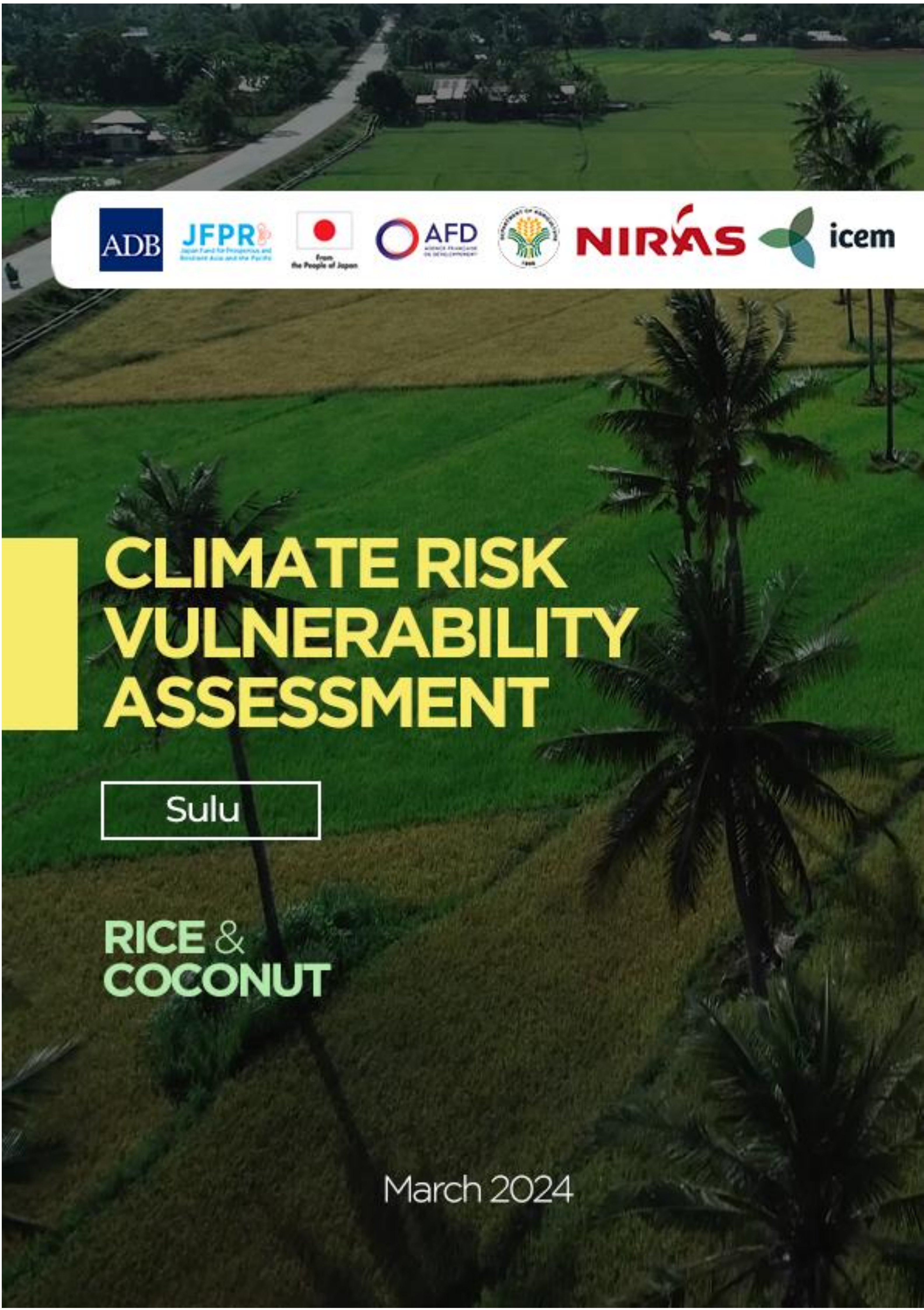

CLIMATE RISK VULNERABILITY ASSESSMENT

Sulu

RICE & COCONUT

March 2024

CLIMATE RISK VULNERABILITY ASSESSMENT SULU

(RICE AND COCONUT)

MARCH 2024

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AC	Adaptive Capacity
ADB	Asian Development Bank
AMIA	Adaptation and Mitigation Initiative in Agriculture
BARMM	Bangsamoro Autonomous Region of Muslim Mindanao
BSWM	Bureau of Soils and Water Management
CIAT	International Center for Tropical Agriculture
CMCI	Cities and Municipalities Competitiveness Index
CMIP	Coupled Model Intercomparison Model
CRA	Climate-Resilient Agriculture
CRVA	Climate Risk Vulnerability Assessment
CRVA	Climate Risk Vulnerability Assessment
DA	Department of Agriculture
DA-CRAO	Department of Agriculture – Climate Resilient Agriculture Office
DENR-MGB	Department of Environment and Natural Resources - Mines and Geosciences Bureau
DILG	Department of the Interior and Local Government
DOST	Department of Science and Technology
DRRM	Disaster Risk Reduction and Management
GCM	Global Circulation Model
GEE	Google Earth Engine
IPCC	Intergovernmental Panel on Climate Change
KII	Key Informant Interview
LGU	Local Government Unit
MAOs	Municipal Agriculture Officers
MaxEnt	Maximum Entropy Model
MPDC	Municipal Planning and Development Coordinator
NCC	National Competitiveness Council
NWRB	National Water Resources Board
PSA	Population by the Philippine Statistics Authority
QGIS	Quantum Geographic Information System
RCC	Regional Competitiveness Committee
RCP	Representative Concentration Pathway
SDM	Species Distribution Modelling
UNEP	United Nations Environment Programme
UNISDR	United Nations Office for Disaster Risk Reduction
WFP	World Food Programme

EXECUTIVE SUMMARY

Vulnerability to climate change impacts of rice and coconut systems in the province of Sulu were assessed using the Climate Risk Vulnerability Assessment (CRVA) framework of the Department of Agriculture – Climate Resilient Agriculture Office (DA-CRAO). An automated system for operationalizing the CRVA framework was developed and utilized in generating the CRVA maps. Data for the major components of vulnerability – exposure, sensitivity, and adaptive capacity for the 19 municipalities in Sulu were collected using available secondary sources and through participatory workshops with Municipal Agriculture Officers (MAOs) in the province. All the data collected were preprocessed, standardized, and utilized as inputs to the Automated CRVA Tool. The automated system was used to produce the sensitivity, hazards, adaptive capacity, and overall vulnerability shapefiles for map generation. Final maps, including intermediate results for hazards and adaptive capacity, were generated using QGIS.

Analysis of the CRVA maps revealed that the majority of the rice and coconut areas in Sulu have high vulnerability to climate change impacts. Specifically, results showed that:

- Most areas in Sulu are susceptible to drought, landslides, sea level rise, and erosion.
- Future projections using the RCP 8.5 scenario (high emission scenario) showed that there would be less conducive environments for rice and coconut production throughout the province.
- Municipalities in Sulu generally have low adaptive capacity because of limited economic, human, physical, and social capacities.
- Overall indices showed that 53% and 47% of rice and coconut production areas in Sulu, respectively, have high to very high vulnerability to climate change impacts.

Given the results of the assessment, climate-resilient adaptation options were also provided to serve as guide in developing investment plans and programs to help rice and coconut farming communities in the province reduce their vulnerability. These include the adoption of sustainable agricultural practices, integrated land use management, and Nature-based Solutions (NbS).

Agricultural planners are encouraged to use the CRVA maps as guide in targeting areas most-at-risk to climate change impacts. Likewise, it is envisioned that the results of the assessment shall be utilized in creating an enabling environment that will support farmers not only in managing climate risks, but more importantly in sustaining their livelihoods.

1. INTRODUCTION

1.1. Rationale

Climate change and variability continue to exert increasing pressure upon the agricultural sector of the Philippines. Projected climate change impacts will continue to reduce long-term economic growth in the country by 0.02% per year, which equates to a 3.8% reduction in Gross Domestic Product (GDP) by 2050 (Rosegrant et. al., 2015). Hence, a better understanding of major agricultural vulnerabilities to climate risks is fundamental to achieving more resilient farming systems, especially among poor rural households. Therefore, as a first step, identifying and prioritizing crops that are most vulnerable to climate risks is necessary at a high-resolution scale. In this context, the progressive building of resilience is an intermediate outcome contributing to improve communities' coping capacities to a high degree of climate risks (Béné et al., 2015).

The Department of Agriculture (DA) launched the Adaptation and Mitigation Initiative in Agriculture (AMIA) program in 2014 as the flagship program of the Department to address the impacts of climate change on the agriculture and fisheries sector. As its overall approach, AMIA develops and promotes climate-resilient agriculture (CRA) by applying innovative technologies and practices, introducing institutional and social reforms, and accessing climate-relevant support services.

To target the most vulnerable areas in the country, a Climate Risk Vulnerability Assessment (CRVA) tool was developed through the AMIA program. The CRVA tool helps define priorities and design targeted solutions for the most vulnerable populations based on the expected impacts from climate change and capacities for adaptation. Results of the CRVA can be integrated into broader development approaches for agenda setting, program planning, and investment prioritization. Specifically, it can be used for policy analysis and formulation for national/sub-national development plans; local-level vulnerability assessment by communities, government agencies, and other stakeholder groups; participatory assessments; and investment prioritization for potential actions and interventions in climate adaptation and mitigation.

The Asian Development Bank, through NIRAS, implemented the Technical Assistance project titled “Accelerating Climate Resilience in Agriculture, Natural Resources, and the Environment”, to strengthen the Philippine’s legal, policy, and institutional frameworks for climate adaptation and resilience in the agricultural and environmental sectors. The project was implemented in close collaboration with the Department of Agriculture Climate Resilient Agriculture Office (DA-CRAO). The project aimed to support DA-CRAO in preparing CRVA maps for priority crops in the six (6) provinces of the Bangsamoro Autonomous Region of Muslim Mindanao (BARMM) following the AMIA CRVA framework. Additionally, the project pioneered the development of an automated system for operationalizing CRVA for crops which was utilized in generating the CRVA maps for BARMM.

Specifically, this report covers the results of the CRVA for identified priority crops in the province of **Sulu** and the potential management strategies to address the adverse climate change impacts in the province.

1.2. Objectives

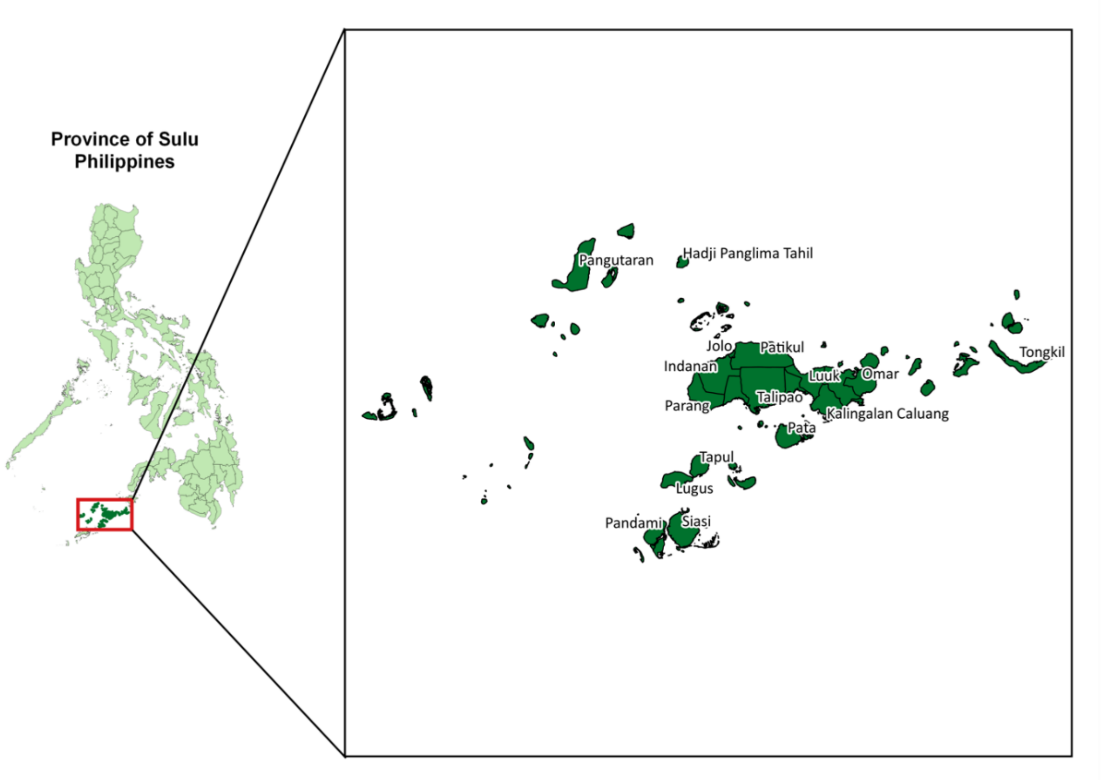
Given these contexts, this study aimed to assess the climate risk vulnerability status of **rice** and **coconut** in a geospatial landscape at the municipal level in the province of Sulu. Specifically, it aimed to integrate spatial and secondary data clustered under the three major components of vulnerability – sensitivity, exposure, and adaptive capacity, to produce maps that shall serve as basis for developing CRA-related decision support tools, and recommended guidelines for disseminating climate-related information services, among others.

2. METHODOLOGY

2.1. Study Area

Sulu is one of the six provinces of the Bangsamoro Autonomous Region of Muslim Mindanao (BARMM). It is composed of 19 municipalities, with the Municipality of Jolo being the province capital (**Figure 1**). Sulu has a land area of 4,547.16 km^2 and a total population of 1,000,108 based on the 2020 Census of Population of the Philippine Statistics Authority (PSA).

Figure 1. Location map of Sulu



2.2. Agriculture in Sulu

According to the Philippine Statistics Authority, the agriculture and fisheries sector of Sulu had an estimated value of P11,050,0900 – a -1.2% decline from the previous year. The province makes up 0.48% of the total Philippine Agriculture and Fisheries production value (PSA, 2023).

There are 64,354 individuals in the province engaged in agricultural activities aged 10 and above according to the 2012 Census of Agriculture and Fisheries. This making up 0.68% of the overall agricultural workforce in the Philippines (PSA, 2020).

In terms of rice production, the Philippine Rice Institute (PhilRice) reported a declining trend in Sulu. In 2023, the province had a total rice area of 288 hectares, producing around 490 metric tons of rice - a sharp 53% decrease in production from the previous year (PhilRice, 2023).

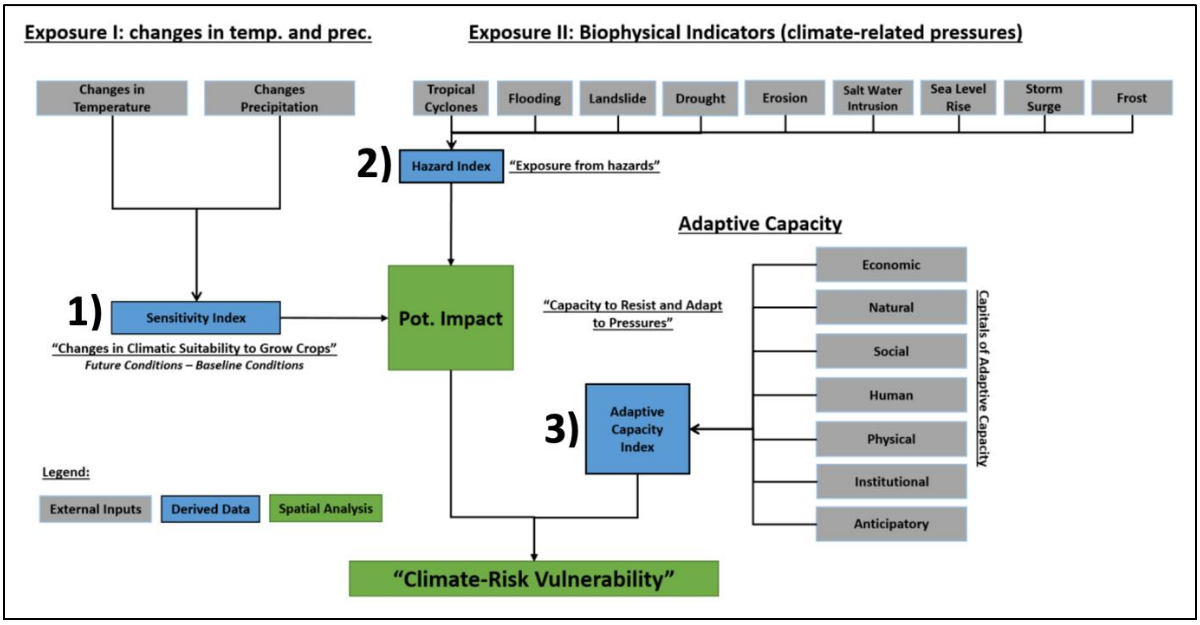
In 2018, the province had a total area of 69,000 hectares for coconut production, which produced 217,286 metric tons of coconut during the year. The province makes up 1.48% of the national coconut production in the Philippines (Philippine Coconut Authority, n.d.).

While the province generally receives sufficient rainfall to support crop growth, incidence of excessive rainfall was already reported leading to crop losses (PAGASA-DOST, 2022). In 2014, a state of calamity was declared in the city of Jolo due to widespread flooding and landslides caused by prolonged rainfall (Laude, 2024).

2.3. Conceptual Framework

The CRVA framework used for the study was adapted from the International Center for Tropical Agriculture (CIAT, n.d.) as shown in **Figure 2**.

Figure 2. DA-AMIA CRVA framework for crops



The CRVA framework developed for DA was based on the Intergovernmental Panel on Climate Change (IPCC) Assessment Report 4 (AR4) which defines vulnerability in terms of: **Exposure** to climate-induced shocks (a biophysical phenomenon); **Sensitivity** of the unit to such shocks; and the **Adaptive Capacity** to deal with such shocks. Each of the dimensions and indicators is used to assess the vulnerability of each municipality within a province. The components of vulnerability are further defined as:

- Sensitivity: The increase or decrease of climatic suitability of selected crops to changes in temperature and precipitation (Parker et al., 2019).
- Exposure: The nature and degree to which a system is exposed to significant climate variations (IPCC, 2014).
- Adaptive Capacity: The ability of a system to adjust to climate change (including climate variability and extremes) to moderate potential damages, to take advantage of opportunities, or to cope with the consequences (IPCC, 2014).

2.3.1. Sensitivity

The sensitivity of crops to changes in temperature and rainfall was measured by analyzing climate suitability by the year 2050 vis-à-vis the baseline (current) condition. The difference, expressed as a percentage, in future and baseline suitability determines the change in crop climate suitability and reflects the degree of crop sensitivity to changing environmental conditions (see Equation 1). Negative values reflect negative impact or decrease in suitability, while positive values reflect positive impact or gain in suitability in the future.

$$\text{Sens} = \frac{Future - Baseline}{Baseline} \times 100 \quad (1)$$

Species Distribution Modelling (SDM) using the Maximum Entropy (MaxEnt) model[1] was employed in the study to analyze climate suitability of the selected crops. The model requires climate and crop occurrence data in order to predict the potential geographic distribution of the crops and generate the suitability maps (baseline and future).

A total of 19 bioclimatic variables (**Annex 1**) from WorldClim (https://www.worldclim.org/) with a spatial resolution of about 1 km^2 (or 30 arc-seconds) was used to run the model and generate the baseline suitability of the selected crops. These bioclimatic variables are gridded climate data derived from monthly temperature and rainfall values and were processed to generate more biologically meaningful climate variables (Hijmans et al., 2005; Apdohan et al., 2021).

On the other hand, thirty-three (33) Global Circulation Model (GCMs) (**Annex 2**) based on Coupled Model Intercomparison Model (CMIP) 5 under the Representative Concentration Pathway (RCP) 8.5[2] scenario was used to run the model and generate the suitability of the selected crops by year 2050 (future). These climate data was processed and downscaled (same resolution as WorldClim) by CIAT using the method of Ramirez-Villegas and Jarvis (2010) and can be downloaded from the Climate Change and Food Security website http://www.ccafs-climate.org/data_spatial_downscaling/.

As mentioned, another input to the model is the crop occurrence data which identifies the presence of a specific crop within a geographic area. There are several methods to generate the crop occurrence data such as collecting points on the ground using participatory mapping approach and/or the use of satellite images via remote sensing. Specific methodology used for the study is presented in Section 2.4.

The resulting baseline and projected crop suitability data (in raster format) from the MaxEnt model were used as inputs to obtain the difference of the values in each pixel to measure the change in suitability. The resulting pixel values range from negative to positive values, and were converted into an index, which serves as the basis for assessing the impact of climate change. As shown in **Table 1**, the index ranges from -1.0 to 1.0 wherein 0.25 to 1.0 indicate a decrease in suitability, while -0.25 to -1.0 indicate a gain in suitability, and zero indicates no change in suitability (Palao et al., 2016).

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[1] Maximum entropy modeling (MaxEnt) "uses techniques developed from machine learning, allowing empirical data to be used to predict the probability of finding something under certain conditions distributed in space" - Dudík, M., S. J. Phillips,and R. E. Schapire. 2007. Maximum entropy density estimation with generalized regularization and an application to species distribution modeling. Journal of Machine Learning Research 8: 1217–1260.

[2] The RCP 8.5 scenario was used in the analysis because climate risks tend to rise in extremely high emission scenario and temperature conditions (Katzfey, 2015). It represents potentially high greenhouse gas emission levels in the atmosphere and the subsequent increase in solar energy that would be absorbed (radiative forcing) (IPCC AR5, 2014). Under RCP 8.5, the projected increase in temperature is +1.4 – 2.6 degree Celsius (ºC) for the mid-century and +2.6 – 4.8ºC for the end of the century (IPCC, 2013). Compared to other scenarios, the RCP 8.5 provides emphasis on risk assessment by providing understanding of the upper limits of potential climate change impacts that can contribute to policy and decision-making.

Table 1. Sensitivity index based on percent change of crop suitability from baseline to future conditions

Percent Change in Suitability (Range in %)	Index	Description
≤ -50 (High decrease)	1.0	Decrease
> -50 ≤ -25 (Moderate decrease)	0.5	
> -25 ≤ -5 (Low decrease)	0.25	
> -5 ≤ 5 (No change)	0	No Change
> 5 ≤ 25 (Low gain)	-0.25	Gain
> 25 ≤ 50 (Moderate gain)	-0.5	
> 50 (High gain)	-1.0	

2.3.2. Exposure

Eight (8) natural hazards were used to assess the exposure of the province to climate-induced shocks (a biophysical phenomenon). These hazards were obtained from historical data of different databases, as listed in **Table 2.** The set of hazard weights[3] presented in **Table 2** was also used to reflect the relative impact of each hazard.

Table 2. Hazard dataset used for exposure assessment

Hazards	Description	Source	Weights % (CIAT, 2017)
Typhoon	Typhoon incidence based on frequency	UNEP/UNISDR	16.95
Flood Susceptibility	Identifies areas at different levels of risk to flood based on physical characteristics	DENR-MGB	15.25
Drought	Identified areas at risk to agricultural drought based on physical characteristics	AMIA	16.95
Erosion	Identifies areas at different levels of risk to erosion based on physical characteristics	BSWM	12.71
Landslide	Identifies areas at different levels of risk to landslide based on physical characteristics	DENR-MGB	14.41
Saltwater Intrusion	Identifies areas that are potentially affected by saltwater intrusion based on ground water potential	NWRB	10.17
Sea Level Rise	Identifies areas that can be potentially affected by sea level rise	AMIA	5.08
Storm Surge	Identifies areas that are potentially affected by storm surge based on	DOST	8.47

[3] The hazard weights in Table 2 were developed by the International Center for Tropical Agriculture (CIAT) through a workshop participated by State Universities and Colleges (SUC) experts and Department of Agriculture (DA) focal persons. Specific weights per island group (Luzon, Visayas, and Mindanao) were generated, and the weights presented in Table 2 were for Mindanao. The probability/impact of the hazard risk was measured from a semi-quantitative assessment by scoring different sets of criteria: 1) frequency of occurrence, 2) impact of local household income, 3) impact to key natural resources to sustain, 4) impact to food security of the country, and 5) impact to national economy.

The analysis of hazards was limited to baseline conditions because many climate-induced natural hazards occur in large-scale singular events, and projection to the year 2050 may add further layers of uncertainty. Each hazard dataset was in the form of a raster file. To standardize the raster files, the pixels were aggregated for each municipality using the zonal statistics tool in QGIS and selecting mean or sum as the basis for data aggregation (Palao et al., 2016).

After employing zonal statistics, the spatially-weighted sum of the eight (8) hazards was used to develop the hazard index for each municipality. The weighted sum was normalized using equation 2 to standardize the value from 0 to 1, creating the hazard index.
Five equal breaks were used to classify the hazard index into: 0-0.20 (Very Low), 0.20-0.40 (Low), 0.40-0.60 (Moderate), 0.60-0.80 (High), and 0.80-1.00 (Very High).

(2)

$$hazidx\_norm = \frac{X - X_{min}}{X_{max} - X_{min}}$$

2.3.3. Adaptive Capacity

Adaptive capacity forms one of the pillars of vulnerability which measures the ability of a system to deal with climate change-induced shocks. In the process of developing the adaptive capacity index, a diverse range of locally compiled data were used including socio-economic factors, institutional capabilities, and agricultural data. These datasets were categorized into seven capitals to provide a more comprehensive lens of a system's strengths and weaknesses. These include: Anticipatory, Economic, Human, Institutional, Natural, Physical, and Social capitals.

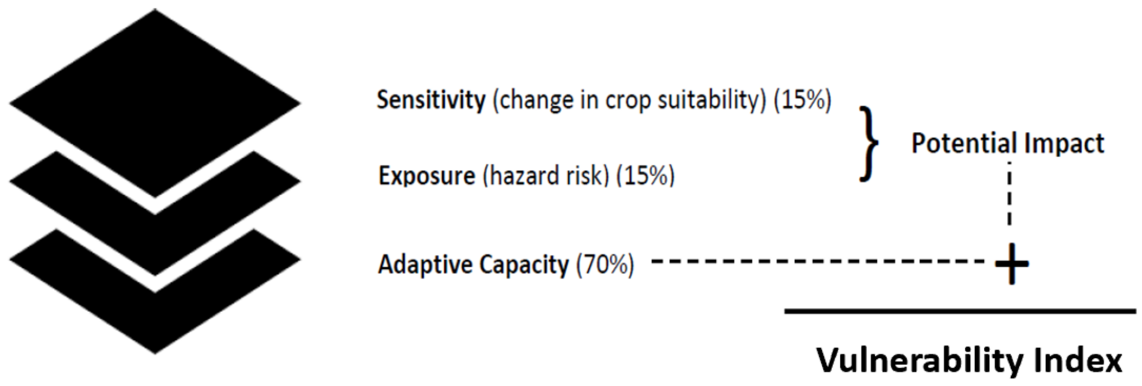
Anticipatory Capital refers to the ability of a system to anticipate and minimize negative impacts of climate hazards through foresight, prior planning, and preparation. This capital includes indicators related to information dissemination, forecasting, and building capacity and awareness of local stakeholders related to climate change. *Economic capital* includes indicators which relate to economic assets and financial resources, which local citizens may tap to bear the costs of adaptation to climate-related hazards and impacts. This capital includes existing financial institutions and local economic activities and conditions in the city/municipality. For this assessment, *Human Capital* pertains to education and health sectors. It includes indicators which measure the available manpower in the city/municipality and resources which can support human well-being as well as development of knowledge and skills of local citizens. *Institutional Capital* refers to established mechanisms within the local government which can support and facilitate management, development, and implementation of climate change-related activities. *Physical Capital*, on the other hand, includes infrastructure-related indicators, as well as facilities which sustain operation and flow of activities within the city/municipality. Lastly, *Social Capital* relates to farmer organizations and gender-related factors and considerations.

The composite index for each capital was constructed by averaging the normalized values of all the indicators. The composite adaptive capacity (AC) index is derived using the sum function of all capital indices which were normalized and treated with equal weights. Five equal categories were developed to establish the thresholds: 0-0.20 (Very Low), 0.20-0.40 (Low), 0.40-0.60 (Moderate), 0.60-0.80 (High), and 0.80-1.00 (Very High).

2.3.4. Vulnerability Index

The vulnerability of each municipality is expressed as the weighted sum of the potential impact (i.e., sensitivity and exposure to hazards as presented in **Figure 2**), weighted at 30%, and the inverted adaptive capacity index, weighted at 70%. These percentages were based on the other CRVAs completed by the DA-AMIA program, highlighting the importance of building a strong capacity of the province to moderate the impacts of climate change. The values obtained were normalized linearly from an interval of 0 to 1 using Equation 2. Based on the minimum and maximum values, the municipalities were classified from very high to very low using five (5) equal breaks: 0-20 (Very Low); 20-40 (Low); 40-60 (Moderate); 60-80 (High); and 80-100 (Very High). **Figure 3** illustrates how the different dimensions of vulnerability are integrated to produce the final vulnerability index.

Figure 3. Integration of the three key dimensions of vulnerability



2.4. Data Collection and Validation

2.4.1. Crop Occurrence Data

As mentioned in the previous section, one of the inputs of the MaxEnt model is crop occurrence data. The use and analysis of satellite images via remote sensing and the participatory mapping approach were both utilized in this project.

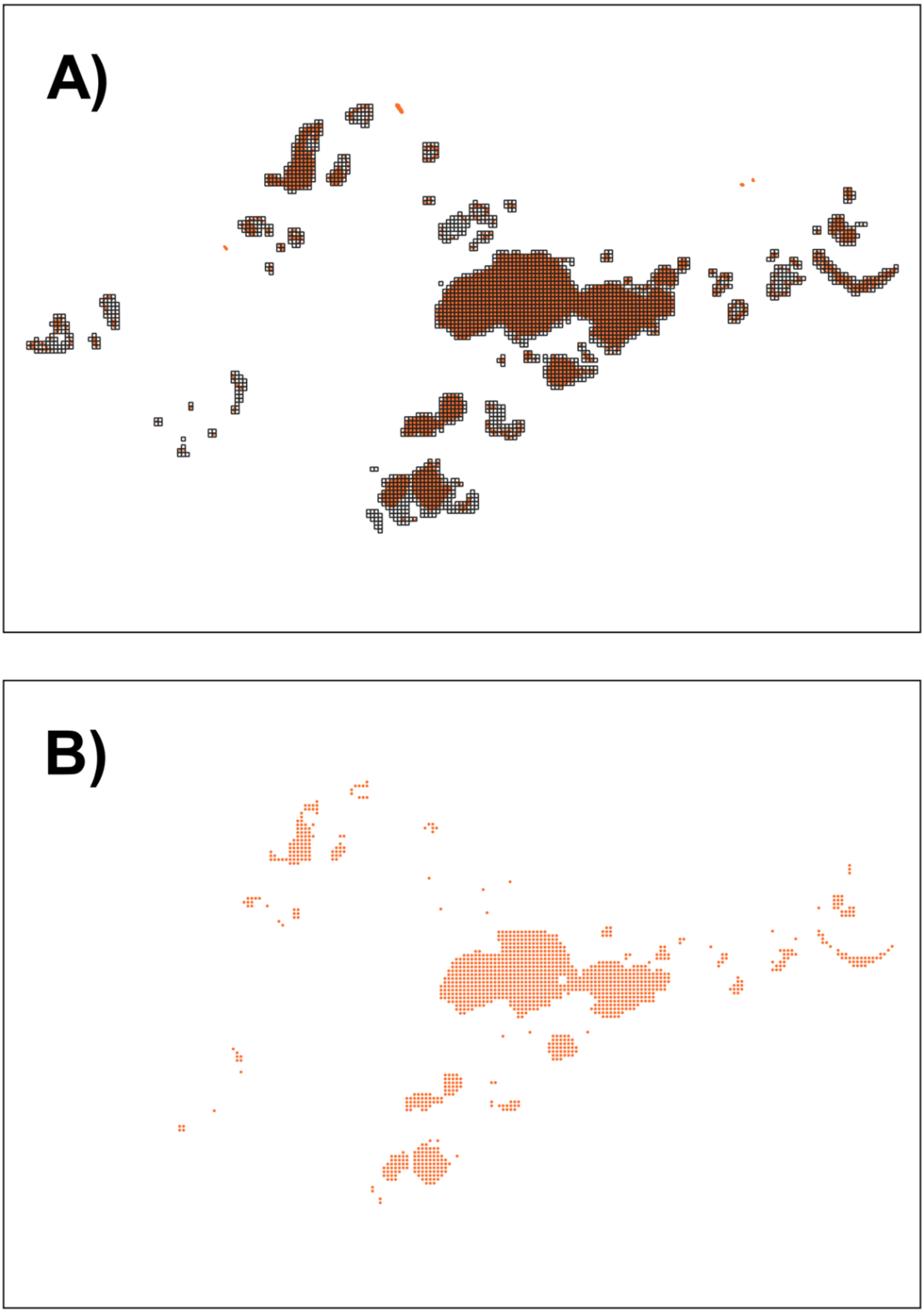
The crop occurrence data were initially mapped by collecting crop presence points via remote sensing by leveraging Google Earth Engine (GEE), a powerful cloud-based platform for planetary-scale environmental data analysis. This platform utilizes a multi-petabyte catalog of satellite imagery and geospatial datasets, enabling analysts to detect changes, map trends, and quantify differences on the Earth's surface. Using GEE, the team was able to efficiently access and process large volumes of satellite images to identify areas of crop cultivation in the region. The process involved selecting specific satellite data that provided high-resolution images suitable for agricultural analysis, such as those from the Landsat and Sentinel series. By applying advanced image processing algorithms and machine learning techniques within the GEE framework, the team was able to extract detailed information about crops including location and types. This process is explained in more detail in **Annex 3**.

Complementary to the remote sensing process, and to ensure accuracy of the collected crop presence points, a participatory mapping and validation workshop was conducted from 13-14 February 2024 in Zamboanga City and participated by representatives from the Municipal Agriculture Offices of Sulu (**Figure 4**).

Figure 4. Data collection and validation workshop in Zamboanga City held on 13-14 February 2024

During this activity, the crop presence points were presented to the LGUs using a 1x1 km gridded map. Participants confirmed the presence of crops at specific point locations on the map, indicated the presence of crops not detected in the remote sensing process by drawing a point, and removed points when the crop was absent, guided by their local data and knowledge. To reduce the spatial autocorrelation which can affect the performance of the model and result in overfitting, we removed duplicate points that were within the 1x1 km grid, assuming there are no considerable changes in the bioclimatic variables with the 1-km^2 distance (Palao et al., 2016). **Figure 5** shows the sampling distance of the crop presence points before and after the validation and filtering was applied. Image A (top) illustrates rice crop presence points collected using GEE for remote sensing, and image B (bottom) shows rice crop presence points validated and filtered within the 1-km^2 distance.

Figure 5. Map showing the filtering crop occurrence points based on a 1x1 km grid



2.4.2. Exposure to Climate-related Hazards

The maps generated using these sources were also validated during the workshop conducted in Zamboanga City from 13-14 February 2024. A spatially weighted sum was computed to develop the hazards index level in the province. Hazard indices were classified into five categories: 0.00 - 0.20 (Very Low), 0.20 - 0.40 (Low), 0.40 - 0.60 (Moderate), 0.60 - 0.80 (High), and 0.80 - 1.0 (Very High).

2.4.3. Adaptive Capacity

Key Informant Interviews (KII) were conducted among representatives of Municipal Agriculture Offices (MAOs) in Sulu to gather data for the Adaptive Capacity indicators listed in **Table 3**. The Adaptive Capacity indicators were grouped into seven capitals, namely: Anticipatory, Economic, Human, Institutional, Natural, Physical, and Social.

Data that were not available from the MAOs were obtained from the Cities and Municipalities Competitiveness Index (CMCI) developed by the National Competitiveness Council (NCC) through the Regional Competitiveness Committees (RCCs) with the assistance of the United States Agency for International Development.

Table 3. List of Adaptive Capacity Indicators collected

Capitals	Indicators	Source
Anticipatory	Budget of DRRMP	CMCI
	Average number of trainings held in a year related to climate change	MAO/MPDC
	No. of Telephone Companies and Mobile Services Providers	MAO/MPDC
	Presence of Disaster Risk Reduction and Management Office (DRRMO) | Yes=1 and No=0	MAO/MPDC
	Presence of Early Warning Systems Yes=1 and No=0	MAO/MPDC
Economic	Average Diesel Price (in Php)	MAO/MPDC
	Average Agricultural Minimum Wage (Non-Plantations) (in Php)	MAO/MPDC
	Average Agricultural Minimum Wage (Plantations) (in Php)	MAO/MPDC
	Cost of Doing Businesses	CMCI
	Active Businesses in the Locality	CMCI
	Local Economy Growth	CMCI
	Municipality Classification	MAO/MPDC
	Number of Commercial Banks	MAO/MPDC
	Number of Finance Cooperatives	MAO/MPDC
	Number of Microfinance Institutions	MAO/MPDC
	Number of Rural Banks	MAO/MPDC
	Number of Thrift and Savings Banks	MAO/MPDC
Human	Number of Health Services Manpower	MAO/MPDC
	Number of Local Citizens with PhilHealth coverage	CMCI
	Number of Private Doctors	MAO/MPDC
	Number of Private Health Services	MAO/MPDC
	Number of Public Doctors	MAO/MPDC

Capitals	Indicators	Source
	Number of Public Health Facilities	MAO/MPDC
	Number of Public Health Services	MAO/MPDC
	Number of Public Secondary Schools	MAO/MPDC
	Number of Public Teachers	MAO/MPDC
	Number of Public Technical ad Vocational Schools	MAO/MPDC
	Number of Public Tertiary Schools	MAO/MPDC
	Ratio of Public Teachers to Students	MAO/MPDC
Institutional	Average number of Farmers visited by or consulted with agriculture extension officers in a year	MAO/MPDC
	Number of DA Officers	MAO/MPDC
	Getting Business Permits	CMCI
	Peace and Order	CMCI
	Number of DILG recognized awards	CMCI
	Presence of Implementing Comprehensive Land Use Plan (CLUP) | Yes=1 and No=0	MAO/MPDC
	Presence of DRRM Plan | Yes=1 and No=0	MAO/MPDC
Natural	% of Crops Irrigated	MAO/MPDC
	% of Farmers Owning their agricultural land	MAO/MPDC
	Average Farm Size per Farmer (ha)	MAO/MPDC
	Intact Forest Cover (ha)	Gobal Forest Watch
Physical	% of Household with Electricity Services	MAO/MPDC
	% of Household with Water Services	MAO/MPDC
	LGU Infrastructure Investment	CMCI
	Transport Vehicles	CMCI
	Road Network	CMCI
	Total Budget Allocation for Infrastructure	MAO/MPDC
Social	% of Farmers Covered with Insurance	MAO/MPDC
	% of farmers who are members of coops/unions/groups	MAO/MPDC
	% of Women in Local Government	MAO/MPDC
	Number of registered farmer groups or unions	MAO/MPDC
	Professional Business/Organizations	CMCI

2.5. Generation of Maps

All the data collected were preprocessed and standardized generating intermediate outputs to be utilized as inputs to the Automated CRVA Tool Ver. 2023 (see **Annex 4**). For the sensitivity component, the crop occurrence data which consists of crop presence points, were organized into a comma-separated values (.csv) format consisting of the name of the species and the latitude and longitude values of the specific point. The climate data were also organized into two (2) sets of folders (baseline and projected) being fed into the system to run the MaxEnt automatically. Then, the hazard datasets in raster format were clipped in QGIS using a shapefile of the political boundary of the province. Lastly, the adaptive capacity indicators, grouped into different capitals, were encoded in a .csv file that could be read by the automated system.

Using the intermediate files, the automated system will individually run each of the three components of the CRVA – sensitivity, hazards, and adaptive capacity. The automated system will then integrate the output of the three components to produce shapefiles of the sensitivity, hazards, and adaptive capacity indices, as well as the overall vulnerability. These shapefiles were used to develop the final maps in QGIS for visualization and further analysis.

3. RESULTS AND DISCUSSION

3.1. Sensitivity Index

Agricultural production in the Philippines is projected to be significantly affected by climate change. A study by the World Food Programme (WFP) in 2022 showed that future crop suitability in most areas in BARMM, including Sulu, will be unfavorable for growing several crops because of the projected increase in temperature and annual rainfall by the year 2050 using the RCP 8.5 scenario. Similarly, results of the sensitivity analysis in Sulu as shown in **Figure 6**, **Figure 7**, and **Table 4** revealed that rice and coconut production areas in the province will be generally less suitable by 2050.

Figure 6. Sensitivity map for rice production areas in Sulu. A) Baseline (current) suitability; B) Future suitability

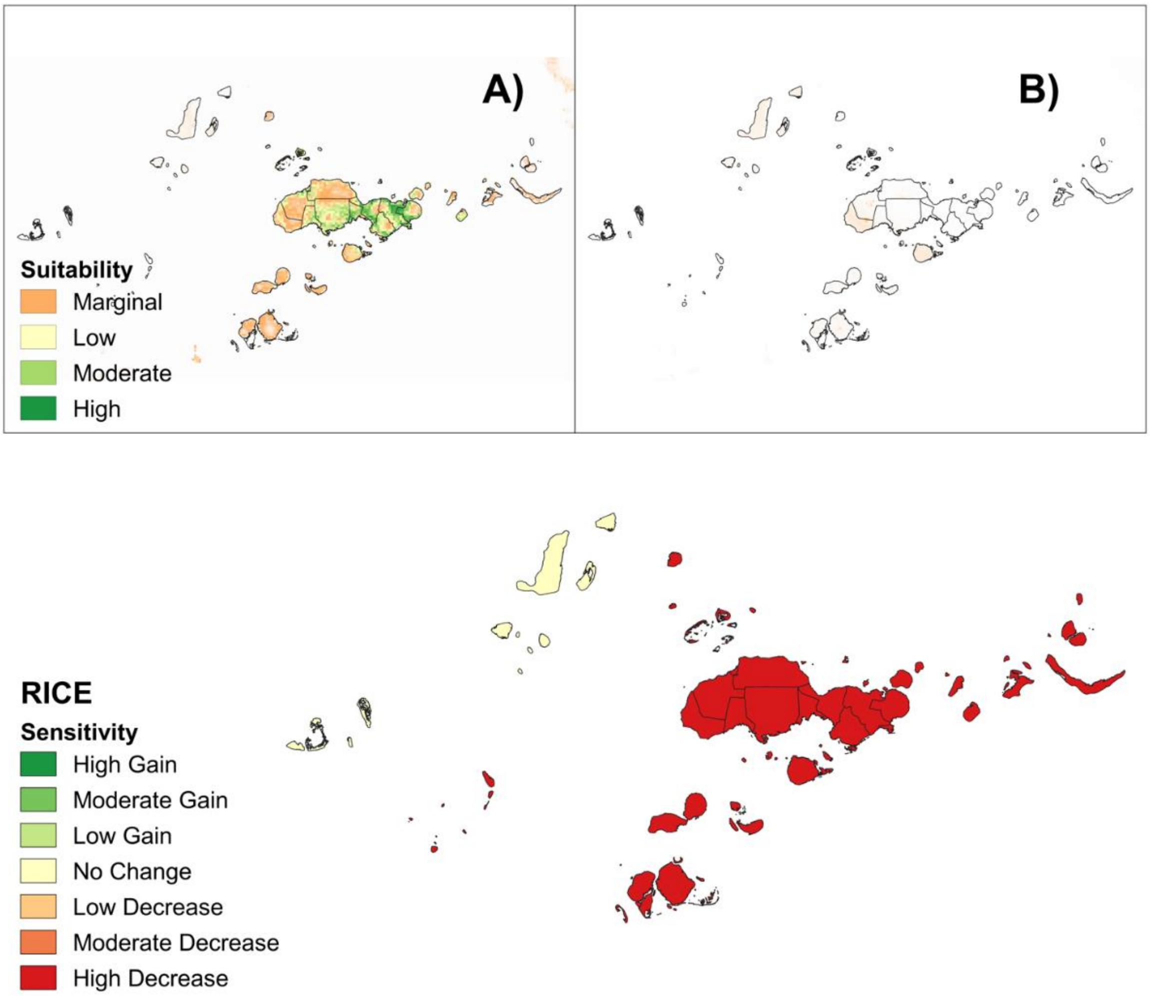


Figure 7. Sensitivity map for coconut production areas in Sulu. A) Baseline (current) suitability; B) Future suitability

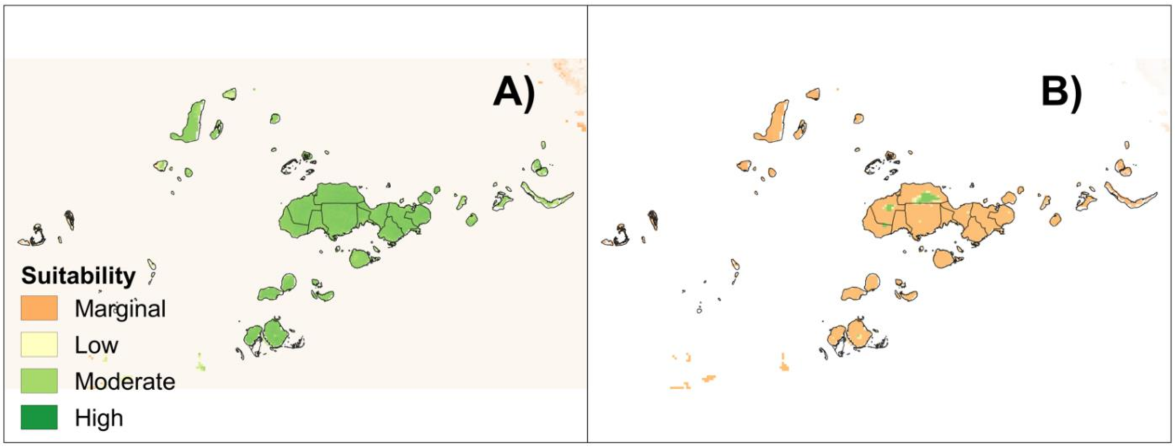


Table 4. Summary of sensitivity indices for rice and coconut production areas in Sulu

Crop	Sensitivity	City/Municipality
Rice	High Decrease	Tongkil, Talipao, Kalingalan Caluang, Lugu, Maimbung, Jolo, Patikul, Pata, Omar, Luuk, Tapul, Pandami, Siasi, Parang, Indanan, Panglima Estino, Old Panamao, Hadji Panglima Tahil
	No Change	Pangutaran
Coconut	Low Decrease	Patikul
	High Decrease	Pangutaran, Tongkil, Talipao, Kalingalan Caluang, Lugus, Maimbung, Jolo, Pata, Omar, Luuk, Tapul, Pandami, Siasi, Parang, Indanan, Panglima Estino, Old Panamao, Hadji Panglima Tahil

For rice sensitivity, the municipality of Pangutaran will remain having marginal suitability by 2050 while the rest of the 18 municipalities will have high decrease in suitability.

Based on the results of the MaxEnt model, the potential distribution of rice in Sulu is strongly influenced by bioclimatic factors (see **Annex** 1) including precipitation seasonality (Bio 15), minimum temperature of the coldest month (Bio 6), isothermality (Bio 3), and maximum temperature of the warmest month (Bio 5), which contribute 33.4%, 16.3%, 11.8%, and 23.7%.

to the suitability of rice, respectively. The changes in temperature heavily affect soil moisture content, in turn affecting rice growth, which contributes to climate-driven production variability, especially during the dry season (Stuecker et al., 2018).

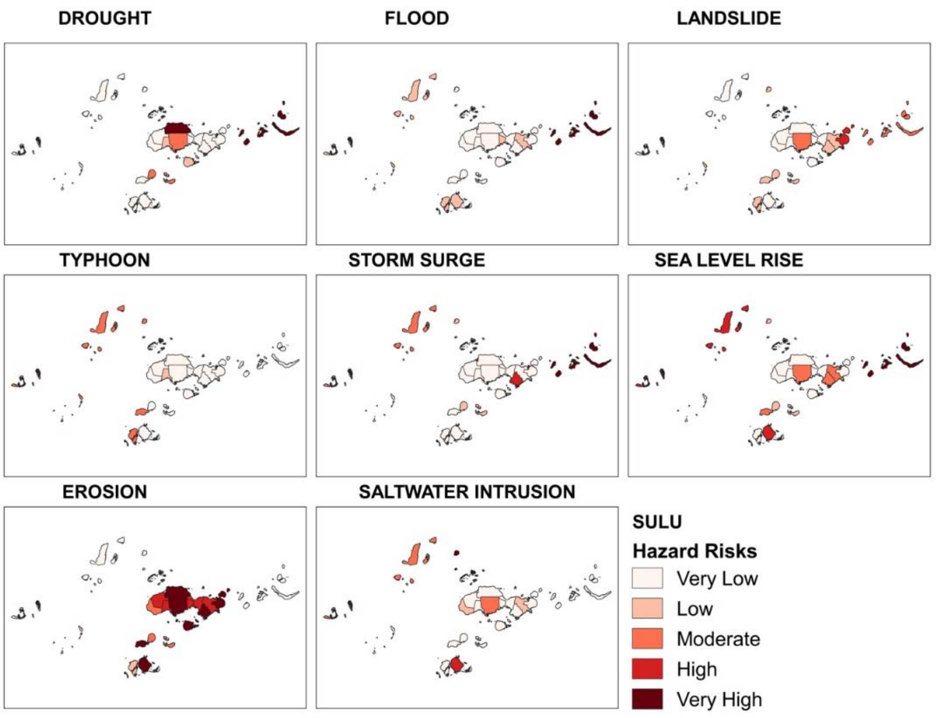
On the other hand, coconut production areas in Sulu will also be less suitable by 2050. The municipality of Patikul will have a low decrease while the rest of Sulu will have a high decrease in coconut suitability.

As a tropical plant, production of coconut is also determined by temperature and changes in precipitation. Results of the MaxEnt model showed that precipitation seasonality (Bio 15), mean diurnal range (Bio 2), and isothermality (Bio 3) had the highest percent contribution affecting future suitability of coconut in the province, contributing 39.1%, 16.6%, 11.7% to the suitability of coconut. According to Hebbar et. al. (2022), the optimal temperature for growth of coconut is 27°C ± 5°C. However, analysis from the study by WFP (2023) revealed that most areas in BARMM will experience higher temperatures (greater than 30ºC) and a 5% increase in the amount of annual rainfall in 2050 under the RCP 8.5 scenario. This analysis, together with the results of the Maxent model showing that variations in monthly precipitation and temperature are determinants of coconut suitability, may explain the high sensitivity of coconut production areas in the province.

3.2. Exposure Index

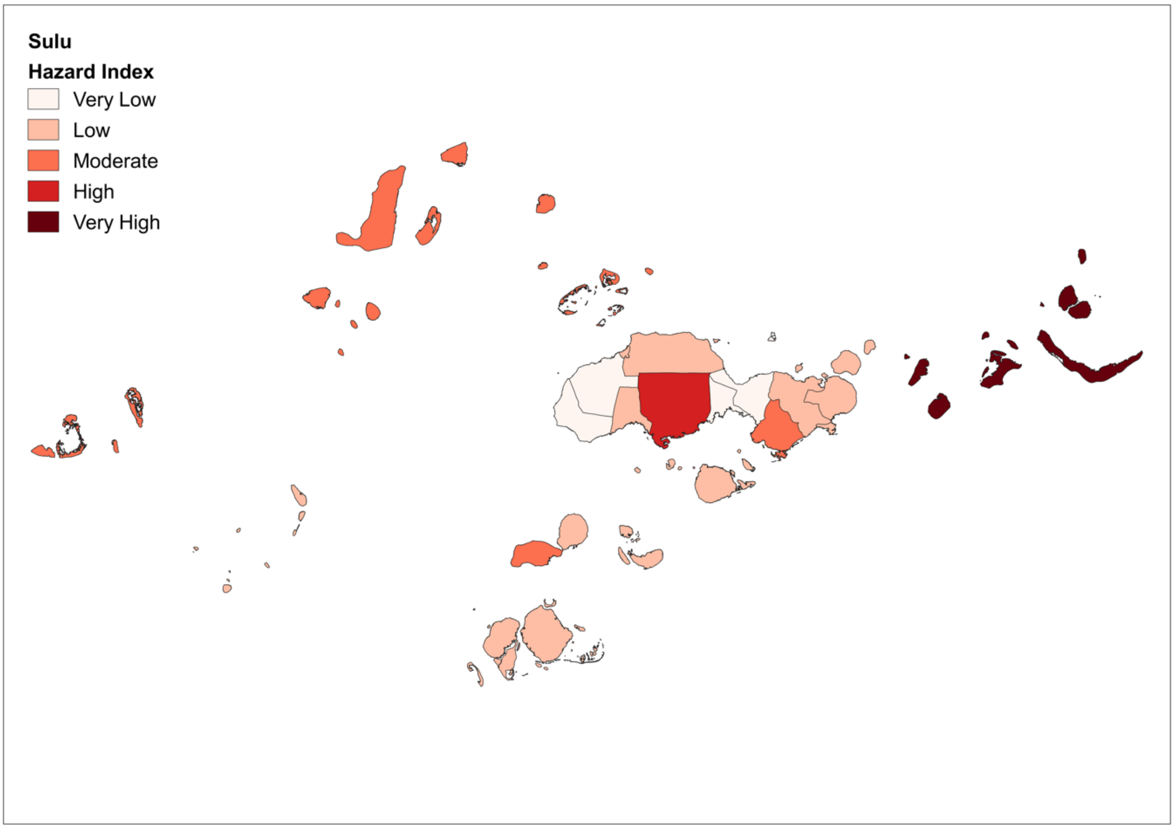
Figure 8 shows the degree of exposure to hazards across the municipalities of Sulu. Based on the assessment, these municipalities have higher exposure to drought, landslides, sea level rise, and erosion. On the other hand, all of the municipalities in Sulu have very low to moderate exposure to flood, typhoon, storm surge, and saltwater intrusion except for the municipality of Banguingui which has the highest incidences for flood and storm surge.

Figure 8. Individual hazard maps for eight climate risks in Sulu



The overall hazard map (**Figure 9*)*** shows that the municipalities of Banguingui and Talipao have very high and high exposure to hazards, respectively. Aside from flood and storm surge, Banguingui is also susceptible to drought (very high), landslides (moderate), and sea level rise (very high). The municipality of Talipao, on the other hand, has moderate exposure to drought, landslide, sea level rise, and saltwater intrusion, and very high exposure to erosion. On the other hand, the municipalities of Maimbung, Jolo, Patikul, Pata, Omar, Luuk, Tapul, Pandami, and Siasi (low); and Parang, Indanan, Panglima Estino, and Old Panamao (very low) have low to very low exposure indices.

Figure 9. Overall exposure map of Sulu



3.3. Adaptive Capacity Index

Figure 10 and **Table 5** show the overall adaptive capacity of the municipalities in Sulu.

Figure 10. Overall adaptive capacity map of Sulu

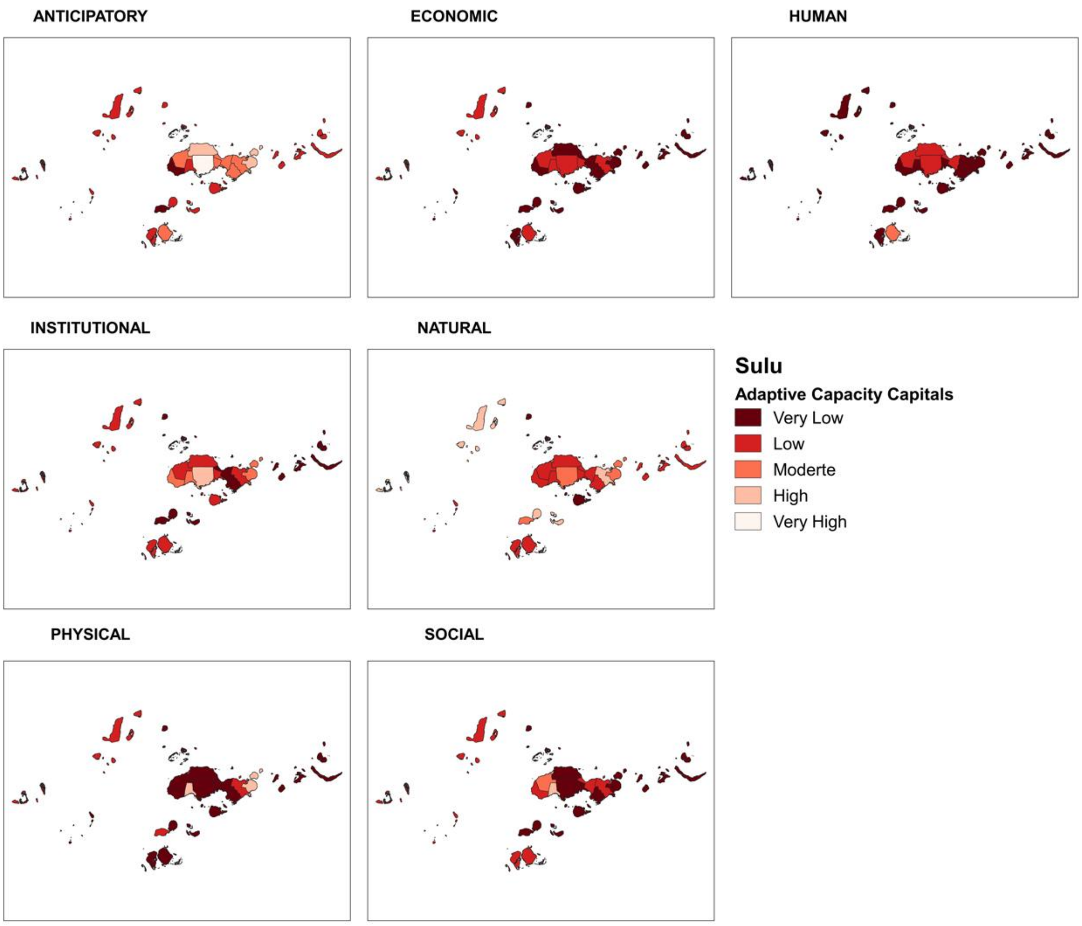
Results of the assessment showed that the municipalities of Jolo and Maimbung have very high and high adaptive capacities, respectively. These are both first class municipalities which have the highest capitals, except for human indicators.

On the other hand, 63% or 12 out of the 19 municipalities in Sulu have low to very low adaptive capacity. As seen in **Table 5** and **Figure 11**, the municipalities of Banguingui, Pandami, Lugus, Tapul, Pata, Kalinganan Caluang, Panglima Estino, Parang and Hadji Panglima Tahil have very low adaptive capacity while Pangutaran, Patikul, and Old Panamao have low indices for this component.

Table 5. Summary of adaptive capacity indices of the municipalities in Sulu

Adaptive Capacity	Municipality
Very High	Jolo
High	Maimbung
Moderate	Luuk, Omar, Siasi, Indanan, Talipao
Low	Pangutaran, Patikul, Old Panamao
Very Low	Banguingui, Pandami, Lugus, Tapul, Pata, Kalinganan Caluang, Panglima Estino, Parang, Hadji Panglima Tahil

Figure 11. Individual maps for adaptive capacity capitals in Sulu



Moreover, it is also evident that the majority of the areas in Sulu have low values across all the adaptive capacity capitals, particularly on economic, human, physical, and social indicators. Human capital includes health and education sectors and since most of the areas do not have many amounts of manpower for health- and education-related services such as doctors and teachers, values are generally low for the province. Additionally, low infrastructure investments, particularly for road networks and transport vehicles resulted in low to very low physical capitals for Sulu.

3.4. Overall Vulnerability

Figure 12 and **Figure 13** show the overall vulnerability maps of rice and corn, respectively.

Figure 12. Overall vulnerability map of rice production areas in Sulu

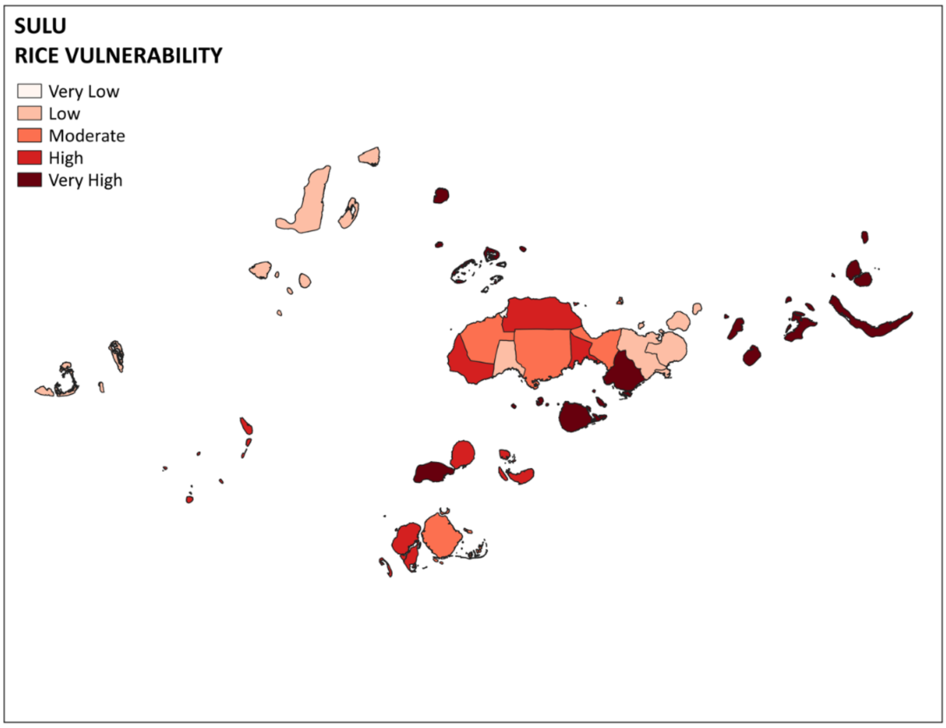
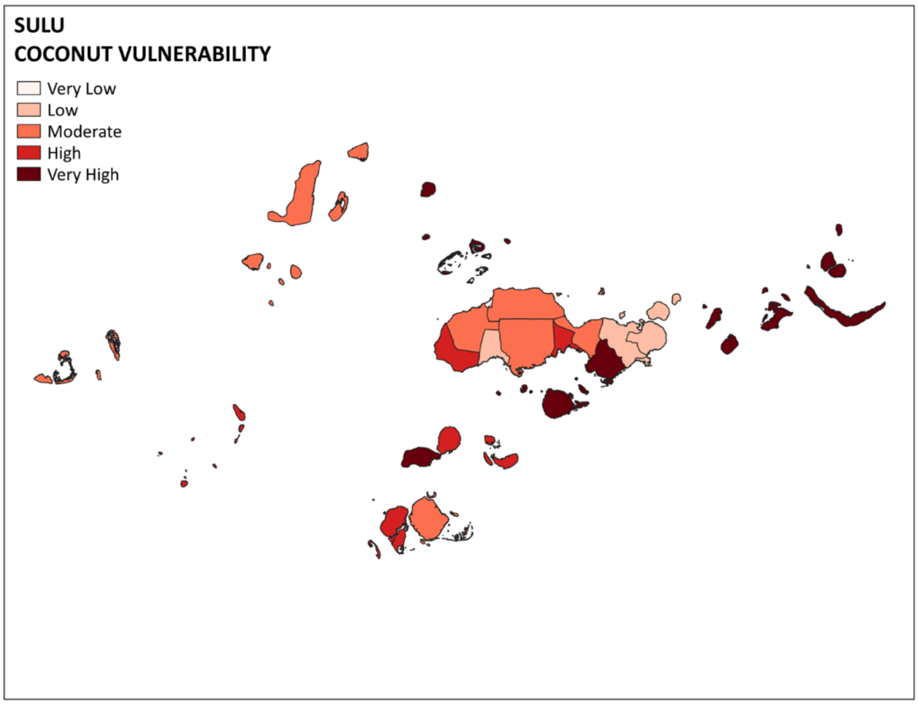


Figure 13. Overall vulnerability map of coconut production areas in Sulu



As also seen in **Table 6**, 53% of municipalities in Sulu have high to very high vulnerability for rice, including the municipalities of Banguingui, Kalingalan Caluang, Pata, Lugus, and Hadji Panglima Tahil (very high); and Patikul, Parang, Panglima Estino, Tapul, and Pandami (high).

On the other hand, municipalities with higher adaptive capacities were classified with low to very low vulnerability including Maimbung, Luuk, Omar, and Pangutaran (low); and Jolo (very low).

Table 6. Summary of overall vulnerability indices of rice production areas in Sulu

Vulnerability	Municipality/City
Very High	Banguingui, Kalingalan Caluang, Pata, Lugus, Hadji Panglima Tahil
High	Patikul, Parang, Panglima Estino, Tapul, Pandami
Moderate	Indanan, Talipao, Old Panamao, Siasi
Low	Maimbung, Luuk, Omar, Pangutaran
Very Low	Jolo

On the other hand, **Table 7** shows that 47% of coconut production areas in the province were highly to very highly vulnerable to climate change impacts. These include Parang, Panglima Estino, Tapul, and Pandami (high); and Banguingui, Kalingalan Caluang, Pata, Lugus, and Hadji Panglima Tahil (very high). Meanwhile, Maimbung, Luuk, and Omar (low) and Jolo (very low) have low to very low vulnerability results.

Table 7. Summary of overall vulnerability indices of coconut production areas in Sulu

Vulnerability	Municipality/City
Very High	Banguingui, Kalingalan Caluang, Pata, Lugus, Hadji Panglima Tahil
High	Parang, Panglima Estino, Tapul, Pandami
Moderate	Pangutaran, Indanan, Patikul, Talipao, Old Panamao, Siasi
Low	Maimbung, Luuk, Omar
Very Low	Jolo

4. CLIMATE RESILIENT AGRICULTURE PRACTICES

Rice is a staple food in the province, and in the face of growing demand and worsening climate conditions, production may become insufficient which would jeopardize food security. Hence, it is important to promote climate-resilient practices to help agricultural communities reduce their vulnerability. Strategies to increase resilience may include cultivation of more resilient crops, the adoption of sustainable agricultural practices, crop diversification, and technological innovations. As many areas in Sulu are more susceptible to landslide and erosion, terracing has been one of the most important systems for preventing soil erosion, conserving water, and increasing rice production. Other sustainable agricultural practices that can help manage these hazards include crop rotation, cover cropping, mulching, and contour plowing.

The use of more resistant rice varieties or other crops that can naturally tolerate stressful conditions such as drought and flood are also recommended, especially in areas susceptible to these hazards. Using multiple varieties allows greater flexibility to respond to climate-related impacts and promotes biodiversity that is fundamental in building resilient agricultural systems (Mundiriso, 2023).

The coconut sector also faces several challenges such as low productivity and aging palms. For areas with high vulnerability to climate change, it is recommended to practice diversification through agro-forestry and integrated land management. Inter-cropping of other crops such as cacao, and other high value crops allows for higher biodiversity than conventional agricultural systems and provides more sources of livelihood and income. Additionally, this practice will create a more conducive environment for preventing soil erosion since more roots and organic matter are found in soil which enhances its capability to absorb more water to stand adverse conditions such as drought (Schewee, 2021).

For both rice and coconut sectors, nature-based solutions provide more sustainable and strategic options that support environmental protection and socio-economic development. Since majority of the areas in the province are susceptible to landslide and erosion, and that data from the Global Forest Watch (n.d.) shows that from 2002-2022, Sulu province already lost 517 ha (10%) of primary forest, restoration of forest ecosystem is recommended. This will not only minimize the exposure to hazards of areas most-at-risk but can also improve adaptive capacity of communities through increasing their natural capital.

5. SUMMARY AND CONCLUSION

The results of the CRVA showed that most rice and coconut production areas in Sulu have moderate to very high vulnerability to climate change impacts. The hazard maps showed that many areas in the province are most susceptible to drought, landslides, sea level rise, and erosion. Future climate scenarios also showed that there would be less conducive environments for rice and coconut production throughout the province. Moreover, most of the areas have generally high vulnerability because of low adaptive capacity. Across the province, data showed that most of the municipalities have low economic, human, physical, and social capacities.

The use of the automated CRVA tool was also found to increase efficiency as it reduced processing time and minimized potential human errors. Data for the indicators used in the study are also constantly being updated, and the automated CRVA tool provides an opportunity for users to conveniently enhance their respective CRVAs in the future. Given that climate data projections are continuously evolving, it is necessary that the SDM be updated regularly to reflect the most recent climate projections whenever new datasets are available. Additionally, provincial boundaries were used in the analysis as opposed to climatic boundaries, which limited the MaxEnt model's use of the full climatic/environmental ranges. It is recommended to explore preserving the extent of the climate data boundaries at the regional level or at least set a 20-km buffer when clipping the raster file, to avoid overfitting the SDM and to generate more reliable results.

Given the CRVA results, developing climate change adaptation strategies to safeguard the rice and coconut sectors from potential risks is of utmost importance to sustain production, and to promote resilience and structural transformation among the most susceptible areas in the province. As agriculture faces several threats in the future, there is a need to remove dependency on only one form of livelihood, diversify livelihoods and introduce other income generating activities through skills and micro-enterprise development, and integrate climate-resilient interventions into local policies, based on the prevailing vulnerability to climate risks.

It is envisioned that the results of this CRVA will serve as a guide for agricultural planners in Sulu in crafting evidence- and science-based interventions to build more climate-resilient and sustainable agricultural communities in the province.

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7. ANNEXES

7.1. Annex 1. List of the 19 bioclimatic indicators used in running the SDM using MaxEnt

Parameters	Description (O'Donnell, M and Ignizio, D., 2012)
Temperature Related	
Bio_1 - Annual mean temperature	Annual mean temperature derived from the average monthly temperature.
Bio_2 - Mean diurnal range	The mean of the monthly temperature ranges (monthly maximum minus monthly minimum).
Bio_3 - Isothermality	Oscillation in day-to-night temperatures.
Bio_4 - Temperature seasonality	The amount of temperature variation over a given year based on standard deviation of monthly temperature averages.
Bio_5 - Maximum temperature of warmest month	The maximum monthly temperature occurrence over a given year (time-series) or averaged span of years (normal).
Bio_6 - Minimum temperature of coldest month	The minimum monthly temperature occurrence over a given year (time-series) or averaged span of years (normal).
Bio_7 - Temperature annual range	A measure of temperature variation over a given period.
Bio_8 - Mean temperature of wettest quarter	This quarterly index approximates mean temperatures that prevail during the wettest season.
Bio_9 - Mean temperature of driest quarter	This quarterly index approximates mean temperatures that prevail during the driest quarter.
Bio_10 - Mean temperature of warmest quarter	This quarterly index approximates mean temperatures that prevail during the warmest quarter.
Bio_11 - Mean temperature of coldest quarter	This quarterly index approximates mean temperatures that prevail during the coldest quarter.
Precipitation Related	
Bio_12 - Annual precipitation	This is the sum of all total monthly precipitation values.
Bio_13 - Precipitation of wettest month	This index identifies the total precipitation that prevails during the wettest month.
Bio_14 - Precipitation of driest month	This index identifies the total precipitation that prevails during the driest month.
Bio_15 - Precipitation seasonality	This is a measure of the variation in monthly precipitation totals over the course of the year. This index is the ratio of the standard deviation of the monthly total precipitation to the mean monthly total precipitation and is expressed as percentage.
Bio_16 - Precipitation of wettest quarter	This quarterly index approximates total precipitation that prevails during the wettest quarter.
Bio_17 - Precipitation of driest quarter	This quarterly index approximates total precipitation that prevails during the driest quarter.
Bio_18 - Precipitation of warmest quarter	This quarterly index approximates total precipitation that prevails during the warmest quarter.
Bio_19 - Precipitation of coldest quarter	This quarterly index approximates total precipitation that prevails during the coldest quarter.

7.2. Annex 2. List of the 33 GCMs and their corresponding modelling center/institution

Model	Modeling Center	Institution
bcc_csm1_1	BCC	Beijing Climate Center, China Meteorological Administration
bcc_csm1_1_m	BCC	Beijing Climate Center, China Meteorological Administration
bnu_esm	GCESS	College of Global Change and Earth System Science, Beijing Normal University
cccma_canesm2	CCCMA	Canadian Centre for Climate Modelling and Analysis
cesm1_bgc	NSF-DOE-NCAR	National Science Foundation, Department of Energy, National Center for Atmospheric Research
cesm1_cam5	NCAR	National Center for Atmospheric Research
cnrm_cm5	CNRM-CERFACS	Centre National de Recherches Meteorologiques / Centre Europeen de Recherche et Formation Avancees en Calcul Scientifique
csiro_access1_0	CSIRO-BOM	CSIRO (Commonwealth Scientific and Industrial Research Organisation, Australia), and BOM (Bureau of Meteorology, Australia)
csiro_access1_3	CSIRO-BOM	CSIRO (Commonwealth Scientific and Industrial Research Organisation, Australia), and BOM (Bureau of Meteorology, Australia)
csiro_mk3_6_0	CSIRO-QCCCE	Commonwealth Scientific and Industrial Research Organization in Collaboration with the Queensland Climate Change Centre of Excellence
ec_earth	EC-EARTH	EC-EARTH Consortium
fio_esm	FIO	The First Institute of Oceanography, SOA, China
gfdl_cm3	NOAA GFDL	Geophysical Fluid Dynamics Laboratory
gfdl_esm2g	NOAA GFDL	Geophysical Fluid Dynamics Laboratory
gfdl_esm2m	NOAA GFDL	Geophysical Fluid Dynamics Laboratory
giss_e2_h	NASA GISS	NASA Goddard Institute for Space Studies
giss_e2_r	NASA GISS	NASA Goddard Institute for Space Studies
inm_cm4	INM	Institute for Numerical Mathematics
ipsl_cm5a_lr	IPSL	Institut Pierre-Simon Laplace
ipsl_cm5a_mr	IPSL	Institut Pierre-Simon Laplace
ipsl_cm5b_lr	IPSL	Institut Pierre-Simon Laplace
lasg_fgoals_g2	LASG-CESS	LASG, Institute of Atmospheric Physics, Chinese Academy of Sciences; and CESS, Tsinghua University
miroc_esm	MIROC	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies
miroc_esm_chem	MIROC	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies
miroc_miroc5	MIROC	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology
mohc_hadgem2_cc	MOHC (additional realizations by INPE)	Met Office Hadley Centre (additional HadGEM2-ES realizations contributed by Instituto Nacional de Pesquisas Espaciais)
mohc_hadgem2_es	MOHC (additional realizations by INPE)	Met Office Hadley Centre (additional HadGEM2-ES realizations contributed by Instituto Nacional de Pesquisas Espaciais)
mpi_esm_lr	MPI-M	Max Planck Institute for Meteorology (MPI-M)
mpi_esm_mr	MPI-M	Max Planck Institute for Meteorology (MPI-M)
mri_cgcm3	MRI	Meteorological Research Institute
ncar_ccsm4	NCAR	National Center for Atmospheric Research
ncc_noresm1_m	NCC	Norwegian Climate Centre
nimr_hadgem2_ao	NIMR/KMA	National Institute of Meteorological Research/Korea Meteorological

7.3. Annex 3. Detailed methodology for crop occurrence generation using remote sensing

The team employed the latest technologies, including remote sensing, satellite imagery, and artificial intelligence/machine learning, for the collection of crop occurrence data. The utilization of these advanced technological methods offers numerous advantages. It enables the rapid collection of data across vast and potentially inaccessible areas, bypassing the logistical challenges and time-consuming nature of traditional ground surveys. Moreover, remote sensing and satellite technologies provide high-resolution imagery that can be analyzed to detect crops.

The crop occurrence data was collected by leveraging Google Earth Engine (GEE), a powerful cloud-based platform for planetary-scale environmental data analysis. This platform utilizes a multi-petabyte catalog of satellite imagery and geospatial datasets, enabling researchers and analysts to detect changes, map trends, and quantify differences on the Earth's surface. Using GEE, the team was able to efficiently access and process large volumes of satellite images to identify areas of crop cultivation in the region. The process involved selecting specific satellite data that provide high-resolution images suitable for agricultural analysis, such as those from the Landsat and Sentinel series. By applying advanced image processing algorithms and machine learning techniques within the GEE framework, the team was able to extract detailed information about crops including location and types. The GEE Script prepared for this project to identify crop occurrence in the BARMM provinces can be access from the following link.

https://code.earthengine.google.com/?accept_repo=users/rynekem/CRVA

For identifying the crop occurrence using GEE, the following steps were followed:

Access Google Earth Engine

Begin by accessing the GEE platform, which requires a Google account and registration for access to its resources. GEE provides a web-based IDE (Integrated Development Environment) for developing and executing your analysis scripts.

Define the Study Area / Area of Interest

The identification of the area of interest or study area, which encompasses specific provinces, was accomplished by uploading the shapefile representing the boundaries of these provinces. This shapefile was formatted in EPSG: 4326 (WGS 84), ensuring it adheres to the global coordinate system for accurate geospatial analysis.

Select Satellite Datasets

Appropriate satellite imagery datasets, deemed suitable for crop analysis, were selected. Given the emphasis on high spatial resolution, Sentinel-2 emerged as the common choice. These datasets were provided free of charge within the Google Earth Engine (GEE) data catalog. The dataset (image) was selected based on the following aspect:

- Growing season of crops: Specific images were selected based on the growing season of the selected crops.
- Recent data: Image that were taken recent time were prioritized.
- Cloud coverage: Images that have less cloud coverage were selected.

Preprocess the Data

Preprocessing steps were applied to the selected satellite images. This included correcting for atmospheric conditions, implementing cloud masking to remove images with significant cloud cover, and normalizing images to account for differences in satellite passes.

Training Data Preparation

This process involved the gathering of data necessary for training machine learning models or conducting analysis on crop types and distribution, utilizing Google Maps, a tool that provides access to satellite imagery and often includes labels or annotations for various features, including agricultural fields. This dataset called "Ground Truth" was then used to train algorithms to recognize crop types automatically or to analyze the spatial distribution of different crops.

- Careful Inspection of Crops on Google Maps: The initial step was the navigation through Google Maps for the visual inspection of areas known or suspected to be agricultural fields. The high-resolution satellite images available on Google Maps allowed for the observation of different land use patterns and the distinction between various types of vegetation, including different crop species.
- Identification of Crop Fields Labeled on Google Maps: Often, agricultural fields on Google Maps were found tagged with names or types of crops being cultivated. These labels, which could be user-generated or derived from various data sources integrated into Google Maps, helped in confirming the types of crops grown in each field.

The ground truth data was divided into training and validation sets for the Training and Validation Split. The training set was utilized to train the classification model, whereas the validation set was employed to evaluate its performance.

- Training Set: A subset of the ground truth data used to train the model. The model learns to make predictions or classify data points based on the patterns it identifies in this dataset. Around 300-500 training data for each corps were used depending on the accuracy for each province.
- Validation Set: Another subset of the ground truth data, separate from the training set, used to evaluate the model's performance. The validation set tests how well the model generalizes to new, unseen data. It's crucial for detecting overfitting, where the model performs well on the training data but poorly on new data.

Classification Model Selection and Training

A suitable machine learning algorithm for classification was chosen. In the context of Google Earth Engine (GEE), Random Forest is a common choice for crop classification due to its effectiveness and efficiency in handling spatial data and its ability to manage high-dimensional datasets.

The chosen algorithm - Random Forest, was trained using the training data. This process involved providing the algorithm with features and the corresponding labels of different crop types. The training phase allows the algorithm to learn the relationship between the features of the imagery and the crop types, enabling it to classify the type of crop present in unseen data accurately.

Classification and Accuracy Assessment

The trained model was applied to classify the entire image or image collection, predicting the crop type for each pixel. This step involved processing the satellite images through the model to assign a crop label to every pixel based on the learned patterns during training. This process transforms the raw satellite imagery into a classified map showing the distribution of different crops across the area of interest.

The model's performance was evaluated using the validation data. Key metrics were calculated to assess the accuracy of the model, including overall accuracy (the proportion of total pixels correctly classified), producer's accuracy (the accuracy for each crop class from the perspective of the data producer, indicating the likelihood that a certain class is correctly classified), and user's accuracy (the proportion of pixels classified into a certain class that were correctly classified, indicating the reliability of the model's classification for each class). This step is critical for understanding the model's strengths and weaknesses and for identifying areas where model performance might be improved.

Export Data

The classified data was exported as point shapefile for further analysis, which included the validation of the data during a workshop and its incorporation into the automated Climate Risk and Vulnerability Assessment (CRVA) system.

7.4. Annex 4. The Automated CRVA Tool

The CRVA system was architected to provide a holistic evaluation of climate risk vulnerabilities through an automated, multidisciplinary approach. The methodology synthesizes a vast array of data sources, leveraging sophisticated programming languages and analytical tools to automate the assessment process.

Following the DA-AMIA CRVA framework and methodology for crops, the automated system was designed integrating the three components of vulnerability: exposure to climate hazards, the sensitivity of crops to climate change, and the adaptive capacity of local communities:

Exposure Assessment utilizes spatial analysis to quantify the risk posed by various climate hazards, including but not limited to typhoons, floods, droughts, and sea-level rise. The assessment draws upon historical climate event data and predictive modeling to determine the frequency, intensity, and geographic distribution of these hazards.

Sensitivity Analysis is conducted using the Maximum Entropy (MaxEnt) modeling approach to predict the climatic suitability of key agricultural crops under future climate scenarios. This component employs an ensemble of Global Circulation Models (GCMs) to project environmental variables, such as temperature and precipitation changes, that influence crop viability. The sensitivity analysis is vital in identifying crops at risk of reduced suitability due to climatic shifts, informing adaptive agricultural practices.

Adaptive Capacity Evaluation examines the resilience of communities to climate impacts through a comprehensive set of indicators encompassing economic, natural, human, physical, and institutional capitals. This assessment is informed by current and projected socio-economic data, infrastructure, health, and educational resources, as well as governance and policy frameworks that influence the ability of communities to respond to climate change.

The automation of the CRVA process is enabled by a robust technological framework comprising several programming languages and tools:

- **PHP** is utilized for server-side scripting, managing dynamic web content, and facilitating user interaction with the assessment platform.
- **Python** serves as the backbone for data analysis, running MaxEnt models, and handling large datasets. Python's extensive libraries support sophisticated statistical analysis and machine learning tasks.
- **R** is employed for its statistical computing capabilities, particularly in analyzing the adaptive capacity indicators and generating complex visualizations of vulnerability data.
- **Java** ensures the system's backend stability, scalability, and security, managing the processing of large-scale data analyses.
- **JavaScript** enhances the system's front end, enabling the dynamic presentation of assessment results through interactive maps and visualizations.

Use of the Automated System on Future CRVAs

The inception of the automated CRVA system represents a paradigm shift in climate risk assessment methodology, transitioning from manual, labor-intensive processes to a streamlined, automated, and data-driven approach. This shift is underscored by several key advancements:

- **Consistency and Accuracy**: The automated system ensures methodological consistency across different assessments, reducing human error and increasing the reliability of vulnerability analyses.
- **Efficiency and Scalability**: Leveraging advanced computing and analytical models allows for rapid processing of complex data sets, enabling timely updates and scalable assessments across broader geographical regions.
- **Comprehensive Data Integration**: Automated data handling and integration capabilities facilitate a holistic view of climate risks, combining diverse data sources into a coherent assessment framework.
- **Enhanced Decision-Making**: The system provides stakeholders with detailed, accessible insights into climate vulnerabilities, supporting informed decision-making for climate adaptation and resilience-building efforts.

By automating the CRVA process, the system not only enhances the efficiency and scope of vulnerability assessments but also significantly improves the quality and accessibility of information available for climate adaptation planning. This technological advancement marks a critical step forward in the global effort to mitigate climate risks and build resilient communities in the face of accelerating climate change.

7.5. Annex 5. Vulnerability indices for Sulu

Municipality	Hazard Index	AC Index	AC Inverted	Coconut Sens Index	Coconut Vulnerability	Rice Sens Index	Rice Vulnerability
Hadji Panglima Tahil	0.44	0.04736	0.95264	1	0.86	1	0.86
Indanan	0.05	0.4705	0.5295	1	0.41	1	0.41
Jolo	0.37	1	0	1	0	1	0
Kalingalan Caluang	0.44	0.06908	0.93092	1	0.85	1	0.85
Lugus	0.49	0	1	1	0.91	1	0.91
Luuk	0.37	0.55533	0.44467	1	0.4	1	0.4
Maimbung	0.3	0.6843	0.3157	1	0.27	1	0.27
Old Panamao	0	0.25396	0.74604	1	0.59	1	0.59
Omar	0.36	0.56111	0.43889	1	0.38	1	0.38
Pandami	0.36	0.10781	0.89219	1	0.79	1	0.79
Panglima Estino	0.11	0.13259	0.86741	1	0.72	1	0.72
Pangutaran	0.48	0.38399	0.61601	1	0.56	0	0.37
Parang	0.04	0.17431	0.82569	1	0.67	1	0.67
Pata	0.29	0.00264	0.99736	1	0.87	1	0.87
Patikul	0.39	0.29743	0.70257	0.5	0.54	1	0.63
Siasi	0.38	0.42433	0.57567	1	0.51	1	0.51
Talipao	0.72	0.55926	0.44074	1	0.46	1	0.46
Tapul	0.4	0.16	0.84	1	0.76	1	0.76
Tongkil (Banguingui)	1	0.01506	0.98494	1	1	1	1