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Promoting Safety Societies with a Non-Stationary Multidimensional Model that Prioritizes Flood Risks under Climate Change Effects

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Managing floods is already a challenging task, but climate change combined with the unprecedented growth of cities aggravates their multiple adverse consequences. Current papers outlined trends in the intensity and frequency of some climate and weather extremes over periods, including rainfall patterns. Thus, interrelations among the society, economic sector, critical infrastructure, and sustainability lead policymakers, public managers, and professionals of different fields to tackle a variety of aspects in order to adopt strategic policies for enhancing life quality in urban societies and then preventing future losses. In this field, Multi-Criteria Decision Making-Aiding is suitable because it takes into account the DM's preference structure to assess future risks. Given this backdrop, this work introduces a novel multicriteria decision model for enhancing future risks under climate change and socioeconomic forecasting. Our model differs from the current approaches in the literature because it deals with non-stationary probabilities to model the hazard scenarios and their implications to estimate flood damages and prevent its losses. An in-depth discussion regarding the state-of-the-art in climate and urban modeling, this work provides a step-by-step procedure that assesses social, human, sanitary, and economic risks with the Multi-Attribute Utility Theory and Decision Analysis. A numerical application in an urban area in the Northeast of Brazil is conducted with views to accredit the novel approach in which the time dependency is highlighted. Our results map and evaluate flood risks for 2021 – 2060, exploring then insights for designing long-term adaptation policies that confront the damaging effects of this natural hazard.
Keywords: urban flood risk, multicriteria decision-making, climate change, emerging risks.

1. Introduction

The complex interaction between the atmosphere, hydrosphere, and biosphere has shown that climate issues, whether caused by humans or Nature, certainly impact the way natural hazards, especially floods, affect urban functioning, specifically on human infectious diseases, social vulnerability, and water supply, and financial issues. That is why some researchers, on seeking approaches that aid risk-based problems, have applied Multi-Criteria Decision Making-Aiding (MCDM/A) which takes a DM's preference structures into account in many contexts (de Almeida et al., 2015). The benefit of applying this methodology for assessing future flood risks is that multicriteria metrics have the potential to gather multiple risk information of different criteria, as a starting point for basing climate adaptation measures against this disaster.

Given this context, from a critical analysis of the main benefits and limitations of forecasting methods that usually estimates the climate impacts, it should be highlighted that managers usually face a hard task when dealing with time-dependency when assessing future risks. Particularly in our context, most of the FRM-related papers assumed the decision-making process to be stationary, simplifying the risk analysis. For instance, the non-stationary analysis of flooding was deeply discussed by (Khaliq et al., 2006). From a statistical analysis of hydrological observations, in terms of flood frequency or likelihood estimation of this

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event, they recommend non-stationarity to be incorporated into new risk assessment frameworks. In fact, (Hesarkazzazi et al., 2021) affirmed from their findings that the use of non-stationary modeling of flood dynamics serves as an informative climate indicator for decision-making.

Specifically, in the context of MCDM/A, a systematic literature review by (da Silva, Alencar, et al., 2020) evidenced a lack of temporal-based models in the literature. They found that few papers use forecasting techniques to predict the future CC impacts on flooding. Additionally, non-stationary modeling of flooding and its potential consequences is still scarce. The modeling proposal to be presented next covers this gap.

Based on this backdrop, this paper puts forward a new spatiotemporal multidimensional model for ranking urban flood risks under urbanization and CC effects. This methodology is based on the Multi-Attribute Utility Theory (MAUT) and Decision Analysis, in which axiomatic structure analyzes the flood impacts in a probabilistic manner (da Silva et al., 2022). Thus, the model estimates risk measures for a set of urban zones considering four criteria: social, human, economic, and health & sanitation. The temporal analysis is integrated by using forecasting techniques of CC and urbanization.

2. The modeling proposal for prioritizing urban flood risks with non-stationary probabilities

This section presents the spatiotemporal decision model for ranking multidimensional flood risks in urban areas, according to (da Silva et al., 2022).

2.1 Predicting the sources of hazard with General Circulation Models

It is worth knowing that the modelling proposal can be applied in any urban space in the world, considering its particular characteristics and obeying the underlying assumptions adopted by the model.

At first, it must be clearly established the role of each actor in the decision-making process (de Almeida et al., 2015); this is essential to guarantee a trustworthy recommendation, what is, the risk ranking of floods. Here, the DM is responsible to state his/her preferences regarding the risk behavior and relative preferences among criteria.

The urban delimitation should be addressed carefully by the DM. Then, contour conditions of local flood dynamics are settled by using historical rainfall records and data from climate stations on its surrounding. Rainfall is the trigger event that is converted into the water flow, and its interaction with the urban system results in floods. Here, the rainfall works as the uncontrolled event, θ, that drives the flood disaster. The relation between rainfall and water depths characterizes, then, the sources of hazard.

The model aims to assess future floods, so that must be specified the time window (T) of the risk analysis, from t_0 to $t_0 + T$. This is crucial to understand that the risk measures are subject to uncertainty during this period, and it should be treated adequately (Aven, 2019).

Given this context, the model quantifies in terms of probability density functions (PDFs) the future likelihood of the rainfall records. To do so, GCMs are useful to forecast the precipitation patterns in T. Local conditions allow experts to simulate, under downscaling methods and RCP scenarios, future rainfall indexes.

Then, a performance analysis of the climate simulations can be done by comparing their predictions to historical data. Broadly speaking, we run GCM in a period in which past events (historical data) are compared to their simulations. Index measures used by (da Silva et al., 2022) , such as the Mean Absolute Error (MAE) and the Root-Mean-Square Error (RMSE) can support this selection. Apart from this, the Mann-Kendall trend test can evidence statistically if the rainfall behavior follows a monotonic trend, which means a correlation with the CC effects. Then, the selected GCM model will simulate in T the flood frequency curve, denoted as the a-priori probability function $\Pi(\theta, t)$ under a non-stationary perspective.

As mentioned in (da Silva et al., 2020), the Generalized Extreme Value (GEV) distribution is suitable to model hydrological events, so that the model proposes different GEV equations according to the time-dependency of its required parameters. The GEV PDF uses three parameters, namely (ξ, σ, μ) the shape, scale, and location. For didactic purposes, the notation $GEV(\xi, \sigma, \mu)$ indicates here the order of the polynomial function over time of each parameter. Thus, from the maximum likelihood estimation, it can be useful to check if non-stationarity improves flood modeling.

2.2 Estimating flood consequences & stating preferences

In this phase, the urban space must be divided into urban zones ($z_i, i \epsilon [1, N]$), strategically delimited according to geopolitical division, homogenous characteristics, or other factors. After modeling the state of Nature θ over time, the model analyzes the impact (c) of a given flood severity level in four criteria ($crit$):

- Human – fatalities occurred directly from the natural disaster, measured in number of individuals;

- Social – people homeless or displaced after being affected by inundations, estimated in number of individuals;
- Economic – financial damages to public and private properties, and urban infrastructures, in terms of monetary losses;
- Health & Sanitation – environmental impact in water bodies and urban drainage system, in terms of contamination by enteric pathogens such as leptospirosis, rotavirus, E. Coli, etc.

Flood impacts were estimated for each criterion in terms of probabilities. An underlying assumption adopted by the model is that the consequence behavior follows proportionally the population growth projections. Then, urban computational simulations and global or local reports can introduce the time-dependency in this estimation. Hence, the consequence functions $p_{crit}(c|\theta, t, z_i)$ are estimated, assuming that probabilities are independent between criteria and urban zones.

In terms of utilities, the model elicits utility functions for each criterion $u_{crit}(c|\theta)$ by using the Utility Theory. Here, risk behavior when facing flood losses is measured to insert preferential information in risk calculation. From experimental studies, (da Silva et al., 2020) suggested some utility functions according to the DM's risk behavior in FRM studies.

2.3 Calculating the multidimensional risk with MAUT and Decision Analysis

Altogether, the risk indexes for each criterion represent the combined effect of hazard scenarios, consequence functions, and utilities. Then, the main task is to gather these information into a multidimensional and valued risk metric. To do so, the model uses the MAUT approach to quantify the compensatory relationship among the criteria. The relative importance is taken into account in this modeling. As a result, scaling constants, k_{crit} are used to calculate the average global risk index, in terms of expected utilities, for each urban zone in the time window T, as schemed in Equation 1.

$$r_{global}(z_i) = -\frac{1}{T}\sum_{crit} k_{crit} \left\{ \int_{t_0}^{t_0+T} \int_{\theta} \Pi(\theta, t) p_{crit}(c|\theta, t, z_i) u_{crit}(c|\theta)\, d\theta\, dt \right\} \tag{1}$$

Da Silva et al., 2022) justified in Equation 1 the negative signal in order to rank the urban zones according to their risk priorities, i.e., the most critical to the lowest ones. It must be clarified the assumptions of additive and utility independence lead the linear and additive form in Equation 1 to calculate $r_{global}(z_i)$.

As a result, the flood risk ranking, and mapping of urban zones drive policymakers to implement strategic adaptation measures according to the future effects. Even though (Aven, 2019) states that climate risks lose information when adopting expected values, the modeling proposal tries to overcome this issue by inserting not only preferential information with utilities but also the temporal analysis of the climate and urban effects on flood impacts. Then, the non-stationary perspective has the potential to detect in risk evaluation "surprising events" that could not be assessed in current models.

Output reports can also include the use of statistical and sensitivity analysis for treating the uncertainty of climate variability, urban growth, and DM's preference statements. Next, a numerical application in a Brazilian town validates our proposal, sharing new insights for planning urban adaptation against floods.

3. Numerical application on Barreiros, Pernambuco: results and discussion

The site study encompasses the urban district of Barreiros, Pernambuco. This urban area faced torrents of floodwater in 2010. There, the hydrological disaster devastated the town located in north-eastern Brazil. From local reports, the 2010's floods killed in the Barreiros and its surroundings at least 38 people and leaving more than 600 missing (The World Bank, 2012).

This numerical application used public and open-access data from institutional organizations to simulate the impact of flooding, in terms of risk, for the next 40 years (2021 – 2060). This way, the first phase of the model comprises the flood frequency analysis. From simulation data of maximum daily rainfall in a month (mm), the model analyzes the performance of four GCMs by using the PROJETA platform available by the National Institute for Space Research (CPTEC/INPE, 2021). To do so, simulated data from 1963 to 2005 were compared to historical rainfall records measured by pluviometric stations in Barreiros. With the aid of analysts, the GCMs' performance over time was measured with both MAE and RMSE indexes, as shown in Figure 1.

The boxplot chart schemed below evidenced that the lower median of error indexes and its interquartile interval indicates the BESM climate model as the more adequate to simulate the future rainfall patterns of Barreiros. It should be noted that the Mann-Kendall trend test was applied in all GCM, thereby showing under

95% of confidence level a clear monotonic trend of the rainfall records, which indicates a correlation between the flood frequency and CC effects.

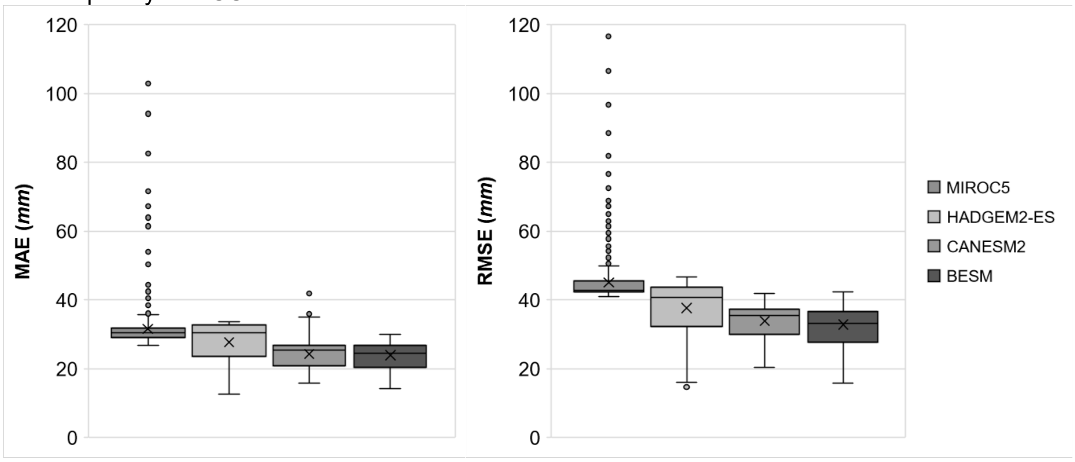

Figure 1. Boxplot chart of the performance indexes of GCMs

On considering the GCM chosen to simulate the future sources of hazard, the BESM climate model uses a downscaling method to regionalize the simulation under local characteristics. As a result, monthly records of maximum precipitation from 2021 to 2060 were obtained. Next, our model uses the Maximum Likelihood Estimation (MLE) procedure to estimate stationary and non-stationary floods, assuming that the GEV function characterizes well the flood behavior.

Table 1 summarizes three GEV functions, differing from each other according to the degree of time dependency. As observed there, the a-priori functions $GEV(0,1,0)$ and $GEV(0,1,1)$ provide an improvement in fit over $GEV(0,0,0)$. Under a 99% confidence level, the non-stationary function $GEV(0,1,1)$ is worthwhile, evidencing that this function explains substantially more the rainfall data variation than the stationary function.

Table 1. Summary of the GEV functions with MLE

$GEV(\xi,\sigma,\mu)$	ξ	$\mu(t)=a+bt$		$\sigma(t)=a+bt$		Likelihood-ratio test (p-value)
		a	b	a	b	
$GEV(0,0,0)$	0.277	19.382	-	18.090	-	-
$GEV(0,1,0)$	0.292	17.640	3.147E-3	17.915	-	0.065
$GEV(0,1,1)$	0.245	21.823	-3.998E-3	23.412	-0.010	< 1.0E-5

After characterizing the flood frequency curve in terms of future rainfall patterns, the DM needs to gather the efforts of analysts and experts to estimate, in terms of consequence functions, the flood damages for all criteria: human, social, economic, and health & sanitation.

Public reports by the World Bank (The World Bank, 2012) supported by estimations of flood depth-damage functions were essential to guide the model in modeling PDFs for each $p_{crit}(c|\theta,t,z_i)$. In this application, the consequence function of human, social, economic and health & sanitation criteria were assigned by Poisson, Lognormal and Beta-Poisson distributions. It must be clarified that the health & sanitation criterion estimate the potential contamination of water bodies from rotavirus (Vieira et al., 2016).

Under data scarcity of the local population projections of Barreiros, the model introduces the non-stationary perspective by adjusting the key parameters adopted by the consequence functions proportionally with the average rate of population change in Brazil, reported by the United Nations (Gragnolati et al., 2011).

Finally, the DM's preferences statement should assign utilities to the set of consequences of all criteria. This application elicits $u_{crit}(c|\theta)$ assuming that the DM is risk-averse in the human and health & sanitation criteria, while he/she is prone to risk in the other ones. It uses the functions proposed by (da Silva et al., 2020).

The structured protocol by (Keeney & Raiffa, 1976), i.e., the MAUT elicitation, leads the DM to establish preferences among criteria. This is crucial to gather the risk information and provide the results in the next section. The multidimensional risk is obtained after calculating, under DM's preferences, the interaction between the hazard scenarios and their potential damages over time. Then, for each urban zone, a global risk index represents the average magnitude of flood risks for the next 40 years. Table 2 summarizes the urban flood risk ranking for this time window.

Table 2. Urban Flood Risk Ranking, their incremental risks, and ratios for 2012 – 2060

Urban zone	Incremental risk	Risk ratio
z_6	2.954E-03	2.25
z_7	1.315E-03	0.47
z_5	2.826E-03	101.93
z_{10}	2.773E-05	0.21
z_2	1.322E-04	0.16
z_9	8.207E-04	1.41
z_3	5.821E-04	0.05
z_1	1.089E-02	2.30
z_4	4.730E-03	-
z_8	-	-

This tabular information focuses on risk prioritization, being the most critical zones allocated to the first positions; the incremental and ratio of risk increase. The last data is useful to open the DM's mind to understand the relation regarding the magnitude of adjacent zones in the ranking, while it is hard for him/her to comprehend the scale of the global risk values. These metrics were used properly in (da Silva et al., 2020).

Additionally, the risk mapping in Figure 2 permits the DM to evaluate how the risk prioritization is spatially distributed. The results point out that the most critical zone is z_6, while z_8 has the fewest priority when planning strategic adaptation measures.

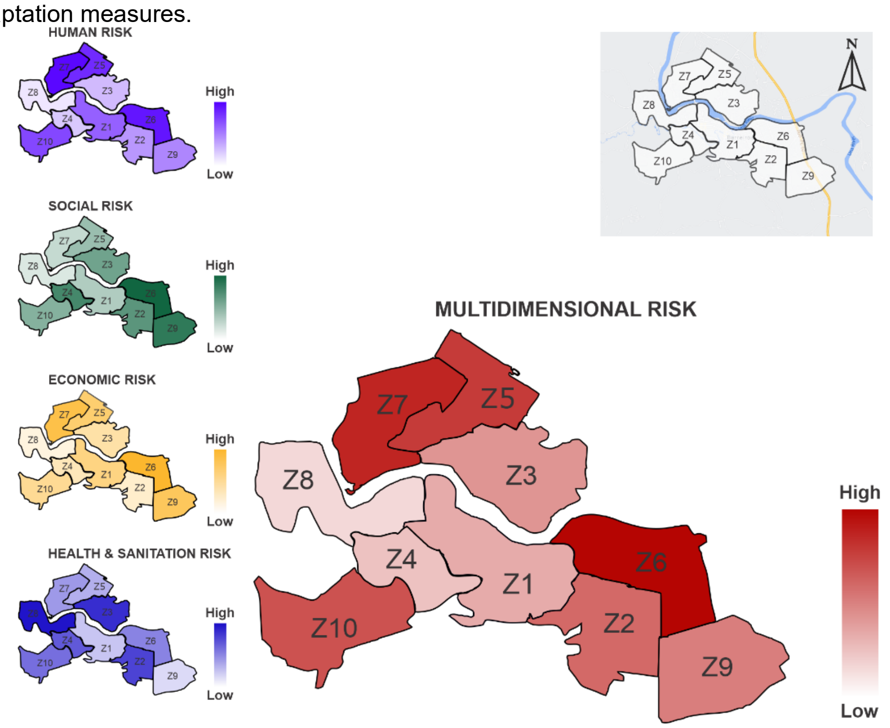

Figure 2. Urban Flood Risk Mapping of Barreiros for 2021 – 2060

The results provided by the model can aid the DM to base his/her future decisions for flood prevention and mitigation. At first, incremental risks and their ratios mean valuable information regarding the future risk magnitudes. For example, the increase in magnitude for z_{10} to z_5 grows, approximately, 101 times. In real practice, the DM can use these data as a guideline to define a better resource allocation. Here, the non-stationary analysis allows the DM to predict, what are the most critical zones in the future if no preventive actions would be implemented for climate adaptation.

Forecasting techniques of CC and urbanization effects contributed to taking into account the time-dependency in the risk modeling. Even though the final results are shown on average, the DM can disaggregate the risk analysis over time, which generates complementary information to him/her. Indeed, future researches can assess statistically the time influence on flood prioritization and their magnitudes.

4. Conclusions

This paper presented, in the light of the MCDM/A approach, a new spatiotemporal decision model for assessing and ranking flood risks in urban areas due to climate changes and urbanization effects. A critical analysis of recent papers in the literature regarding the main challenges of FRM practices has shown how the combined effect of CC and population growth can alter patterns of temperature, rainfall, sea-level rise, and other climate indexes.

The new model cover the main gaps pointed out by (da Silva et al., 2020): it takes into account a probabilistic approach to models the flood frequency, impacts, and DM's preferences; it encompasses forecasting models of the urban growth and climate variability, in order to quantify the time influence in risk modeling; and it uses a non-stationary perspective to calculate the future flood risks, being capable to detect "potential surprises", even if it based on expected utilities.The risk mapping schemed in Figure 2 can be also disaggregate the analysis into the risks for human, social, economic, and health & sanitation perspectives. The DM can evaluate the risk ranking for a particular criterion. Thus, the multiple risk mapping has the potential to add spatial evidence concerning the prominence of a particular risk in certain urban zones. This information can aid DMs, policymakers, to design innovative structural and non-structural measures that engage many stakeholders for strengthing the urban resilience against floods.

After applying the new model for assessing flood risks, this cross-analysis of the results contributes to base the DM's risk perception, turning the decision recommendation accreditable. Consequently, the benefits of mitigation actions to be implemented by the policymakers work in such a way that could prevent future flood damages aggravated by CC and urbanization.

Hence, DMs can improve their local resource allocations, humanitarian logistics, healthcare system planning, shelter location, and other important measures with the potential to reduce flood. Altogether, these perspectives focus to avoid and/ or mitigate fatalities and injuries to people and economic losses of urban spaces in a changing climate and complex urbanization.

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