related to social assets	**VHLD19**	Has the village recorded the loss/damage of public infrastructure and/or institution (health center, school, mosque) in the last 6 year	1. No 2. Yes	The schools are used to shelter homeless people during flooding. Because rainfall start well in holidays of pupils, this makes easy the use of classroom as shelter.
	VHLD20	Has the household stopped to have access to public institutions (education, heath, income,)	1. No 2. Yes	
4. Dynamic of Household Flood Vulnerability				
Perception and Evaluation of Hazard and Risk	**VDHV1**	Do you consider River/ rainfall flooding as most important hazard in your community?	1. Yes 2. No 3. Other, mentions it ----------------------------	Assess the potential vulnerability of Household and how this vulnerability level would move in the future.
	VDHV2	Do you personally consider the risk of River flooding as relevant or rather rainfall flooding from hinterland?	1. River flooding 2. Rainfall flooding 3. Both 4. Don't know	
	VDHV3	How would you evaluate the risk of flooding in your community?	1. Very high 2. High 3. Medium 4. Low 5. Very low 6. Not at all	

Experience with and information about events	**VDHV4**	Do you live in flood prone area (The area that could be flooded in case of river overflow, extreme rainfall, and dike breach of dam)?	1. Yes 2. No 3. Don't know	The household who have experienced flooding and have access to information would interest to self-protection
	VDHV5	Have you ever experienced the impact of a flooding event?	1. Yes, once 2. Yes, more than once 3. No	
	VDHV6	IF yes, when did you experience the last event and what happened **[V_DHV5=1,2]**	Year of event and short description	
	VDHV7	Do feel sufficiently informed by the local authorities on occurrences of flooding and prevention measures?	1. Yes 2. No 3. Don't know	
	VDHV8	Please outline your answer to previous question **QDV7**	--------------------------	
	VDHV9	Where did you learn how to protect yourself against flood events? [Multiple answers allowed]	1. From my own experience with flooding event 2. By taking others affected by flooding (citizens initiatives) 3. By media coverage (mail circulars, brochures, radio, TV, etc.) 4. By public informative event (of community or of local water boarders) 5. I don't know exactly how to protect myself against flooding	
Capacities of residents	**VDHV10**	Have you personally taken measures against flooding	1. Yes 2. No	Evaluate the level of self-protection already implemented by the households.
	VDHV11	Considering the following of self-protection measures, have you personally applied one or more of these measures [Multiple answers allowed] IF	1. I applied a structural measure (House is built with materials allowing it to resist flooding) 2. I applied a behavioral measure (I have taken preparation for flooding event and what has to be done) 3. I applied financial risk transfer measures (I hold an insurance policy)	

			4. No, None of these measures 5. No, I applied other measure (s): --------- ---------	
Attitude towards Measures and Future Expectations of Residents	**VDHV12**	Do you think that you can personally diminish the impacts of flooding by self-protection measures?	1. Yes 2. No 3. Don't know	These questions allow to determine Households' expectation to use self-protection measures
	VDHV13	IF previous question answer is YES [**V_DHV12=1]**, by what kind of self-protection measures?	----------------------------	
	VDHV14	Do you think that losses due flooding will increase in the future for you personally?	1. Yes 2. No 3. Don't know	
	VDHV15	Assuming that the risk of flooding increases in the future, to what extent do you agree with the following statement? "Due to the structural and non-structural measures taken by government in the community no further measures of self-protection are necessary."	1. I fully agree 2. I rather agree 3. I rather not agree 4. I do not agree at all	
Preferences for self-protection strategies	**VDHV16**	Assuming that risk of flooding increase in the future, then would you? …	1. Still live here 2. migrate to less exposed areas 3. Other	Self-protection strategies that the households prefer and see how they could be accompanied in order to heighten their resilience against flooding.
	VDHV17	Please outline, IF the answer of question **QDHV16 = 3 "Other"**	-----------------------------	
	VDHV18	Are you interested in events that inform you about self-protection measures?	1. Yes 2. No 3. Don't know	
	VDHV19	How much time would you spend on it? [**IF QDV18 = 1**]	1. One event every month 2. One event every three months 3. One event every six months 4. One event a year	
	VDHV20	Assuming that the risk of flooding increases in the future, would you choose to be insured against flood losses?	1. Yes 2. No 3. Don't know	
	VDHV21	Assuming that the risk of flooding increases in the future, would you implement measures if	1. Yes 2. No 3. Don't know	

		incentives/subsidies were given by government?		
	VDHV22	Which other measures do you think to be effective in reducing impacts of flooding here in your community?	1. Dike heightening 2. Better flood barriers 3. Adaptation of land use in flood-prone areas 4. Better self-protection of residents 5. Better scientific findings 6. Better early warning by responsible authorities 7. Other comments: ---------------------	

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Abstract: In recent decades, heavy rainfall has been the main driver of numerous flood disasters in the Southern part of Burkina Faso, with enormous consequences for people and their properties. However, the studies that have been conducted regarding the extreme rainfall were carried out at national or supranational scale using low density climate station and such studies provided large scale information rather than local information. Such results are not detailed enough to develop risk management and climate adaptation measures at local scale. Additionally, flood risk assessment is still a challenge in Burkina Faso as flood risk management is focused on reactive actions rather than proactive strategies as a basis for sustainable adaptation strategies. Most studies about flooding risk management and adaptation have been performed in Ouagadougou city, as a direct consequence of flooding in September 2009. Other regions received little attention, despite all regions of Burkina Faso being highly vulnerable to floods. This thesis aims to understand the space-time variations of extreme rainfall events and assess flood risk and community vulnerability to floods in southern Burkina Faso. The results show substantial spatial heterogeneity in rainfall trends across the study area, with more downward than upward trends observed, particularly for indices representing extreme rainfall. Additionally, the concurrence probabilities of extreme rainfall events were moderate, with RX5day and RX1day indices found suitable for local-scale and large-scale flood risk assessment, respectively. Households pointed out the management of runoff from the nearest urban areas and poorly designed civil engineering infrastructures, such as roads, as significant factors contributing to their increased vulnerability. Furthermore, it was found that flood risk perception is largely influenced by informational and behavioural factors among households. These results can provide valuable information to municipal and regional authorities involved in disaster risk management.

Keywords: Extreme rainfall, extreme values theory, community vulnerability, flood risk, flood risk perception, indicator-based method, ordered logistic modelling, southern Burkina Faso.

Résumé: Les dernières décennies ont été marquées par de nombreuses inondations causées par des précipitations extrêmes q travers tout le sud du Burkina Faso, avec des conséquences considérables pour les personnes et leurs biens. Cependant, les études précédentes concernant les précipitations extrêmes ont principalement été réalisées à l'échelle nationale ou supranationale, utilisant une faible densité de stations pluviométriques. Telles études fournissaient des informations moins détaillées à l'échelle locale, ce qui rend difficile l'élaboration de mesures et stratégies de gestion des risques et d'adaptation au climat à l'échelle locale. La gestion des risques d'inondation reste un défi au Burkina Faso, car la gestion des risques est axée sur des actions réactives plutôt que sur des stratégies proactives visant à mettre en place des stratégies d'adaptation durables. À la suite des inondations de septembre 2009, la majorité des études sur la gestion des risques d'inondation et l'adaptation ont été menées dans la ville de Ouagadougou, tandis que les autres régions du pays, également très vulnérables aux inondations, ont reçu peu d'attention. Cette thèse vise à comprendre les variations spatio-temporelles des pluviométriques extrêmes et à évaluer le risque d'inondation ainsi que la vulnérabilité des communautés dans le sud du Burkina Faso. Les résultats montrent une hétérogénéité spatiale dans les tendances des indices pluvieux, avec plus de tendances à la baisse, particulièrement pour les indices représentant les précipitations extrêmes. De plus, les probabilités de concurrence des événements pluvieux extrêmes étaient relativement faibles. Les maxima journaliers et les maxima de cinq jours consécutifs de pluies extrêmes ont été jugés appropriés pour la gestion des inondations à grande échelle et à l’échelle locale, respectivement. Les ménages interrogés ont souligné que la gestion des eaux de ruissellement provenant des zones urbaines adjacentes et la mauvaise conception des infrastructures de génie civil étaient des facteurs potentiels contribuant à leur vulnérabilité face aux inondations. De plus, il a été constaté que la perception du risque d'inondation est largement influencée par des facteurs informationnels et comportementaux chez les ménages. Ces résultats peuvent fournir des informations précieuses aux autorités municipales et régionales impliquées dans la gestion des risques de catastrophes.

Mots-clés: Pluies extrêmes, théorie des valeurs extrêmes, vulnérabilité des communautés, risque d'inondation, perception du risque d'inondation, méthode des indicateurs, modèle logistique ordonné, Sud du Burkina Faso.