Weather shocks on farmers' adaptation behaviors: Exploring asymmetric impacts and experience moderation

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Abstract

Farmer is the profession closest to the natural environment and is often at the forefront of the fight against climate change, and the changes compared to historical conditions could be seen as a kind of shock to farmer's life. In this research, we examine the effect of weather shocks on three adaptive decisions by farmers, labor allocation, protective facilities, and conservation agriculture practice. Spatial seemingly unrelated regressions method is used to deal with the problem of spatial autocorrelation and correlated disturbances between equations. Using census data of vegetable farm households and historical weather data in Taiwan, our findings indicate that the effects of positive and negative shocks are asymmetric. Rainy shocks increase the ratio of households engaged in non-agricultural work and the adoption rate of organic practices, while drier shocks do not. The ratio of greenhouse increases with higher temperatures. We also observe that experience moderates the effects resulting from rainfall shocks. Furthermore, among specific groups of farm households, we found that elderly farm households show stronger effects on the nonfarming ratio compared to others, whereas the behaviors of mini farm households are less likely to be affected by weather shocks.

Keywords Weather shock, farmer's behavior, spatial dependence

JEL code Sustainable Development Q01; Micro Analysis of Farm Firms, Farm Households, and Farm Input Markets Q12; Valuation of Environmental Effects Q51

1. Introduction

Effects of climate change are highly discussed over past years. Phenomenon of climate change present in higher sea level, global warming, increasing frequency and intensity of storm and flooding, shifting season, etc. (Koetse & Rietveld, 2009). Agriculture had been taken as the sector closest to the natural environment and often at the forefront of the fight against climate change. In previous literature, they sometimes examine for how climatic factors (e.g., temperature and rainfall) matter farmers' life (Mendelsohn, 2014; Luh & Chang, 2021), and there are also studies focus on the effect of longer-term changes in temperature and precipitation on agricultural sector (Burke & Emerick, 2016), to emphasize the concept of climate change. Besides the mean climate change, climate variability and extreme events also yield significant damage and impacts on farmers' production and behaviors (Kurukulasuriya & Rosenthal ,2013; Mahato, 2014). In such extreme events, precipitation shocks—floods and droughts—are often discussed (Salazar-Espinoza et al., 2015; Mehar et al., 2016; Khanal et al., 2018; Carrillo, 2020). Floods may lead to fields being inundated, damaging crops and affecting their growth. Soil degradation, increased vulnerability to pests and diseases, as well as erosion and damage to irrigation infrastructure, are common consequences of floods on agricultural land. Conversely, droughts can result in water scarcity, limiting crop growth, reducing yields, and potentially causing crop failure. These shocks can also severely affect farmers' livelihoods as their primary income source is often derived from agriculture. Compared to the precipitation extreme events like floods and droughts, in temperature, continuous warming trends tend to receive more attention (Burke & Emerick, 2016).

In certain studies, shock is defined as deviations from historical conditions, indicating changes that occur beyond what was previously observed (Chuang, 2019; Matsuura et al., 2023; Carrillo, 2020). Carrillo (2020) defined floods and droughts as rainfall exceeding or falling below one standard deviation from the 20-year historical average. As Chuang (2019) and Matsuura et al. (2023) defined in their studies, climate change leads to the shocks which are quantified as the variation from long-run historical average. In this research, we apply the concept of such shocks, to observe more nuanced effects, as farmers might still perceive the changing climate despite not reaching the extremes. However, for farmers, while these shocks are quantified as values relative to historical conditions, the positive and negative shocks lead to two different kinds of extremes. These two shocks may lead to varying levels of perception and result in different adaptation behaviors by farmers. To our knowledge, the inconsistency in their directions or even asymmetry hasn't been extensively discussed in past research about farmers' adaptation. In the context of climate change, a notable rise in precipitation variability is observed while the average rainfall has not shown a clear upward or downward trend over the long term (Thornton et al., 2014; Hatfield & Walthall, 2014; Kurukulasuriya & Rosenthal, 2013), so it's crucial to explore whether the asymmetry exists in two directions. Moreover, even under global warming conditions, certain regions might experience instances of lower temperatures, and the effects of such shocks remain unclear. So, not only considering for the rainfall shock as in previous studies, our research extends similar definition and make examination on temperature shocks.

To address the gaps in previous research, the primary objective of this study is to examine the inconsistent and even asymmetric effects of weather shocks. The inconsistency manifests as a greater likelihood of increased adaptive behavior with deeper shocks, meaning that when the shock is negative, smaller (larger absolute value) shock is more likely to prompt farmers to adapt, and vice versa. Figure 1 depicts the effect of weather shocks (x-axis) on the probability of adoption (y-axis). In Figure 1(a), the inconsistency is represented by its V-shaped pattern. Under this inconsistency, two kinds of asymmetric scenarios may arise. When farmers exhibit stronger adaptive responses to positive shocks than negative ones, the pattern is presented as Figure 1(b). Conversely, when farmers exhibit weaker adaptive responses to positive shocks compared to negative ones, pattern emerges in Figure 1(c). Understanding this asymmetry can help us more comprehensively assess and address the impacts of various weather shocks

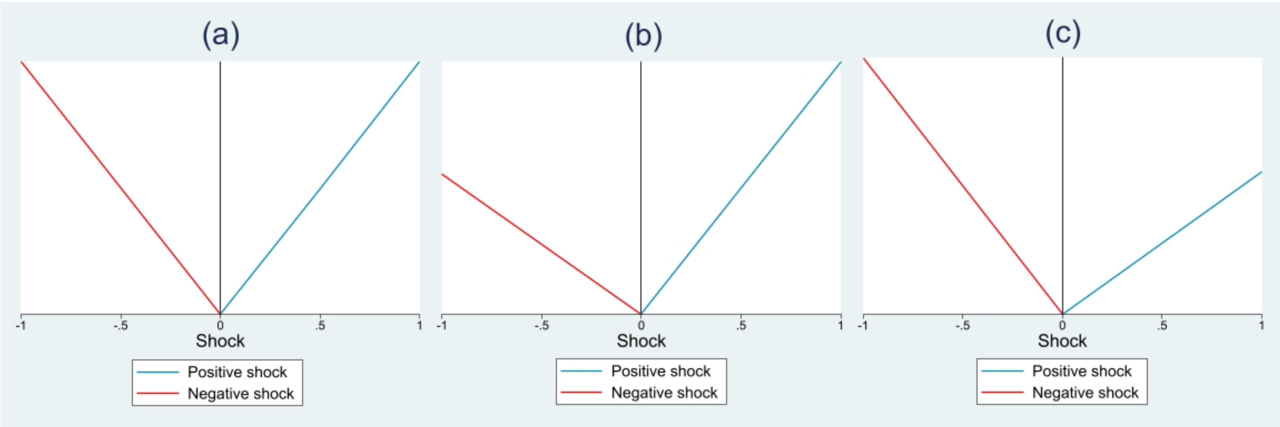


Figure 1 Patterns of inconsistent and asymmetric effects on probability of adaptation
Source: This study.

Besides, the past weather experience can have various impacts on farmers. It can influence farmers' perception or opinion of current and future climate change. If farmers have experienced extreme weather events or climatic anomalies, they may be more likely to recognize the presence of climate change and could become more attentive and sensitive to climate-related risks (Howe, 2021). However, the findings for this relationship are not clear (Sisco, 2021). Marlon et al.'s (2019) study showed that the perception of climate change is not significantly affected by their individual experience, but get noticed by the reminder from experts. Additionally, past weather experiences also influence farmers' coping and adaptation strategies. Regarding the weather experience, most of past studies have focused more on how it influences attitudes about climate change rather than adaptive behavior so far (Sisco, 2021). Farmers with rich climate experiences may be more inclined to adjust planting seasons, change crop varieties, adopt new cultivation techniques, or invest in the insurance as ways to cope with continually changing climatic conditions, such as the consequence in Khanal et al. (2018) indicated the experience of flood or drought make higher probability to do some adaptation due to risk aversion. However, despite the perception was enhanced by the experience, people adapt less due to the absence of technique or knowledge support (Hamilton-Webb et al., 2017). There are also studies such as Chuang (2019) discuss for how it influences the response when farmers facing shocks, reporting that the farmers living in risky area, e.g. higher climate variation in the past, will moderate the response to the weather shocks since they have already done some adaptation. Therefore, the heterogeneity should exist within farmers with different experience about long-term weather conditions. This research will show how weather experience interact with the asymmetric effects of shocks.

To cope with the damage caused by climate change, adaptive strategies emerge among farmers. Numerous adaptive strategies have been discussed in past studies focused on the agricultural sector (Gutu et al., 2012; Mehar et al., 2016; Huang et al., 2020; Branco & Féres, 2021). Smit and Skinner (2002) categorizes adaptive behaviors into four main types: technical improvement, farming practice, financial management and seeking external assistance. Some studies concentrate on one specific adaptive behavior, examining determinants that enhance adoption or their impact on farmers' welfare (Salazar-Espinoza et al., 2015; Huang et al., 2020), while others compare different adaptive behaviors (Mehar et al., 2016; Gutu et al., 2012; Tofu et al., 2022). In this research, we examine three decision equations on each adaptive strategy respectively. However, the disturbances in equations are likely correlated, given that the strategies originate from the same households. The seemingly unrelated regression (SUR) method is often used to address this issue and makes estimation more efficient than that generated by respective equations of least squares (Zellner, 1962; Angulo et al., 2010; Katchova, 2013). In a related topic, Mulwa and Visser (2020) also use SUR to explore the effect of weather shocks on two adaptive strategies—crop and livestock diversification. Furthermore, when using cross-section data, estimation under the assumption of spatial independence may lead to incorrect conclusions regarding spatial spill-over effects or spatial heterogeneity (Anselin, 1988). Therefore, this research applies the spatial seemingly unrelated regressions method to consider these factors. With full consideration of inconsistent effects, weather experience, spatial dependence, and correlation between equations, this study provides a more comprehensive view of how weather shocks affect farm households' behaviors.

This research focus on the vegetable farm households in Taiwan. Among numerous studies reporting the effect of climate change in human being's economic activities no matter in developed countries or developing countries, and the damage of global warming had been found deeper in the hotter areas (Acevedo et al., 2020). Muñoz-Rojas et al. (2017) also mentioned that in humid tropical regions, an increase in the intensity of rainfall events may more easily lead to temporary flooding. Taiwan is situated in East Asia, approximately between 21.45-25.56°N latitude and 119.18-124.34°E longitude where belongs to subtropical region. Taiwan is an island that relies to a certain extent on import and export trade in various aspects of life. Its own agricultural sector plays an extremely important role in the country's food security. In addition to serving as an example of a humid tropical region more susceptible to climate change, the characteristics of Taiwan's farmers, such as their intensive practices and small scale, are considered factors that may reduce their resilience when facing the climate change (Cerri et al., 2007). This underscores the importance of studying the climate impacts on the behavior of farmers in the region of Taiwan.

In the following chapter, the data and sample characteristics used in this study will be introduced. Section 3 will outline how this research identifies asymmetric effects, considers the interaction effects of experience, and presents the empirical model framework. Section 4 will present the results of this study, followed by a conclusion in section 5.

2. Empirical Method

2.1 The asymmetric effects and experience interaction

This research focuses on three kinds of adaptive behavior by farm households. We address the effects of weather shocks with consideration of socio-economic characteristics of operators, and the human capital of household members for vegetable farm households. By combining climate data and agricultural census data at the township level, this research examines the existence of spatial lag and error dependence, and applies the spatial seemingly unrelated regressions method. The original adaptive behavior equations can be specified as following:

$$\begin{aligned} Y_{15,j} = \alpha_1 RainShock_{14} + \beta_1 TempShock_{14} + \alpha_{LR} RainLR_{15} + \beta_{LR} TempLR_{15} + \mathbf{X_{15}\theta} \\ + u_j, \qquad where\ j = 1, 2, 3 \end{aligned} \tag{1}$$

In the above equation, the outcome variable, $Y_{15,j}$, is the adaptive behavior j (represent for non-agricultural share, greenhouse ratio or organic adoption) of the farm household. The weather shocks in 2014 are denoted by $RainShock_{14}$ and $TempShock_{14}$, the corresponding coefficients are α_1 and β_1, which show the effects of weather shocks. The long-run weather conditions, $RainLR_{15}$ and $TempLR_{15}$, are also controlled, and coefficients are α_{LR} and β_{LR}, respectively. The vectors of farm's socio-economic characteristics in 2015 and associated coefficients are denoted by $\mathbf{X_{15}}$ and $\boldsymbol{\theta}$. To identify the interaction effect of past weather experience, we can capture the effect through the interaction term of the standard deviation of average daily rainfall (temperature) from 1995 to 2014, denoted as $RainSD_{15}$ and $TempSD_{15}$, along with the weather shock variable. The corresponding coefficients, α_2 and β_2, present how the weather experience affect the effect of shocks.

$$\begin{aligned} Y_{15,j} = \alpha_1 RainShock_{14} + \alpha_2 RainShock_{14} * RainSD_{15} + \alpha_3 RainSD_{15} \\ + \beta_1 TempShock_{14} + \beta_2 TempShock_{14} * TempSD_{15} + \beta_3 TempSD_{15} \\ + \alpha_{LR} RainLR_{15} + \beta_{LR} TempLR_{15} + \mathbf{X_{15}\theta} + u_j, \qquad where\ j = 1, 2, 3 \end{aligned} \tag{2}$$

Due to one of the primary objectives of this study being to investigate whether there are asymmetric effects of weather shocks between positive and negative values, we also create interaction terms using a dummy variable, D_{rain} and D_{temp}. When the shock takes positive value, the dummy variable equals to 1 and 0 otherwise. This allows us to examine the differences in effects in both directions. The model is specified as equation (3), and expanded as equation (4).

$$\begin{aligned}Y_{15,j} = {} & (\alpha_1 + \alpha_1' * D_{rain}) * RainShock_{14} + (\alpha_2 + \alpha_2' * D_{rain}) RainShock_{14} * RainSD_{15} \\ & + (\beta_1 + \beta_1' * D_{temp}) TempShock_{14} + (\beta_2 + \beta_2' * D_{temp}) TempShock_{14} \\ & * TempSD_{15} + \alpha_{LR} RainLR_{15} + \beta_{LR} TempLR_{15} + \mathbf{X_{15}\theta} + u_j \qquad (3) \\ = {} & \alpha_1 RainShock_{14} + \alpha_1' RainShock_{14} * D_{rain} + \alpha_2 RainShock_{14} * RainSD_{15} \\ & + \alpha_2' RainShock_{14} * D_{rain} * RainSD_{15} + \beta_1 TempShock_{14} \\ & + \beta_1' TempShock_{14} * D_{temp} + \beta_2 TempShock_{14} * TempSD_{15} \\ & + \beta_2' TempShock_{14} * D_{temp} * TempSD_{15} + \alpha_{LR} RainLR_{15} \\ & + \beta_{LR} TempLR_{15} + \mathbf{X_{15}\theta} + u_j, \qquad where\ j = 1,2,3 \qquad (4)\end{aligned}$$

2.2 Spatial seemingly unrelated regressions method

As the presence of spatial dependence and potential correlation in error terms between equations, the spatial seemingly unrelated regressions (spatial SUR) method can be used to deal with them (Mínguez et al., 2022). The adoption equations of farm households were shown in the previous section. While SUR model can be used in multiple panel data in Anselin's (1988) case, it could be applied into the analyses for multiple equations in one time period. Using the cross-sectional data in 2015, this research constructs three behavior equations simultaneously in SUR model, where the number of equations, G, equals to three, time period, T, equals to one and N individuals in our data, following the structure of method in Mínguez et al. (2022) and Anselin (1988). The basic SUR model without spatial consideration can be shown as equation (5) with $\mathbf{A}$ and $\boldsymbol{\kappa}$ denote for the vector of all related weather variables and corresponding coefficients.

$$Y_{15,j} = \mathbf{A}_j \boldsymbol{\kappa}_j + \mathbf{X_{15}\theta} + u_j, \ \ where\ j = 1, \dots G \qquad (5)$$

Specifically, the serial dependence in the errors is not explicitly parameterized, but estimated in the $G \times G$ covariance matrix $\sum$, where $\sum = (\rho_{js}; j, s = 1, \dots, G)$. This approach allows us to simultaneously estimate the parameters of all three equations at one period, leveraging the information contained in the cross-sectional data. By using the spatial data of township level, the potential spatial effects might be raised from spatial dependence on outcome variables, covariates, and error term (Mínguez et al., 2022; Elhorst, 2014). To simplify the effect of weather shocks, this research conducts the spatial econometric model as following, without spatial effect on the covariates.

$$\begin{gathered} Y_{15,j} = \rho_j \mathbf{W}_j Y_{15,j} + \mathbf{A}_j \boldsymbol{\kappa}_j + \mathbf{X_{15}\theta} + u_j \Rightarrow \mathbf{A}_j Y_{15,j} = \mathbf{A}_j \boldsymbol{\kappa}_j + \mathbf{X_{15}\theta} + u_j \\ u_j = \delta_j \mathbf{W}_j u_j + \varepsilon_j \Rightarrow \mathbf{B}_j u_j = \varepsilon_j, \qquad (6) \\ where\ E[\varepsilon_j] = 0, \qquad E[\varepsilon_j \varepsilon_s] = \rho_{js} I, \end{gathered}$$

$$\mathbf{A}_j = I - \rho_j \mathbf{W}_\mathrm{j}, \qquad \mathbf{B}_j = I - \delta_j \mathbf{W}_\mathrm{j}, \qquad j, s = 1, \dots, G$$

In equation (6), the spatial weight matrix, $\mathbf{W}_\mathrm{j}$, is specified by the spectral-normalized inverse-distance spatial weighting matrix between townships, with the associated parameters for spatial autocorrelation denoted as ρ_j and δ_j respectively for the outcome variable and error term, and I represents the identity matrix. Under the construction of equation (6), different constraints lead to four kinds of spatial SUR model, labeled as types A to D.

A. The SUR-SIM (spatial independence model): when $\rho_j = 0;\ \delta_j = 0,\ \forall j$

B. The SUR-SLM (spatial lag model): when $\rho_j \neq 0;\ \delta_j = 0,\ \forall j$

C. The SUR-SEM (spatial independence model): when $\rho_j = 0;\ \delta_j \neq 0,\ \forall j$

D. The SUR-SARAR (spatial autoregressive with spatial error model): when $\rho_j \neq 0;\ \delta_j \neq 0,\ \forall j$

To identify which model should be used in our case, the tests for the spatial dependence in seemingly unrelated regression model in Mur et al. (2010) are done before estimation of spatial seemingly unrelated regression. The LM statistics show whether the null hypothesis of no spatial dependence in outcome variable (adaptive behaviors) or error term. The results of tests show that all the models reject the null hypothesis of no spatial dependence on outcome variables and error terms in three behavior equations. Therefore, the following analyses use the spatial autoregressive with spatial error SUR model.

3. Data and Sample

The dataset for the socio-economic characteristics of farm households, including the characteristics of operator, farm and family members, is drawn from the 2015 Census of Agriculture, Forestry, Fishery and Animal Husbandry (hereafter, Agriculture Census). The shock of two kinds of weather condition accounts for the rainfall and temperature. The dataset of weather conditions shows the daily average temperature and rainfall across years from Taiwan Climate Change Projection Information and Adaptation Knowledge Platform (TCCIP)[2]. Since it is more reasonable that farmers devise strategies for the current year by considering the shocks encountered in the previous year than the current one (Salazar-Espinoza et al., 2014). In this study, weather shock is defined as the deviation from the 20-year mean (1994-2013) to the average condition in 2014. The data of adaptive behaviors and characteristics of farm households are from the year 2015. Since this research considers for the spatial relationships, the data is constructed into township level. The number of townships in Taiwan is 368, however, after deleting townships with no data (we drop the vegetable farm households that didn't produce any crops in 2015 or just produced for their own use from the data), the township-level data used for

[2] Taiwan Climate Change Projection Information and Adaptation Knowledge Platform(TCCIP), Available from: https://tccip.ncdr.nat.gov.tw/.

analyses has 357 observations.

This research focus on three kinds of adaptive behaviors- labor allocation, protective facilities, and conservation agriculture practice. Labor allocation is often employed as a strategy to spread the risk in household income, aiming to diversify the sources of income (Gutu et al, 2012; Branco & Féres, 2021; Huang et al., 2020). In this research, the proportion of non-agricultural labor within the family is considered as an indicator of labor allocation behavior in farm households. The second adaptive behavior involves the ratio of greenhouses on their farmland. This can be viewed as a protective facility that controls the environment in which plants grow. A strategy with similar concept was also mentioned by Gutu et al. (2012), where farms will plant trees beside or around the fields. The third adaptive behavior is the adoption of organic farming. In this research, the organic farming defined as the farm did not use any chemical fertilizer or pesticide on their fields (FAO, 2022; Chang et al., 2023). Organic farming is one conservation agriculture practice since organic farming help improve the healthy status of the soil system, and it belongs to one of resilient agricultural practice to improve the capacity to cope with climate change from improved carbon storage. Organic farming is a conservation agriculture practice since it helps improve the health status of the soil system (Tuck et al., 2014). It belongs to a resilient agricultural practice aimed at enhancing the capacity to cope with climate change through carbon storage (Luh et al., 2023). Although there are not only these three types of adaptation strategies, using the data provided by Agriculture Census, this research selects these three adaptation behaviors from the perspective of farms' management, hardware, and agricultural practices, corresponding to the three categories for farmers' adaptive strategies in Smit and Skinner (2002), including financial management, technical improvement and farming practice. In Table 1, the definition of variables and the descriptive statistics are presented.

Table 1 Definition and descriptive statistics of variables

Variable	Definition	Mean	S.D.
Adaptive behaviors			
Nonagri_share	The share of family members taking non-agricultural work as their main job (%)	0.399	0.10
Greenhouse_ratio	The share of greenhouse constructed on their farmland (%)	0.006	0.03
Organic_adoption	Adoption of organic farming (0/1)	0.292	0.25
Weather variables			
RainShock	Average daily rainfall in 2014 minus long-run average in 1994-2013 (mm)	-1.067	0.82
RainSD	Standard deviation of average daily rainfall in years from 1995-2014 (mm)	1.546	0.45
LR_Rain	Long-run average daily rainfall in 1995-2014 (mm)	5.081	1.66
Rain	Average daily rainfall in 2015 (mm)	4.475	1.55
TempShock	Average daily temperature in 2014 minus long-run average in 1994-2013 (˚C)	0.035	0.23
TempSD	Standard deviation of average daily temperature in years from 1995-2014 (˚C)	0.353	0.07
LR_temp	Long-run average daily temperature in 1995-2014 (˚C)	22.5	2.12
Temp	Average daily temperature in 2015 (˚C)	23.014	2.16

Operator and farm's characteristics			
Male	Gender of the principal operator (0/1)	0.778	0.11
Age_young	Age of principal operator: under 45 (0/1)	0.060	0.05
Age_strong	Age of principal operator: 45-64 (0/1)	0.506	0.11
Age_old	Age of principal operator: 65 up (0/1)	0.434	0.12
Elementary	Education level of the operator: elementary school and below (0/1)	0.452	0.15
Junior	Education level of the operator: junior high school (0/1)	0.229	0.09
Senior	Education level of the operator: senior high school (0/1)	0.228	0.10
College	Education level of the operator: college and above (0/1)	0.090	0.10
Days29	Farming days in 2015: under 29 days (0/1)	0.104	0.10
Days59	Farming days in 2015: 30-59 days (0/1)	0.218	0.16
Days89	Farming days in 2015: 60-89 days (0/1)	0.231	0.10
Days149	Farming days in 2015: 90-149 days (0/1)	0.193	0.11
Days179	Farming days in 2015: 150-179 days (0/1)	0.123	0.10
Days249	Farming days in 2015: 180-249 days (0/1)	0.076	0.08
Days365	Farming days in 2015: above 250 days (0/1)	0.056	0.08
Land	Farmland of the farm (are; 0.01ha)	80.150	62.51
Worker	Total hired labor in 2015(calculated by the number of workers hired per month)	3.507	5.06
HH_population	Number of population size in the family	3.562	0.66
HH_elementary	Share of members with elementary school education and below (%)	0.324	0.10
HH_junior	Share of members with junior high school education (%)	0.178	0.06
HH_senior	Share of members with senior high school education (%)	0.277	0.07
HH_college	Share of members with college education and below (%)	0.221	0.10

Source: This research

Note: The observation of the data is 357.

In Figure 2, the graphs present the long-run condition of past rainfall and temperature. During the period from 1993 to 2014, Taiwan experienced higher long-run daily average rainfall in the northern and mountainous regions, while temperatures were higher in the flatlands of the southern region, likely due to their proximity to the equator. In this study, our "weather shock" variable represents the different climatic conditions that farmers faced in 2014 compared to the past. Figure 3 shows the maps of two weather shocks. From the aspect of rainfall, we found that the weather shock in 2014 primarily manifested as negative, indicating reduced rainfall in most areas during the year. In terms of temperature, it is noteworthy that not all regions experienced warming shocks. In fact, over one-third of the areas encountered temperatures in 2014 lower than the long-run historical average.

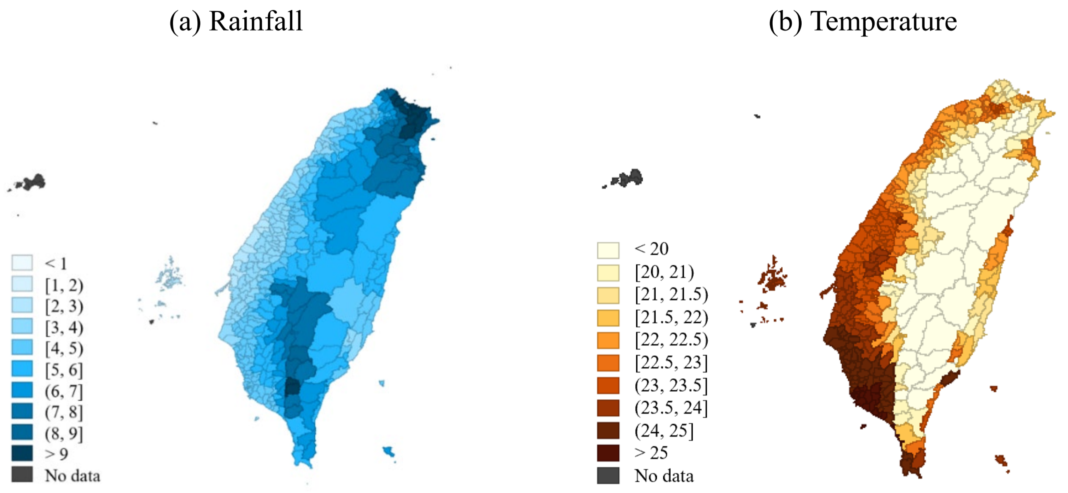


Figure 2 Maps of long-run weather condition from 1993 to 2014
Source: This study.

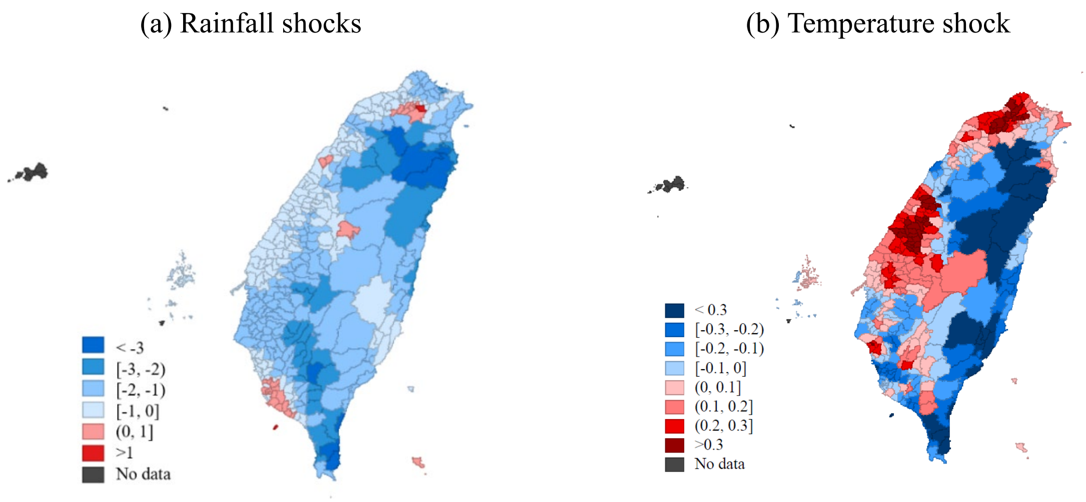
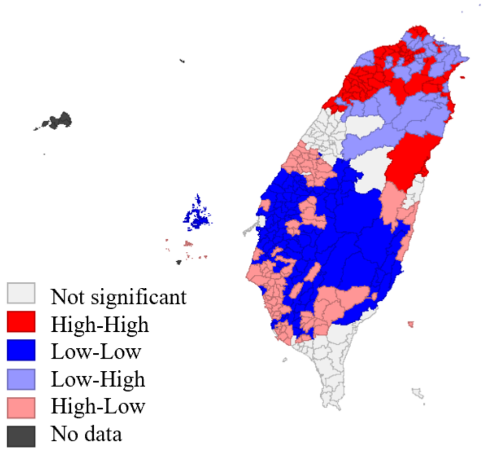


Figure 3 Maps of two weather shocks in 2014
Source: This study.

4. Results and Discussions

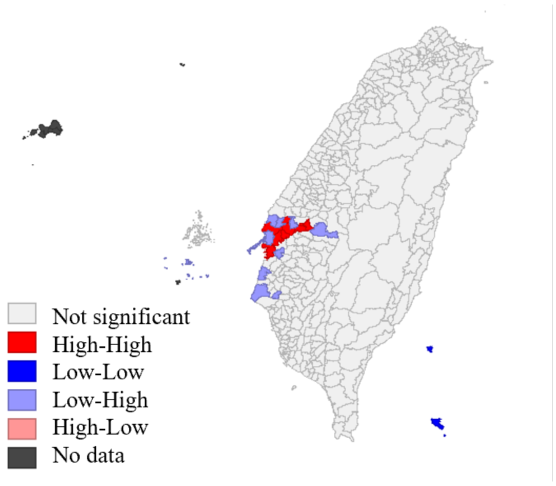
4.1 The spatial patterns of behaviors

Global and local indicator of spatial autocorrelation (GISA and LISA) are often used in spatial analysis, presenting the spatial relationships from a global and local aspect. GISA present a spatial correlation for all units while LISA present for each unit separately (Anselin, 1995). For the analysis of GISA and LISA, GeoDa software was used to draw the cluster maps and calculated the index which called global Moran’s I. Moran's I values range between -1 and 1. A positive value indicates positive spatial autocorrelation, suggesting that neighboring regions exhibit similar characteristics. Conversely, a negative value indicates negative spatial autocorrelation, implying dissimilarity among adjacent regions. Values close to 0 suggest the absence of spatial autocorrelation, indicating that neighboring regions do not show systematic similarities or differences (Anselin, 1995; Anselin, 2003). From LISA analysis, the cluster maps are shown in Figure 4. Following Anselin (1995), the four types of spatial autocorrelation— high-high, high-low, low-high, and low-low are labeled in maps. Each of the spatial patterns implies that when the chosen unit is the former, then its neighbors tend to be the latter. The weight used in the analysis is inverse distance matrix based on the Euclidian distance between any two locations. The cluster maps for both non-agricultural share and organic adoption in Figure 4(a) and (c) show the agglomeration appears in northern and eastern Taiwan, while the positive correlation is more obvious in organic adoption. However, the spatial autocorrelation is weak in greenhouse ratio in Figure (b).



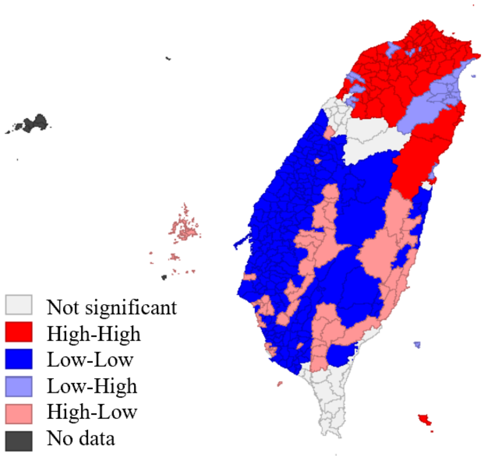
(a) Non-agricultural share

Moran’s I= 0.022***



(b) Greenhouse ratio

Moran’s I= -0.005



(c) Organic adoption

Moran’s I= 0.142***

Figure 4 Cluster maps for three adaptive behaviors

Source: This study.

Note: Significance levels of 1%, 5% and 10% are denoted by ***, ** and *.

In Figure 4, the presenting global Moran's I statistics for the three variables—non-agricultural share, greenhouse ratio, and organic adoption rate—are 0.022, -0.005, and 0.142 respectively. After conducting 999 random simulations, the corresponding p-values are calculated for the null hypothesis of no spatial autocorrelation between townships. For the non-agricultural share, Moran's I of 0.022 suggests a positive spatial autocorrelation, indicating that neighboring regions exhibit similar trends in non-agricultural population proportion. This spatial pattern is statistically significant with a p-value of 0.003, suggesting that the observed correlation is unlikely to be a result of random chance. Regarding the greenhouse ratio, its Moran's I of -0.005 indicates a weak negative spatial autocorrelation. This implies that adjacent towns may exhibit some contrasting trends in proportion of greenhouse on their farmland. However, this spatial autocorrelation is not statistically significant with a p-value of 0.219, suggesting that this pattern may be attributed to random factors. Lastly, for organic adoption, the Moran's I of 0.142 suggests a stronger positive spatial autocorrelation in the organic adoption rate. This indicates that neighboring regions tend to have similar trends in organic adoption rates. The spatial autocorrelation is statistically significant with a p-value of 0.001, supporting the hypothesis of spatial dependence in organic adoption rates. While these spatial analyses didn't consider for other factors like characteristics of farm households, it still offers a preliminary indication that there might be spatial autocorrelation in these adaptive behaviors.

4.2 Effects of weather shocks

This research aims to examine for the effects of weather shocks while considering inconsistent effects, the experience of weather conditions by spatial seemingly unrelated regressions method. According to equation (4), the effects of weather shocks in Table 2 are calculated by adding the estimated coefficient of $RainShock$ (if it's statistic significantly, and 0 otherwise) and average experience interaction effect. Due to the interaction effect of weather experience is presented by the coefficients for the interaction terms of $RainShock$ and $RainSD$ (or $TempShock$ and $TempSD$), the average experience interaction effect is obtained by multiplying it with the sample mean of $RainSD$ (or $TempSD$). The interaction effects of weather experience are displayed in Table 3. By adding the dummy of positive shocks, we can discern the difference between negative and positive and calculate their respective effects.

Table 2 Effects of weather shocks

	Nonagri_share	Greenhouse_ratio	Organic_adoption
(a) Rainfall shocks only			
Rainfall shock (-)	-0.034	0	-0.079
Rainfall shock (+)	0.003	0	0.022
Rho	0.0552	0.959 ***	0.8732 ***
Lambda	0.6892 **	-6.012 ***	0.8521 ***
(b) Temperature shocks only			
Temperature shock (-)	0	0.118	0
Temperature shock (+)	0	0.118	0

Rho	0.0862	0.9647 ***	0.8561 ***
Lambda	0.6689 **	-5.8499 ***	0.8706 ***
(c) Rainfall and temperature shocks			
Rainfall shock (-)	0	0	0
Rainfall shock (+)	0.029	0	0.114
Temperature shock (-)	0	0.109	0
Temperature shock (+)	0	0.109	0
Rho	0.1589	0.958 ***	0.8759 ***
Lambda	0.6025 *	-6.2035 ***	0.8505 ***

Source: This study.

Note: Significance levels of 1%, 5% and 10% are denoted by ***, ** and * besides spatial statistics.

Table 3 Estimation of interaction with weather experience

	Nonagri_share	Greenhouse_ratio	Organic_adoption
(a) Rainfall shocks only			
Rainfall shock (-)	0	0	-0.051
Rainfall shock (+)	-0.265	0	-0.607
(b) Temperature shocks only			
Temperature shock (-)	0	0	0
Temperature shock (+)	0	0	0
(c) Rainfall and temperature shocks			
Rainfall shock (-)	0	0	0
Rainfall shock (+)	-0.262	0	-0.560
Temperature shock (-)	0	0	0
Temperature shock (+)	0	0	0

Source: This study.

We provide the results of three model setting, consider for only rainfall shock and normal temperature condition, only temperature shocks and normal rainfall condition, and both rainfall and temperature shocks. Our findings reveal that the impacts of positive and negative weather shocks are not consistent. In the model (a) in Table 2, non-agricultural share and the organic adoption rate increase with deeper shocks in both negative and positive rainfall shocks. When only consider for temperature shocks in model (b), higher temperature only leads to an increase in greenhouse ratios and the signal of shocks didn't lead to inconsistent effects. After controlling both rainfall and temperature in model (c), rainy shocks increase the ratio of households engaged in non-agricultural work and the adoption rate of organic practices, whereas drier shocks have no effects. The effects of temperature are smaller than model (b), but they still show consistent between negative and positive shocks. Additionally, the statistics of spatial dependence are represented by the coefficients of rho and lambda, which signify the spatial lag and spatial error, respectively. The spatial error appears in all the equations of three adaptive behaviors while the spatial lag is shown in greenhouse ratio and organic adoption.

Moreover, we observed that variations in past weather conditions moderate the effects of weather shocks in rainfall from the different signal of effect and interaction term, as indicated in Table 3. The result, similar to Chuang (2019), indicates that it might be due to the farm in those risky areas having implemented adaptive strategies before. Though the interaction effect of negative rainfall shock for organic adoption in model (a) is negative, which is the same as the average effect of shock. It's much smaller than positive ones, and it becomes insignificant when considering both rainfall and temperature shocks in model (c). Additionally, as this study primarily focuses on the effects of climate impacts, the estimation results of other variables in the model are presented in Appendix A to streamline the discussion.

4.3 Heterogeneous effects between groups

This research examines for whether the effect vary from the farm households with different characteristics. We follow with the formal definition in the Agency of Agriculture in Taiwan and compare the results between three groups. The first type of farm households is the core farm households, which constitute the primary farming productivity in the country. The core farm households must have the income from agricultural sales not less than 200,000 NTD (approximately 6,500 USD) and have at least one agricultural worker under the age of 65 in their family. Second type, elderly farm households, are defined as households in which all members involved in farming activities are 65 years of age or older. The last category pertains to mini farm households, characterized by an income ranging from 20,000 to 200,000 in 2015, despite having at least one agricultural worker under the age of 65 in their family. The vegetable farmers in these three categories, according to agricultural census data, comprise 30,064 households, 31,399 households, and 15,234 households, respectively.

In Table 4, descriptive statistics for three adaptive behaviors are provided for each group. The highest proportion of non-agricultural workers in the family is observed in mini farm households, while the lowest is found in core farm households. T-tests for mean differences were conducted between each pair of groups for the three adaptive behaviors. Statistically significant differences in means were observed at a 10% significance level for most comparisons, except for the greenhouse ratio and organic adoption between elderly and mini farm households. Hence, it is evident that the adaptive behaviors should vary among different groups.

Table 4 Descriptive statistics for three types of farm households

	Core		Elderly		Mini	
Variable	Mean	S.D.	Mean	S.D.	Mean	S.D.
Adaptive behaviors						
Nonagri_share	0.278	0.10	0.292	0.10	0.341	0.11
Greenhouse_ratio	0.016	0.05	0.002	0.01	0.003	0.01

Organic_adoption	0.239	0.26	0.278	0.25	0.279	0.26

Source: This study.

The spatial autoregressive with spatial error SUR model are used for the analyses of three subgroups. Table 5 shows the average effects of weather shocks under controlling both rainfall and temperature shocks. The effects are calculated using the same method as employed for all the vegetable farmers mentioned earlier. Table 6 displays the estimation of the experience interaction effects. We present the results for core farm households under type (a) in Table 5, where rainy shocks lead to an increase in the non-agricultural share, while dryer and temperature shocks show no effect. Although there is no inconsistency in the positive or negative direction of the effects in the greenhouse ratio, it is observed that both rainfall shocks and temperature shocks have an impact on this behavior. Notably, the organic adoption is affected largely by hotter shocks, which is different from the results in previous section. For the type (b) in Table 5, the behaviors of elderly farm households are affected by weather shocks only in the non-agricultural share and greenhouse ratio. The organic adoption doesn't vary by weather shocks. The findings reveal a larger impact of rainy shocks compared to core farm households, indicating that elderly farm households allocate a higher proportion of their labor force to non-agricultural jobs when confronted with rainy shocks, in contrast to core farm households. But we can also find the effect on greenhouse ratio is much smaller than core ones. Finally, the behaviors by mini farm households, as the type (c) in Table 5, are less likely to be affected by weather shocks than other groups, as indicated by the insignificant effects shown in the table. The results demonstrate a different impact on labor allocation behavior, which hotter shocks lead to a reduction in the proportion of non-agricultural members. This divergence may be attributed to the fact that mini farm households, when confronted with weather shocks, have a relatively less agricultural workers within their households. Consequently, they need to increase agricultural manpower to cope with the shocks. The observed insignificant effect on the greenhouse ratio may suggest a diminished capacity to adapt, possibly due to technical or financial constraints. Additionally, organic adoption significantly increases with rainy shocks.

Table 5 Effects of weather shocks for three subgroups

	Nonagri_share	Greenhouse_ratio	Organic_adoption
(a) Core			
Rainfall shock (-)	0	-0.005	0
Rainfall shock (+)	0.014	-0.005	0
Temperature shock (-)	0	0.075	0
Temperature shock (+)	0	0.122	0.697
Rho	0.350	0.845 ***	0.903 ***
Lambda	-3.440 ***	-6.651 ***	-2.580 **
(b) Elderly			
Rainfall shock (-)	0	0	0

Rainfall shock (+)	0.029	0	0
Temperature shock (-)	0	0	0
Temperature shock (+)	0.062	0.014	0
Rho	-0.480 ***	-0.961	0.825 ***
Lambda	-5.814 ***	0.052	0.869 ***
(c) Mini			
Rainfall shock (-)	0	0	0
Rainfall shock (+)	0	0	1.044
Temperature shock (-)	0	0	0
Temperature shock (+)	-0.559	0	0
Rho	0.639 ***	-0.457	0.757 ***
Lambda	-0.300	-2.248 *	0.678 *

Source: This study.
Note: Significance levels of 1%, 5% and 10% are denoted by ***, ** and * besides spatial statistics.

The spatial statistics in the models are also displayed in Table 5, below the estimated shock effect. Spatial dependence is more or less evident in the equations of each model, except for the greenhouse ratio equation in the case of elderly farmers, where neither the outcome variable nor the error term exhibits significant spatial dependence. This also supports the appropriateness of incorporating spatial econometric considerations in SUR. In Table 6, we present the estimation of experience interaction effects for these three types of farm households. Most of them show the moderation to the effect of weather shocks, except for the positive temperature shocks on non-agricultural share in elderly and mini farm households, and greenhouse ratio in core farm households. These interaction effects further enhance the impact of shocks on the behavior. Therefore, it can be inferred that in regions with higher temperature variations, the mitigating effects may not necessarily manifest.

Table 6 Estimation of interaction with weather experience for three subgroups

	Nonagri_share	Greenhouse_ratio	Organic_adoption
(a) Core			
Rainfall shock (-)	0	0.009	0
Rainfall shock (+)	-0.291	0.009	0
Temperature shock (-)	0	-0.470	0
Temperature shock (+)	0	0.956	-5.669
(b) Elderly			
Rainfall shock (-)	0	0	0
Rainfall shock (+)	-0.179	0	0
Temperature shock (-)	0	0	0
Temperature shock (+)	1.100	-0.302	0

(c) Mini			
Rainfall shock (-)	0	0	0
Rainfall shock (+)	0	0	0
Temperature shock (-)	0	0	0
Temperature shock (+)	-1.585	0	0

Source: This study.

5. Conclusion

This research mainly provides the empirical evidence for the effect of weather shocks no matter for rainfall or temperature. This study supports the need for considering spatial relationships in farm households' adaptive behaviors. Results for the effect of weather shocks show the vegetable farm households in Taiwan tend to be affected by positive shocks, especially in rainfall. This might provide evidence indicating that farm households are more risk-averse in response to positive shocks. And the negative shock of rainfall can be compensated by local well-constructed infrastructure like irrigation facilities. The effect of weather shocks also varies between behaviors in our results, such as the labor allocation and conservational farming practice are affected by rainy shocks while the ratio of greenhouse increases with hotter weather. The finding of the moderation of weather experience suggests that prior experience reduces their sensitivity the shocks. Similar to the finding in Chuang (2019), this might due to the farm households in the area already implemented some adaptive measures in past year. And the effect presents in both positive and negative shocks. The differences appear in the response from different types of farm households. From subgroup analyses, it's noteworthy that elderly farm households tend to allocate their family labor to non-agricultural sectors when facing shocks. This consequence might indicate lower motivation for subsequent agricultural operations among this demographic. Additionally, mini farm households may exhibit lower responsiveness to climate shocks due to implementation costs or limited capabilities. It shows the mini farm households need more support from government to do adaptation. With the full consideration of inconsistent effect, weather experience, spatial dependence, and correlation between equations, this study can provide a more comprehensive view on how weather shocks affect farm households' behaviors.

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Appendix A. The estimation of covariates in spatial SUR models

	Rainfall shocks only			Temperature shocks only			Rainfall and temperature shocks		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(Intercept)	0.223	-0.127 ***	0.601 **	0.252	-0.109 ***	0.623 *	0.172	-0.105 ***	0.583 *
Male	0.025	0.062 ***	-0.494 ***	0.050	0.041 ***	-0.515 ***	0.033	0.058 ***	-0.522 ***
Age_strong	0.021	0.150 ***	1.051 ***	-0.038	0.136 ***	0.819 ***	0.030	0.136 ***	1.017 ***
Age_old	0.044	0.092 ***	0.868 ***	-0.006	0.082 ***	0.693 ***	0.049	0.074 ***	0.837 ***
Junior	-0.250 ***	-0.112 ***	-0.308	-0.278 ***	-0.110 ***	-0.313	-0.238 ***	-0.113 ***	-0.316
Senior	-0.304 ***	-0.017	-0.134	-0.312 ***	-0.015	-0.189	-0.289 ***	-0.028	-0.170
College	-0.395 ***	0.026	0.068	-0.377 ***	0.026	0.094	-0.388 ***	0.025	0.049
Days59	-0.103 **	0.009	0.179	-0.101 *	-0.004	0.210	-0.107 **	0.005	0.178
Days89	-0.057	-0.059 ***	-0.227 *	-0.048	-0.070 ***	-0.239 *	-0.055	-0.056 ***	-0.242 *
Days149	-0.217 ***	0.058 ***	0.153	-0.222 ***	0.060 ***	0.150	-0.213 ***	0.055 ***	0.140
Days179	-0.333 ***	0.004	-0.127	-0.314 ***	-0.011	-0.044	-0.335 ***	-0.003	-0.128
Days249	-0.247 ***	-0.042 **	-0.014	-0.244 ***	-0.053 ***	-0.061	-0.247 ***	-0.037 *	0.003
Days365	-0.353 ***	0.011	0.251 *	-0.351 ***	0.011	0.289 *	-0.356 ***	0.011	0.259 *
Land	0.000	0.000 **	0.000 *	0.000	0.000 **	0.000 *	0.000	0.000 *	0.000 **
Worker	-0.003 ***	0.000	-0.007 ***	-0.003 ***	0.000	-0.007 ***	-0.003 ***	0.000	-0.007 ***
HH_population	0.006	-0.007 ***	-0.047 **	0.008	-0.006 **	-0.051 **	0.008	-0.006 **	-0.054 ***
HH_junior	0.338 **	0.196 ***	0.162	0.368 ***	0.239 ***	0.263	0.317 **	0.203 ***	0.171
HH_senior	0.562 ***	0.060 *	-0.063	0.572 ***	0.095 ***	-0.002	0.542 ***	0.086 **	-0.032
HH_college	0.650 ***	0.022	0.268	0.650 ***	0.036	0.241	0.649 ***	0.025	0.233
R2	0.597	0.522	0.593	0.591	0.510	0.586	0.604	0.544	0.599

Note: 1. Significance levels of 1%, 5% and 10% are denoted by ***, ** and *. 2. Column (1) to (3), (4) to (6) and (7) to (9) represent the three adaptive behaviors, non-agricultural share, greenhouse ratio and organic adoption.

Source: This study.