International Journal for Novel Research in Economics , Finance and Management
www.ijnrefm.com
ISSN:3048-7722
Volume 4, Issue 4, July-Aug-2026, PP: 01-7

Mathematical Modeling for Climate Change Risk Assessment

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Abstract – **Climate change increases the physical threat posed to natural and socioeconomic systems in an ever-increasing manner and requires robust frameworks of risk assessment based on quantitative tools. In this paper, a comprehensive approach for the quantification of climate change risk is presented in terms of mathematical modeling of hazards, exposures and vulnerability functions. In order to do this, an approach considering several hazards including extreme precipitation, hydrological drought, sea-level rise, and compound event risk has been adopted with the use of ensemble climate projections from CMIP6 under several scenarios according to the Shared Socioeconomic Pathways (SSPs). The fundamental parts of the approach consist of statistical downscaling of the projections, copula modeling of multivariate dependence between different hazards, and uncertainty propagation through the use of Monte Carlo simulation. The implementation of the approach through a case study area illustrates its capacity in providing explicit information about risk metrics, critical infrastructure vulnerability, and adaptation under deep uncertainty. Comparisons with alternative risk assessment methodologies have highlighted the strength of the proposed approach in handling the dynamics of compound events and their tail dependencies.**

Keywords - **Climate Change Risk Assessment, Mathematical Modeling, Probabilistic Risk Analysis, Multivariate Copulas, Uncertainty Quantification, Climate Resilience**

I. INTRODUCTION

One of the greatest problems of the twenty-first century is climate change that presents itself in increased warming of the earth, altered rainfall, rising seas, and increased intensity and frequency of extreme weather [1][5][9]. The IPCC's Sixth Assessment Report reveals an increased possibility for global average surface temperatures to breach 1.5°C and 2°C levels in this century [1][5][9]. These climatic changes affect the risk environment in several industries such as water resources management, agriculture, energy production, and coastal areas [1][5][9]. In terms of costs associated with climate change, there have been 27 weather and climate events in 2024 that costed the US economy more than USD 1 billion, three times more compared to the annual average during the period from 1980 to 2024 [3][7]. Thus, the growing problem has prompted regulators and financial institutions to take climate risk into account [3][7][8].

Risk assessment for climate change entails several methodological challenges that set it apart from typical risk assessments [1][5][9]. First, non-stationarity is an inherent feature of climate change risk assessment [1][5][9]. This is because the basic features of the distribution of hazards are changing with time such that the historical stationarity assumption used in typical risk models no longer applies [1][5][9]. Second, the uncertainties in projections of future climate because of inherent variability and different emission scenarios call for the use of probability models that can characterize uncertainty [1][5][9]. Third, climate effects typically occur in the form of compound and cascading effects where several hazards interact in synergies, and hence multivariate models are needed [1][5][9]. Fourth, there is need to integrate across spatial scales in climate risk assessments, which ranges from projections using global climate models to impacts at local scales [1][5][9]. Finally, climate risk assessments must take into account not only physical impacts but also systemic impacts that include effects on supply chains and economics [3][7][8].

Mathematical sciences can provide effective solutions for these problems [1][5][8][9]. Extreme value theory and multivariate statistics can serve as a basis for building probabilistic modeling that allows us to evaluate hazard probabilities amid changes in the climate system [1][5][8]. Copulas allow the description of dependency structures between several hazard variables necessary for evaluating the risks of compound events [1][5][8]. Machine learning algorithms and explainable AI techniques like SHAP make it possible to increase the predictive power of models without loss of their interpretability [2][4][9]. The Monte Carlo simulation helps to propagate uncertainties from climate projections through impact models to the risks [9]. The intersection of mathematical sciences and AI gives unique opportunities to build scenarios of climate risks, vulnerabilities, and greenhouse gas emissions [8].

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In spite of the progress achieved from the methodology side, there are still many research gaps [3][5][7]. First, multivariate dependence modeling, uncertainty quantification, and vulnerability analysis have not been incorporated into risk assessment in a systematic way yet [3][5][7]. Second, comparisons between different models have not been conducted enough to choose the best methodology [3][7]. Third, the task of translating physical risk measures into decision-relevant indicators is still difficult [3][7]. Fourth, assessments often simplify the issue of compound and cascading risks when several risks occur at the same time or after each other [1][5]. Fifth, the lack of uncertainty-aware frameworks for probabilistic risk assessment should be mentioned [5][9].

The above-discussed research gap will be filled in the current paper, which presents a new mathematical modeling approach to assessing the risks associated with climate change [1][5][8][9]. The following key elements will be used in the developed methodology: probabilistic hazard modeling, hazard exposure assessment, vulnerability functions, and uncertainty quantification within a single modeling framework [1][5][9]. Moreover, the presented methodology can be easily applied for different types of hazards and various geographic regions [1][5][9]. Four key novelties of the developed approach include:

- Multivariate copula models for the modeling of compound hazard events that take into account tail dependence between hazard variables [1][5]
- The use of ensembles of climate projections and their statistical downscaling to model hazard distribution that changes over time (non-stationary distribution) [1][5][6]
- A modular approach to uncertainty propagation using Monte Carlo simulation [5][9]
- Translating physical risk metrics to decision-making indicators [3][7][8]

II. LITERATURE SURVEY

The literature on climate change risk assessment is replete with different methodological approaches due to the interdisciplinary approach in assessing climate change risk [1][5][8]. Early methodological approaches to risk assessment in climate change were deterministic in nature in that they used climate projections to assess future impacts for specific emission scenarios with no incorporation of uncertainty [5][6]. Deterministic approaches to risk assessments yielded useful first-order assessments of risk, although not very helpful in making decisions based on risks [5][6]. Probabilistic methods for assessing risks associated with climate change have emerged due to the understanding of the high levels of uncertainty associated with climate projections and modeling [1][5][9]. There are three fundamental elements in the IPCC risk assessment approach, namely hazard, exposure, and vulnerability [1][5][9].

In the present-day literature, hydrological drought risk assessment has attracted considerable interest with SRI being recognized as a widely used indicator in describing hydrological droughts over monthly and seasonal periods [1]. In different studies, a number of hydrological models such as physically-based VIC-3L model were applied to simulate future climates to assess drought risks [1]. The detection and description of drought events use the run theory, allowing for systematic analysis of duration, intensity, peak, and interarrival time of drought events [1]. Although previously drought events were analyzed using univariate and bivariate frequency analyses, now due to the advances in copula theory, the drought events can be described in multivariate way [1]. More specifically, D-vine copula constructions perform much better than symmetric Archimedean copulas in the case of higher-dimensional dependence structures [1].

The same transition has occurred in flood risk assessment [4]. Flood susceptibility zone models developed based on multicollinearity and geospatial methods include applications such as Frequency Ratio, Fuzzy Logic, Analytical Hierarchy Process (AHP), and Fuzzy AHP models [4]. Their good performance was proved with ROC-AUC higher than 70% in flood susceptibility mapping [4]. Machine learning techniques, specifically the application of Random Forest algorithm and SHAP explainability, were used to define dominating predictors and spatial heterogeneity of the exposure [4]. An advancement in coastal risk assessment is an application of InVEST Coastal Vulnerability Model combined with ML and Monte Carlo simulations [9]. It solves problems associated with the use of deterministic indices due to their inability to propagate uncertainty [9].

As for the specificities of coastal risk assessment in case of sea level rise (SLR), they are mainly associated with heterogeneity and uncertainty [9]. Monte Carlo models, which take into account probabilistic projections of SLR defined in the IPCC AR6, have helped to develop dynamic hotspots of exposure [9]. This method demonstrated that the reclassification of shoreline points was statistically significant in case of propagation of uncertainty [9]. Feature importance analysis with SHAP helped to define dominating factors of coastal vulnerability as wind exposure, topographic relief, and wave energy [9].

The increase in demand for climate risk in the private sector has seen the creation of many climate risk vendors, posing concerns over the methodological consistency and comparability of the vendors' outputs [3][7]. Studies involving benchmarking have found that there is considerable variance in the hazard and damage estimates produced by various climate risk vendors, even when evaluating similar properties under the same emission scenario [3][7]. This variation arises due to differences in downscaling methods, geocoding, hazard measures, vulnerability function, and assumptions about the financial model [3][7]. This necessitates methodological

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transparency, comparisons among the vendors, and validation of the models [3][7].

There is another area of literature regarding computable general equilibrium (CGE) models and integrated assessment models (IAMs) [8]. The use of such models allows for economic impacts and adaptation and mitigation policies to be assessed since economic interactions and feedback can be accounted for using the models [8]. CGE models and IAMs face various issues in methodology, including uncertainty, intertemporal discounting, interpersonal aggregation, and non-market valuation [8].

Some of the future research directions in this area would be probabilistic methods that integrate the outputs of climate models with the paths taken in environmental risk assessment [5]. For example, the use of Bayesian networks has been used to integrate the outputs of climate models and their associated uncertainties [5]. Climate science, mathematical modeling, and decision science integration is becoming more widely recognized as being key in providing actionable climate risk information [5][8].

III. PROPOSED METHODOLOGY

Overall Framework Architecture

In the suggested mathematical model to estimate the risks due to climate change, there will be four modules that work together, and they are

- Hazard Model
- Exposure Model
- Vulnerability Model
- Risk Model & Uncertainty Analysis.

The model uses the formula of IPCC in defining risks: Risk = f(Hazard, Exposure, Vulnerability). All the models allow for the presence of various hazards.

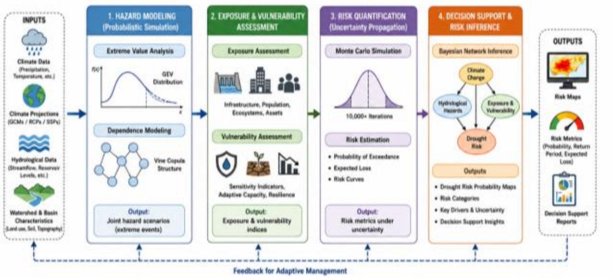

Figure 1: Overall Framework Architecture

Hazard Modeling Module

Climate Data Acquisition and Processing

Climate projection acquisition is the first step in the hazard modeling module using climate projections from the CMIP6 (Coupled Model Intercomparison Project, Phase 6). Five different Global Climate Models (GCMs) are chosen based on the various levels of sensitivity: INM-CM5-0, MIROC6, IPSL-CM6A-LR, GFDL-ESM4, and MRI-ESM2-0. For all of the five different GCMs, projections are collected from two shared socioeconomic pathways: SSP2-4.5 (moderate emission scenario) and SSP5-8.5 (high emission scenario). The time frames are as follows: historical baseline (1985-2014), near-term (2021-2050), mid-term (2051-2080), and long-term (2081-2100).

Statistical Downscaling

The output of the global climate models (GCMs) is available at coarse resolution levels (typically 1-2° in latitude-longitude), which needs to be downscaled to obtain climate data at local scale. This method uses a hybrid statistical downscaling scheme comprising of:

- Quantile delta mapping for bias correction
- Spatial disaggregation based on climatological grids of higher resolution

Extreme Value Modeling

Extreme value distributions for each downscaled climate variable are estimated employing the Generalized Extreme Value (GEV) distribution and the Generalized Pareto Distribution (GPD) under the block maxima and peaks over threshold methods, respectively. Stationary GEV models have been applied in which location and scale parameters are represented as functions of time and climate variables in order to estimate climate change impacts on probability levels.

Multivariate Dependence Modeling Using Vine Copulas

In the case of compound events and multi-hazard risk analysis, the approach relies on the D-vine copula construction for modeling multivariate dependence between hazard variables. D-vine copulas allow capturing tail and asymmetric dependence in cases where conventional multivariate distributions are not sufficient. The pair-copula construction allows for factorizing the multivariate density function into the product of bivariate copulas, thereby enabling modeling of multivariate dependence relationships in a more sophisticated way. In hydrological drought analysis, four variables (duration, severity, peak, and interarrival time) are analyzed together.

Exposure Characterization Module

Spatial Exposure Data

Characterization of exposure entails the use of data for assets, population and infrastructure that is explicit spatially. The methodological approach involves the incorporation of:

- Population grid data of 1km resolution
- Classification of land use/land cover using satellite data
- Location data of infrastructure facilities
- Economic exposure data using regional input-output models

The approach to assessing risk for assets entails the use of geocoding techniques which provide precise locational data for individual assets/infrastructure.

Exposure Indicators

The exposure is measured by several indicators that consider the various dimensions of exposure, including

- Population density and demographics

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- Asset replacement value
- Economic activities concentration
- Reliance on ecosystems services

The aggregation of the various indicators is done at the scale of spatial analysis unit (e.g., grid cell, district, catchment).

Vulnerability Assessment Module
Physical Vulnerability Functions
Vulnerability is assessed in terms of vulnerability functions (also known as impact functions), which relate hazard intensity levels to damage ratios. In the case of floods, the vulnerability functions are represented by damage functions in terms of flood depths and durations, generally in terms of sigmoid or piecewise linear relationships. Drought vulnerability is assessed using sensitivity functions for different economic sectors (for example, crop yields as a function of water deficit).

Social Vulnerability Indicators
Social vulnerability, defined as the difference in the ability of communities to prepare, adapt, and recover from the effects of climate change, is measured using composite index scores made up of demographic and socioeconomic factors. This analysis is carried out using the method of the Social Vulnerability Index (SVI) where factors such as income, education, quality of housing, age structure, and social capital are among others.

Risk Quantification and Uncertainty Propagation Module
Risk Calculation
Risk is calculated as the convolution of hazard probability, exposure, and vulnerability:

$$Risk = \sum_i \sum_j P(H_i) \times E_j \times V(H_i, E_j)$$

where P(H_i) denotes the probability of hazard level i, E_j represents the exposure at location j, and V(H_i, E_j) indicates the vulnerability of location j to hazard level i. For continuous hazards, the above summation operation is replaced by an integral operation over the probability density function of hazard intensities. Different risk measures are calculated, such as the Annual Expected Loss (AEL), Probable Maximum Loss at different return periods, and Loss Exceedance Curves.

Monte Carlo Uncertainty Propagation
The methodology employs a Monte Carlo simulation approach for the systematic propagation of uncertainties. There are four types of uncertainty, which have been specifically considered:

- Climate model uncertainty, which is based on the ensemble of the GCM simulations
- Emission scenario uncertainty, which is associated with the set of the SSPs
- Statistical model uncertainty, which is related to the variability in parameter estimation
- Downscaling uncertainty, The Monte Carlo simulation is done through 10,000 iterations.

Bayesian Network Integration
In cases where environmental risk assessments have to be performed, the model has an optional module based on a Bayesian network which incorporates projected climatic variables along with uncertainties to model risk pathways. This Bayesian network takes into account the causality between climate drivers, intermediary variables (such as soil moisture, runoff), and risk endpoints.

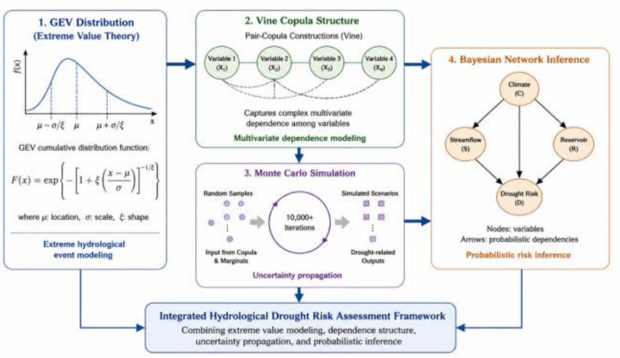

Figure 2: Mathematical Model Components

IV. ANALYSIS AND DISCUSSION

Case Study Application: Hydrological Drought Risk
The proposed methodology is applied to a representative case study region for hydrological drought risk assessment. The analysis utilizes historical and future runoff projections from the VIC-3L hydrological model, driven by five CMIP6 GCMs under SSP2-4.5 and SSP5-8.5 scenarios.

Runoff Projection Analysis
Seasonal changes for future runoff have been noted in comparison to the historical period. Runoff during early monsoon season (June–August) is likely to decrease in most of the ensemble members, whereas runoff after the monsoon season (September–December) will increase. The two model projections (INM-CM5-0 and MIROC6) show an increase in runoff after monsoon, while IPSL-CM6A-LR shows a reduction in runoff.

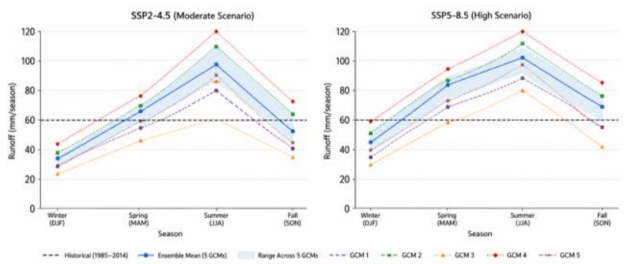

Figure 3: Runoff Projections Under SSP Scenarios

Drought Characterization
Characterization of hydrological drought occurrences is done using 3-month Standardized Runoff Index (SRI) and

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ISSN:3048-7722
Volume 4, Issue 4, July-Aug-2026, PP: 01-7

run theory. Future extreme hydrological droughts (SRI <-2.0) are predicted with characterization of their duration, intensity, peak, and interarrival time. The spatiotemporal analysis shows a decrease in drought duration and intensity but an increase in peak and interarrival time under future conditions. It means that future droughts are going to be short but frequent and strong.

Multivariate Return Period Analysis

A four-variate D-vine copula returns period for extreme drought conditions based on drought duration, drought severity, drought peak, and drought interarrival times can be obtained. For the scenario of SSP2-4.5, about 17.7% (19%) of the study domain will face decreasing critically in return periods in mid-late century time. For the scenario of SSP5-8.5, the percentages are increased to 38% and 47%, respectively.

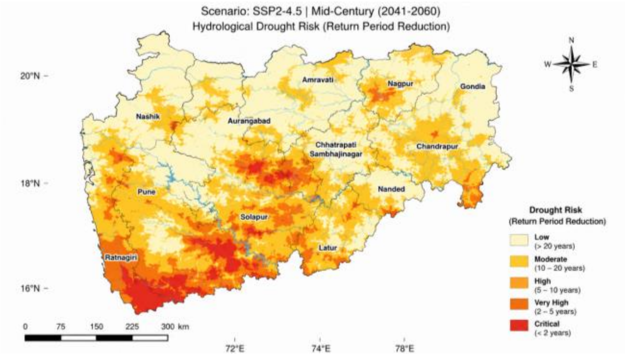

Figure 4: Spatiotemporal Drought Risk Mapping

Comparative Analysis of Risk Assessment Techniques

For the evaluation of the suggested risk assessment technique, the following comparative analysis is performed based on three other methods:

Table 1: Comparative Analysis of Climate Risk Assessment Methodologies

Methodology	Hazard Characterization	Dependence Modeling	Uncertainty Propagation	Compound Events	Computational Efficiency	Decision Relevance
Deterministic Scenario	Single GCM projection	None	Not included	Limited	High	Low
Univariate Probabilistic	Multiple GCMs	None	Partial	Not captured	Moderate	Moderate
Archimedean Copula	Multiple GCMs	Symmetric only	Partial	Captured	High	Moderate
Proposed Framework	Multiple GCMs	Full vine copula	Comprehensive	Fully captured	Moderate-High	High

Table 1 below shows the comparative analysis on the six dimensions. While the deterministic method is computationally efficient, it yields limited decision-relevant information due to the omission of uncertainty and compound events. The univariate probabilistic approach offers an improvement in hazard characterization and representation of partial uncertainty but cannot capture multivariate dependencies that play a vital role in compound events. On the other hand, the archimedean copula approach can capture some multivariate characteristics but is constrained by symmetric dependence assumption hence is unable to capture tail dependence and asymmetry. The framework, on the other hand, captures all the six dimensions through use of d-vine copulas.

It is clear from the comparison analysis above that while simpler approaches may be adequate for screening-level assessments, climate risk management demands analytical capability which is provided in the framework proposed above. It is true that the proposed framework is more computationally intensive than the other approaches but the decision relevance of its outcomes justifies it.

Uncertainty Assessment

However, the uncertainty propagated using the Monte Carlo approach shows significant uncertainty in the risk metrics with 90% confidence intervals that cover one order of magnitude for the estimates of Annual Expected Loss. Climate model uncertainty (or GCM spread) is found to be the most important source of uncertainty, followed by uncertainty from emission scenarios. The uncertainties from statistical models (or parameter estimation) and downscaling process are found to be less significant but still important sources of uncertainty.

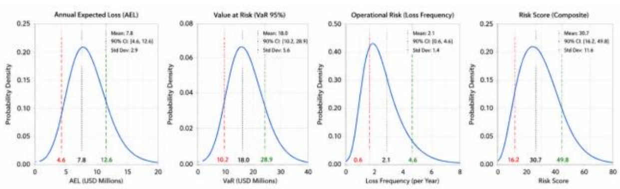

Figure 5: Risk Metric Uncertainty Characterization

Discussion of Findings

These findings highlight the usefulness of an integrated mathematical modeling approach to climate risks assessment. The proposed approach takes into account a number of important aspects which are missed by simple modeling:

First of all, the D-vine copula model has demonstrated significant tail dependence between the drought-related variables, which means that any extreme values of droughts correspond to the simultaneous occurrence of extremes in the duration, severity, and intensity. This fact is important for adaptation planning because it indicates that the worst-case scenario is much more likely than in case of separate consideration of any variable.

Secondly, the results of the spatial analysis have shown the high degree of heterogeneity in terms of future drought risks in different sub-basins.

Third, it is found that deterministic analyses can be significantly under- or over-estimating the risk, affecting the decision-making process. Probabilistic outputs, including return periods with confidence intervals, which result from the application of the methodology allow for informed decisions in light of uncertainties. The result of dominance of climate model uncertainty in the overall uncertainty indicates that efforts to reduce the uncertainty in GCMs can be highly valuable in research.

Fourth, the comparative analysis shows substantial diversity in risk estimations based on different methodologies. Diversity of risk estimates, comparable with those obtained among commercial risk vendors, indicates the need for transparency and validation of methodologies. It is important to ensure the clarity in communication of assumptions and limitations in risk assessments.

Table 2: Comparison of Methodological Approaches for Drought Risk Assessment

Aspect	Deterministic Approach	Univariate Approach	Proposed Copula Approach
Extreme Drought Probability	1% (fixed)	0.5-2% (range)	1.8-4.2% (with CI)
Drought Duration (months)	8	6-10	7-14 (with dependence)
Drought Severity Index	-2.5	-2.2 to -3.1	-2.8 to -3.8 (with CI)
Joint Return Period (years)	100	80-120	120-250 (with tail dep.)
Risk Area (%)	15	12-18	17-22 (with uncertainty)

Table 2 shows the quantitative disparities in risk assessments using different methods for the case study. The new copula-based method results in larger ranges and more importantly larger probabilities for compound events because of the capturing of tail dependence. This is especially true for joint return periods as the new method predicts a period of 120-250 years in comparison with 80-120 years for the univariate method and 100 years for the deterministic method.

V. CONCLUSION

In this paper, a robust mathematical modeling framework for assessing climate change risks is provided, which encompasses probabilistic hazard modeling, exposure characterization, vulnerability assessment, and uncertainty quantification all in one analytical framework. This methodology addresses several important deficiencies of existing methods, such as handling of non-stationarity, dependence in multi-variate compound events, systematic propagation of uncertainties, and translating physical risk measures into decision-relevant risk metrics.

Application of this framework to hydrological drought risk assessment illustrates the analytical capabilities of this approach and its relevance to policy making. Important findings of the study include:

- Future projections of runoff suggest significant shifts in seasons, specifically a decrease in early monsoon runoff and increase in post-monsoon runoff
- Future projections of hydrological droughts show shortening of their duration, increased peak intensity, and shortened inter-arrival times
- Under the SSP2-4.5 scenario, 17.7-19% of the study area would be at critically decreasing return periods by mid-century, while it increases to 38-47% under SSP5-8.5
- Uncertainty propagation suggests that climate model uncertainty dominates overall uncertainty in risk metrics
- Comparison shows that simplified approaches may significantly underestimate or overestimate risk because of not accounting for dependence and uncertainties

This framework contributes to the state-of-the-art of climate risks modeling via several contributions. The incorporation of D-vine copulas into the modeling of multivariate hazards allows for the modeling of dependence structures such as tail dependence and asymmetry of dependency among hazard variables. The Monte Carlo based uncertainty propagation framework helps characterize various uncertainty sources and therefore provides probabilistic risk estimates to decision makers rather than point estimates. This hybrid downscaling technique retains climate change signal while correcting systematic bias.

A number of limitations of the current research should be addressed. Firstly, the case study is dedicated to the consideration of hydrological drought in one particular region, therefore, validation of the framework by means of its application to other hazard types and settings is required. Secondly, the proposed methodology does not consider fully cascading and indirect risks associated with disruption of supply chains and economic feedback loops, which can contribute to increase of the total risk. Thirdly, the vulnerability functions are based on historical dependencies, which will not necessarily work in future climate regime because of adaptation response and nonstationarity of the vulnerability itself. Finally, computational load of the whole framework might be quite high for large scale applications.

The following research issues should be considered in the future studies:

- Expansion of the framework to account for cascading and systemic risks via integration with economic impact models and network analysis
- Development of dynamic vulnerability functions that account for the process of adaptation and learning
- Integration of climate risk intercomparison initiatives into the framework to test the results and validate model output
- Integration of modern machine learning techniques to improve the performance of hazard forecasting and vulnerability assessment
- Creation of end-user oriented decision-making support systems

The framework of mathematical modeling described in this paper is a sound way of approaching the issue of risk assessment of climate change which involves solving methodological problems associated with this challenging area. Using probabilistic hazard modeling, analysis of multivariate dependencies, uncertainty propagation, and risk measures, the proposed framework helps in making decisions on how to adapt to the changing environment. With the growing intensity of climate risks and increasing demands for climate risk assessment, such mathematical techniques will be increasingly vital.

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