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RESEARCH

What Influences the Demand for a Potential Flood Insurance Product in an Area with Low Previous Exposure to Insurance? – A Case Study in the West African Lower Mono River Basin (LMRB)

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Abstract
Floods portray a severe problem in the riverine areas of West Africa while more frequent and intense heavy precipitation events are projected under climatic change scenarios. Already, floods cause manifold impacts, leaving the population to cope with the financial impacts of floods through their own means. As formal risk transfer mechanisms (e.g., insurance) are not yet widely available to the population, efforts to increase their accessibility are being intensified. However, studies assessing flood insurance demand currently mostly focus on regions with more established markets. Also, they are majorly applying conventional statistical modeling approaches that consider only a small number of parameters. Contrarily, this study aims to provide an approach for assessing flood insurance in a context of low previous exposure to such products, to allow for a better consideration of the research context. Therefore, a parameter selection framework is provided and machine learning and deep learning models are applied to selected parameters from an existing household survey data set. In addition, the deep learning sequential neural networks outperformed all machine learning models achieving an accuracy between 93.5—100% depending on the loss function and optimizer used. The risk to be covered, insurance perception, no access to any source, access to support from community solidarity funds, access to governmental support, or drawing upon own resources for financial coping, financial recovery time, lack of means and prioritizing more essential needs emerged as important model parameters in researching insurance demand. Future roll-out campaigns could consider the parameters pointed out by this study.

Keywords Floods · Machine learning · Deep learning · Willingness to insure · Togo · Benin

Introduction

Over the past decades, there have been observations of an increasing trend of hydrological extremes (i.e. maximum peak discharge) in West Africa, leading to an increase of disastrous flood events in areas located in proximity to large rivers (Ranasinghe et al. 2021).

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Moreover, while overall precipitation is projected to decrease in West Africa, heavy precipitation events are expected to occur more frequently and intensively according to scenarios considering medium to high emission levels, which leads to accumulated hydro-climatic stress through drought and flood events in the region (Trisos et al. 2022; Giorgi et al. 2019). Already, floods cause a wide variety of impacts in West Africa, such as damaged buildings, disruption of livelihoods, damaged goods, fatalities, displacement, sickness and spreading of diseases, damaged infrastructure and crop damage (Wagner et al. 2021; Afriyie et al. 2018; Brisibe and Pepple 2018; Addo and Danso 2017; Ahadzie et al. 2016; Enete et al. 2016; Adewole et al. 2015; Adelekan and Fregene 2015; Codjoe et al. 2014). With regards to the financial implications of flood impacts in the Lower Mono River Basin (LMRB) in particular, it was found that floods regularly affect households financially through agricultural (lost investments through loss and destruction of crops and plantations, loss of livestock), material (repair and replacement cost for damage or destruction of residential houses and personal material belongings), health (sickness and subsequent payment for medical care), and commercial/trade impacts (lost income from damaged stored products for sale, lack of market access, and affected marketplaces) (Wagner et al. 2022). While mutual support among affected households, especially in the phases of response and reconstruction (especially hosting flood victims and helping neighbors to rebuild) (Lamond et al. 2019; Amoako et al. 2019; Ahadzie et al. 2016; Codjoe and Issah 2016; Adelekan and Asiyanbi 2016), seems to be very prevalent in the West African region, there appears to be a lack of risk transfer instruments that are designed to address the financial consequences of floods (Wagner et al. 2021). Thus, people in the region frequently resort to informal mechanisms that are not originally designated for alleviating the diverse financial implications of flood impacts, which sets households back in their financial achievements (Wagner et al. 2022; Boubacar et al. 2017; Addo and Danso 2017).

Moreover, the frequency and severity of flood impact levels in the LMRB require more concerted risk reduction activities before establishing risk transfer mechanisms, such as insurance, that enable spreading the risk of financial losses across a larger pool of beneficiaries (Wagner et al. 2022). Also, whether insurance is an appropriate risk management tool in developing economies or not remains a contested issue (Pill 2022; Mechler and Deubelli 2021; Dehm 2020; Linnerooth-Bayer et al. 2019; Schäfer et al. 2019; Gewirtzman et al. 2018). While there are increased efforts to raise insurance penetration and insurance coverage against climate-related extreme events in developing economies (InsuResilience Global Partnership 2021), insurance protection against flood impacts remains difficult to be established, even globally (Léger 2022; Flood Resilience Initiative 2020; Lloyd’s 2018). In addition, much of the research on the uptake of or willingness to pay for flood insurance focusses on the Asian, North American and European region, in which the establishment of flood insurance in the market and familiarity with such products are very different from the West African region. Aside from a few studies (Berg et al. 2022; Oduniyi et al. 2020; Navrud and Vondolia 2020; Adzawla et al. 2019), this topic has not been widely researched in the African context. Also, insurance penetration on the African continent in general is only half of the global average while also the average premiums per person are eleven times lower (Bagus et al. 2020). Thus, to better inform future roll-out campaigns of flood insurance products it is important to research the parameters that are associated with insurance take-up in settings where a large number of people at risk have not yet been insurance customers, such as the LMRB.

Most studies researching the willingness to insure (WTI) against floods/willingness to pay (WTP) rely on parameter selection directly based on literature and subsequently apply regression methods (Netusil et al. 2021; Robinson and Botzen 2019; Reynaud et al. 2018;

Fahad and Jing 2018; Turner et al. 2014; Botzen et al. 2013, Botzen and van den Bergh 2012), that usually only consider a low number of parameters. Contrarily, it presents a challenge to derive such parameters from a considerable body of studies for the West African region, due to the limited number of available publications from this area. Thus, established frameworks or reasons for parameter inclusion from other contexts might not be the best fitting for this research context. To address this gap, this study investigates the following central research question: *Which parameters influence the decision-making process of households to take up a potential insurance product against flood damages in a setting with low previous exposure to such products, such as the LMRB?*

Constrained by the limited literature base for the West African region, this study initially reviews literature on WTI against floods/WTP for flood insurance on a global scale. Based on this body of literature, a framework is developed that summarizes six thematic areas of parameters (subjective perception of flood risk, objective flood risk, interactions with insurance institutions, Interaction with other institutions & social environment, attributes of HH/individuals, assets to be potentially insured) to guide which factors are influential on the demand for insurance in the research setting. To structure the parameter selection, feature columns for the entire data set were initially assessed for the entire data set. Then, the remaining parameters were categorized into the six thematic areas of the framework. Moreover, the grouped parameters were assessed through pairplots and a heatmap correlation matrix. As a final step of verification, crosstabs were used for assessing the correlation between the parameters and the output value. This data-driven parameter selection approach is deemed suitable for this study due to researching a context in which people at risk have not been widely exposed to insurance products. Subsequently, on the basis of the selected parameters, machine learning and deep learning models are trained that serve in explaining the observed demand for a potential flood insurance product in the research area.

Background

Insurance and Risk Transfer for Floods in Togo and Benin

Currently, insurance products against the impacts of floods are not widely offered on a household level in Togo and Benin. The insurance industry is mostly centered around motorcycle/car insurance and less on natural hazards (Meton 2019). In addition, there are efforts in Benin to establish health insurance in pilot communities free of charge for its beneficiaries in the first three years (Government of the Republic of Benin 2021). With regards to floods, calls for a feasibility assessment of a flood insurance system through a national insurance fund are even dating back to at least 2011, as stated in a post-disaster needs assessment of the 2010 floods (Government of the Republic of Benin 2011). Also, the Togolese government expressed a strong interest in feasibility studies of an agricultural insurance system within its National Adaptation Plan (Government of the Republic of Togo 2017). In addition, in 2018 Togo was chosen by the pan-African risk pool mechanism African Risk Capacity (ARC) to serve as a pilot country for the implementation of a flood insurance scheme (Akoda 2018). However, no information on its current status could be found, and the most recent available report for the Togolese Republic only contains information for the event of drought (African Risk Capacity 2021b), similarly for Benin (African Risk Capacity 2021a). Moreover, the Beninese government also stated a practical absence of an insurance system for climate-related impacts, such as floods, droughts, wind storms, or heat waves, despite their potentially high impact on the country's gross domestic product (Government of the Republic of Benin 2020). Regarding the LMRB in particular, a recent study points out a strong need for risk-reducing flood adaptation measures and that a conventional, market-based flood insurance approach could be impractical due to the high severity and frequency levels of reported flood impacts from a household perspective (Wagner et al. 2022). As a consequence, this study aims to show relevant insights into the potential flood insurance market, for the case that risk-reducing flood adaptation measures are successfully implemented in the LMRB. Moreover, the research provides insight for insurers to see if they could help to opening a market for themselves by contributing to investing into flood adaptation measures in the area. Finally, this research could benefit the previously mentioned endeavors of establishing flood insurance that are already taking place and support their potential rollout campaigns.

Studies Researching the Demand for Flood Insurance

Various studies on the demand for insurance and their influential factors have been published in the past years under the fields of willingness to pay (WTP) or willingness to insure (WTI). Whereas the former stride is mainly focusing on calculating a premium that potential insurance clients are willing to pay, the latter usually researches the general interest level among targeted groups. The latter aspect also portrays the main focus of this study. However, only a small number has researched the influential factors on demand for flood insurance in the African context (Berg et al. 2022; Oduniyi et al. 2020; Navrud and Vondolia 2020; Adzawla et al. 2019). The major share of studies from that stride of research focused on the Asian (Hossain et al. 2022, Senapati 2020a, b, Liu et al. 2019, Dewi et al. 2018, Reynaud et al. 2018, Sidi et al. 2018, Fahad and Jing 2018, Arshad et al. 2016, Ren and Wang 2016, Abbas et al. 2015, Aliagha et al. 2015, Aliagha et al. 2014, Turner et al. 2014, Hung 2009), North American (Darlington and Yiannakoulias 2022; Huang and Lubell 2022; Netusil et al. 2021; Thistlethwaite et al. 2020; Atreya et al. 2015; Oulahen 2015; Kousky 2011; Browne and Hoyt 2000) or European contexts (Osberghaus and Reif 2021; Robinson and Botzen 2020, 2019; Botzen et al. 2013; Seifert et al. 2013, Botzen and van den Bergh 2012) – areas in which flood insurance systems and insurance in general are more widely established. In studies from this stride of research, the influential factors mentioned have often been grouped into different categories to provide better orientation for researchers in the selection of relevant parameters (summarized in Table 1). For example, Seifert et al. (2013) state the influence of perceptions of flood risks (subjective views), experiences with flood impacts (objective views) as well as factors relating to interactions with disaster assistance from institutions (humanitarian/public compensation). Similarly, Netusil et al. (2021) also point out the importance of factors expressing subjective and objective views on flood risk, while adding the characteristics of residential houses (assets) and demographic characteristics of the respondents (attributes of HH/individual). Aliagha et al. (2014) as well raise the influence of objective and subjective views on flood risk and socio-economic/demographic factors. To achieve its objective, this study compiles further influential factors from further WTP/WTI studies from a global scope/various geographical contexts and grouped them as well into distinct categories while drawing upon and complementing the suggested categories from the previously mentioned studies. In that way, a framework to support the selection of influential factors was created for this study (Fig. 1).

Table 1 Summary of parameters mentioned in WTP/WTI studies

Category	Thematic area	Parameter	References	Comparable parameter in survey data set
Flood risk	"Subjective" perception of flood risk	Flood risk perception	(Hossain et al. 2022, Reynaud et al. 2018, Oulahen 2015, Seifert et al. 2013, Botzen and van den Bergh 2012, Hung 2009)	Yes
		Recently) experienced flood events	(Osberghaus and Reif 2021; Senapati 2020a; Liu et al. 2019; Adzawla et al. 2019; Fahad and Jing 2018; Ren and Wang 2016; Atreya et al. 2015; Aliagha et al. 2014; Turner et al. 2014; Hung 2009; Browne and Hoyt 2000)	Yes
		Perception on climate change	(Adzawla et al. 2019; Oulahen 2015, Botzen and van den Bergh 2012)	Yes
		Awareness	(Senapati 2020b)	Yes
		Anticipated worry and regret about uninsured losses	(Robinson and Botzen 2020, 2019)	Yes
		The observation of other's losses	(Turner et al. 2014)	Yes
	"Objective" Flood Risk	(Externally defined) level of flood risk	(Huang and Lubell 2022; Netusil et al. 2021; Kousky 2011)	Yes
		Proximity to rivers	(Sidi et al. 2018, Botzen and van den Bergh 2012, Kousky 2011)	Indirectly contained in other parameter of flood risk
		Living in a low lying area	(Botzen and van den Bergh 2012)	Indirectly contained in other parameter of flood risk
		House elevation	(Aliagha et al. 2015)	Yes
		Experienced flood impacts	(Hossain et al. 2022, Osberghaus and Reif 2021, Paopid et al. 2020, Senapati 2020a, Liu et al. 2019, Fahad and Jing 2018, Reynaud et al. 2018, Arshad et al. 2016, Oulahen 2015, Atreya et al. 2015, Turner et al. 2014, Seifert et al. 2013, Hung 2009, Browne and Hoyt 2000)	Yes
		Flood depth and duration	(Paopid et al. 2020, Aliagha et al. 2015)	Yes
		Presence of other risk-reduction measures/levee protection	(Hossain et al. 2022; Thistlethwaite et al. 2020; Kousky 2011)	Yes

Table 1 (continued)

Category	Thematic area	Parameter	References	Comparable parameter in survey data set
Interaction	Interaction with insurance institutions	Price of insurance	(Navrud and Vondolia 2020; Reynaud et al. 2018; Browne and Hoyt 2000)	No
		Multi-year insurance policies/billing frequency	(Reynaud et al. 2018; Botzen et al. 2013)	No
		The amount offered in the insurance contract	(Senapati 2020a; Reynaud et al. 2018)	No
		Trust in insurers	(Sidi et al. 2018; Reynaud et al. 2018; Aliagha et al. 2014)	Yes
		Types of risk covered	(Reynaud et al. 2018)	Yes
		Previous insurance purchase	(Senapati 2020a)	Yes
		Insurance provider	(Reynaud et al. 2018)	Yes
		Perception of effectiveness of insurance	(Abbas et al. 2015)	Yes
		Awareness of insurance (understanding)	(Oduniyi et al. 2020; Senapati 2020b)	Yes
	Interaction with other institutions & social environment	Perceived responsibility for preventing damage	(Oulahen 2015)	Yes
		Humanitarian/public compensation	(Seifert et al. 2013, Botzen and van den Bergh 2012)	Yes
		Flood risk communication	(Botzen et al. 2013)	Yes
		Flood prediction (warning)	(Sidi et al. 2018)	Yes
		Access to information and extension services	(Hossain et al. 2022; Adzawla et al. 2019)	Yes
		Membership in farmer's groups	(Hossain et al. 2022; Adzawla et al. 2019)	Yes
		Perception towards government effort in handling flood	(Sidi et al. 2018)	Yes
		Risk sharing between agents	(Berg et al. 2022)	Yes
		Social influence	(Lo 2013)	No

Table 1 (continued)

Category	Thematic area	Parameter	References	Comparable parameter in survey data set
Attributes	Attributes (of HH/individual)	Income	(Dewi et al. 2018, Sidi et al. 2018; Arshad et al. 2016; Ren and Wang 2016; Aliagha et al. 2015, 2014; Abbas et al. 2015; Kousky 2011; Hung 2009; Browne and Hoyt 2000)	Yes
		Education	(Oduniyi et al. 2020; Adzawla et al. 2019; Sidi et al. 2018; Atreya et al. 2015)	Yes
		Age	(Oduniyi et al. 2020; Atreya et al. 2015; Abbas et al. 2015)	Yes
		Ethnicity	(Atreya et al. 2015)	Yes
		Attitudes towards risk taking (e.g., risk averse)	(Hossain et al. 2022; Reynaud et al. 2018, Botzen and van den Bergh 2012)	Yes
		Internal locus of control	(Robinson and Botzen 2020)	Yes
		Ability to pay	(Fahad and Jing 2018; Arshad et al. 2016)	Yes
		Alternative income sources (non-agricultural)	(Hossain et al. 2022; Adzawla et al. 2019; Abbas et al. 2015)	Yes
		Preference uncertainty	(Hung 2009)	Yes
		Conservatism	(Hung 2009)	No
		Farmer's experience	(Oduniyi et al. 2020)	Yes
		Marital status	(Oduniyi et al. 2020)	Yes
		HH dependents	(Oduniyi et al. 2020)	Yes
		Remittances	(Adzawla et al. 2019)	Yes
		Having the location of the house in an affluent area	(Adzawla et al. 2019)	No

Table 1 (continued)

Category	Thematic area	Parameter	References	Comparable parameter in survey data set
	Potential assets to be insured	House price/dwelling value	(Darlington and Yiannakoulias 2022, Paopid et al. 2020, Kousky 2011)	No
		Amount of land owned	(Kousky 2011)	Yes
		Land status (ownership)	(Dewi et al. 2018, Abbas et al. 2015)	Yes
		Farm typology	(Fahad and Jing 2018; Arshad et al. 2016)	Yes
		Cultivated land size	(Senapati 2020a)	No
		Farm size	(Dewi et al. 2018)	No
		Seed prices	(Senapati 2020a)	No
		Fertilizer prices	(Senapati 2020a)	No
		Expenditure of farmer	(Dewi et al. 2018)	No
		House conditions	(Hung 2009)	Yes
		Commercial production	(Adzawla et al. 2019)	No

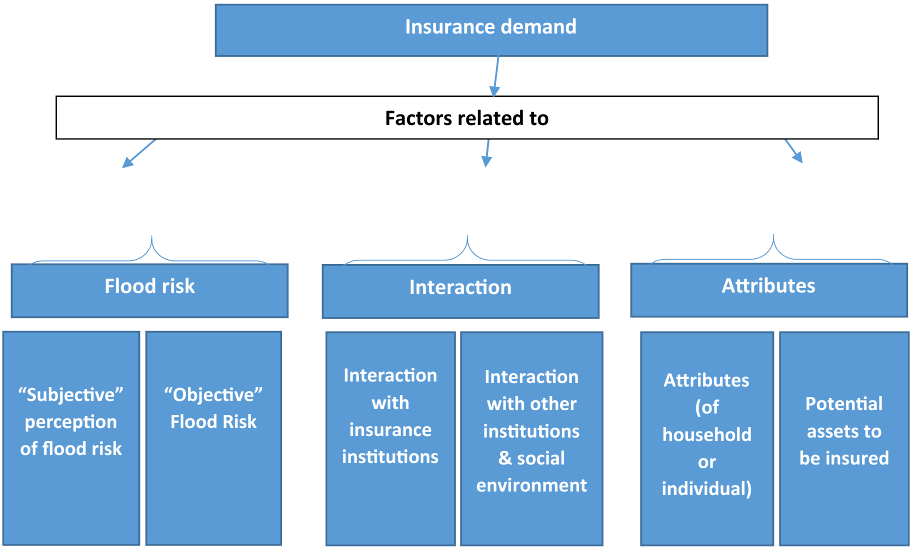

Fig. 1 Factors mentioned in literature about influential factors of insurance demand; own figure, grouping of thematic areas based on (Netusil et al. 2021; Aliagha et al. 2014; Seifert et al. 2013)

In the studies reviewed, generally there are two major strides of influential factors that can be identified with regards to flood risk. On the one hand, there are studies that emphasize the importance of flood risk-related parameters from a “subjective” perspective, such as flood risk perception (Hossain et al. 2022, Reynaud et al. 2018, Oulahen 2015, Seifert et al. 2013, Botzen and van den Bergh 2012, Hung 2009), (recently) experienced flood events and impacts (Osberghaus and Reif 2021; Senapati 2020a; Liu et al. 2019; Adzawla et al. 2019; Fahad and Jing 2018; Ren and Wang 2016; Atreya et al. 2015; Aliagha et al. 2014; Turner et al. 2014; Hung 2009; Browne and Hoyt 2000), perception on climate change (Adzawla et al. 2019; Oulahen 2015, Botzen and van den Bergh 2012), awareness (Senapati 2020b), anticipated worry and regret about uninsured losses (Robinson and Botzen 2020, 2019), and the observation of other’s losses (Turner et al. 2014). On the other hand, there are studies that point out the significance of flood risk-related parameters from an “objective” perspective, such as the externally defined level of flood risk (Huang and Lubell 2022; Netusil et al. 2021; Kousky 2011), proximity to rivers (Sidi et al. 2018, Botzen and van den Bergh 2012, Kousky 2011), living in a low lying area (Botzen and van den Bergh 2012), house elevation (Aliagha et al. 2015), experienced flood impacts (Hossain et al. 2022, Osberghaus and Reif 2021, Paopid et al. 2020, Senapati 2020a, Liu et al. 2019, Fahad and Jing 2018, Reynaud et al. 2018, Arshad et al. 2016, Oulahen 2015, Atreya et al. 2015, Turner et al. 2014, Seifert et al. 2013, Hung 2009, Browne and Hoyt 2000), flood depth and duration (Paopid et al. 2020, Aliagha et al. 2015), presence of other risk-reduction measures/levee protection (Hossain et al. 2022; Thistlethwaite et al. 2020; Kousky 2011).

Also, there is a body of literature that presents the significance of parameters that relate to experiences that people at risk have made with institutions/actors that are potentially involved in post-disaster compensation (such as insurance companies, NGOs, governmental agencies or family/friends). Relevant factors that relate to experiences made with insurance in particular include the price of insurance (Navrud and Vondolia 2020; Reynaud et al. 2018; Browne and Hoyt 2000), multi-year insurance policies/billing frequency (Reynaud et al. 2018; Botzen et al. 2013), the amount offered in the insurance contract (Senapati 2020a; Reynaud et al. 2018), trust in insurers (Sidi et al. 2018; Reynaud et al. 2018; Aliagha et al. 2014), types of risk covered (Reynaud et al. 2018), previous insurance purchase (Senapati 2020a), insurance provider (Reynaud et al. 2018), perception of effectiveness of insurance (Abbas et al. 2015), and awareness of insurance (understanding) (Oduniyi et al. 2020; Senapati 2020b). Also, there are parameters that relate to the "wider" social environment and its role in flood risk management such as the perceived responsibility for preventing damage (Oulahen 2015), humanitarian/public compensation (Seifert et al. 2013, Botzen and van den Bergh 2012), flood risk communication (Botzen et al. 2013), flood prediction (warning) (Sidi et al. 2018), access to information and extension services (Hossain et al. 2022; Adzawla et al. 2019), membership in farmer's groups (Hossain et al. 2022; Adzawla et al. 2019), perception towards government effort in handling flood (Sidi et al. 2018), risk sharing between agents (Berg et al. 2022), and social influence (Lo 2013).

In addition, there are various studies that emphasize the influence of attributes of households/individuals as well as potential assets to be insured. Examples of the former include income (Dewi et al. 2018, Sidi et al. 2018; Arshad et al. 2016; Ren and Wang 2016; Aliagha et al. 2015, 2014; Abbas et al. 2015; Kousky 2011; Hung 2009; Browne and Hoyt 2000), education (Oduniyi et al. 2020; Adzawla et al. 2019; Sidi et al. 2018; Atreya et al. 2015), age (Oduniyi et al. 2020; Atreya et al. 2015; Abbas et al. 2015), ethnicity (Atreya et al. 2015), attitudes towards risk taking (e.g., risk averse) (Hossain et al. 2022; Reynaud et al. 2018, Botzen and van den Bergh 2012), internal locus of control (Robinson and Botzen 2020), ability to pay (Fahad and Jing 2018; Arshad et al. 2016), alternative income sources (non-agricultural) (Hossain et al. 2022; Adzawla et al. 2019; Abbas et al. 2015), preference uncertainty (Hung 2009), conservatism (Hung 2009), farmer's experience (Oduniyi et al. 2020), marital status (Oduniyi et al. 2020), HH dependents (Oduniyi et al. 2020), remittances (Adzawla et al. 2019), and having the location of the house in an affluent area (Adzawla et al. 2019). Studies that mention the latter are pointing out house price/dwelling value (Darlington and Yiannakoulias 2022, Paopid et al. 2020, Kousky 2011), amount of land owned (Kousky 2011), land status (ownership) (Dewi et al. 2018, Abbas et al. 2015), farm typology (Fahad and Jing 2018; Arshad et al. 2016), cultivated land size (Senapati 2020a), farm size (Dewi et al. 2018), seed prices (Senapati 2020a), fertilizer prices (Senapati 2020a), expenditure of farmer (Dewi et al. 2018), house conditions (Hung 2009), and commercial production (Adzawla et al. 2019).

Most studies researching the willingness to insure (WTI) against floods/willingness to pay (WTP) rely on parameter selection directly based on literature and subsequently apply regression methods, such as least-squares-, logit-, linear-, and Tobit-models (Netusil et al. 2021; Robinson and Botzen 2019; Reynaud et al. 2018; Fahad and Jing 2018; Turner et al. 2014; Botzen et al. 2013, Botzen and van den Bergh 2012). Nonetheless, the application of those methods will not allow for analyzing a larger amount of parameters, and mean using a simplistic model, implying the use of several hypotheses and with high uncertainties. Regarding the lack of studies and lack of widespread previous exposure to such products in the West African context, a synthesis of factors based on studies from various regions will assist in the selection of parameters that could prove to be influential in assessing a household's interest level in a potential insurance product. To structure the parameter selection, feature columns for the entire data set were initially assessed for the entire data set. Then, the remaining parameters were categorized into the six thematic areas of the framework (Fig. 1). Moreover, the grouped parameters were assessed through pairplots and a heatmap correlation matrix. As a final step of verification, crosstabs were used for assessing the correlation between the parameters and the output value. As a subsequent step, machine learning and a deep learning models on neural networks were trained on the basis of the selected parameters that serves in predicting the demand for a potential flood insurance product in the LMRB.

The aim of this research is to deliver a basis in case decision makers decide to launch a roll out concept of a flood insurance product in this area where insurance penetration is still very low. Moreover, this study also aims to generate an approach that is applicable to research the demand for insurance in other contexts and regions. The approach can serve as a framework for follow-up studies assessing the willingness to insure in contexts that have not yet been exposed much to insurance before and beyond. Therefore, this study assesses the question of which parameters influence the decision-making process of households to take up insurance against flood damages in a setting where people have barely been exposed to such products before, such as the LMRB?

Methods: Data Collection and Analysis

Data Collection: Household Survey

The data collection process for this study comprised of a household survey carried out in 2021 in the period of March—April. Data was collected by approaching the LMRB based on selected villages located in a low, medium or high flood risk zone. Those flood risk zones were distinguished by criteria of their distance to the river as well as elevation levels. Out of those flood risk zones, 24 villages were selected based on levels of flood-affectedness mentioned in media or situational assessment reports (Fig. 2).

The selection of households within the selected villages took place by drawing a censored proportional sample (11.2%) from each village. The interviewers selected the households randomly by starting out from a centrally located and easily identifiable point in the village and then select houses along a randomly selected walking direction at a randomly selected interval (Levy and Lemeshow 2008). The interviewers then repeated the process, as soon as they arrived at the end of the village. The data collection took place in the scope of the joint research project CLIMAFRI in which several project partners surveyed households. The questionnaire yielded a data set containing more than 400 parameters from 744 households with data, among others, on household characteristics and assets, experiences with floods, flood risk perception, flood impacts, financial coping mechanisms, experience with and perception of insurance, willingness to buy of a potential product. A summary of the basic household charactersistics is provided in Table 2. This data set provided a highly suitable basis to carry out the data-driven analysis approach of this study, applying machine and deep learning methods that consider a wider range of parameters than conventional statistical modeling approaches. Moreover, the research area proved to be highly suitable to research the demand for insurance in a setting with low previous exposure to insurance products. Only 2.3% among the interviewed population had any form of insurance at the time of data collection and 1.1% had insurance previously yet terminated it before the data collection.

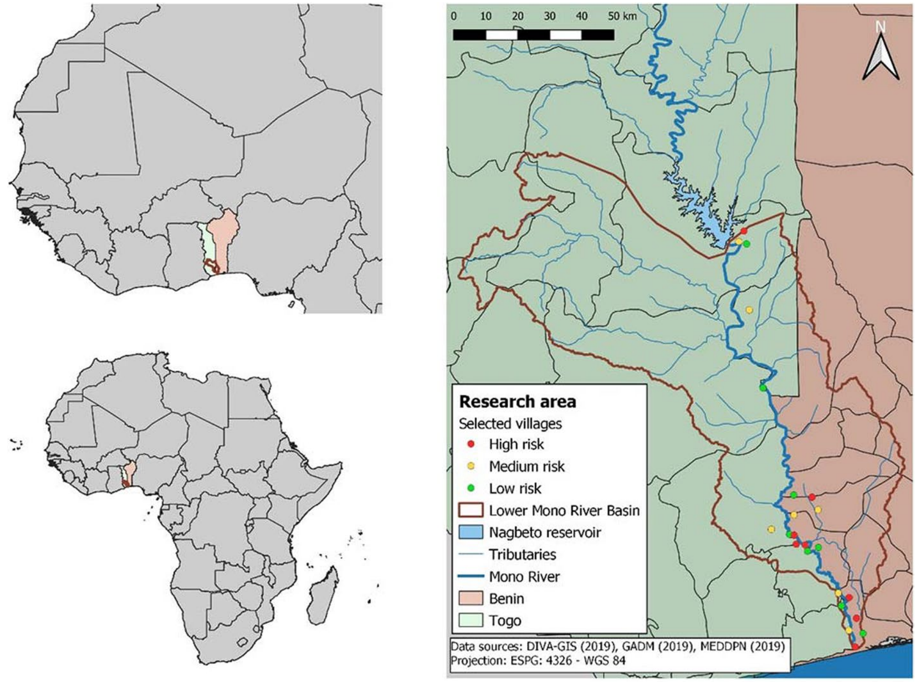

Fig. 2 Location of research area and selected villages

Data Analysis

The aim of this study is to predict the level of interest of an interviewee being inclined to purchase a potential flood insurance product. As illustrated in Fig. 3, the target classes of the generated models are divided into five different responses (very likely, likely, indifferent, unlikely, very unlikely). The respondents of the questionnaire expressed a higher level of interest within the Togolese subset as compared to the Beninese subset.

Usually, WTP/WTI studies look at the amount of money that respondents would be willing to spend on/the general level of interest in buying one specific insurance type. This study differs slightly by asking for the level of interest in flood insurance, while leaving it up to the respondent to choose one of four different forms of coverage (agricultural, material, health, and commercial impacts from floods) in a hypothetical policy. Due the current absence and hypothetical nature of flood risk-related insurance products in the research area this study refrained from researching a monetary value in order to better avoid generating false expectations among the interviewees. In that sense this study is aiming at solve a classification and not a regression problem. In addition, this study aims at providing helpful information for shaping a potential flood risk insurance product for the LMRB in case it will be pursued at some point. All analyses were performed in Python.

Table 2 Summary of basic household characteristics

Parameters	Responses	Frequency	Percentage
Country of residence	Togo	496	66.7
	Benin	248	33.3
	Total	744	100
Gender of respondent	Female	296	39.8
	Male	488	60.2
	Total	744	100
Relationship of respondent to head of household	Head of household	508	68.3
	Spouse of the head of household	213	28.6
	Daughter/son of head of household	15	2.0
	Parent of head of household	1	0.1
	No response/others	7	0.9
	Total	744	100
Marital status	Married	656	88.2
	Widow/widower	53	7.1
	Single	25	3.4
	Divorced/seperated	10	1.3
	Total	744	100
Household is female-headed	Yes	81	10.9
	No	663	89.1
	Total	744	100
Age of respondent	Below 25 years	30	4.0
	Between 25 and 50 years	472	63.5
	Above 50 years	242	32.5
	Total	744	100

Table 2 (continued)

Parameters	Responses	Frequency	Percentage
Size of household	Small (1–4 members)	162	21.8
	Medium (5–8 members)	355	47.7
	Large (> 8 members)	227	30.5
	Total	744	100
Household income per year (in CFA)	Up to 100 000	140	18.8
	> 100 000 – 200 000	173	23.2
	> 200 000 – 300 000	185	24.9
	More than 300 000	226	30.4
	No response	20	2.7
	Total	744	100
Highest level of education in household	None completed	51	6.9
	Primary	213	28.6
	Secondary	394	53.0
	University	84	11.3
	No response	2	0.2
	Total	744	100
Level of agricultural dependency	Low dependency (< 25%)	29	3.9
	Medium dependency (25%- < 50%)	132	17.7
	High dependency (50%—< 75%)	389	52.3
	Very high dependency (75%—100%)	194	26.1
	Total	744	100

Table 2 (continued)

Parameters	Responses	Frequency	Percentage
Additional sources of income (multiple responses possible)	Raising cattle	213	28.6
	Fishing	86	11.6
	Hunting	7	0.9
	Local industries	188	25.3
	Manufacturing industries	14	1.9
	Construction and public works	13	1.7
	Commerce, catering and accomodation	182	24.5
	Transport and communication	26	3.5
	Banks and insurance	1	0.1
	No response	91	12.2
Currently owning any form of insurance	Yes	17	2.3
	No	727	97.7
	Total	744	100
Previously owned insurance but terminated the contract	Yes	8	1.1
	No	736	98.9
	Total	744	100

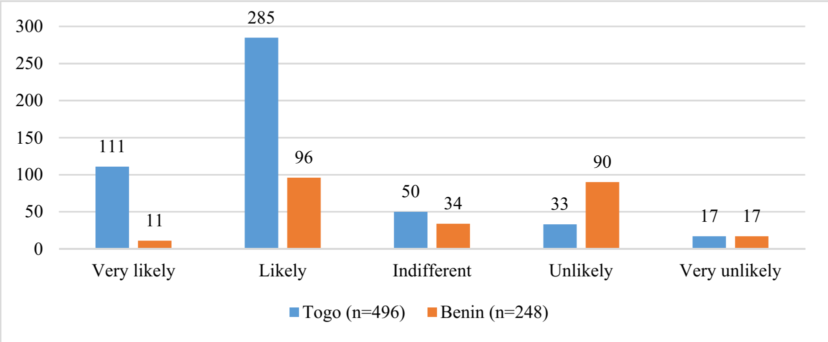

Fig. 3 Distribution of responses within outcome variable (likelihood of purchase of a potential flood insurance product)

Data Preparation and Variable Selection

Initially, data had to be separated into categorical and numerical parameters while cleaning the data and removing NaN (Not a Number) values. The latter was necessary since the presence of NaN values will stop the calculation of fitting the model if not removed, but will also generate NaN values after calculation. For the creation of the model, one-hot encoding was used for the categorical parameters (transformation into binary 0–1 parameters) and standard scaling for the numerical data (discarding mean and scaling according to variance of the unit) to be able to create a processor for the model.

The process of parameter selection is illustrated in Fig. 4. In order to begin the initial selection of relevant parameters, feature columns were assessed based on the p-value and (Spearman) correlation value to uncover the relationships between parameters. This steps allowed for a reduction of the initially more than 400 parameters to around 100. The remaining parameters were then grouped by topic into the six areas of the framework presented in Fig. 1. Then, pair plots (showcasing pairwise bivariate distributions) and a (Pearson) correlation heat map were generated to further facilitate the selection of influential parameters. Based on the heat map correlation matrix, it was decided to use the parameters with low correlation values while disregarding the others, as the high correlation parameters can be connected and related in two ways: if the values of correlation are higher than + 0.5, then these parameters are directly correlated and if less than -0.5 then they are inversely correlated, which means if one parameter tends to increase, then the connected one decrease for negative values while it increases for positive values. For additional verification, cross-tabulations that illustrate the correlations between the parameters and the output parameter were used before further steps were conducted in the analysis. Moreover, it allowed for deciding which parameters to retain or drop.

Comparison of Machine Learning Models

Machine learning models were tested by using the Scikit-learn sklearn package. For all models, the data was split into training (67%) and test data (33%). The first model was the multinomial logistic regression model, and is considered a supervised learning technique. This technique serves to predict if an object belongs to a certain class by providing

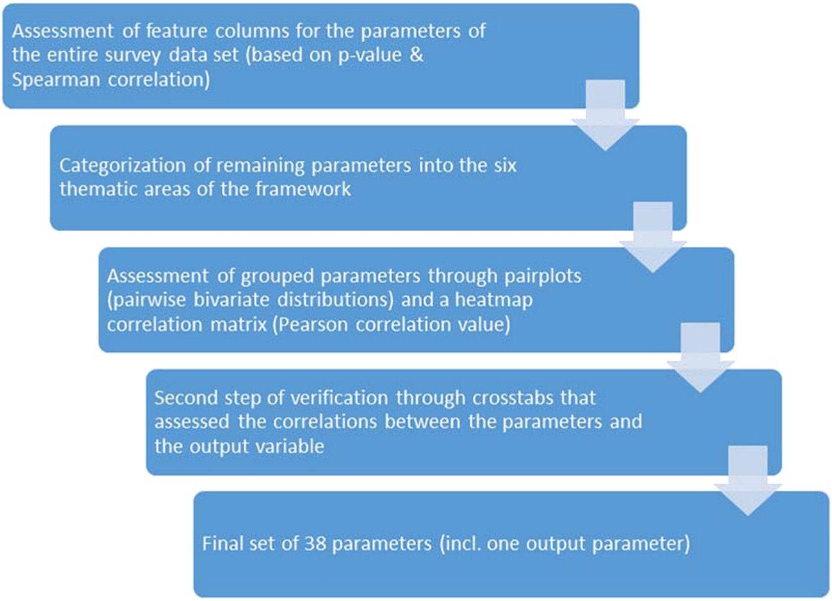

Fig. 4 Selection process of the final set of model parameters

a probability on a range between 0 and 1 (James et al. 2021). Furthermore, the Histogram-based Gradient Boosting classifier model was applied, which considers gradient values obtained by prior update steps from moving into the steepest direction of descent (Feng et al. 2018). Also hyperparameter tuning and gridsearch were applied to this classifier, which however did not lead to a satisfactory improvement of the model accuracy. Finally, additional machine learning tests were applied by using decision trees, a method drawing upon the Gini-Index (James et al. 2021). In addition, bagging was applied to the decision trees to lower the variance in the prediction function, as well a random forest model, drawing upon an assembly of various decision trees (Hastie et al. 2009).

Deep Learning Model (Sequential Neural Network)

In order to attempt achieving better results than the ones obtained from more conventional machine learning approaches (see 3.2.2), this study added a deep learning (DL) model (sequential neural network model) to the analysis using both the TensorFlow and Keras packages. Sequential models are part of artificial neural networks, which usually consist of several layers (input layer, hidden layers, and output layer) that each are equipped with several nodes/neurons, containing activation functions, that are connected through weighted connections between the layers (Jung 2022; James et al. 2021). In general, a sequential model processes the inputted data in a one-directional, linear sequence from the input layer, passing through the hidden layers, and arriving at the output layer (Chollet 2021). Usually, DL approaches are chosen in cases where extremely large data sets are processed and when the possibility to interpret the model does not play and important role (James et al. 2021). Still, this study applied this approach to clarify if a DL model would improve the accuracy of prediction. With regards to the large amount of categorical data, that were encoded, it also helped to consider a larger amount of available data. To analyze numerical and categorical features in a combined manner in this DL model, feature columns were defined by using a Dense Features layer and using it as an input into the Keras model. The sequential model built for this study uses the Relu (Rectified Linear Unit) activation function for the input layer, not allowing activation of the neuron if input values are below 0 (James et al. 2021), and a Softmax function for the output layer, which is best suited if a categorical output is desired (Klimo et al. 2021). Each neuron of the input layer receives a variable of the dataset and passes that information to another neuron, which leads to a higher number of neurons with a higher number of variables. This model contains 256 neurons. Besides, the Softmax layer must have the same number of nodes as the output layer, which is five in the case of this model (Fig. 5). The activation layer is actually the nonlinear function and it transforms the values of the first hidden layer into weighted sums to the next layer. In addition, the Adam as optimizer with a cross entropy and 200 epochs was applied for fitting the model. To compare this model, a second DL model was generated containing 50 neurons, the he_uniform function as kernel initializer, drawing samples from a truncated normal distribution centred on 0 and the stochastic gradient descent (SGD) optimizer.

Sequential models bear the disadvantage that they only allow to provide input into the model only once at the beginning, in contrast to functional models in which layers can be connected to one another in a multi-directional way, allowing for feed-back loops (Chollet 2021). Yet, sequential models still better allow for a consideration of a large number of input parameters in comparison to a conventional regression model approaches, as currently widely used in the field of WTP/WTI. In addition, in comparison to conventional ML approaches a neural network can learn from the data in a better and more complex way and even work with unstructured data (Janiesch et al. 2021) and thus better reflect the research context. This consideration was of high importance to this research project to not directly infer findings and assumptions from studies in regions with more established insurance markets. Instead this study wants to consider a wider range of parameters to better represent the interest levels of a population that has not been widely exposed to the usage of such products before.

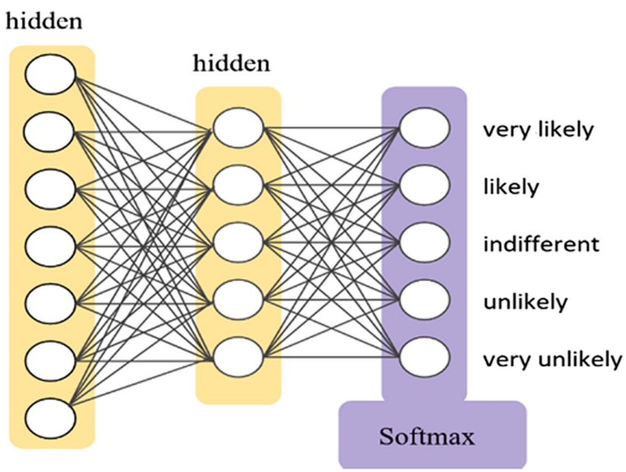

Fig. 5 Application of Softmax on the DL model output layer

Results

Selected Relevant Parameters According to Pairplots, Correlation Matrix and Cross Tabs

For parameter selection, feature columns for the entire data set were initially assessed for the entire data set. Then, the remaining parameters were categorized into the six thematic areas of the framework (Fig. 1). Moreover, the grouped parameters were assessed through pairplots and a heatmap correlation matrix. As a final step of verification, crosstabs were used for assessing the correlation between the parameters and the output value. The relevant parameters reflected all six thematic areas of the presented framework on influential factors on insurance demand. As visualized in Table 1, parameters on potential assets to be covered were only sparsely represented in this data set, which can be seen as the reason for them only appearing once in the final selected set of parameters.

Finally, 38 parameters (including one output parameter) make up the final set of selected parameters (Table 3). The selected parameters of the model covered the following categories of parameters from the framework: Perception on climate change; Flood risk perception; Experienced flood impacts; (Externally defined) level of flood risk; Awareness of insurance (understanding); Trust in insurers; Perception of effectiveness of insurance; Previous insurance purchase; Insurance provider; Types of risk covered; Perceived responsibility for preventing damage; Humanitarian/public compensation; Membership in farmer's groups; Risk sharing between agents; Income; Marital status; Ability to pay; Preference uncertainty; Land status (ownership).

Model Accuracies

All models were applied to three separate data sets each, namely one overall data set containing submissions from both Togo and Benin ($n = 744$) as well as two subsets from Togo ($n = 496$) and Benin ($n = 248$) exclusively. Initially, six machine learning models were run on the data sets and compared by their model accuracy. The applied model types for the classification are logistic regression, a histogram-based gradient boosting classifier, an optimized histogram-based gradient boosting classifier, decision trees, a bagging trees classifier, and a random forest classifier. Moreover, a sequential neural network was applied to the data sets to compare if a DL model would yield higher accuracies than the conventional ML models.

As illustrated in Table 4, almost all models (except for the optimized histogram-based gradient boosting classifier) returned the highest accuracies for the Togo subset. The logistic regression classifier returned an accuracy of 54.0% (stdv = 0.029) for the combined data set, 48.0% (stdv = 0.0042) for the Benin subset, and 61.7% (stdv = 0.049) for the Togo subset. Overall, this classifier therefore ranked among the ones with the weakest performances of the conventional ML models. The histogram-based gradient boosting classifier achieved 64.0% (stdv = 0.00) for the combined data set, 55.5% (stdv = 0.00) for the Benin subset, and 65.3% (stdv = 0.00) for the Togo subset. Thus, it ranked among the better performing conventional ML models, especially for the combined data set and the Benin subset. The model was even improved further through hyperparameter tuning and applying grid search. The model then achieved 67.0% (stdv = 0.00) accuracy for the combined data set, 58% percent (stdv = 0.00) for the Benin subset, which were the highest for all conventional

Table 3 Summary of included model parameters for assessing the demand for flood insurance

Category	Thematic area	Associated category of parameters from framework	Description of selected parameters from the survey data set
Flood risk	"Subjective" perception of flood risk	Perception on climate change	Interviewee heard of climate change before
		Flood risk perception	Perceived likelihood of future flooding
	"Objective" Flood Risk	Experienced flood impacts	Financial recovery time from commercial impacts
			Frequency of commercial impacts (past 20 years)
			Intensity of commercial impacts (past 20 years)
			Financial recovery time from all four impact types combined
			Frequency of all four impact types combined (past 20 years)
			Severity of all four impact types combined (past 20 years)
		(Externally defined) level of flood risk	Flood risk zone based on distance to the river, elevation, and reports of flood affectedness
Interaction	Interaction with insurance institutions	Awareness of insurance (understanding)	Understanding of how insurance works
			No previous insurance purchase due to lack of information
		Trust in insurers	Level of trust that insurance companies will deliver payout as promised
			No previous insurance purchase due to general lack of trust in companies
		Perception of effectiveness of insurance	Insurance as an instrument only suited for the needs of wealthy people
			No previous insurance purchase due to too much paperwork
		Previous insurance purchase	Household has access to insurance in case of experiencing flood impacts
		Insurance provider	No insurance provider/products present in the area
		Types of risk covered	Desired risk to be covered in potential flood insurance product
	Interaction with other institutions & social environment	Perceived responsibility for preventing damage	Desiring to have access to remittances to deal with flood impacts
		Humanitarian/public compensation	Household has access to governmental support in case of experiencing flood impacts
			Household has access to NGO support in case of experiencing flood impacts
		Membership in farmer's groups	Household has access to support from cooperatives in case of experiencing flood impacts
		Risk sharing between agents	Household is member of a savings group
			Household has access to credits from banks in case of experiencing flood impacts
			Household draws upon their own resources in case of experiencing flood impacts
			Household has access to support from community solidarity funds in case of experiencing flood impacts
			Household has access to credits from savings groups in case of experiencing flood impacts
			Household has access to credits from a private lender in case of experiencing flood impacts
			Household has no access to any previously mentioned source in case of experiencing flood impacts
			Household has not bought any insurance previously because they had access to other mechanisms of coverage

Table 3 (continued)

Category	Thematic area	Associated category of parameters from framework	Description of selected parameters from the survey data set
Attributes	Attributes (of HH/individual)	Income	Household income per year
		Marital status	Household is female-headed
		Ability to pay	Fear that insurance purchase will affect more essential needs of the household to be covered
			Household has not bought any insurance before due to lack of means
		Preference uncertainty	Household has not bought any insurance before due to not being interested in the topic
			Uncertainty on the reason why no insurance has been purchased before
	Assets to be covered	Land status (ownership)	Household is owner of the house they are living in

Table 4 Model accuracies of ML/DL models applied to the selected parameters

	Conventional Machine learning						Deep learning	
	Logistic Regression	Histogram-based Gradient Boosting Classifier	Optimized Histogram-based Gradient Boosting Classifier	Decision Trees	Bagging trees classifier	Random Forest Classifier	Sequential Neural Network First model	Sequential Neural Network second model
Accuracy both countries ($n = 744$)	0.540 ± 0.029	0.64 ± 0.000	0.67 ± 0.000	0.437 ± 0.034	0.612 ± 0.045	0.636 ± 0.035	$1 \pm 5.67 \times 10^{-5}$	0.9350 ± 0.2329
Accuracy Benin subset ($n = 248$)	0.480 ± 0.0042	0.550 ± 0.000	0.58 ± 0.000	0.476 ± 0.051	0.552 ± 0.035	0.585 ± 0.048	1 ± 0.0013	0.9756 ± 0.1614
Accuracy Togo subset ($n = 496$)	0.617 ± 0.049	0.653 ± 0.000	0.69 ± 0.000	0.534 ± 0.049	0.704 ± 0.041	0.716 ± 0.051	$1 \pm 8.17 \times 10^{-5}$	0.9512 ± 0.1291

ML models, and 69% (stdv = 0.00) for the Togo subset. Moreover, a decision tree classifier was applied, which merely reached 43.7% (p = 0.034) for the combined data set, 47.6% (stdv = 0.051) for the Benin subset, and 53.4% (stdv = 0.049) for the Togo subset. As a consequence, this classifier achieved the lowest accuracies among all conventional ML models. However, it was improved by applying bagging to then reach 61.2% (stdv = 0.043) for the combined data set, 55.2% (stdv = 0.035), and even 70.4% (stdv = 0.041) for the Togo subset. Finally, as the last conventional ML model, a random forest classifier was applied achieving 63.6% (stdv = 0.035) for the combined data set, 58.5% (stdv = 0.048) for the Benin subset, and even 71.6% (stdv = 0.051) for the Togo subset. These results clearly show that the datasets of Togo rendered the highest accuracies. The latter is due to the fact that there is higher correlation in the answers provided by respondents in Togo.

Since the accuracies of the conventional ML models did not yield higher accuracies (over 75–80%), two sequential neural networks from the realm of DL were applied as a comparison. The first sequential neural network model returned 100.0% of accuracy for the combined data set, as well as for the Benin and Togo subsets. As a consequence, it yielded the best performance by far in comparison to the applied conventional ML models. This finding emerged somewhat surprising, since deep learning is rather recommended for data sets that are much larger than the survey data set. The second model however exhibited a slightly lower accuracy with 93.5% for the combined data set, 97.6% for the Benin subset and 95.12% for the Togo subset. A more detailed overview on the loss, precision, F1 score and recall are provided in Annex 1 as well as a confusion matrix in Annex 2 in the supplementary information to this article.

Contribution of Parameters to Predicting Likelihoods of Insurance Purchase in the Deep Learning Model

For the sequential neural network model an overview of the most important parameters based on the feature importance value was generated (Fig. 6). The feature importance value expresses the level of influence of a parameter on the output variable of the model (likelihood of insurance purchase). When identifying the most important features, a subset of relevant features can be selected for use in building a model. Therefore, the dimensionality is reduced as well as noise in the data. Moreover, the model interpretability is improved in that way. The selection of feature importance furthermore assists in reducing the number of parameters, therefore reducing the data and decreasing the time needed to obtain the results. The feature importance values were generated for the combined data set of both countries, as well as for the Togo and Benin subsets. In general, it can be observed that the feature importance varies in parts to a large extent across the parameters for the individual data sets.

With regards to the parameter categories outlined by the framework presented in the study, interaction-related parameters were the most important category of parameters by far. Important parameters related to the thematic area of interaction with insurance institutions were the desired risk (agricultural, material, health, or commercial impacts) to be covered in potential flood insurance product (Togo). Also, the degree to which insurance was perceived as an instrument only suited for the needs of wealthy people (all) exhibited a high feature importance. In addition, parameters relating the interaction with other institutions and the social environment emerged as the thematic area with the most numerous important values. Feature importance was high when a household had no access to any source mentioned in the questionnaire for financial coping in case of experiencing flood

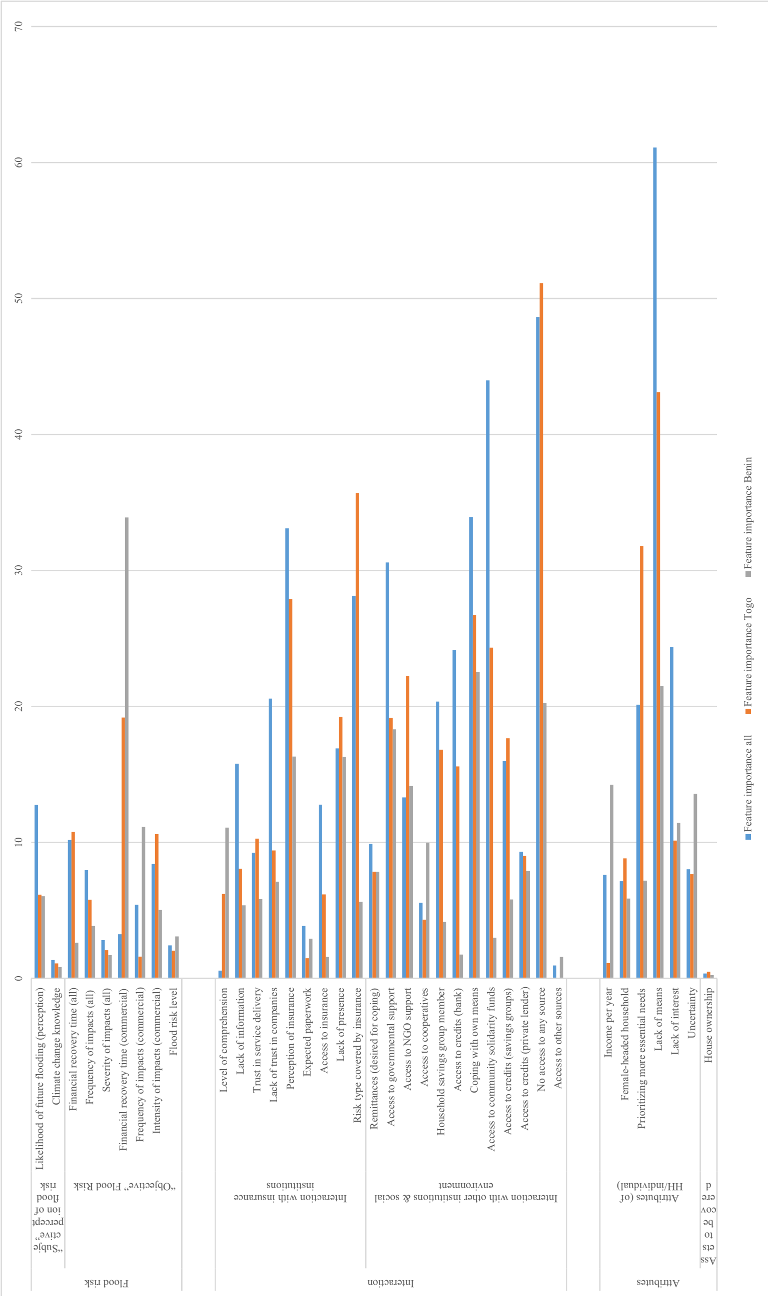

Fig. 6 Feature importance of parameters in the sequential neural network model

impacts (all, Togo). In addition, important parameters were if a household had access to support from community solidarity funds in case of experiencing flood impacts (all), a household drawing upon their own resources to cope financially in case of experiencing flood impacts (all), and a household having access to governmental support in case of experiencing flood impacts (all).

Moreover, three further parameters achieved a high feature importance. From the parameter category of flood risk and thematic area of "objective" flood risk the financial recovery time from commercial impacts (Benin) appeared as important. Finally, from the parameter category attributes and the thematic area of attributes of HH/individuals important parameters were if a household has not bought any insurance before due to lack of means (all, Togo), and the fear that an insurance purchase will affect the ability to cover more essential needs of the household (Togo).

Discussion

This study has enabled the consideration of a large number of parameters to research the demand for a potential flood insurance product in an area with low previous insurance exposure. To achieve this, it drew upon a data set considering manifold aspects on the household level from the areas of household characteristics and assets, experiences with floods, flood risk perception, flood impacts, financial coping mechanisms, experience with and perception of insurance, willingness to buy of a potential product. The identified parameters identified as highly important for the most accurate model type (sequential neural network model) resonate with the results of other studies. The parameters if a household has not bought any insurance before due to lack of means, and the fear that an insurance purchase will affect more essential needs of the household to be covered relate to the general aspect of the ability to pay, as also raised by Fahad and Jing (2018) and Arshad et al. (2016). Moreover, the findings that it was important if a household had no access to any source mentioned in the questionnaire, access to support from community solidarity funds, or drawing upon their own resources to cope financially in case of experiencing flood impacts, reflects the importance of risk-sharing between agents, as also pointed out by Berg et al. (2022). The aspect of having access to governmental support, was previously mentioned as humanitarian/public compensation by Seifert et al. (2013) and Botzen and van den Bergh (2012), the risk type covered by insurance by Reynaud et al. (2018), and the perception of insurance as being suited for one's needs was also raised in similar manner as the perception of effectiveness of insurance by Abbas et al. (2015). Finally, the parameter describing the financial recovery time from commercial flood impacts broadly relates to the aspect of experienced flood impacts, which has been found to be influential by a wide range of authors (Hossain et al. 2022, Osberghaus and Reif 2021, Paopid et al. 2020, Senapati 2020a, Liu et al. 2019, Fahad and Jing 2018, Reynaud et al. 2018, Arshad et al. 2016, Oulahen 2015, Atreya et al. 2015, Turner et al. 2014, Seifert et al. 2013, Hung 2009, Browne and Hoyt 2000). While those parameters have already been pointed out previously in other research contexts, this study was able to achieve a summary of parameters that could also be tested to be influential in further contexts with low previous exposure to insurance products. Also, the results indicate that interaction-related parameters play a very important role in this context.

In the field of researching the demand for flood insurance ML/DL models have not yet been applied. Even research that addresses the demand for other types of insurance is only recently picking up the use of such models. As some of the previously published studies Wanyan et al. (2022) researched the effect of air pollution on the decision to buy health insurance coupled with a deep learning method (artificial neural networks). Also, Fuino et al. (2022) used models that combine conventional statistical modeling with machine learning approaches to assess customer profiles and highlight variables that are influential to their level of interest for long-term care insurance. Finally, Nguyen et al. (2022) compared several ML models for a case study in Vietnam and found that especially the cubist, random forest, and support vector machines models were best suited to predict the WTP for insurance for shrimp farming. Similarly, it could be of high relevance to further explore the use of ML/DL models in predicting the WTP for flood insurance addressing a regression problem to predict the monetary value of a potential product drawing upon the framework of parameters suggested by this study. Especially in a context where people have mostly not been insurance customers before, those methods enable researchers and practitioners to better pay attention to the research context without transferring a too narrow set of assumptions from other geographical research settings. In that way, the method can rather learn from the data and adjust the model to the context. Concerning Flood Risk Management in the West African context, the need for a better involvement of the targeted communities in decision-making and the design of risk-reducing measures, including insurance, has been pointed out before (Parkoo et al. 2022; Wagner et al. 2021).

Regarding the globally increasing problem of climate change, a large portion of people at risk in least-developed economies has no insurance coverage against weather-related hazardous events (InsuResilience Global Partnership 2021). In order to scale up efforts of making insurance coverage more suitable and accessible to such groups, shedding more light on their preferences and demands will help to make more meaningful progress in this area. Without such mechanisms, vulnerable communities are left too often to address the losses and damages from climate-related events, such as floods by drawing upon their own means (Amaechina et al. 2022; Wagner et al. 2022). On the one hand, it has to be borne in mind that (market-based) risk transfer instruments such as insurance are seen to be generally well-suited to address hazardous sudden-onset events, such as floods (Mechler and Deubelli 2021). On the other hand, a point of critique of insurance in the context of climate-related losses and damages is that due to the increase in severity and frequency of both slow- and sudden onset events as well as of impacts that span beyond the economic dimension the usefulness of current insurance approaches is limited (Nordlander et al. 2020). While this critique holds true it has to be borne in mind that insurance is best used in a combined and integrated manner with other risk management measures and not as a stand-alone tool (Schäfer et al. 2019). Nevertheless, it will be important to address concerns of affordability and climate justice, which could be addressed by providing subsidies to lower the premiums for an insurance product addressing flood impacts (Linnerooth-Bayer et al. 2019).

This study bears its limitations. In order to contribute even further to researching the preferences and demands of vulnerable populations with regard to insurance mechanisms, further studies could research the WTP for a potential flood insurance product in the LMRB with ML/DL models, when more concrete forms of potential flood insurance schemes have been elaborated. In that way, coverage could eventually be raised even faster and the amount of potential subsides could be determined in a better way. Moreover, future studies could better consider parameters describing potential assets to be insured, which were not extensively represented in the data set used for this study. It could also be worth conducting studies drawing upon the framework presented in this study to already guide the data collection process and ensure coverage of all dimensions potentially relevant to flood insurance demand. Finally, the authors encourage future studies to try out additional ML models that were not yet used in this study for comparison as well as to try out other DL models, e.g. functional models.

Conclusion

This study presents a novel approach to research the demand for a potential flood insurance product by applying ML/DL models to a large number of relevant parameters. This approach was found to be especially useful for research contexts, in which people have not yet been widely exposed to insurance products. In particular, the results especially highlighted the importance of the parameters of the desired risk to be covered, perception of insurance, having no access to any source, access to support from community solidarity funds, access to governmental support, or drawing upon their own resources to cope financially, the financial recovery time (commercial impacts), no previous insurance purchase due to lack of means and the prioritization of more essential needs over purchasing insurance. In addition, the framework on relevant thematic areas of parameters provided by this study can be a useful basis for follow-up studies, using similar data-driven approaches.

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Data Availability The datasets generated during and/or analysed during the current study are not publicly available due to confidentiality and shared data ownership with works in progress.

Declarations

Institutional Review Board Statement The study was conducted in accordance with the Declaration of Helsinki, and approved by the Institutional Review Board of the Center for Development Research (ZEF) (protocol code 1a_21 11/02/2021).

Informed Consent Statement Informed consent was obtained from all subjects involved in the study.

Competing Interests The authors declare no competing interests.

Conflicts of Interest The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

References

Abbas A, Amjath-Babu TS, Kächele H, Müller K (2015) Non-structural flood risk mitigation under developing country conditions: an analysis on the determinants of willingness to pay for flood insurance in rural Pakistan. Nat Hazards 75:2119–2135. https://doi.org/10.1007/s11069-014-1415-x

Addo IY, Danso SY (2017) Sociocultural factors and perceptions associated with voluntary and permanent relocation of flood victims: a case study of Sekondi-Takoradi Metropolis in Ghana. Jamba 9:303. https://doi.org/10.4102/jamba.v9i1.303

Adelekan IO, Asiyanbi AP (2016) Flood risk perception in flood-affected communities in Lagos, Nigeria. Nat Hazards 80:445–469. https://doi.org/10.1007/s11069-015-1977-2

Adelekan I, Fregene T (2015) Vulnerability of artisanal fishing communities to flood risks in coastal southwest Nigeria. Climate Dev 7:322–338. https://doi.org/10.1080/17565529.2014.951011

Adewole IF, Agbola SB, Kasim OF (2015) Building resilience to climate change impacts after the 2011 flood disaster at the University of Ibadan, Nigeria. Environ Urban 27:199–216. https://doi.org/10.1177/0956247814547679

Adzawla W, Kudadze S, Mohammed AR, Ibrahim II (2019) Climate perceptions, farmers' willingness-to-insure farms and resilience to climate change in Northern region, Ghana. Environ Dev 32:100466. https://doi.org/10.1016/j.envdev.2019.100466

African Risk Capacity (2021a) Africa Risk View Rapport de Mi-Saison Benin (2021). https://www.arc.int/sites/default/files/2021-12/BJ_RapportMiSaison_2021.pdf. Accessed 23 May 2022

African Risk Capacity (2021b) Africa RiskView Rapport de mi-saison Togo (2021). https://www.arc.int/sites/default/files/2021-12/TG_RapportMiSaison_2021_FR.pdf. Accessed 23 May 2022

Afriyie K, Ganle JK, Santos E (2018) 'The floods came and we lost everything': weather extremes and households' asset vulnerability and adaptation in rural Ghana. Climate Dev 10:259–274. https://doi.org/10.1080/17565529.2017.1291403

Ahadzie DK, Dinye I, Dinye RD, Proverbs DG (2016) Flood risk perception, coping and management in two vulnerable communities in Kumasi, Ghana. Int J SAFE 6:538–549. https://doi.org/10.2495/SAFE-V6-N3-538-549

Akoda S (2018) Le Togo, membre de l'African Risk Capacity, veut protéger ses agriculteurs des risques d'inondations. https://www.togofirst.com/fr/agro/2805-922-le-togo-membre-de-l-african-risk-capacity-veut-proteger-ses-agriculteurs-des-risques-d-inondations. Accessed 23 May 2022

Aliagha UG, Jin TE, Choong WW, Nadzri Jaafar M, Ali HM (2014) Factors affecting flood insurance purchase in residential properties in Johor, Malaysia. Nat Hazards Earth Syst Sci 14:3297–3310. https://doi.org/10.5194/nhess-14-3297-2014

Aliagha GU, Mar Iman AH, Ali HM, Kamaruddin N, Ali KN (2015) Discriminant factors of flood insurance demand for flood-hit residential properties: a case for Malaysia. J Flood Risk Manage 8:39–51. https://doi.org/10.1111/jfr3.12065

Amaechina EC, Anugwa IQ, Agwu AE, Ifelunini AI, Umeonuora TG, Okwor CA (2022) Assessing climate change-related losses and damages and adaptation constraints to address them: Evidence from flood-prone riverine communities in Southern Nigeria. Environ Dev 44:100780. https://doi.org/10.1016/j.envdev.2022.100780

Amoako C, Cobbinah PB, Mensah Darkwah R (2019) Complex twist of fate: the geopolitics of flood management regimes in Accra, Ghana. Cities 89:209–217. https://doi.org/10.1016/j.cities.2019.02.006

Arshad M, Amjath-Babu TS, Kächele H, Müller K (2016) What drives the willingness to pay for crop insurance against extreme weather events (flood and drought) in Pakistan? A hypothetical market approach. Climate Dev 8:234–244. https://doi.org/10.1080/17565529.2015.1034232

Atreya A, Ferreira S, Michel-Kerjan E (2015) What drives households to buy flood insurance? New evidence from Georgia. Ecol Econ 117:153–161. https://doi.org/10.1016/j.ecolecon.2015.06.024

Bagus U, Jurd de Girancourt F, Mahmood R, Manji Q (2020) Africa's insurance market is set for takeoff. https://www.mckinsey.com/featured-insights/middle-east-and-africa/africas-insurance-market-is-set-for-takeoff. Accessed 08 Dec 2022
Berg E, Blake M, Morsink K (2022) Risk sharing and the demand for insurance: theory and experimental evidence from Ethiopia. J Econ Behav Organ 195:236–256. https://doi.org/10.1016/j.jebo.2021.12.035
Botzen W, van den Bergh J (2012) Risk attitudes to low-probability climate change risks: WTP for flood insurance. J Econ Behav Organ 82:151–166. https://doi.org/10.1016/j.jebo.2012.01.005
Botzen WW, de Boer J, Terpstra T (2013) Framing of risk and preferences for annual and multi-year flood insurance. J Econ Psychol 39:357–375. https://doi.org/10.1016/j.joep.2013.05.007
Boubacar S, Pelling M, Barcena A, Montandon R (2017) The erosive effects of small disasters on household absorptive capacity in Niamey: a nested HEA approach. Environ Urban 29:33–50. https://doi.org/10.1177/0956247816685515
Brisibe GW, Pepple TD (2018) Lessons Learnt from the 2012 Flood Disaster: Implications for Post-flood Building Design and Construction in Yenagoa, Nigeria. cea 6:171–180. https://doi.org/10.13189/cea.2018.060307
Browne MJ, Hoyt RE (2000) The demand for flood insurance: empirical evidence. J Risk Uncertain 20:291–306. https://doi.org/10.1023/A:1007823631497
Chollet F (2021) Deep learning with python, Second Edition, 2nd edn. Manning Publications, Greenwich
Codjoe SNA, Issah AD (2016) Cultural dimension and adaptation to floods in a coastal settlement and a savannah community in Ghana. GeoJournal 81:615–624. https://doi.org/10.1007/s10708-015-9641-7
Codjoe SNA, Owusu G, Burkett V (2014) Perception, experience, and indigenous knowledge of climate change and variability: the case of Accra, a sub-Saharan African city. Reg Environ Change 14:369–383. https://doi.org/10.1007/s10113-013-0500-0
Darlington JC, Yiannakoulias N (2022) Experimental evidence for coverage preferences in flood insurance. Int J Disaster Risk Sci 13:178–189. https://doi.org/10.1007/s13753-022-00397-3
Dehm J (2020) Climate change, 'slow violence' and the indefinite deferral of responsibility for 'loss and damage.' Griffith Law Review 29:220–252. https://doi.org/10.1080/10383441.2020.1790101
Dewi N, Kusnandar, Rahayu ES (2018) Risk mitigation of climate change impacts on rice farming through crop insurance: an analysis of farmer's willingness to participate (a case study in Karawang Regency, Indonesia). IOP Conf Ser Earth Environ Sci 200:12059. https://doi.org/10.1088/1755-1315/200/1/012059
Enete AA, Obi JN, Ozor N, Mba CL (2016) Socioeconomic assessment of flooding among farm households in Anambra state, Nigeria. Int J Climate Change Strateg Manag 8:96–111. https://doi.org/10.1108/IJCCSM-07-2014-0084
Fahad S, Jing W (2018) Evaluation of Pakistani farmers' willingness to pay for crop insurance using contingent valuation method: The case of Khyber Pakhtunkhwa province. Land Use Policy 72:570–577. https://doi.org/10.1016/j.landusepol.2017.12.024
Feng Z, Xu C, Tao D (2018) Historical Gradient Boosting Machine. In: GCAI-2018. 4th Global Conference on Artificial Intelligence, 68–54
Flood Resilience Initiative (2020) Zurich Flood Resilience Alliance commitments and recommendations. https://www.mercycorps.org/sites/default/files/2020-02/979-PA-ZFRP-FS-UN-EVENT-V3a.pdf. Accessed 08 Dec 2022
Fuino M, Ugarte Montero A, Wagner J (2022) On the drivers of potential customers' interest in long-term care insurance: evidence from Switzerland. Risk Manage Insur Rev 25:271–302. https://doi.org/10.1111/rmir.12218
Gewirtzman J, Natson S, Richards J-A, Hoffmeister V, Durand A, Weikmans R, Huq S, Roberts JT (2018) Financing loss and damage: reviewing options under the Warsaw International mechanism. Climate Policy 18:1076–1086. https://doi.org/10.1080/14693062.2018.1450724
Giorgi F, Raffaele F, Coppola E (2019) The response of precipitation characteristics to global warming from climate projections. Earth Syst Dynam 10:73–89. https://doi.org/10.5194/esd-10-73-2019
Government of the Republic of Benin (2011) Inondations au Bénin: Rapport d'evaluation des besoins post catastrophe. http://documents1.worldbank.org/curated/en/750141468208769683/pdf/694130ESW0P1240lood0Recovery0Report.pdf. Accessed 22 July 2023
Government of the Republic of Benin (2020) Plan d'actions du Bénin 2020–2024 pour la mise en place du cadre national pour les services climatologiques (CNSC) du Bénin, Cotonou, Benin. https://gfcs.wmo.int/sites/default/files/Benin%20Final%20Report%202020-2024%20NFCS.pdf. Accessed 23 May 2022
Government of the Republic of Benin (2021) Projet ARCH : Le Gouvernement généralise le volet Assurance-maladie dans les communes du Bénin. https://www.gouv.bj/actualite/1145/projet-arch-gouvernement-generalise-volet-assurance-maladie-dans-communes-benin/. Accessed 26 Dec 2022

Government of the Republic of Togo (2017) Plan National d'Adaption aux Changements Climatiques du Togo (PNACC). https://www4.unfccc.int/sites/NAPC/Documents%20NAP/Togo%20NAP.pdf. Accessed 23 May 2022

Hastie T, Tibshirani R, Friedman J (eds) (2009) The Elements of Statistical Learning. Springer Series in Statistics. Springer New York, New York

Hossain MS, Alam GM, Fahad S, Sarker T, Moniruzzaman M, Rabbany MG (2022) Smallholder farmers' willingness to pay for flood insurance as climate change adaptation strategy in northern Bangladesh. J Clean Prod 338:130584. https://doi.org/10.1016/j.jclepro.2022.130584

Huang C, Lubell M (2022) Household flood risk response in San Francisco Bay: linking risk information, perception, and behavior. Reg Environ Change 22. https://doi.org/10.1007/s10113-022-01875-6

Hung H-C (2009) The attitude towards flood insurance purchase when respondents' preferences are uncertain: a fuzzy approach. J Risk Res 12:239–258. https://doi.org/10.1080/13669870802497702

InsuResilience Global Partnership (2021) Annual Report 2021. Milestones, Achievements and Progress Towards Vision 2025

James G, Witten D, Hastie T, Tibshirani R (2021) An introduction to statistical learning. Springer US, New York

Janiesch C, Zschech P, Heinrich K (2021) Machine learning and deep learning. Electron Markets 31:685–695. https://doi.org/10.1007/s12525-021-00475-2

Jung A (2022) Machine learning. Springer Nature Singapore, Singapore

Klimo M, Lukáč P, Tarábek P (2021) Deep neural networks classification via binary error-detecting output codes. Appl Sci 11:3563. https://doi.org/10.3390/app11083563

Kousky C (2011) Understanding the demand for flood insurance. Nat Hazards Rev 12:96–110. https://doi.org/10.1061/(ASCE)NH.1527-6996.0000025

Lamond J, Adekola O, Adelekan I, Eze B, Ujoh F (2019) Information for adaptation and response to flooding, multi-stakeholder perspectives in Nigeria. Climate 7:46. https://doi.org/10.3390/cli7040046

Léger T (2022) Insurers need to step up to close the flood protection gap. https://www.swissre.com/risk-knowledge/risk-perspectives-blog/insurers-step-up-to-close-flood-protection-gap.html. Accessed 08 Dec 2022

Levy PS, Lemeshow S (2008) Sampling of populations: methods and applications, 4th edn. Wiley, Hoboken

Linnerooth-Bayer J, Surminski S, Bouwer LM, Noy I, Mechler R (2019) Insurance as a response to loss and damage? In: Mechler R, Bouwer LM, Schinko T, Surminski S, Linnerooth-Bayer J (eds) Loss and damage from climate change. Springer International Publishing, Cham, pp 483–512

Liu X, Tang Y, Ge J, Miranda MJ (2019) Does experience with natural disasters affect willingness-to-pay for weather index insurance? Evidence from China. Int J Disaster Risk Reduct 33:33–43. https://doi.org/10.1016/j.ijdrr.2018.09.006

Lloyd's (2018) A world at risk. Closing the insurance gap. https://assets.lloyds.com/assets/pdf-lloyds-underinsurance-report-final/1/pdf-lloyds-underinsurance-report-final.pdf. Accessed 08 Dec 2022

Lo AY (2013) Household preference and financial commitment to flood insurance in South-East Queensland. Aust Econ Rev 46:160–175. https://doi.org/10.1111/j.1467-8462.2013.12009.x

Mechler R, Deubelli TM (2021) Finance for loss and damage: a comprehensive risk analytical approach. Curr Opin Environ Sustain 50:185–196. https://doi.org/10.1016/j.cosust.2021.03.012

Meton A (2019) Gestion des risques et catastrophes: L'assurance comme une priorité, selon le professeur Théodore Adjakpa. https://lanation.bj/gestion-des-risques-et-catastrophes-lassurance-comme-une-priorite-selon-le-professeur-theodore-adjakpa/. Accessed 26 Dec 2022

Navrud S, Vondolia GK (2020) Farmers′ preferences for reductions in flood risk under monetary and non-monetary payment modes. Water Resour Econ 30:100151. https://doi.org/10.1016/j.wre.2019.100151

Netusil NR, Kousky C, Neupane S, Daniel W, Kunreuther H (2021) The willingness to pay for flood insurance. Land Econ 97:17–38. https://doi.org/10.3368/wple.97.1.110819-0160R1

Nguyen KAT, Nguyen TAT, Nguelifack BM, Jolly CM (2022) Machine learning approaches for predicting willingness to pay for shrimp insurance in Vietnam. Mar Resour Econ 37:155–182. https://doi.org/10.1086/718835

Nordlander L, Pill M, Romera BM (2020) Insurance schemes for loss and damage: fools' gold? Climate Policy 20:704–714. https://doi.org/10.1080/14693062.2019.1671163

Oduniyi OS, Antwi MA, Tekana SS (2020) Farmers' willingness to pay for index-based livestock insurance in the North West of South Africa. Climate 8:47. https://doi.org/10.3390/cli8030047

Osberghaus D, Reif C (2021) How do different compensation schemes and loss experience affect insurance decisions? Experimental evidence from two independent and heterogeneous samples. Ecol Econ 187:107087. https://doi.org/10.1016/j.ecolecon.2021.107087

Oulahen G (2015) Flood insurance in Canada: implications for flood management and residential vulnerability to flood hazards. Environ Manage 55:603–615. https://doi.org/10.1007/s00267-014-0416-6
Paopid S, Tang J, Leelawat N (eds) (2020) Willingness to pay for flood insurance: a case study in Phang Khon, Sakon Nakhon Province, Thailand. IOP Conference Series: Earth and Environmental Science
Parkoo EN, Thiam S, Adjonou K, Kokou K, Verleysdonk S, Adounkpe JG, Villamor GB (2022) Comparing expert and local community perspectives on flood management in the lower Mono River Catchment, Togo and Benin. Water 14:1536. https://doi.org/10.3390/w14101536
Pill M (2022) Towards a funding mechanism for loss and damage from climate change impacts. Clim Risk Manag 35:100391. https://doi.org/10.1016/j.crm.2021.100391
Ranasinghe R, Ruane AC, Vautard R, Arnell N, Coppola E, Cruz FA, Dessai S, Islam AS, Rahimi M, Ruiz D (2021) Climate Change Information for Regional Impact and for Risk Assessment. In: Masson-Delmotte V, Zhai P, Pirani A, Connors SL, Péan C, Berger S, Caud N, Chen Y, Goldfarb L, Gomis MI, Huang M, Leitzell K, Lonnoy E, Matthews J, Maycock TK, Waterfield T, Yelekçi O, Yu R, Zhou B (eds) Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge
Ren J, Wang HH (2016) Rural homeowners' willingness to buy flood insurance. Emerg Mark Financ Trade 52:1156–1166. https://doi.org/10.1080/1540496X.2015.1134867
Reynaud A, Nguyen M-H, Aubert C (2018) Is there a demand for flood insurance in Vietnam? Results from a choice experiment. Environ Econ Policy Stud 20:593–617. https://doi.org/10.1007/s10018-017-0207-4
Robinson PJ, Botzen WJW (2019) Determinants of probability neglect and risk attitudes for disaster risk: an online experimental study of flood insurance demand among homeowners. Risk Anal 39:2514–2527. https://doi.org/10.1111/risa.13361
Robinson PJ, Botzen W (2020) Flood insurance demand and probability weighting: the influences of regret, worry, locus of control and the threshold of concern heuristic. Water Resour Econ 30:100144. https://doi.org/10.1016/j.wre.2019.100144
Schäfer L, Warner K, Kreft S (2019) Exploring and managing adaptation frontiers with climate risk insurance. In: Mechler R, Bouwer LM, Schinko T, Surminski S, Linnerooth-Bayer J (eds) Loss and damage from climate change. Springer International Publishing, Cham, pp 317–341
Seifert I, Botzen WJW, Kreibich H, Aerts JCJH (2013) Influence of flood risk characteristics on flood insurance demand: a comparison between Germany and the Netherlands. Nat Hazards Earth Syst Sci 13:1691–1705. https://doi.org/10.5194/nhess-13-1691-2013
Senapati AK (2020b) Insuring against climatic shocks: Evidence on farm households' willingness to pay for rainfall insurance product in rural India. Int J Disaster Risk Reduct 42:101351. https://doi.org/10.1016/j.ijdrr.2019.101351
Senapati AK (2020a) Do farmers value insurance against extreme droughts and floods? Evidence from Odisha, India. Glob Bus Rev: 097215092095761. https://doi.org/10.1177/0972150920957616
Sidi P, Mamat MB, Sukono, Supian S, Putra AS (2018) Demand analysis of flood insurance by using logistic regression model and genetic algorithm. IOP Conf Ser Mater Sci Eng 332:12053. https://doi.org/10.1088/1757-899X/332/1/012053
Thistlethwaite J, Henstra D, Brown C, Scott D (2020) Barriers to insurance as a flood risk management tool: evidence from a survey of property owners. Int J Disaster Risk Sci 11:263–273. https://doi.org/10.1007/s13753-020-00272-z
Trisos CH, Adelekan IO, Totin E, Ayanlade A, Efitre J, Gemeda A, Kalaba K, Lennard C, Masao C, Mgaya Y (2022) Africa. In: Pörtner H-O, Roberts DC, Tignor M, Poloczanska ES, Mintenbeck K, Alegría A, Craig M, Langsdorf S, Löschke S, Möller V, Okem A, Rama B (eds) Climate Change 2022: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, pp 1285–1455
Turner G, Said F, Afzal U (2014) Microinsurance demand after a rare flood event: evidence from a field experiment in Pakistan. Geneva Pap Risk Insur Issues Pract 39:201–223. https://doi.org/10.1057/gpp.2014.8
Wagner S, Souvignet M, Walz Y, Balogun K, Komi K, Kreft S, Rhyner J (2021) When does risk become residual? A systematic review of research on flood risk management in West Africa. Reg Environ Change 21:84. https://doi.org/10.1007/s10113-021-01826-7
Wagner S, Thiam S, Dossoumou NIP, Hagenlocher M, Souvignet M, Rhyner J (2022) Recovering from financial implications of flood impacts—the role of risk transfer in the West African context. Sustainability 14:8433. https://doi.org/10.3390/su14148433
Wanyan R, Yang L, Pu M, Zhao T, Zeng L (2022) The nexus between air pollution and life insurance demand in china: evidence from deep machine learning. In: Sun X, Zhang X, Xia Z, Bertino E (eds)

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