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Climate-risk vulnerability assessment of the agriculture sector in the municipalities and cities of Bukidnon, Philippines

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Abstract

Climate change is happening and is causing a huge problem to agriculture. It is affecting the agriculture sector of many places and certainly the province of Bukidnon, known as the food basket of Mindanao, is included. With its limited resources, the government has to target and prioritize sites that urgently need for programs relative to climate change adaptation and mitigation. To achieve this, an assessment of the climate-risk vulnerability of the agriculture sector in the municipalities and cities of Bukidnon was conducted. The CIAT framework to vulnerability assessment was employed in this study. Our results have shown that the municipalities of Kitaotao and Damulog have the most vulnerable agriculture sector in Bukidnon. This is mainly because these two municipalities obtained the lowest adaptive capacity ratings. As the results have indicated, this study recommends for the prioritization of Kitaotao and Damulog in the selection of sites to implement climate change adaptation and mitigation initiatives and projects to uplift the agriculture sector of Bukidnon.

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Introduction

Agriculture is an important component of the Philippine economy, employing more than 1/3 of all workers and contributing 13% of its GDP (World Bank, 2015). Its top 2 most important crops are rice and corn. Lowest income households rely heavily on rice for their daily caloric requirement (David and Balisacan, 1995) while many upland settlers still consume corn. The growing livestock industry of the country also relies on adequate production of corn because it is mostly used as feeds. Despite this, the country is facing various challenges in food production including the other crops like Coffee, Tomato and Cacao. Extreme weather events like typhoon and flooding are very common occurrences and had always brought agricultural production to its lowest.

Climate impacts many aspects of agriculture both in direct and indirect ways (Wiréhn *et al.* 2015). Food production, which is the heart of agriculture, is heavily dependent on climate (Lobell and Gourdji, 2012), specifically on appropriate temperature and precipitation ranges for ideal growth of crops. Slight shifts in climate might mean heavy losses in production. Farmers are in the frontline in terms of food production. As climatic shifts continue to worsen, the livelihood of farmers is in jeopardy. Crops are both affected by extreme weather as well as the different climate hazards. These include typhoon, landslides, flooding and soil erosion and the magnitude and incidence of these hazards is projected to rise under a climate change scenario (Field, 2012). Climate change can become an obstacle in poverty reduction efforts and sustainable development (Fahad and Wang, 2018). It is therefore imperative that adaptation and mitigation strategies be developed to aid our farmers most especially those who are in the marginalized sector in coping up with climate change.

The Philippines is reported as one of the most affected countries in terms of climate related risks to agriculture. While rainfall is needed during the dry season, it is the above-average rainfall during the wet season that is causing damage (Lansigan *et al.* 2000). In the country, communities also have varied adaptive capacity because of economic, social, and environmental dynamics in their place. Analysis of adaptive capacity is an important component of CRVA because it enables planners to look at which capitals need improvement to enhance the resiliency of communities. The analysis of Climate-Risk Vulnerability (CRV) can be aided by geospatial means. GIS alongside other tools have been revolutionizing the way information is analyzed and presented. Assessing CRV of crops would require the modeling of its species distribution (SDM). Various modeling tools of such specification are available, however some were proven to be more robust than others. A popular modeling tool called Maxent is typically utilized in many SDM studies (Paquit *et al.* 2017). Maxent was employed in this study to come up with a crop suitability model for the five (5) crops namely; Corn, Rice, Cacao, Coffee and Tomato.

This study aimed to deepen our understanding of climate change and climate change vulnerability. This research can advance the means by which government decides on matters related to climate change mitigation and adaptation initiatives. Reliable information about the presence of highly vulnerable communities enables the LGU to see where to make relevant investments and eventually implement more pro-active measures.

Materials and Methods

Study area

Bukidnon is a landlocked province in Northern Mindanao, southern part of the Philippines (Philippine Information Agency, u.d.).

It extends geographically from 7°20' – 8°40' N to 124°30' – 125°30' E, with land area of 918, 715 hectares (calculated in GIS) representing 2.76 % of the country's total land area (Paquit *et al.* 2017). The Province comprises 20 municipalities and 2 component cities. The province is bordered by forested mountains where headwaters of various rivers originate.

A large part is gently rolling grassland and plains from which the bulk of the agricultural production comes from. Bukidnon has two prevailing types of climatic variations in the rainfall pattern existing between the northern and southern sections. The northern part falls under the third or intermediate A type. While the southern part, beginning from Malaybalay, falls under the fourth type of intermediate B type (PAGASA, 2011).

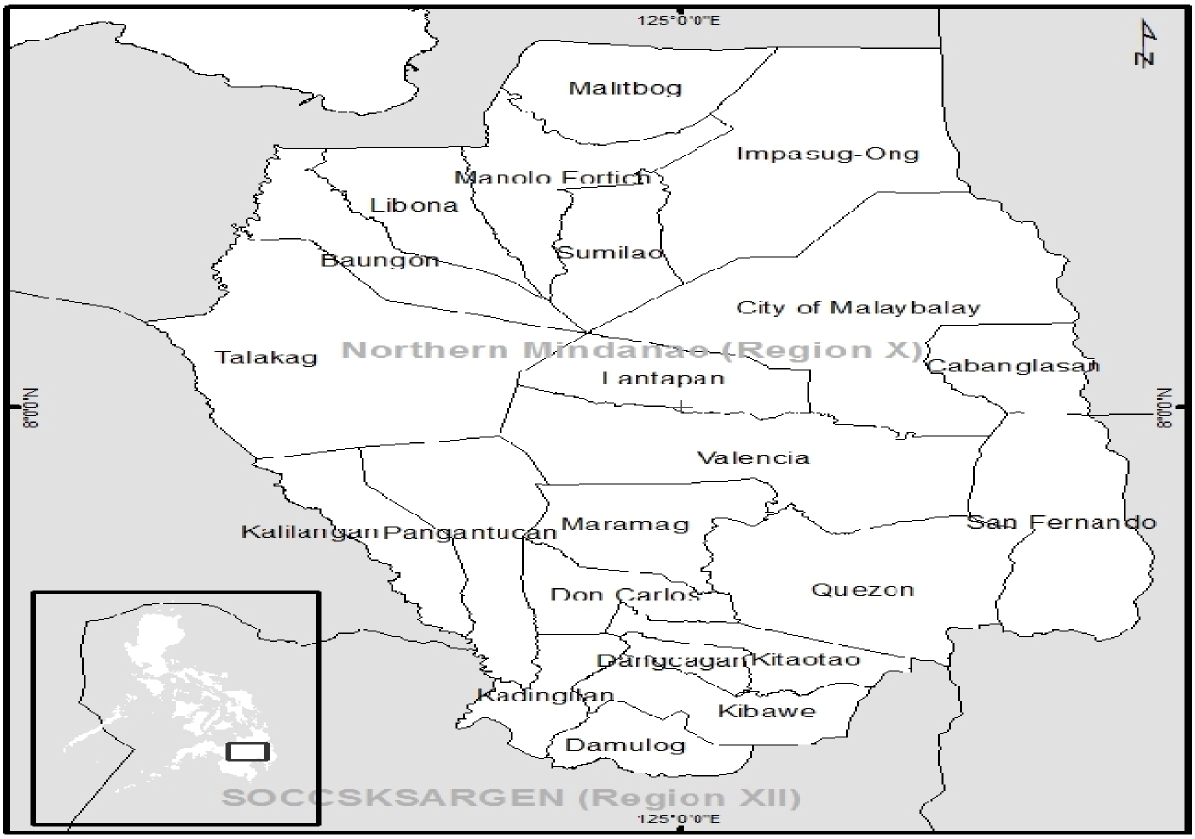

Fig. 1. Map of Bukidnon Province (Paquit and Rama, 2018).

Data Collection

Species Occurrence Points (SOPs)

Species Occurrence Points (SOPs) were gathered from local experts through a participatory mapping workshop. Representatives from the local agriculture offices, local government units and regional field offices gathered for the purpose of locating existing crop presence in the municipalities. The mapping exercise was designed to rapidly collect data instead of actual field collection. The team enhanced the map provided by CIAT by integrating the use of Google Earth. The map that depicts grids representing the resolution of the environmental variable that also contains features that can assist in locating the occurrence of crops, such as road network, river network, digital elevation model, municipal and barangay political boundaries (Philgis.org) was exported to Google Earth. The team did not solely rely on paper maps but also on digital maps. This enabled the team to validate the information drawn from local experts. The participants located the different crops that occur for each grid based on personal knowledge and also on relevant reports. The local experts also provided a data on crop yield based from national yield averages reported by the Philippine Statistics Authority. The knowledge of experts differed from crop to crop. Experts seemingly have more knowledge regarding the occurrences of Corn and Rice than on Cacao, Coffee and Tomato. This resulted to a variation in terms of the total number of occurrence points per crop. SOP data were largely in analog format after the workshop. Hence, the team initiated the digitization of the data using ArcMap ver. 10.1. Eventually, the digital data was stored in our database and later forwarded to CIAT. The integrity of the presence data was made sure by repeatedly undertaking Google Earth-based validation.

Climatic variables

20 baseline and projected climate variables were sourced out from worldclim.org (Hijmans *et al.* 2005) were used in Maxent modeling. These variables are derived from the monthly temperature and rainfall values for the purpose of producing variables that are biologically relevant. These variables represent annual, quarterly, monthly and even daily ranges in climate (Table 1.)

Geographic distribution of plants is primarily regulated by climate (Woodward, 1987). Variations in species richness, composition and diversity across latitudinal and altitudinal gradients are clearly dictated by climate. To analyze climate change impacts, we used a future downscaled climate data (year 2050) (IPCC, 2001). The 2050 data is the projected average for 2041-2060. Global Circulation Models (GCMs), which are important tools for projected climate data were spatially downscaled by CIAT using spatial statistical downscaling techniques to produce the 1-km resolution bioclimatic variables. Outputs of GCMs have coarse resolutions that require spatial downscaling for resolution enhancement. RCP 8.5 was used because of its relevance given the observed trends in greenhouse gas emissions at present.

Model Building using Maxent

Maxent (Philips *et al.* 2005) was used to model the climatic suitability of the five (5) crops. Maxent uses environmental data to model the distribution of species (Galletti *et al.* 2013). Compared with other tools, Maxent has been shown to perform better (Leathwick *et al.* 2006). Most of the data pre-processing was done in GIS. A .csv file was prepared containing all needed information regarding the species occurrence points. The coordinate reference system for all environmental variables was set to WGS 1984.All environmental raster layers were formatted to American Standard Code for Information Interchange (ASCII) format. ASCII is the common file format in modeling. For model accuracy evaluation, the AUC-ROC that was produced as one of the Maxent outputs was used. The percent influence of each environmental variable on the distribution of the species was determined using jackknife test. The result of the test was automatically produced by Maxent.

Sensitivity Analysis

Crop sensitivity was assessed by analyzing changes in climatic suitability of crops by the year 2050 in comparison with the baseline crop suitability. Sensitivity is the degree to which a system is affected, either adversely or beneficially, by climate variability or change (Läderach *et al.* 2011). The change in climatic suitability of crops between baseline and future predictions was analyzed in ArcMap using a step-by-step process that involved the use of tools such as; raster calculation, reclassification and zonal analysis. Using this protocol the potential effect of climate change to crop suitability was analyzed. Our hypothesis was centered on the idea that the 5 crops have different baseline climatic suitability and therefore would have varied response to climate change. For instance, Coffee is known to thrive in cooler areas in the province while Rice is more adapted to a warmer climate. Thus these crops will have different suitability models, both baseline and projected. CIAT formulated a sensitivity index based on percent change as depicted in Table 2. An index of 1.0 means a very high loss in suitability while and index of -1.0 means very high gain. The index equal to 0 means there is no change in suitability detected from baseline to projected.

Analysis of Exposure to Hazards

Exposure is the character, magnitude and rate of climate change and variation (Läderach *et al.* 2011). Several biophysical indicators of exposure to climate change were factored-in as summarized in Table 3 as hazards.

All hazard data were sourced-out from CIAT who managed the pooling of datasets from different sources for distribution to different SUC partners. Flood and drought data were extracted from the AMIA 1 dataset. The factors were weighted based on its impact on agriculture on the national scale and then later downscaled to the provincial level. The weighting process involved the analysis of the impact of these hazards to the economy, food security, household income and crop productivity for each municipality in Bukidnon. For each municipality, the mean value of aggregate weight was computed. Normalization was employed to generate an index from 0 to 1. Five equal breaks were used to establish the thresholds for the following classes: 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).

Analysis of Adaptive Capacity

Adaptive capacity is the ability of a system to adjust to climate change (Läderach *et al.* 2011). It is one the three components of the vulnerability assessment in addition to exposure and sensitivity. Adaptive capacity is directly correlated with resilience. Measured on a municipal scale in the context of climate change effects to agriculture, an AC index provides information on how resilient to climate change a particular area is. The AC parameters used are those that are relevant to the agricultural sector in the province. The indicators are summarized in Table 4.

As previously mentioned, the analysis of adaptive capacity in this study was contextualized for the agricultural sector. Several socioeconomic information from each municipality that are relevant to its agricultural situation was gathered from credible sources both local (PPDO of Bukidnon and local Agriculture offices) and national (Competitiveness.org) and analyzed to generate a measure of adaptive capacity per municipality in form of an index. The formulation of an index involved the process of data standardization to bring the values of the different AC parameters to a common range that is 0-1. Five equal breaks were used to establish the thresholds for the following classes: 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).

Climate Risk Vulnerability Assessment (CRVA)

Vulnerability is the degree to which a system is susceptible to, or unable to cope with, adverse effects of climate change, including climate variability and extremes. Vulnerability is a function of the character, magnitude, and rate of climate variation to which a system is exposed, its sensitivity, and its adaptive capacity (IPCC, 2001). Based on the definition, vulnerability is a function of sensitivity, exposure and adaptive capacity. A national workshop led by national experts was conducted with the objective of coming up with final weight of each factor. The CRV equation adopted in this study is presented below.

$$f(Haz, Sens, AC) = \sum_{\mathrm{n}=i} ((Haz_{(w_{\mathrm{h}})} + Sens_{(w_s)}) + 1 - AC_{(w_a)})$$

Where: *Haz* = hazard index, *Sens* = sensitivity index (*i* = crop), and *AC* = adaptive capacity index. *Wh* = weight given for hazard, *Ws* = weight given for sensitivity, and *Wa* = weight given for adaptive capacity.

The analysis of weights for each component of vulnerability has been assigned to a group of national experts. The weights have been a contentious issue as many have questioned how the experts have come up with such, especially the version that had AC at 70%.

It was obvious from the beginning that such process of using experts will be highly subjective. To remedy the problem, CIAT did a sensitivity analysis undertaken in one province per island group to explore the impact of varying proportions of weights to the overall vulnerability.

This involved the use of other weight proportions that are based on literatures. CIAT however cautioned that when comparing weights, variations in spatial scale, resolution, and type of vulnerability being assessed must be considered. The result of the sensitivity analysis revealed consistent detection of vulnerable municipalities since majority of the versions considers AC as a factor with higher weight.

The team relied on the output of CIAT since a national scale analysis incorporating all the data from partner SUCs was done. The different weight proportions used by them are shown in Table 5.

Results and discussion

Existing Occurrences of Crops

Fig. 3 depicts the distribution of occurrence points of the 5 crops under study. Corn had the greatest number of occurrence points with 748 (Table 6) wherein majority are found in Valencia city.

The generation of occurrence points relied mainly on the knowledge of local experts who joined the participatory mapping. As part of digitization, the team ran some validation tests to filter the data. Originally, there were about 900 occurrences for Corn that was later trimmed to its current number.

Table 1. List of Bioclimatic Variables.

Code	Variable
BIO1	Annual Mean Temperature
BIO2	Mean Diurnal Range (Mean of monthly (max temp – min temp))
BIO3	Isothermality (BIO2/BIO7) (* 100)
BIO4	Temperature Seasonality (standard deviation *100)
BIO5	Max Temperature of Warmest Month
BIO6	Min Temperature of Coldest Month
BIO7	Temperature Annual Range (BIO5-BIO6)
BIO8	Mean Temperature of Wettest Quarter
BIO9	Mean Temperature of Driest Quarter
BIO10	Mean Temperature of Warmest Quarter
BIO11	Mean Temperature of Coldest Quarter
BIO12	Annual Precipitation
BIO13	Precipitation of Wettest Month
BIO14	Precipitation of Driest Month
BIO15	Precipitation Seasonality (Coefficient of Variation)
BIO16	Precipitation of Wettest Quarter
BIO17	Precipitation of Driest Quarter
BIO18	Precipitation of Warmest Quarter
BIO19	Precipitation of Coldest Quarter
BIO20	Number of consecutive dry days

Table 2. Sensitivity index based on percent change in crop suitability from baseline to future condition.

Percent Change in Suitability (Range in %)	Index	Description
<= -50 (Very high loss)	1.0	
>-50 &<= -25 (High loss)	0.5	Loss
> -25 &<= -5 (Moderate loss)	0.25	
> -5 &<= 5 (No change)	0	No Change
> 5 &<= 25 (Moderate gain)	-0.25	
> 25 &<= 50 (High gain)	-0.5	Gain
> 50 (Very high gain)	-1.0	

This proved the significance of the validation procedure. The distribution of occurrence points per municipality is shown in Table 6.

Crop Suitability

The mean test AUCs for the 5 crops (Table 7) were all greater than random (0.5) which implies that the resulting suitability models gained an acceptable accuracy. An AUC value of 0.50 and below indicates that model did not perform better than random whereas a value of 1.0 indicates perfect discrimination (Khanum *et al.* 2013).

The bioclimatic variables that contributed best to the model differed across the 5 crops. As depicted in Table 7, the variables with greatest percent contribution wereBio2 (30.3%), Bio9 (22%), Bio7 (30.2%), Bio7 (38.4%), Bio4 (35%) for Corn, Rice, Cacao, Coffee and Tomato respectively. These values are means over 10 replicate runs.

Table 3. Percent score of Hazards in Bukidnon Province.

Hazard	Percent Score (Mindanao)
Typhoon	16.95
Flood	15.25
Drought	16.95
Erosion	12.71
Landslide	14.41

Note: Hazards such as Storm surge (8.47%), Sea level rise (5.08%) and saltwater intrusion were considered irrelevant for Bukidnon.

Table 4. Adaptive Capacity indicators.

Indicator	Sub-indicators	Weight
Economic capital	Income level, water and sanitation, electricity, banks and financial institutions, commodity prices, farm income, agricultural insurance, employment in agriculture.	14.29
Natural capital	Forest cover, groundwater availability, irrigation system	14.29
Social capital	Farmer unions, farmer cooperatives	14.29
Human capital	School enrolment, student teacher ratio, number of class rooms, number of school buildings, health services, nutrition sufficiency	14.29
Physical capital	Land tenure, farm size, farm equipment, value of livestock, irrigated area, access to quality seeds, roads, market access	14.29
Institutional capital	CSO programs, government response to calamities	14.29
Anticipatory capital	Presence of MDRRMC, Early warning systems, Radio/TV stations, Telecommunications	14.29

Percent contributions are a result of Jackknife test, which rely mainly on how the occurrence points relate to the spatial pattern of bioclimatic variables. Since this study made use of all bioclimatic variables without prior testing multicolinearity, caution is required in the interpretation of percent contribution.

As modeled, there is a gain in suitable areas for Corn, Rice, Cacao and Tomato. Previously unsuitable areas that are located at higher elevations are predicted to change because of shifts in temperature and precipitation levels. Corn is an upland crop that is predicted to benefit from increasing temperature that could potentially turn cooler areas across the mountains into much warmer areas. However, expansion of Corn plantations is not encouraged in the mountains, as it would involve conversion of available forests and grassland ecosystems into agricultural use. Meanwhile, even though rice gained more suitable habitats as far as the model is concerned, recommendations for expansion of rice farms unto the identified suitable areas should be subjected to prior research. In the case of lowland rice, the main considerations are slope and available irrigation.

These considerations must always be factored-in in decision making for rice farm expansion. In the case of Cacao, it is one of the commodities that are promoted by the Agriculture department.

The crop is ideal for climate change adaptation and mitigation since it is a perennial crop that could potentially sequester large amounts of carbon.

Table 5. Weights used to assess CRVA.

Version	Sensitivity (%)	Exposure (%)	Adaptive Capacity (%)
1	15	15	70
2	33	33	33
3	25	25	50
4	20	20	60
5	30	30	40

Table 6. Number of Species Occurrence Points per Municipality.

Location	Corn	Rice	Cacao	Coffee	Tomato
Baungon	0	6	0	0	0
Cabanglasan	0	18	0	0	0
Damulog	17	12	7	6	0
Dangcagan	14	11	3	1	0
Don Carlos	27	18	7	9	0
Impasug-ong	0	12	4	7	5
Kadingilan	19	5	9	5	0
Kalilangan	0	9	7	0	0
Kibawe	28	13	3	8	0
Kitaotao	36	10	0	0	0
Lantapan	1	1	1	2	0
Libona	0	15	11	11	0
Malaybalay city	100	67	21	34*	30*
Malitbog	0	7	0	0	0
Manolo Fortich	0	5	7	0	0
Maramag	160	57	0	21	0
Pangantucan	0	13	4	7	0
Quezon	33	25	0	0	0
San Fernando	49	11	0	4	0
Sumilao	0	10	6	6	0
Talakag	36	13	0	11	2
Valencia	228*	227*	62*	7	21
Total	748	555	152	139	58

Note: *= greatest occurrence value per crop/ municipality.

The information about the predicted increase in Cacao suitability is great news for both decision makers and the farmers. For tomato, the projected suitable areas would increase and are concentrated along the Eastern, Central and Southern part of the province. Tomato is known to thrive in areas with cool climate but intolerant to extremely cool weather. Mountainous regions along the eastern part are modeled to get warmer in the future and hence becoming suitable for vegetables such as tomato. A different result has been observed for Coffee since its climatic suitability is projected to diminish. Our results have shown that coffee would likely be impacted negatively by climate change. This is an alarming finding since many areas in the province are harboring coffee plantations and are doing fine at present. In fact, there is a coffee plantation located at San Jose Malaybalay City, the barangay where we conducted many activities related to CRA.

Table 7. Mean test AUC of the Crops.

Crop	Mean test AUC	Standard deviation
Corn	0.772	0.008
Rice	0.767	0.015
Cacao	0.748	0.017
Coffee	0.694	0.034
Tomato	0.801	0.044

Table 8. Mean Percent contributions of Variables.

Variable	Percent Contribution				
	Corn	Rice	Cacao	Coffee	Tomato
Bio1	1.1	3.2	0.1	1.3	0.3
Bio2	30.3*	0.7	1.6	0.9	0.3
Bio3	0.5	0.4	0.7	0.6	0.6
Bio4	0.7	5.4	1.3	16.3	35*
Bio5	9.1	9.6	0.7	1.1	0
Bio6	0.3	1.1	0.2	1.3	0
Bio7	1.4	1.5	30.2*	38.4*	0.9
Bio8	1.3	10	1.8	1.9	0.1
Bio9	3	22*	7.6	2.6	1.7
Bio10	1.2	0.5	1.3	0.6	0
Bio11	0.6	1.8	0.3	0.1	0
Bio12	8.9	7.7	7.7	6.1	6.6
Bio13	1.7	9.4	7.7	1	7.9
Bio14	0.1	0.8	8.1	1.4	0.4
Bio15	5.5	2.2	12.5	11.5	2.6
Bio16	5	7.5	1.7	3.9	13.7
Bio17	0.8	2.2	2.5	2	0.7
Bio18	23.7	7	5.1	3.5	3.5
Bio19	4.8	7.2	8.9	4.9	25.6

*Note: = The value of the variable with highest mean percent contribution to the Maxent model.

It is further emphasized that the suitability being referred to was measured using climatic parameters only. The model did not factor-in other parameters such as soil, aspect, and slope, which are deemed essential for plant growth and survival at the local scale. Therefore, it is recommended that the term climatic suitability be adapted when referring to the suitability information presented in this paper.

Sensitivity

Corn, Rice, Cacao and Tomato were found to be negatively sensitive to climate change.

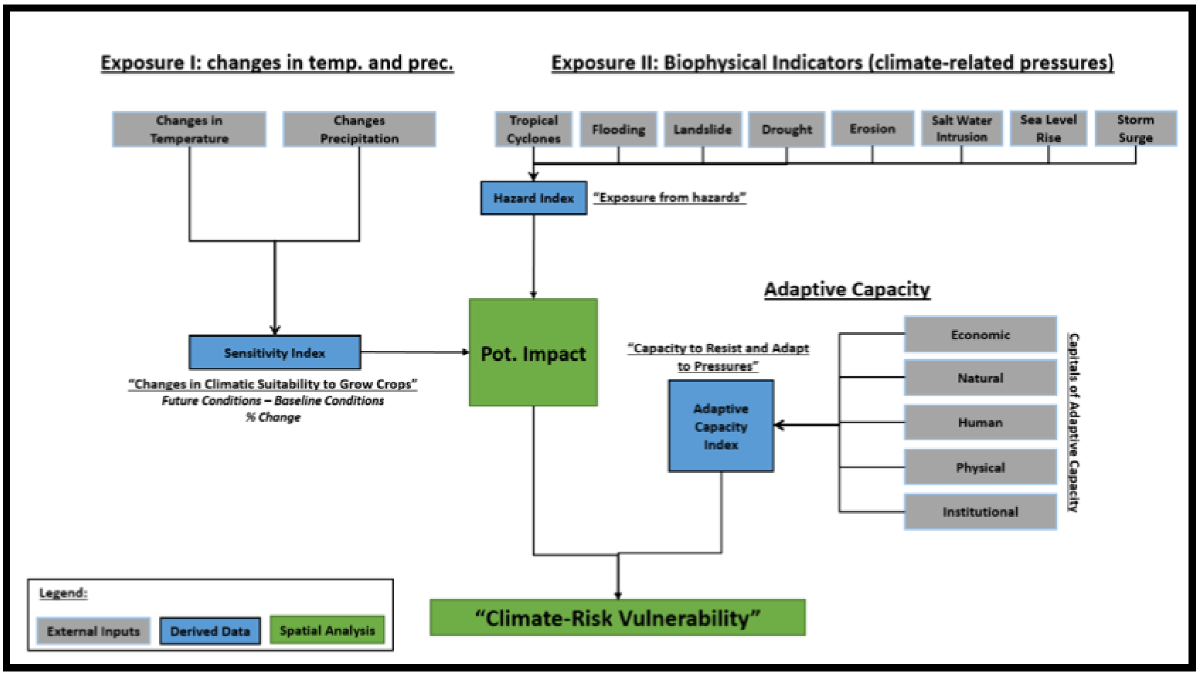

Fig. 2. Framework for CRVA (Source: CIAT).

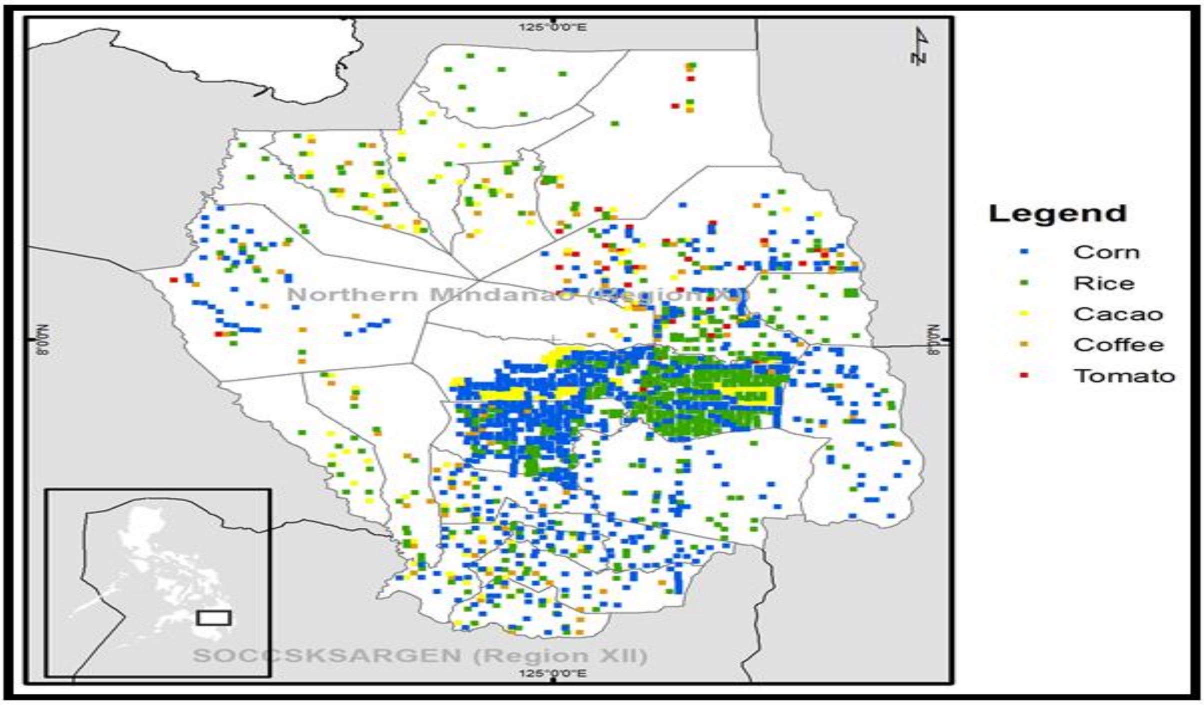

Fig. 3. Map of the occurrence points of the 5 crops.

The negative indices of the four mentioned crops means that they have gained more suitable areas as predicted. However, with a projected decrease is suitability, Coffee had a more positive sensitivity (loss in suitable areas). Thorough analysis of the results however revealed that all crops are sensitive to climate change, the difference is on whether it is positive or negative. Results on the sensitivity at the municipal level (Fig. 4) considering all crops revealed that 5 municipalities are highly sensitive (diminishing suitability). These are, Kitaotao and Damulog in the south, Kalilangan in the west, and Baungon and Malitbog in the North. In contrast the neighboring cities of Valencia and Malaybalay as well as the municipalities of Sumilao and Manolo Fortich were the least sensitive among the 22 areas.

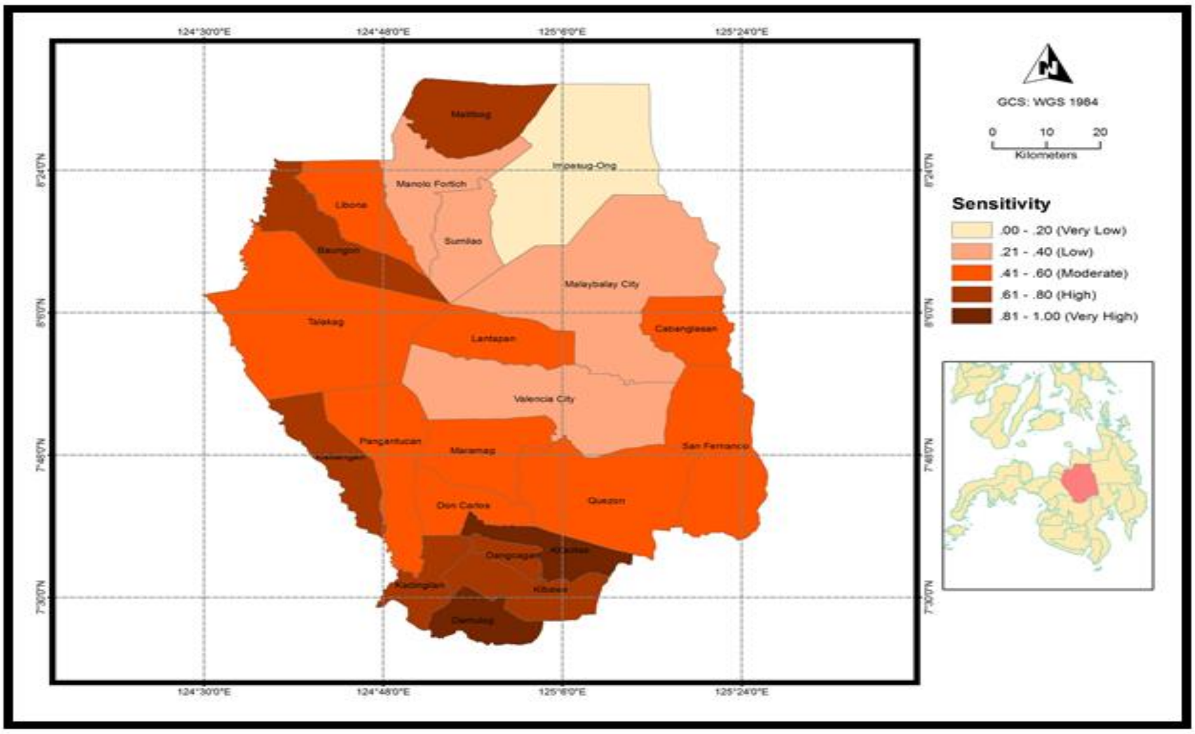

Fig. 4. Map of Sensitivity of municipalities.

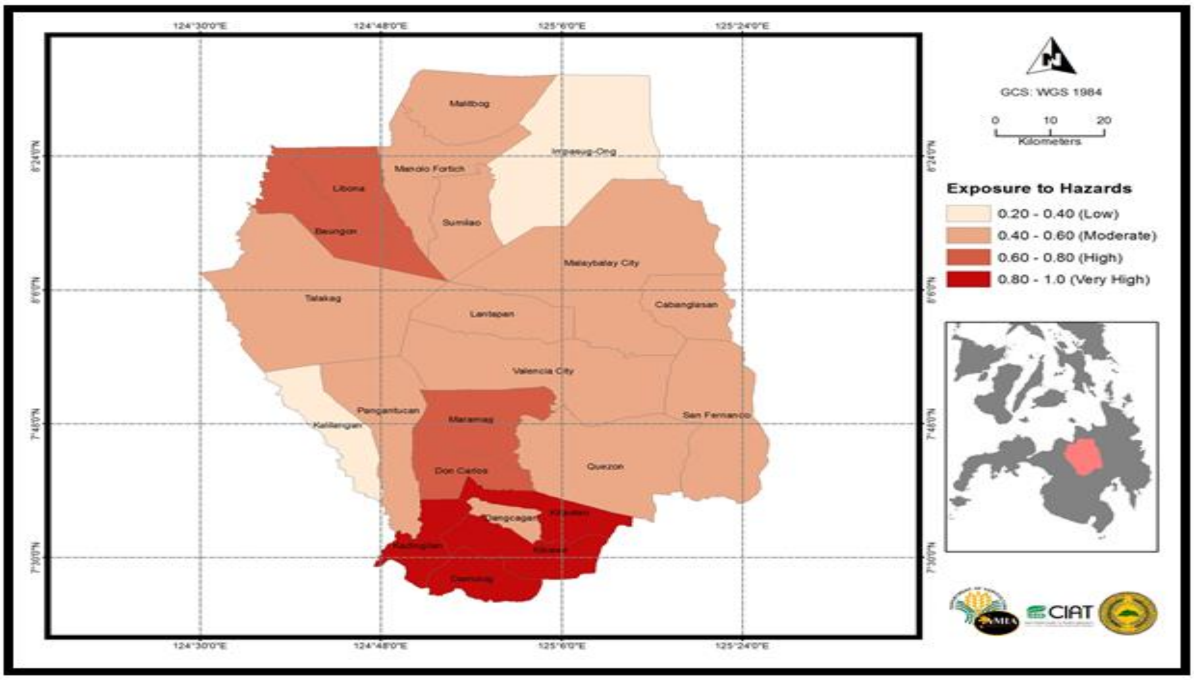

Fig. 5. Map of Exposure to hazards per municipality.

Exposure to Hazards

Results have shown that the most exposed municipalities to climate change induced hazards are Kitaotao, Damulog, Kibawe and Kadingilan (Fig. 5). This implies that a much higher pressure to the agricultural sector is exerted by hazards such as typhoon, flood, drought, erosion and landslide. When it comes to typhoon, the Philippines is 2nd to China as the most exposed country in the world (NOAA, 2010). However, the frequency of typhoons in the island of Mindanao is way much lesser as compared to that of Visayas and Luzon. In general, typhoons can be very destructive to agricultural crops. Meanwhile, in the context of agriculture, flooding caused by overflowing of rivers and irrigation canals is commonly reported in the province. This problem is a close consequence of the diminishing health of the watersheds in the province. The slopy nature and poor vegetation cover of mountains in Bukidnon also causes varying levels of erosion thereby affecting soil fertility. Landslides are also reported especially in areas near Kitaotao.

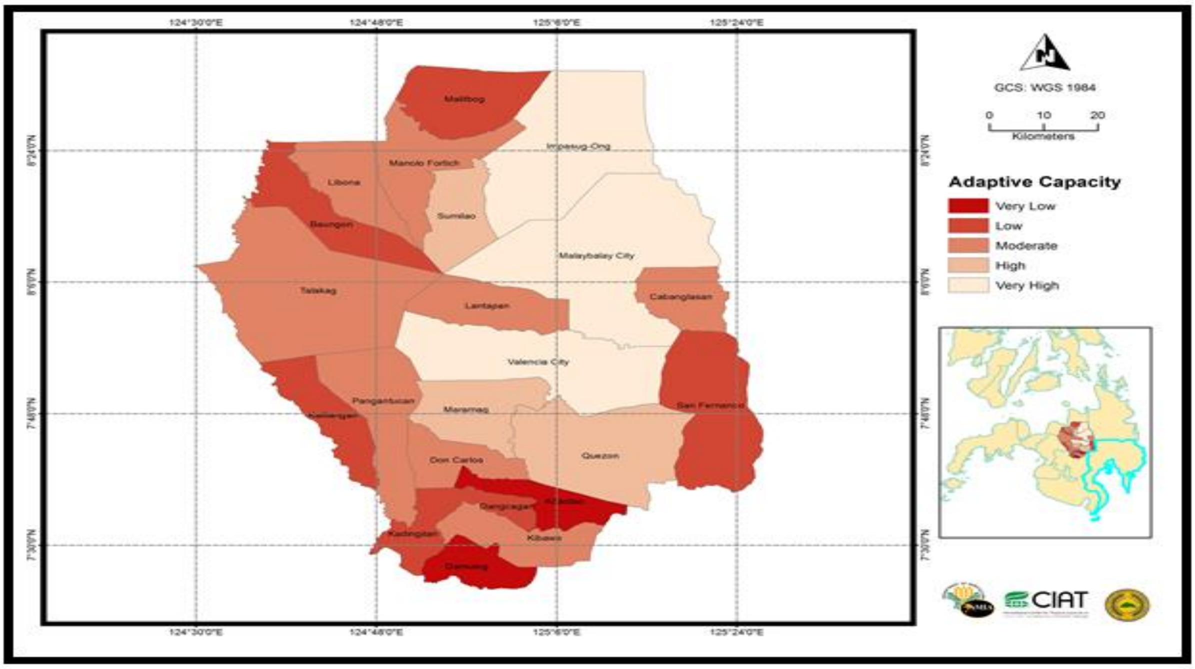

Fig. 6. Map of the Adaptive Capacity of municipalities.

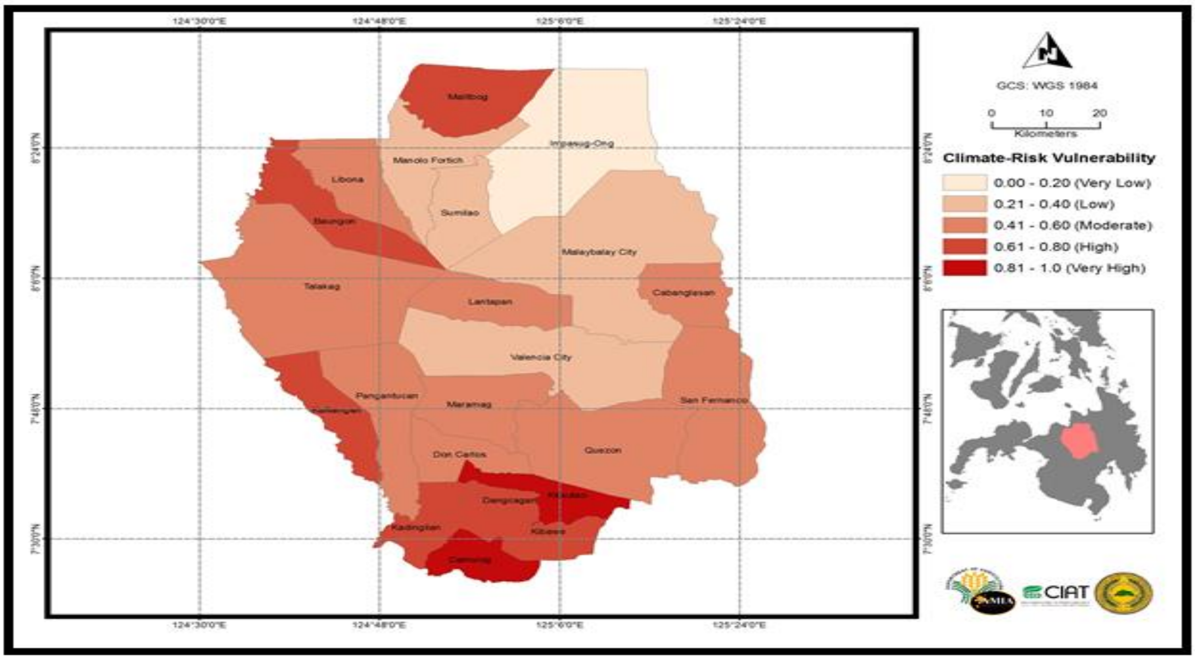

Fig. 7. Climate Risk Vulnerability Map.

Adaptive Capacity

As depicted in Fig. 6, the municipalities of Damulog and Kitaotao obtained a very low adaptive capacity rating. Close examination of the adaptive capacity parameters revealed that one of the prime reasons that of their low adaptive capacity is their income. As observed, the mentioned municipalities have lower income compared to other municipalities. Damulog and Kitaotao are among the municipalities with the least number of banks and financial institutions that are crucial components of their economic capital. It is also among the lowest in terms of farmer membership to cooperatives, a critical social capital. They are almost consistently lower in all parameters aside from Natural capital where both obtained a higher rating.

Meanwhile, Valencia city, Malaybalay city and Impasug-ong were rated very high in adaptive capacity. These areas are on top in terms of economic, human, social and institutional capital. This implies that they have the necessary tools to better adapt to climate change pressures to the agricultural sector of the area. Fig. 6 presents the adaptive capacity of the municipalities.

Climate Risk Vulnerability (CRV)

The final Climate Risk Vulnerability (CRV) map for the year 2050 is an integration of the exposure, sensitivity and adaptive capacity components. The weights used in coming up with the CRV map was 15% for exposure, 15% for sensitivity and 70% for adaptive (Fig. 7).

With 70% coming from adaptive capacity, the final CRV map is closely correlated with the adaptive capacity of terms of where municipalities are positioned in the classification. The current CRV map provides information on a municipal scale that is useful for provincial level planning and prioritization. As the results have indicated, the team recommends the prioritization of Kitaotao and Damulog when it comes to climate change adaptation and mitigation initiatives and projects of the Agriculture department. Aside from the being highly exposed to climate related hazards, the adaptive capacities of the two municipalities are very low. Effective interventions must be in place in order to enhance their adaptive capacity.

Conclusions and recommendations

The utilization of the information generated in this study is crucial not only for AMIA but also for the prioritized municipalities. The regional DA office maybe looking at other areas to implement their interventions considering other reasons. However, the very important information we have could be very well put to waste if not applied. As more and more effective initiatives are implemented in municipalities that were prioritized not only in Bukidnon but also throughout the Philippines, the conduct of CRVA at the barangay level is also becoming important. However, the approach have to be refined in terms of data types and methods to better address challenges in resolution, accuracy, currency and overall credibility of the outputs.

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References

David CC, Balisacan A. 1995. Philippine Rice Supply and Demand: Prospects and policy Implications, Makati City, Philippines: Philippine Institute for Development Studies.

Fahad S, Wang J. 2018. Farmers' risk perception, vulnerability, and adaptation to climate change in rural Pakistan. Land Use Policy **79,** 301-309. https://doi.org/10.1016/j.landusepol.2018.08.018

Field CB. 2012. Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation: Special Report of the Intergovernmental Panel on Climate Change. Cambridge University Press.

Galletti CS, Ridder E, Falconer SE, Fall Pl. 2013. Maxent modeling of ancient and modern agricultural terraces in the Troodos foothills, Cyprus. Applied Geography **39,** 46–56. http://dx.doi.org/10.1016/j.apgeog.2012.11.020

Hijmans R, Cameron S, Parra J, Jones P, Jarvis A. 2005. Very high resolution interpolated climate surfaces for global land areas. International Journal of Climatology **25**, 1965-1978. http://dx.doi.org/10.1002/joc.1276

IPCC. 2001. Climate change 2001: impacts, adaptation, and vulnerability: contribution of Working Group II to the third assessment report of the Intergovernmental Panel on Climate Change. Ed. James McCarthy. Cambridge, UK; New York, USA: Cambridge University Press.

Khanum R, Mumtaz A, Kumar S. 2013. Predicting impacts of climate change on medicinal asclepiads of Pakistan using Maxent modeling. Acta Oecologica **49**, 23–31. http://dx.doi.org/10.1016/j.actao.2013.02.007

Läderach P, Eitzinger A, Bunn C, Benedikter A, Quiroga A, Pantoja A, Rizo L. 2011. Adaptation by agricultural communities to climate change through participatory & supply chain inclusive management. International Center for Tropical Agriculture (CIAT), Managua, Nicaragua and Cali, Colombia Cali, Colombia.

Lansigan FP, de Los Santos W, Coladilla JO. 2000. Agro-economic impacts of climate variability on rice production in the Philippines. Agriculture Ecosystems & Environment **82,** 129-137. http://dx.doi.org/10.1016/S0167-8809(00)00222-X

Leathwick JR, Elith J, Hastie T. 2006. Comparative performance of generalized additive models and multivariate adaptive regression splines for statistical modelling of speciesdistributions. Ecological Modelling **199(2),** 188–196. http://dx.doi.org/10.1016/j.ecolmodel.2006.05.022

Lobell D, Gourdji S. 2012. The influence of climate change on global crop productivity. Plant Physiology **160(4),** 1686–1697.

NOAA. 2010

Paquit J, Pampolina N, Tiburan C Jr, Manalo MM.2017. Maxent modeling of the habitat distribution of the critically endangered Pterocarpus indicus Willd. forma indicus In Mindanao, Philippines. Journal of Biodiversity and Environmental Sciences **10(3),** 112-122

Paquit J, Rama RI. 2018. Modeling the effect of climate change to the potential invasion range of Piper aduncum Linnaeus. Global Journal of Environmental Science and Management **4(1),** http://dx.doi.org/10.22034/gjesm.2018.04.01.00

Philippine Atmospheric, Geophysical & Astronomical Services Administration (PAGASA). 2011. Climate Change in the Philippines.

Philippine Information Agency. Undated.pia.gov.ph/Bukidnon

Philips S, Anderson R, Schapire R. 2005. Maximum entropy modeling of species geographic distributions. Ecological Modelling **190,** 231–259.

Wiréhn L, Opach T, Neset T. 2017. Assessing agricultural vulnerability to climate change in the Nordic countries–an interactive geovisualization approach, Journal of Environmental Planning and Management **60,** 115-134, http://dx.doi.org/10.1080/09640568.2016.1143351

World Bank, World Development Report. 2011. Conflict, Security, and Development, The World Bank, Washington D.C., 2012. , “World Development Indicators