CHAPTER 2

Literature Review

2.1 Climate variability and its impacts on rice production

Climate variability refers to variations in the mean state and other climate statistics (standard deviations, the occurrence of extremes, etc.) on all temporal and spatial scales beyond those of individual weather events. Variability may result from natural internal processes within the climate system (internal variability) or from variations in natural or anthropogenic external forces (external variability) (Parry, 2007). We are not always assured of getting same amount every growing season or year. Also what needs to be taken into consideration is that actual rainfall variance from the mean of which droughts and flooding conditions which can negatively impact rice production.

A study by Lansigan et al. (2000) reported the occurrence of weather episodes such as extremes characterized by maximum or minimum temperature, sequences of dry or wet days and high winds particularly during occurrence of tropical cyclones (typhoons) may significantly affect crop growth and development, which results in reduced crop yield. In the Philippines, monsoon currents, tropical cyclones, and the inter-tropical convergence zone divide the year into wet and dry seasons. Many areas have rain from May to November, the peak amounts falling between August and September. During the dry months (February-April), rainfall is generally deficient and some areas may experience drought. Climate variability can be readily observed from the fluctuations in rainfall, wind speed and direction, and temperature. Fluxes in rainfall volume below or above normal annual values may be experienced in areas affected by the anomaly. Similarly, shifts in temperature regimes in comparison with the temperature range for specific periods of the year and/or across several years also indicate climate variability. Inter-annual variability in wind speed and direction also reflect climate variability.

Agricultural producers face a number of risks in their operations. Seasonal climate variability is a major source of production risks (Ibarra and Hewitt, 1999). FAO (2006) estimates that there are still over 850 million undernourished people, of which 820 million are in developing countries. These 820 million people in developing countries tend to be poor, live in rural areas, are dependent on agriculture and/or agriculture-related activities for their livelihood, and are among the most vulnerable to disaster climate risks.

Meinke and Stone (2005) stated that climate variability often is portrayed as negatively impacting agricultural systems and the inability to predict or adapt to it has led to the development of conservative management approaches. These approaches may be of limited effectiveness in buffering against severe downside conditions and more importantly they may fail to take advantage of potential opportunities to capitalize on seasonal variability. The growing evidence of global environmental change and increased climate variability demands that adaptation options, adaptive capacity and way to reduce risk should be prioritized.

Rice crops have varying sensitivity to temperature. There are temperature threshold values beyond which crops become vulnerable to sharp temperature shifts. Yoshida and Parao (1976) reported that spikelet sterility in rice varieties was induced when exposed to high temperature immediately before and during anthesis. The same study attributed the major causes of high temperature-induced sterility in rice to disturbance of pollen shedding and decreased viability of pollen grains. This resulted in decreased number of germinated pollen grains on the stigma. Thus, rice yield is expected to decrease during instances of high temperature during flowering. Occurrence of sequences of wet and dry periods can affect crop physiological processes that may prematurely hasten or retard crop growth and development. Prolonged periods of heavy rainfall (which may result in flooding) during initial crop development may abort crop growth, and may lead to significant yield reduction especially when a heavy rainfall events occurs during the critical period of crop growth before harvesting.

In Philippines, the climatic variability is by far higher than the recorded yield variability through the period from 1985 to 2002 in the six selected provinces (Angulo-Villacís, 2009). No parallel ascending or descending trends between climatic and recorded yield variability could be identified, thus, the climatic variability represented in potential yields could not be correlated to the variability on recorded rice yield in this study. Hansen and Jones (2000) indicate that climate data in regional or (in our case provincial) level are commonly calculated by averaging and aggregating the climatic factors in a smaller plot to be translated into regional data. The effect of the mentioned aggregation of climatic data could be important factors, which can disturb the observation of the real climatic effect on a hyper-plot scale.

Climate variability determines crop yields through direct effects on crop growth and development, but also through indirect pathways such as factor farmers' decisions on crop timing, cropping sequence/rotation, etc. (Lansigan et al., 2000). Climatic factors i.e. temperature, solar radiation, and rainfall influence effectively all processes involved in grain production such as: vegetative growth, formation of storage organs, and grain filling (Yoshida, 1981). Wassmann et al. (2009) provide a detailed description of the physiological phenomena involved in rice production which could be affected by climate anomalies.

Moreover, the study of Bhandari (2013) researched the case study in Dadeldhura of Nepal about the impact of precipitation and temperature variation on major cereals such as rice, maize, wheat, millet, etc. by using the time series data of yield and seasonal meteorological data. This study confirmed that temperature and rainfall had significant influence on the yield of rice. The low precipitation and high temperature during the growing seasons of crops had severely affected the yield of major cereals in Dadeldhura district.

Mahmood et al. (2012) pointed out that in Punjap province of Pakistan, a rising temperature by 15^{o}C and 3^{o}C would increase rice yield by 2.09% and 4.33% respectively. However, an increase in rainfall by 5% and 15% during September-October had effect rice productively by 5.71% and 15.26% respectively. Therefore, enhancing farm management activities, creating awareness among farmers about climate change and the strengthening of extension departments are some measures that help to adapt to climate change in the rice region.

Case study of Bhattacharya and Panda (2013) at Kharagpur, West Bengal also worked how the trends of monthly maximum, minimum, mean temperatures and rainfall for the crop-growing season effected to rice yield. The results indicated that there was decrease in yield with per °C increase in temperature and increase in yield with per mm increase in rainfall in Subtropical region. The results of the study revealed that the average rice yield will increase of 0.35 kg/ha with per mm increase in rainfall and decrease by 156.2 kg/ha if mean temperature increase at $1^{o}C$ at that region.

Finally, MONRE (2009) revealed that rice yield decline is observed in all climate change scenarios in Vietnam, ranging from 4.2% to 12.5% in 2030 by the effect of climate variability. The impact is especially large in the Central Highlands and the northern zones, highlighting the enlarged gaps in food supply in these regions. Although the impact of climate change is relatively moderate in the major rice-producing region of the Mekong River Delta, the average rice yield is projected to drop by 1.4–8.3 percent by 2030.

2.2 Seasonal Weather Forecasts

2.2.1 Definition

The scientific climate information is provided by meteorological agencies is often classified into weather forecasts, climate forecasts and SWFs (Hellmuth et al., 2011; Mavi and Tupper, 2004). Weather forecasts refer to the information on the state of the atmosphere which is expected at specific time and location such as temperatures, wind velocity and direction, precipitation, relative humidity, sunshine duration and the rapid onset of weather hazards (e.g., tornados, blizzards and hurricanes). These forecasts are normally valid for 48 hours (i.e., short-range weather forecasts) or up to five days (i.e., extended weather forecasts). Climate forecasts on the other hand refer to average atmospheric conditions in form of probabilities or confidence level over periods of weeks, months, seasons (i.e., SWFs) or even decades (i.e., long-range climate forecasts). The seasonal forecasts often focus on the rainfall, temperature to forecast whether the season ahead (3–6 months) is likely to be wetter or drier, warmer or hotter than average.

2.2.2 Sources of Seasonal Weather Forecast Data

There is a variety of ways to disseminate SWFs and agro-meteorological information to users. Walker (2006) classified the modes of dissemination of climate information into three groups: individual contacts, group methods and mass and electronic media.

Individual contacts refer to personal communication such as from farmer to farmer, from agro-meteorologists, agricultural extension officers, disaster officers or village leaders to farmers (Walker, 2006). The weakness of this mode is that it can be time consuming to build or establish good rapports that help maintain credibility between the role-players or those individuals involved.

The group methods refer to the use of meetings to disseminate climate information to existing community groups or interest groups such as church or sports groups (Walker, 2006). This mode allows purveyors of weather information and advisories (i.e. meteorologists and agricultural scientists) to receive feedback on the provided information from a large number of users. Sivakumar and Hansen (2007) indicated that participatory workshops or meeting can also be a good option for communicating SWFs to farmers. Brief workshops or village meeting can help farmers understand more about the forecasts, and be more likely to apply them in decision-making (Patt et al., 2005).

The mass and electronic media refers to telephone/fax, radio, newspapers, e-mails, Internet websites and bulletins (Walker, 2006). One of the best reason to use electronic media is that it can disseminate important information to a large number of users within a short amount of time.

The research of Churi et al. (2012) worked about the understanding farmer's information communication strategies for managing climate risks in rural semi-arid areas, Tanzania reported that radio was effective channel for getting climate information while others sources such as researchers, agricultural input group as in banks, chemical and fertilize sellers, NGOs, district and village leader were less effectiveness. Moreover, farmers preferred radio, mobile phones, extension officers and their neighbors or friends to share climate information.

Moreover, television and radio were considered as the common sources of information of weather forecasts in Isabela Philippines (Reyes et al., 2009). The Philippine Atmospheric Geophysical, Astronomical Service Administration has been producing a vast array of climate related forecasts and information but only a few of these were made accessible and applicable to agricultural officers and farmers.

2.2.3 The SWF Use in Farming Decisions

Farmers and those involved in the agricultural sector are well aware of climate variability. The ability to understand, monitor and predict this climatic variability provides an opportunity to put historical experiences into perspective and to evaluate alternative management strategies for making improved decisions to take advantage of good years while minimizing the losses during the poor years (Huda and Packham, 2004).

It is becoming more and more apparent that farmers are recognizing the helpful role of SWFs and the substantial contributions they offer to aid the farmer in their decision making in regards to individual farming activities (e.g., harvesting time, frost protection, forage preservation, irrigation, crop choice, application of fertilizers and pesticide spraying) so they can take advantage of favorable climate conditions as well as to reduce losses caused by climate hazards in terms of personal safety and livelihood assets (Katz and Murphy, 1997; Sivakumar and Hansen, 2007; Sivakumar and Motha, 2007; Troccoli et al., 2008; Ziervogel et al., 2010). Thanks to advanced technologies, SCFs are increasingly enhanced in terms of accuracy, timeliness and accessibility, and thus continue to gain more and more confidence among farmers (Ziervogel et al., 2010).

Farmers normally want to know changes of climatic variables such as temperature, rainfall, radiation, wind, hail, and the extremes in advance for preparedness and arrangement of farming activities (Stigter, 2010). That information is often directly associated with farmer's decisions (Cooper et al., 2008). For example, weather forecasts over several days or weeks are necessary for tactical decisions that are associated with short term measures such as when is the optimal time to plant crops, the amount and type fertilizer to be used and the subsequent timing for application, to determine the best time of crop harvest and the time to sell. Long-term forecasts such as SWFs, inter-annual forecasts and extreme climatic events are more important for strategic decisions which are often linked to long-term adjustments such as altering soil management practices, diversifying farm enterprise, or installing irrigation systems to farmers (Smit and Pilifosova, 2003). The basic difference between tactical and strategic decisions is that tactical decisions are an immediate response making minor changes within the existing system while strategic decisions involve dramatic changes to the system itself in terms of components and dynamics in order to survive over a longer period of drought.

It is evident that farmers do gain benefits from using the forecasts. Weather information normally contributes to tactical decision-making of farmers which aids them in coping with drought conditions, increase the resistance of crop and livestock to drought or improve the efficiency of use of inputs during drought. For example, based on weather forecasts regarding rainfall during drought, choices of when and where to irrigate, how much water that needs to use to ensure that available water resources are managed in the most efficient manner. Similarly, the forecasts with regard to rainfall can help farmers to decide the timing for fertilizer application to minimize the leaching of fertilizer after the application (Stigter, 2010). Also, weather forecasts in regards to rainfall can help to determine the best time for planting. If the rain falls immediately after planting, some crops may produce a high rate of mortality in seedlings and therefore, re-sowing or replanting will be needed (Stigter, 2010).

Strategic decisions, based on long-term climate forecasts, are often related to changes such as land use, cropping systems and patterns, the development of water management systems and conservation of rainwater resources. For example, farmers in low-land of Bangladesh need seasonal forecasts with leading time of 5 months to decide crop varieties to plant. If there is high chance of dry spell to come late, they might choose long duration cultivars which produce higher yields (Ali et al., 2005). If the rain is predicted to cease when crops are at maximum leaf area, reduction of leaf area by thinning, weed control and mulching may be necessary measures to conserve the scarce moisture (Stigter, 2010). Also, seasonal forecasts are of the importance for deciding the planting date. For example, about 55 days after planting is the critical growth stage for the overall yield of corn. Therefore, the choice of planting date so that the critical stage does not coincide with the period of water deficits is crucial. The results of Langisan et al. (2007) illustrated that corn farms which used SWFs to decide the planting dates, gained higher yields as well as incomes rather than those which relied on traditional experience of farmers in Philippines. Similarly, in a study of Viet (2001), he used seasonal temperature forecasts to fit the time of rice flowering to the optimal temperature, which resulted in higher yields of rice. This showed that application of climate information into decision-making could be more effective by using reliable models simulating the interaction of crop and environmental variables. However, fitting the growth stage of crops or animals to proper rainfall and temperature patterns may be feasible only if the forecasts are credible enough.

2.2.4 Seasonal Weather Forecast Data Limitations

Despite the benefits of SWFs, it is argued that the value of it is dependent on the knowledge as well as capacity of farmers to translate such forecasts into profitable decisions. It is also noted that the value of SWFs depends on the accuracy (i.e., the skill) of frequency of the forecasts (Marvi and Tupper, 2004). The accuracy decreases when the lead time of forecasts as well as the scale of forecasts increases. Seasonal forecasts, especially long-range forecasts, often have high level of uncertainty. Therefore, forecasts with the lead time of over one month are not often accurate enough to be used in decision making process (Marvi and Tupper, 2004). This has raised a need for improving forecasting models in order to produce more reliable forecasts.

In addition, communication of these SWFs to end users is still a big challenge to scientists (Hellmuth et al., 2011). It is argued that the forecasts themselves are not always appropriate for all users (Hellmuth et al., 2011; Troccoli et al., 2008). Besides, Ziervogel and Calder (2003) found that SWFs are presented in a probabilistic form and climatic jargons which obviously are not an understandable delivery style to all users, particularly farmers. For instance, rainfall is often forecasted as the chance of being ‘above normal’, ‘below normal’ or ‘near normal’ in comparison with the average rainfall for the past number of years of rainfall data. This causes farmers difficulties in interpreting as well as integrating this information into their decision making. Unfortunately most of the efforts to date have not been focused on teaching recipients climatic jargons rather than teaching climate scientists the essential language or local terms of recipients (Troccoli et al., 2008). Thus, it is advised to use local language and terminology familiar to farmers to make the scientific forecasts more accessible and usable to farmers (Ziervogel and Opere, 2010).

In addition, it is said that there is a considerable gap between information needed by farmers, particularly small-scale ones, and that provided by meteorological services (Blench, 1999). In other words, the forecast is often not tailored to suit users in content or to meet specific user needs. This reflects differences in concepts, interests and needs between scientists and farmers (Stigter, 2010). Forecasts are issued in the form of the total amount of rainfall for a period of one, three or six months, but not the distribution of rainfall within that period (Ziervogel and Calder, 2003).

Furthermore, while SWFs often cover a vast region, in many cases, decision-makers want the SWFs to be localized to know whether or not their area will experience forecasted weather events such as drought, flooding, or cyclones (Ziervogel and Calder, 2003). This might appear to be a challenge to climatic scientists, especially in developing countries, due to the limited number and distribution of local hydro-meteorological stations.

Many problems have also been found regarding the communication channels of SWFs to farmers. Kalanda-Joshua et al. (2011) point out that a problem in dissemination of SWFs in Nessa Village, Malawi, is the ineffective utilization of local resources such as the use of local radio systems and traditional oral transmission, which enable the climate information to reach the larger farming community. According to Hellmuth et al. (2011), decision-makers frequently have problems with the timing of forecasts, which do not always allow them with the lead-time to have good adjustments and preparedness. For example, farmers in South Africa complained about receiving climate forecasts after they had made decisions and done preparations for the upcoming crop (O'Brien et al., 2000). Additionally, in some instances, farmers are probably not aware of weather forecast products due to the poor dissemination systems. For instance, a study on awareness of farmers in Isabela, Philippines on the ten (10) products of SWFs tailored for farmers from the Philippine Atmospheric Geophysical, Astronomical Service Administration shows 94 percent of the interviewed farmers were aware of ENSO forecasts and 85 percent of tropical cyclone warnings while there was a low awareness ranging from 2 percent to 19 percent of the rest of the products (Reyes et al., 2009).

In addition, the current popular means for climate information delivery are written materials, television and radio broadcasts, and internet means which are primarily oriented for the educated and the wealthy farmers rather than the less-educated, elderly, people who have low incomes or cannot access electricity. It is therefore frequently suggested that variety of dissemination methods should be used in order to reach a larger community (Walker, 2006). For example, with limitation in reliable communication networks, the majority of Africa's farmers and herders cannot access the available techno-scientific advances that support them in agricultural decision-making (Salinger et al., 2005).

It is also argued that different users or groups of users have different communication channels, which are more favorable to their situation. For instance, the findings of Archer (2003) indicate that the dissemination of SWFs through radio was more accessible to men than women. Due to time constraints, the women cannot frequently listen to radio programs, but mostly receive climate information through personal interaction with extension workers. Accessibility of scientific climate information to end user's needs to be improved in terms of content, form, and communication channels in the future.

Besides, many studies seek to identify the current and potential patterns of forecast use, the integration of forecasts into decision making, and the most appropriate ways to communicate information to various groups (Orlove et al., 2004). Numerous factors have been identified that influences perception, communication, interpretation, and use of forecasts (Easterling and Stern, 1999). However, Orlove et al. (2004) suggested that the forecast control such as timing of forecast dissemination, accuracy, variability, understandability, etc. influence forecast use in different ways.

The timing of a forecast is often cited as a characteristic that affects forecast use (Bohn, 2000). The intuitive assumption is that the farther in advance information gets into the hands of a decision maker, that is, the longer the "lead time," the better (Orlove et al., 2004). Moreover, Benjamin (2004) indicated that forecasts influenced decisions outside of the decision makers' occupational specialization, suggesting that attention to behavior outside the principal income-generating economic activity may reveal decisions that affect the levels of potential use of forecasts.

In general, human motivation cannot be discussed without reference to both internal (e.g., psychological and social) and external (e.g., technological and situational) factors. Many studies have examined the external factors by studying how forecast type, accuracy, format, and timeliness affect forecast use in farming decisions (Mjelde et al., 1998). Although these properties and formats of the forecasts do affect their usage, forecast use likely is strongly affected by a host of internal psychological and social factors (Glantz, 1977) that have not been fully explored. The result of Hu et al. (2006) shown that the attitudes and other psychological, social and economic influences on farmers' decisions making related to using SWFs.

As Hulme et al. (1992) pointed out, "a forecast in isolation from other information is unlikely to improve on existing indigenous knowledge systems" and, thus, is unlikely to be the only basis for making decisions. Though approaches taken by economists such as Sonka et al. (1987) emphasize information relevant to personal profit maximization, others have argued that the decision-making context also consists of many "rules of-thumb" based on past experience, and is influenced by personal beliefs, community values and commitments, and economic capacity, among other factors that guide an individual's decision making (Nicholls, 1999).

Artikov et al. (2006) reported that the improvement of significant attitude, social norm, and perceived behavioral social controls could enhance forecast use of farmers. This suggests that a focus on changing both the farmers' and their societies' beliefs and values, and perceptions of weather and climate forecasts will greatly affect their use and influence. The easiest way to improve the use and influence of weather and climate forecasts will come from changing the individual's attitude, although such change also depends on the collective "attitude" of his/her community (the social norms), e.g., friends and neighbors, bankers, and university extension, towards the individuals use of climate forecasts.

2.3 Theory of Planned Behavior

The Theory of Planned Behavior (TPB) developed by Ajzen in 1991, which is extension of Theory of Reasoned Action by Fishben and Ajzen (1975) made necessary by the original model's limitations in dealing with behaviors over which people have incomplete volitional control.

According to the TPB model, the individual performance of behavior is caused by his/her intention to act. Intention is in turn determined by three factors related to the behavior such as the person's attitude, subjective norms and perceived behavior control. Moreover, a person's personality, age, occupation, gender, etc., have no impact on his/her behavior intention. In facts, these variables can only affect behavioral intension directly through attitude and subject norms (Ajzen, 1991).

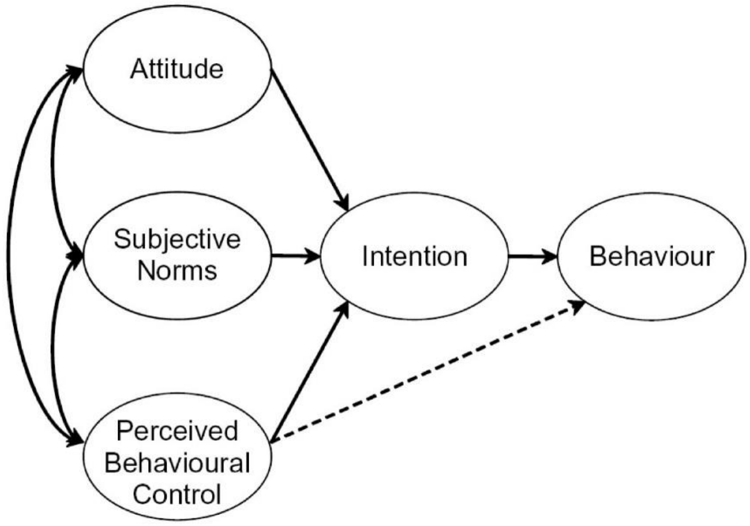

Figure 2.1 Theory Framework of planned behavior
Source: Ajzen (1991)

Attitude described as “the degree to which a person has a favorable or unfavorable evaluation or appraisal of the behavior in question. It means that a person may have positive or negative attitude evaluation of performing a specific behavior (Ajzen, 1991). Taylor and Todd (1995) reported that when someone has more positive attitude, then his/or will be more favorable toward to action intention and vice versa. Attitude toward to behavior is represented by the individual’s beliefs about outcomes or attributes of performing the behavior (behavioral beliefs), weighted by evaluations of those outcomes or attributes (Ajzen, 1991). Thus, a person who holds strong beliefs that positively valued outcomes will result from performing the behavior will have a positive attitude toward the behavior. Conversely, a person who holds strong beliefs that negatively valued outcomes will result from the behavior will exhibit a negative attitude.

Subjective norms are defined as the degree of social pressure felt by person with regard to their behavior. In the other words, this factor is as perceived as a feeling of significance from other group views which are important to an individual and will influence on his/her making decisions (Ajzen, 1991). Many research confirmed that subjective norms had positive influence on behavior intension (Han and Kim, 2010; Taylor and Todd, 1995; Tonglet et al., 2004).

The last determinant of intension is perceived behavioral controls, which are need to consider in TPB model. Perceived behavioral controls refer to an individual's perception of the possible obstacles that his/her meet when performing a specific behavior (Ajzen, 1991). The external and irrational factors such as time, money, chance, etc., may not be under the control of individuals. Therefore, the more difficulties are able to have control over the opportunities and resources to perform a specific behavior, the more likely such a behavior will be integrated in. Moreover, the investigation has shown that people behavior is strongly influenced by their confidence in their ability to perform it. Ajzen (2002) indicated that few researches have conducted perceived control using the underlying measures of control beliefs and perceived power, instead, studies have mostly applied the direct measure of perceive controls.

According to Ajzen (1991; 2002), the TPB measures in both direct and indirect can use either 5 or 7 points scale. These scale should be scored in unipolar (e.g., from 1 to 7 or from 0 to 6) or in bipolar style (e.g., from -3 to +3). In the one hand, behavioral intentions are measured by three methods such as performance, which is used in situations are possible to observe actual behavior; generalized intentions. Whereby when investigating the behavior where multiple options are possible, intention simulation is using scenarios for respondents to evaluate and make choices based upon the information provided. In the other hand, the direct measure of attitude toward performing the behavior is obtain by applying different scale items such as "bad-good" or "unlikely – likely or "pleasant – unpleasant". Addition, a direct measure of subject norm with respect to each referent, 7 points scale uses to point the degree which referent should disapprove or approve as "unlikely - likely" or "disagree-agree", etc. The question used to ask respondent is that "Most of people important to me think I should". Furthermore, the direct measure of perceived behavior control generally applies different scale items as "not under my control to under my control" or "difficult to easy" or "bad to high", etc. These are used to reflect people capable to perform target behavior and people assessing the controllability of behavior.

The TPB model has been applied widely in researches regard to predicting behavioral intension by social physiologist (Fielding et al., 2008). This model also used in different areas in agriculture to provide a better understanding of farmer's decision and adaptation such as farmer’s conservation behavior (Beedell and Rehman, 2000), farmer’s adoption of soil conservation practices (Wauters et al., 2010), farmers’ decisions to diversify or specialize their businesses (Hansson et al., 2012), farmer’s decision making toward ecosystem service determine agricultural land use practices (Poppenborg and Koellner, 2012), farmers' decisions with regard to animal welfare (de Lauwere et al., 2012), understanding the farmer’s uptake of organic farming (Läpple and Kelley, 2013), predicting pro-environmental agricultural practices (Price and Leviston, 2014), farmers’ intention to adopt improved natural grassland (Borges et al,. 2014) and understanding farmers' intention and behavior regarding water conservation (Yazdanpanah et al., 2014).

Hu et al. (2006) reported the descriptive findings from a survey designed consistent with the TPB approach to assess how the current farmer attitudes, social norms, and perceived control factors affect forecast use. According to the TPB, these factors shape farmers' motivation and affect both their intentions to use and their actual use of forecasts in farming decisions. The TPB predicts three kinds of factors likely to affect forecast-use behavior as: 1) attitudes reflecting expectancies and values associated with forecast use, 2) social influences stemming from expectancies about local norms concerning forecast use and extent of personal desire to comply with those social norms, and 3) perceived control over one's forecast-use behavior.

According to Artikov et al. (2006), the findings that the TPB framework is useful for designing ways to enhance the use and influence of climate forecasts in agricultural (and likely other kinds of) decision-making. It suggested that a focus on change both farmer’s attitude and their societies beliefs and their perception of weather and climate forecasts will extremely influence their use.

2.4 Cronbach Alpha Coefficient

Alpha was developed by Lee Cronbach in 1951 (Cronbach, 1951) to provide a measure of the internal consistency of a test or scale. Internal consistency describes the extent to which all the items in a test measure the same concept or construct and hence it is connected to the interrelatedness of the items within the test. Internal consistency should be determined before a test can be employed for research or examination purposes to ensure validity.

Internal consistency is concerned with the interrelatedness of a sample of test items, whereas homogeneity refers to unidimensionality. A measure is said to be unidimensional if its items measure a single latent trait or construct. Alpha, therefore, does not simply measure the unidimensionality of a set of items, but can be used to confirm whether a sample of items is actually unidimensional (Cronbach, 1951).

There are different reports about the acceptable values of alpha, but Cronbach's alpha value should range from 0.70 to 0.95. A low value of alpha could be due to a low number of questions, poor interrelatedness between items or heterogeneous constructs. For example if a low alpha is due to poor correlation between items then some should be revised or discarded. The method to find them is to compute the correlation of each tests item with the total score test; items with low correlations are deleted. If alpha is too high it may suggest that some items are redundant as they are testing the same question but in a different guise.

2.5 The Structural Equation Modeling (SEM)

2.5.1 Definition

Structural equation modeling (SEM) is statistical models that seek to explain the relationship among multiple variable. It checks the structure of interrelationships expressed in a series of equations, similar to a series of multiple regression equations. These equations depict all of relationship among constructs (the dependent and dependent variables) involved in the analysis. Constructs are unobservable or talent factors that represented by multiple variables. SEM is known by many names: covariance structure analysis, talent variable analysis and some is events just referred to the name of specialized software package used (e.g., LISREL or AMOS model). There are three characteristics of SEM: estimation of multiple and interrelated dependence relationships; an ability to represent unobserved concepts in these relationships and correct for measurement error in the estimation process; defining a model to explain the entire set of relationships (Hair et al., 2006).

A model should not be developed without some underlying theory. Theory is often a primary objective of academic research, but practitioners might develop or purpose a set of relationships that are as complex and interrelated as any academically based on theory.

Therefore, in both case, SEM is good tool to establishing a theory (Hair et al., 2006).Kline (2011) indicated that SEM consists the evaluation of two models: a path model and a measurement model as explanation as:

Path analysis is an extension of multiple regression in that it involves various multiple regression models or equations that are estimated simultaneously. This provides a more effective and direct way of modeling mediation, indirect effects, and other complex relationship among variables. Path analysis can be considered a special case of SEM in which structural relations among observed (latent) variables are modeled. Structural relations are hypotheses about directional influences or causal relations of multiple variables (e.g., how independent variables affect dependent variables). Hence, path analysis (or the more generalized SEM) is sometimes referred to as causal modeling.

The measurement of latent variables originated from theories. Unobserved latent variables cannot be measured directly but are indicated or inferred by responses to a number of observable variables (indicators). The measurement model in SEM is evaluated through confirmatory factor analysis.

CFA (Confirmatory Factor Analysis) is used to provide the confirmatory test of measurement theory to show how well the measured variables represent the constructs. CFA differs from Exploratory Factor Analysis (EFA) in that factor structures are hypothesized a priori and verified empirically rather than derived from the data. EFA often allows all indicators to load on all factors and does not permit correlated residuals. Solutions for different number of factors are often examined in EFA and the most sensible solution is interpreted. In contrast, the number of factors in CFA is assumed to be known (Hair et al., 2006; Kline, 20011).

According to review of Xiong et al. (2014) about SEM application in construction researches, there are several models selected for analysis in these studies. That is (1) after evaluating, only one final model is included to analysis; (2) when model is evaluate by splitting a sample, only the model tested with verification sample is included; (3) when parallel constructs are evaluated separately as confirmatory factor analyses, only the model with the best goodness of fit is included; (4) SEM is conducted with good of fit model. The CFA model is utilized for validation of existing and newly developed theory framework, while SEM models is applied to investigate the interrelationships among talent variables.

2.5.2 Measurement Model Validity

After measurement model is specified, the SEM testing “is the measurement model valid” Measurement model validity depends on good-of-fit for the measurement model and specific evidence of construct validity. Good-Of-Fit (GOF) shows how well the specified model reproduces the covariance matrix among indicator items (Hair. Edt). The indicators assess for GOF of model are as follows:

+ Chi-square (χ^2): The difference in the covariance matrices is the key value to assessing the GOF of any SEM models. SEM estimation procedures such as maximum likelihood produce parameter estimates that mathematically minimize this difference for a specific model. A chi-square test provides a statistical test of the resulting difference.

χ^2 = (N-1)(Observed sample covariance matrix – SEM estimated covariance matrix)

$$\text{Or} \qquad \chi^2 = (N - 1)(S - \textstyle\sum_k)$$

N is the overall sample size. If the difference in covariance matrices remained constant, the χ^2 value increase as sample size increases.

+ Degree of freedom: This indicator represents the amount of mathematic information available to estimate model parameters. Degree of freedom for SEM model is determined by:

$$df = 0.5((p)(p + 1)) - k$$

Where, p is the total number of observed variable and k is the number of estimated (free) parameters. In SEM, the degree of freedom is calculated based on the number of unique covariance and variance in the observed variance matrix. The difference compared to other method is that sample size does not affect the degree of freedom in SEM.

+ Goodness-Fit Index (GFI): The GFI is an early attempt to produce a fit statistic that was less sensitive to sample size. The possible range of GFI values is 0 to 1 with higher value is better fit. GFI value is greater than 0.9 typically is considered good.

+ Root mean square error of approximation (RMSEA): It represents how well a model fits a population, not just a sample used for estimation. Lower RMSEA value indicates better fit. This value should be lower than 0.08.

+ Comparative fit index (CFI): This is an incremental index. The CFI is normed so that values range between 0 and 1, with higher value indicates better fit. CFI values are less than 0.9 is usually associated with a model that fits well.

+ Tucker Lewis index (TLI): The TLI predates the CFI and is conceptually similar in that it also involves as mathematical comparison of a specified theoretical measurement model and a baseline null model. The model with good fit has values that approach 1.

2.5.3 Confirmation Factor Analysis (CFA) and Construct Validity

Confirmation factor analysis is a special type of factor analysis and it is first part of a complete test of a structural model in SEM. This analysis tells which variables belong with which indicators before SEM can be conducted. The CFA is not only must provide acceptable fit, but also needs to show evidence of constructing validity. When CFA model fits and displays construct validity, the measurement theory is supported. There are four important components for construct validity as follows:

+ Convergent validity: The items that are indicator of a specific construct should converge and share a high proportion of variance in common, known as convergent validity.

+ Loading factor: The size of loading factor plays importance role. The high convergent validity, high loading factor would indicate that they converge on some common points. At minimum, all loading factors should be statistically significant. A good rule of thumb is that standardized loading estimates should be 0.5 or higher, and ideally 0.7 and Cronbach alpha is higher than 0.7 (Hair et al., 2006).

+ Reliability: Considerable debate centers around which of several alternative reliability estimate is best. Coefficient alpha remains a common applied estimate. The rule of thumb for either reliability estimate is that 0.7 or higher which suggests good reliability. Reliabilities between 0.6 and 0.7 can also be acceptable. High construct reliability means that the measures of all consistently represent the same talent construct.

+ Discriminant validity: Discriminant validity is the extent to which a construct is truly distinct from other construct. Hence, high discriminant validity provides evidence that a construct is unique and captures some phenomena other measures do not (Hair, 2006). The correlation between any two constructs can be specified as equal to one, the discriminant validity is insufficient. Normally, if correlation of two structures is lower than 0.9, then the discriminant validity is sufficient.

2.5.4 Application of SEM in Agriculture

As reviewing by Xiong (2014) about SEM application in construction researches, SEM was initially used as main statistical tool in articles in 31 journals up to April 4, 2013, in which the most using in such journals of construction engineering and management, construction management and economic.

SEM represents a set of integrated multivariate techniques (e.g. measurement theory, factor analysis, regression, path analysis and simultaneous equation modelling), which are used to describe multiple relationships among a number of latent variables. SEM has been widely applied in social science, particularly in psychological studies (Anderson and Gerbing, 1988; Ko and Steward, 2002). It also used in varies fields in agriculture sector such as environmental psychology (Grob, 1995), environment behavior and social ecomonic condition of hillside farmers (Bayard and Jolly, 2007), structure risk perception (Sparrevik et al., 2010), sustainable behavior in contaminated land remediation (Hou et al., 2014), farmers conservation behavior (Beedell and Rehman, 1999; Beedell and Rehman, 2000), ecological pattern (Arhonditsis et al., 2006), agricultural technology (Adrain et al., 2005), farmers adaptation intension to climate change (Dang et al., 2014) and water management (Hurlimann et al 2008; Chen and Lin., 2010; Tang et al., 2013).