FARMERS’ VULNERABILITY TO CLIMATE CHANGE AND PRODUCTION OF MAIZE, BANANA, AND DURIAN IN SOUTHERN PHILIPPINES

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ABSTRACT

This study assessed the vulnerability of the farmer-respondents in Southern Philippines, specifically Region XI and XII to climate change. This was based on the integrated vulnerability assessment approach using vulnerability indicators. Likewise, this study conducted an empirical analysis of the impact of climate change on maize (Zea mays), banana (Musa sapientum), and durian (Durio zibethinus) production. Furthermore, it estimated the determinants of adaptation to climate change and its corresponding effect on farm productivity. The analysis used primary data from 541 farmer-respondents producing maize, banana, and durian in the six provinces, eighteen municipalities of the sample areas.

The vulnerability indicators consisted of socioeconomic and biophysical attributes of six provinces in the study sites. Those were classified into three classes, following the Intergovernmental Panel on Climate Change’s (IPCC 2001) definition of vulnerability. Those indicators were adaptive capacity, sensitivity, and exposure.

The results indicated that the farmers in the provinces of North Cotabato, Compostela Valley, and Davao del Norte were highly vulnerable to climate change. Vulnerability to climate change of farmers in North Cotabato Province and Compostela Valley Province was highly related to marginal total farm size while vulnerability of farmers in Davao del Norte Province was highly related to poor social network (lowest number of relatives in a barangay).

Key words: Adaptive Capacity, Climate Change, Exposure, Principal Component Analysis, Sensitivity, Southern Philippines, Vulnerability, Vulnerability Index
1. INTRODUCTION

The Philippine agriculture sector contributes 12.31% of 2010 GDP according to a World Bank report. The biggest contributors to growth were palay, maize, poultry and livestock (NSCB, 2010). The agriculture sector employs 36.1% of the population (UN data/country profile/Philippines, 2009). The contribution of the agricultural sector to the total economy, however, is challenged by its vulnerability to climate change. It is because agriculture is arguably the most important sector of the economy that is highly dependent on climate. Agriculture systems are vulnerable to variability in climate, whether naturally-forced, or due to human activities.

Climate change extremes have been manifested in the Philippines such as floods and droughts. The disasters these have brought have caused losses amounting to billions of pesos. The decline in production and productivity will possibly threaten the country’s food security. Climate change is a serious risk to poverty reduction and threatens to undo decades of development effort. Climate change will generally reduce production potential and increase risk of hunger and starvation.

Vulnerability can be viewed as a function of the sensitivity of agriculture to changes in climate, the adaptive capacity of the system and the degree of the exposure to climate hazards (IPCC 2001b, p.89). Luers et al. (2003) proposed a method for quantifying vulnerability (given the system, outcome variable, and stressor of concern) based on exposure, sensitivity, and adaptive capacity. In the IPCC report, exposure is defined as “the nature and the degree to which a system is exposed to significant climatic variations,” sensitivity is defined as “the degree to which a system is affected, either adversely or beneficially; by climate-related stimuli,” and adaptive capacity is defined as “the ability of a system to adjust to climate change (including climate variability and extremes), to moderate the potential damage from it, to take advantage of its opportunities, or to cope with its consequences.” Turner et al (2003) recognized that vulnerability is determined not by exposure to hazards (perturbations and stresses) alone, but also depends on the sensitivity and resilience of the system that is experiencing such hazards. These authors developed an integrated conceptual framework of vulnerability built on these three major dimensions of vulnerability, namely, exposure, sensitivity and adaptation/resilience.

The level of vulnerability of different social groups to climate change is determined by both socioeconomic and environmental factors. The selection of indicators was done through an extensive review of previous reports; in particular, the socio-economic factors most cited in the literature and used as indicators in this study included income and education (Cutter et al. 2003; Adger 1996; Haan et al 2001), social networks (Vincent et al. 2010; Gbetibouo et al. 2009; Deressa et al., 2008; Ford, Barry and Wandel, 2005; Nyong et al., 2003), access to formal and non-formal credit, farm income and farm size (Gbetibouo et al., 2009), perception about preparedness, and amount of fertilizer used (www.icrisat.org). The environmental attributes used as indicators in this study included change in temperature and precipitation (Gbetibouo et al. 2009 and Deressa et al. 2008).

There are many conceptual methodological approaches to vulnerability analysis. The major ones include the socioeconomic, biophysical, and integrated approaches. The biophysical approach assesses the level of damage that a given environmental stress causes on both social and biological systems. The biophysical, or impact assessment, approach is mainly concerned with the physical impact of climate change on different attributes, such as yield and income (Fussel and Klein, 2006). Although very informative, the biophysical approach has its limitations. The major limitation it focuses mainly on the physical damages, such as yield, income, and so on. For example, a study on the impact of climate change on yield can show the reduction in yield due to simulated climatic variables such as increased temperature or reduced precipitation. In other words, these simulations can provide the quantities of yield reduced due to climate change but they do not show what that particular reduction means for different people.

The integrated assessment approach combines both the socioeconomic and the biophysical attributes in vulnerability analysis (Fussel, 2007). Fussel (2007) and Fussel and Klerin (2006) argued that the IPCC (2001) definition – which conceptualizes vulnerability to climate as a function of adaptive capacity, sensitivity, and exposure – accommodates the integrated approach to vulnerability analysis. Even though the integrated assessment approach corrects the weaknesses of the other approaches, it has its limitations. The main limitation is that there is no standard method for combining the biophysical and socioeconomic indicators. This approach uses different data sets, ranging from socioeconomic data sets to biophysical factors; these data sets certainly have different and yet unknown weights. Cutter, Mitchell, and Scott (2000) explained that because this analysis provides no common metric for determining the relative importance of the social and biophysical vulnerability, nor for determining the relative importance of each
individual variable, much care is required. The other weakness of this approach is that it does not account for the dynamism in vulnerability. Coping and adaptation are characterized by a continual change of strategies to take advantage of opportunities (Campbell, 1999; Eriksen and Kelly, 2007); thus, this dynamism is missing under the integrated assessment approach. Despite its weaknesses, however, this approach has much to offer in terms of policy decisions. It is used to develop a better understanding of the socio-economic and biophysical factors contributing to vulnerability (Hebb and Mortsch, 2007 and Gbetibouo et al. 2009).

There had been extensive research on the impacts of the climate change, but little attention was devoted to the socio-economic aspects of the vulnerability and risks of climate change in major food crops such as corn, durian, and banana in Region XI and XII, Philippines. To fill this empirical gap, this study carries out a socio-economic analysis of the vulnerability and risk of climate change in Regions XI and XII agricultural sectors at the farm level. The objectives of this research were to measure and analyze the vulnerability of the farmers to climate change.

2. DESCRIPTION OF THE STUDY AREA

The study was undertaken in the major areas of maize, durian, and banana in Southern Philippines, specifically these are in Region XI and XII. The grouping of sample areas are shown below:

Region XI Provinces: 1) Davao del Sur, 2) Davao del Norte, and 3) Compostela Valley. The total land area is 11,098.43 sq. km. Region XII Provinces: 1) North Cotabato, 2) South Cotabato, and 3) Sultan Kudarat. The total land area is 14, 819 sq. km. The study areas are depicted in Figure 1.

3. THEORETICAL FRAMEWORK

3.1. Construction of Vulnerability Index

The theoretical model presented attempts to analyze vulnerability based on an integrated approach by making use of vulnerability index. This was adopted from the work of Deressa et al. (2008). The direction of relationship in vulnerability indicators (i.e., their sign) was adopted from the procedure followed by Moss, Brenkert, and Malone (2001) as cited by Deressa et al. (2008), who assigned a negative value to sensitivity and a positive value to adaptive capacity and then calculated the vulnerability resilience indicator. For this study, we attached a negative value to both exposure and sensitivity. The main argument for this is that areas that are highly exposed to damaging climate are more sensitive to damages, assuming constant adaptive capacity. We assume that areas with higher changes in temperature and precipitation are more exposed. Variables listed under adaptive capacity are given a positive value. In this study, it is assumed that people with higher adaptive capacity were less sensitive to damages from climate change, keeping the level of exposure constant. Therefore, vulnerability is calculated as the net effect of adaptive capacity, sensitivity, and exposure.

Vulnerability = (adaptive capacity) – (sensitivity + exposure) (1)

In this relationship, higher net value indicates lesser vulnerability and vice versa.

The next step was the attachment of weights to the vulnerability indices. For this step, the method of principal component analysis (PCA) was employed. PCA is frequently used in researches that are based on constructing indices for which there are no well-defined weights. Therefore, we let a statistical method (PCA) generate the weights. Principal component analysis is a technique for extracting from a set of variables those few orthogonal linear combinations of variables that most successfully capture the common information. Intuitively, the first principal component of a set of variables is the linear index of all the variables that captures the largest amount of information common to all the variables. For example, suppose we have a set of Z-variables (a1j to aZj) that represents the Z-variables (attributes) of each region j. PCA starts by specifying each variable normalized by its mean and standard deviation. For instance, a1j = (a1j – a1) s1j, where a1j is the mean of a1j across regions and s1j is its standard deviation. The selected variables are expressed as linear combinations of a set of underlying components for each region:
\[
a_{ij} = y_{11}W_{ij} + y_{12}W_{2j} + \ldots + y_{1Z}W_{Zj}
\]

\[
\ldots
j = 1\ldots J
\]

\[
a_{Z1j} = y_{Z1}W_{ij} + y_{Z2}W_{2j} + \ldots + y_{ZZ}W_{Zj}
\]

Where the \(W\)’s are components and the \(y\)’s are the coefficients on each component for each variable (and do not vary across region). Only the left side of each line is observed, thus the solution to the problem is indeterminate. PCA overcomes this indeterminacy by finding the linear combination of the variables with maximum variance (usually the first principal component \(W_1\)) then finding a second linear combination of the variables orthogonal to the first and with maximal remaining variance, and so on. Technically, the procedure solves the equations \((R - \lambda I)v_n = 0\) for \(\lambda_n\) and \(v_n\) where \(R\) is the matrix of correlations between the scaled variables (the \(a\)’s) and \(v_n\) is the vector of coefficients on the \(n\)th component for each variable. Solving the equation yields the characteristic roots of \(R\), \(\lambda_n\) (also known as eigenvalues), and their associated eigenvectors, \(v_n\). The final set of estimates is produced by scaling the \(v_n\)s so that the sum of their squares sums to the total variance – another restriction imposed to achieve determinacy of the problem.

The scoring factors from the model are recovered by inverting the system implied by equation (2). This yields a set of estimates for each of the \(Z\)-principal components:

\[
W_{ij} = b_{i1}a_{1j} + b_{i2}a_{2j} + \ldots + b_{iZ}a_{Zj}
\]

\[
\ldots
j = 1\ldots J
\]

\[
W_{Zj} = b_{Z1}a_{1j} + b_{Z2}a_{2j} + \ldots + b_{ZZ}a_{Zj}.
\]

Where the \(b\)’s are the factor scores. Following Filmer and Pritchett 2001), the first principal component, expressed in terms of the original (unnormalized) variables is an index for each province in Regions XI and XII based on the following expression:

\[
W_{1j} = b_{11}(a^*_{1j} - a^*_1)/(s^*_1) + \ldots + b_{1Z}(a^*_{Zj} - a^*_Z)/(s^*_Z)
\]

For this study, the scale of analysis was the provincial level since we were limited by the availability of the precipitation and temperature data. These were interpolated from the available data from the 5 meteorological stations across the study areas. Interpolation was done in the provincial level, that was why the scale of analysis was on the provincial level.

4. METHODOLOGY

Sampling Procedure. Maize, durian, and banana farmers were the target respondents for the study. A total of 541 farmers-respondents were picked from the study areas. The sampling technique employed was multistage stratified random sampling technique. The first stage involved purposive selection of the vulnerable or barangays prone to climate change. The second stage was simple random sampling through selection of 541 farmers in the study areas.

Source of Data. The project made use of both primary and secondary data. The secondary data used were from the socio-economic profile report of the six provinces and the base maps were from the different Provincial Agriculture Offices and Provincial Planning Offices. Monthly precipitation and temperature data for the past 15 years were taken from the eight meteorological stations distributed across the regions which served as basis for the interpolation procedure (precipitation and temperature). The eight meteorological stations were PAGASA Synoptic Station in Gensan Airport, General Santos City; PAGASA Synoptic Station in Hinatuan, Surigao del Sur, PAGASA Synoptic Station in Butuan City Airport, PAGASA Synoptic Station in Cagayan de Oro, PAGASA Davao City, Davao Airport, Sasa, Davao City; PAGASA Agromet Station, USeP, Apokon, Tagum City; PAGASA Bukidnon, Malaybalay City; and DA-CEMIARC for Upland Plain Agromet Station in Balindog, Kidapawan City. The interpolated precipitation and temperature were also used as indicators in the vulnerability index.
Primary data were taken from the personal interview with the farmers making use of pre-tested questionnaires and interview schedule designed specifically for maize, durian, and banana. These were the sources used to collect data from the farmers for the study.

Data Analysis. The data obtained from the field survey were subjected to analysis using inferential statistics.

Model Specification

Construction of Vulnerability Index. This study attempted to analyze vulnerability based on the integrated approach by making use of vulnerability index. The choice of indices was undertaken based on a review of the literature and adjusting them to the agricultural situation in the study area. The direction of relationship in vulnerability indicators (i.e. their sign) was adopted from the procedure followed by Moss, Brenkert, and Malone (2001) as cited by Deressa et al. (2008), who assigned a negative value to sensitivity and a positive value to adaptive capacity and then calculated the vulnerability resilience indicator. Following the procedure of Deressa et al (2008), we attached a negative value to both exposure and sensitivity. The main argument for this was that areas that were highly exposed to damaging climate were more sensitive to damages, assuming constant adaptive capacity. We assumed that areas with higher changes in temperature and precipitation were more exposed. Variables listed under adaptive capacity were given a positive value. In this study, it is assumed that people with higher adaptive capacity are less sensitive to damages from climate change, keeping the level of exposure constant. Therefore vulnerability is calculated as the net effect of adaptive capacity, sensitivity, and exposure.

\[
\text{Vulnerability} = (\text{Adaptive Capacity}) - (\text{Sensitivity} + \text{Exposure})
\]

In this relationship, high net value indicates lesser vulnerability and vice versa.

The next step is the assignment of weights to the vulnerability indices. For this step, the method of Principal Component Analysis (PCA) was employed. PCA is frequently used in research that is based on constructing indices for which there are no well defined weights. Therefore, we let a statistical method (PCA) generate the weights.

For this analysis, PCA was run using data analysis and statistical softwares (STATA) and (SPSS).

5. RESULTS AND DISCUSSION

5.1. Vulnerability Indices to Climate Change of the Six Provinces of Regions XI and XII

5.1.1. Descriptive Statistics

Preliminary analyses indicated that the provinces of Regions XI and XII varied in their socio-economic and environmental characteristics. Tables 1A depicts the indicators of adaptive capacity, whereas Tables 1B and 1C depict indicators of sensitivity and exposure across the six provinces of Regions XI and XII. Farmers from South Cotabato Province showed the highest income followed by Davao del Norte. The least income farmers were from Davao del Sur Province. Furthermore, Table 4A shows that farmers in Sultan Kudarat Province had the biggest farm size while the least farm size were the farmers in Compostela Valley Province. Farmers in Sultan Kudarat had the greatest number of relatives in the barangay while farmers in Davao del Norte Province had the smallest number of relatives in the barangay. Compostela Valley Province had the highest access to education, as the percentage of farmers in this province were the highest in terms of the number of years of schooling. Farmers in Davao del Sur Province had the lowest number of years of schooling. South Cotabato Province had the highest access to formal credit, whereas Sultan Kudarat Province had the lowest access to formal credit. Accessibility to non-formal credit was highest in North Cotabato Province and lowest in South Cotabato and Davao del Sur Province.

Amount of fertilizer/ha/year and average preparedness were highest both in Sultan Kudarat Province. Amount of fertilizer/ha/year and average preparedness were lowest in Davao del Sur Province and North Cotabato Province, respectively (As seen in Table 1B). In terms of the change in precipitation, Davao del Sur Province stands first, whereas North Cotabato Province experienced the lowest. The change
in temperature was the highest for South Cotabato and lowest for Davao del Norte Province (As seen in Table 1C).

5.1.2. Results from the Principal Component Analysis

Principal Component Analysis (PCA) was run on the indicators listed in Table 2 using data analysis and statistical software (STATA). The PCA of the data set on vulnerability indicators revealed four components with eigenvalues greater than 1 (As seen in Table 3). These components explain 95% of the total variation in the data set. The first principal component explained most of the variation (38%), and the second principal component explained 24%, the third principal component explained 22% and the fourth principal component explained the least (10 percent). Based on the earlier arguments for the use of PCA in constructing indices, the results indicated that the first principal component was by far the most important component for representing the variation in the data set.

Table 2 shows the vulnerability indicators and the factor scores of the first component. It can be observed from the factor scores that the first PCA component vulnerability index was positively associated with two of the indicators (Number of relatives in barangay and total farm size) identified as adaptive capacity while negatively associated with change in precipitation. Thus, for the construction of the vulnerability indices, we selected indicators of adaptive capacity that are positively associated with the first PCA, and the indicators of sensitivity and exposure, which were negatively associated with the first PCA (remaining with a total of 3 indices only). Higher values of the vulnerability index showed less vulnerability and vice versa, as we are dealing with the fact that adaptive capacity is positively loading, the exposure and sensitivity indices were negatively loading to our PCA.

5.1.3. Vulnerability Indices

The factor scores from the first principal component were employed to construct indices for each of the six provinces of Regions XI and XII; that is, the vulnerability index for North Cotabato Province was calculated as follows:

\[ [(0.3153*0.544)+(0.3995*0.725)] - (0.0787*1.233) = -0.56 \]

The calculations for the rest of the provinces followed the same procedure. Table 1D presents the normalized values for each variable by their means and standard deviations for all provinces. Table 4 presents the vulnerability index for each province which was clearly illustrated in Figure 2.

Figure 2 shows that the net effect of adaptation and exposure is positive for the provinces of Sultan Kudarat, South Cotabato and Davao del Sur. This indicates that these provinces were relatively invulnerable to climate change. The lesser vulnerability of Sultan Kudarat Province could be explained by its association to relatively higher number of relatives in the barangay and total farm size.

The number of relatives in the barangay is a social network or capital variable. Theoretically, the greater the number of these (social capital) the lower is a household’s vulnerability (Vincent et al, 2010). Furthermore, social networks act as conduits for financial transfers that may relax the farmer’s credit constraints. Second, they act as conduits for information about new technology. Third, social networks can facilitate cooperation to overcome collective action dilemmas, where the adoption of technologies
involves externalities (Deressa et al, 2008). It is hypothesized that social capital positively influences adaptation to change.

Financial capital as represented by farmholding size is an indicator which provides a general picture of the financial situation of the province. Provinces with larger farms were, therefore, better able to prepare for and respond to adversity (Gbetibouo et al., 2009).

On the other hand, Figure 2 also shows that the net effect of adaptation and exposure was negative for the provinces of Compostela Valley, Davao del Norte and North Cotabato which implies that these latter provinces were vulnerable to climate change. The vulnerability to climate change of the provinces of North Cotabato, Compostela Valley and Davao del Norte is associated with lower gross farm income/year. The vulnerability of North Cotabato Province could be explained by its association to lower total farm size and lower change in precipitation.

On the other hand, the vulnerability of Davao del Norte Province is attributed to its lowest number of relatives in the Barangay. Lastly, the vulnerability of Compostela Valley Province was mainly associated with lowest total farm size. Small-scale farmers, generally subsistence farmers, were more sensitive to climate change and variability because they had less capital-intensive technology and management practices. Thus, a province with a large number of small-scale farmers will be more climate-sensitive than a province with fewer small-scale farmers (Gbetibouo et al., 2009).

6. CONCLUSIONS AND IMPLICATIONS

The following points can be inferred based on the results and analysis made in the study:

1) A few policy options for decreasing the vulnerability to climate change of farmers in the provinces of North Cotabato, Compostela Valley, and Davao del Norte were presented. In general, vulnerability to climate change in North Cotabato and Compostela Valley provinces was highly related to poverty (marginal total farm size) in most of the provinces that were indicated as vulnerable to climate change. The vulnerability of farmers in Davao del Norte Province was highly related to poor social capital or network (lowest number of relatives in the barangay). Integrated rural development schemes aimed at alleviating poverty can play the double role of reducing poverty and increasing the adaptive capacity to climate change. Special emphasis may be given to the provinces more vulnerable to climate change, i.e. North Cotabato, Compostela Valley, and Davao del Norte. In addition to this, strengthening the social capital or network of the farmers in the study sites can may also boost the adaptive capacities of farmers.

Strengthening of the Department of Agriculture extension program to the farmers in the study sites and strengthening the social network or capital will be very helpful in equipping the farmers in the study sites against the adverse effects of climate change.

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Table 1A. Adaptive capacity index of the six provinces of Regions XI and XII, Philippines, 2011-2012

<table>
<thead>
<tr>
<th>Province</th>
<th>ActFC</th>
<th>ActNFC</th>
<th>YRSCH</th>
<th>RelBrgy</th>
<th>Income</th>
<th>FarmHec</th>
</tr>
</thead>
<tbody>
<tr>
<td>Comval</td>
<td>0.27</td>
<td>0.29</td>
<td>10.54</td>
<td>90.71</td>
<td>98126.00</td>
<td>1.90</td>
</tr>
<tr>
<td>Davao del Norte</td>
<td>0.23</td>
<td>0.30</td>
<td>9.65</td>
<td>54.64</td>
<td>116392.50</td>
<td>2.16</td>
</tr>
<tr>
<td>Davao del Sur</td>
<td>0.15</td>
<td>0.18</td>
<td>8.38</td>
<td>78.17</td>
<td>93171.23</td>
<td>2.18</td>
</tr>
<tr>
<td>North Cotabato</td>
<td>0.37</td>
<td>0.42</td>
<td>9.90</td>
<td>73.50</td>
<td>99693.92</td>
<td>2.00</td>
</tr>
<tr>
<td>South Cotabato</td>
<td>0.38</td>
<td>0.24</td>
<td>10.25</td>
<td>97.94</td>
<td>149284.22</td>
<td>2.07</td>
</tr>
<tr>
<td>Sultan Kudarat</td>
<td>0.09</td>
<td>0.37</td>
<td>9.52</td>
<td>110.38</td>
<td>96091.06</td>
<td>2.28</td>
</tr>
</tbody>
</table>

Legend:
ActFC – Access to formal credit
ActNFC – Access to non-formal credit
YRSCH – Number of years in schooling
RelBrgy – Number of relatives in barangay
Income – Gross farm income per year
FarmHec – Farm size
Table 1B. Sensitivity index of the six provinces of Regions XI and XII, Philippines, 2011-2012

<table>
<thead>
<tr>
<th>Province</th>
<th>AvePrepared</th>
<th>FertYR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Comval</td>
<td>2.30</td>
<td>688.94</td>
</tr>
<tr>
<td>Davao del Norte</td>
<td>2.19</td>
<td>858.07</td>
</tr>
<tr>
<td>Davao del Sur</td>
<td>2.45</td>
<td>664.09</td>
</tr>
<tr>
<td>North Cotabato</td>
<td>2.14</td>
<td>670.39</td>
</tr>
<tr>
<td>South Cotabato</td>
<td>2.41</td>
<td>1110.95</td>
</tr>
<tr>
<td>Sultan Kudarat</td>
<td>2.57</td>
<td>1334.62</td>
</tr>
</tbody>
</table>

Legend:
AvePrepared – Perception about preparedness
FertYR – amount of fertilizer used/ha/year (in kgs)

Table 1C. Exposure index of the six provinces of Regions XI and XII, Philippines, 2011-2012

<table>
<thead>
<tr>
<th>Province</th>
<th>t</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Comval</td>
<td>-0.45</td>
<td>-13.80</td>
</tr>
<tr>
<td>Davao del Norte</td>
<td>-0.72</td>
<td>-15.94</td>
</tr>
<tr>
<td>Davao del Sur</td>
<td>-0.05</td>
<td>-17.80</td>
</tr>
<tr>
<td>North Cotabato</td>
<td>-0.36</td>
<td>-9.88</td>
</tr>
<tr>
<td>South Cotabato</td>
<td>0.03</td>
<td>-16.68</td>
</tr>
<tr>
<td>Sultan Kudarat</td>
<td>-0.16</td>
<td>-10.17</td>
</tr>
</tbody>
</table>

Legend:
t – Change in temperature
P – Change in precipitation
Table 2. Factor scores of the first principal component

<table>
<thead>
<tr>
<th>Vulnerability Indicators</th>
<th>Factor Scores</th>
</tr>
</thead>
<tbody>
<tr>
<td>Access to formal credit</td>
<td>-0.3685</td>
</tr>
<tr>
<td>Access to no formal credit</td>
<td>-0.1971</td>
</tr>
<tr>
<td>Years of Schooling</td>
<td>-0.2850</td>
</tr>
<tr>
<td>Number of relatives in Brgy</td>
<td>0.3153</td>
</tr>
<tr>
<td>Total Gross Income/hec/yr</td>
<td>-0.0307</td>
</tr>
<tr>
<td>Total Farm Size</td>
<td>0.3995</td>
</tr>
<tr>
<td>Average Preparedness</td>
<td>0.4964</td>
</tr>
<tr>
<td>Amount of fertilizer/hec/yr</td>
<td>0.3300</td>
</tr>
<tr>
<td>Change in Temperature</td>
<td>0.3502</td>
</tr>
<tr>
<td>Change in Precipitation</td>
<td>-0.0787</td>
</tr>
</tbody>
</table>

Table 3. Total Variance Explained

<table>
<thead>
<tr>
<th>Component</th>
<th>Initial Eigenvalues</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total</td>
</tr>
<tr>
<td>1</td>
<td>3.766</td>
</tr>
<tr>
<td>2</td>
<td>2.425</td>
</tr>
<tr>
<td>3</td>
<td>2.248</td>
</tr>
<tr>
<td>4</td>
<td>1.028</td>
</tr>
</tbody>
</table>
Table 4. Vulnerability indices of the six provinces in Regions XI and XII, Philippines, 2011-2012.

<table>
<thead>
<tr>
<th>Provinces</th>
<th>Vulnerability Index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Comval</td>
<td>-0.48</td>
</tr>
<tr>
<td>Davao del Norte</td>
<td>-0.24</td>
</tr>
<tr>
<td>Davao del Sur</td>
<td>0.23</td>
</tr>
<tr>
<td>North Cotabato</td>
<td>-0.56</td>
</tr>
<tr>
<td>South Cotabato</td>
<td>0.20</td>
</tr>
<tr>
<td>Sultan Kudarat</td>
<td>0.86</td>
</tr>
</tbody>
</table>

Figure 2. Overall vulnerability indices of the farming sector across the six provinces of Regions XI and XII, Philippines, 2011-2012.


