THE SPATIAL RELATIONSHIP BETWEEN WEATHER AND *ONCIDIUM* PRODUCTION

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KEYWORDS: *Oncidium*, Spatial Panel Model, Climate Change, Weather

ABSTRACT: *Oncidium* is one of the essential flower crops in Taiwan. However, climate change and its impacts on extreme weather reduce our *Oncidium* harvest. Therefore, it is necessary to define the spatial relationship between weather and *Oncidium* production. Here we apply the Kriging method and ten weather station datasets in Taichung, Taiwan, to estimate the weather conditions for our study area. Six most common spatial panel models (OLS, Spatial Error, Spatial Lag, and Spatial Autoregressive with fixed effect extensions) were used to estimate the spatial impacts of weather on flower productions. The weather factors here are temperature, relative humidity, pressure, and precipitation. Overall, the results show that several weather variables have significantly positive impacts on *Oncidium* production, such as temperature. This study could be used to evaluate the potential future effects of climate change in the *Oncidium* industries. Also, the results might be helpful for future environmental setting in *Oncidium* greenhouse.

1. INTRODUCTION

The orchid family, *Orchidaceae*, is among the largest of families of angiosperms, containing >25 000 described species within 859 genera (Blanchard and Runkle 2006; Cribb et al. 2005). Orchids are distributed in all regions of the world except Antarctica and are found growing in many different habitats and elevation gradients (Blanchard and Runkle 2006; Pridgeon and Morrison 2006). Despite the diversity of orchids in nature, only a small number of genera are cultivated in large quantities as commercial ornamental crops (e.g. *Cymbidium*, *Dendrobium*, *Oncidium*, and *Phalaenopsis*) (Blanchard and Runkle 2006).

Orchid production has played a significant role in horticultural production in Taiwan (C. S. Lee 2001). Among all orchid sold within Taiwan, *Oncidium* is the second place of most valuable orchids in Taiwan. Statistic by Central of Agriculture (COA) Taiwan in 2016 reveal 1,187 metric tons of *Oncidium* cut flower exported or 80% of total production. This trading value is around US$11.96 million. While the highest demand is Japan (1,151 metric tons) followed by Hongkong (21 metric tons), Singapore (8 metric tons) and U.S. (3 metric tons). The increasing of *Oncidium* demand will also increase the quality requirements. Therefore, the environment condition around *Oncidium* production area must be cared to get the high and good quality production. While this environmental condition should be considered, the climate change issue also happened in Taiwan (Di Giusto, Lavallee, and Yu 2018). Rising sea levels and changes in precipitation and temperature patterns are creating more favorable conditions for diseases and threatening agricultural aspect (Castello et al. 2009; Di Giusto, Lavallee, and Yu 2018; McMichael, Woodruff, and Hales 2006; Myers and Patz 2009; Patz et al. 2014).

(Baylis, Paulson, and Piras 2011) explore the spatial panel methods using the effect of climate change on American agriculture. The earlier literature estimating the climate change effect on agriculture takes a production function approach that uses detailed crop growth models to simulate how different crop yields will respond to changes in climate (Adams 1989; Adams et al. 1990, 1995; Rind et al. 1990). Thus, the spatial panel model used in this study to estimates the climate change through the weather and air pollutant effect to *Oncidium* production in Taichung, Taiwan. This study also implies the fixed effect as additional effect on spatial panel model to identify the correlation between individual effect and explanatory variables.

There is a long history of using weather measures as explanatory variables in statistical models (Auffhammer et al. 2013), such as spatial panel model. Because weather is random in most economic applications, its acts like a natural experiment (Angrist and Krueger 2001; Auffhammer et al. 2013). As example, (Lobell and Burke 2010) predict crop yield responses to climate change through temperature and precipitation as the explanatory variables. (Liu et al. 2010) in Southwestern China analyze the potential challenges of climate change to Orchid conservation using precipitation and relative humidity. Moreover, (P.-H.Lee, Liao, and Yuan 2007) identify the impact of heavy rain and typhoon to agricultural area in Taichung, Taiwan. While (Blanchard and Runkle 2006) study is about controlling *Phalaenopsis* Orchids flowering based temperature setting during the day and night. In (Mozo et al. 2000) use accumulation temperature to study quercus pollen seson in Cordoba and (Chen and Hsu 2003) to study flower quality of *Oncidium* in Taiwan. Not only weather variables that contains in climate change, but also air pollution. Thus, makes air pollution could give an impact to flower production. Many of pollutant have deleterious effect on plants and one of these is sulfur dioxide (SO2) that could spoil *Oncidium* leaf (Darley 1960). Based on these studies, in this study consider accumulation temperature, relative humidity, precipitation, typhoon, wind speed, and SO2 as the explanatory variables to identify their effect on *Oncidium* production.

2. METHODOLOGY

2.1 Study area and data collection

Flower production data as the dependent variables in this study collected from nine greenhouses location in Taichung city, Taiwan, for July to December 2017 productions. Total number of productions in this half year is 482,869 flowers, with 45% from #3 greenhouses. Moreover, flower production and greenhouse location could be seen in table 1 and figure 1. These flowers were cut in each week within July to December.

Table 1. Flower Productions Within July to Decembers in Greenhouses Area.

Greenhouses	Min	Mean	Max	Total
1	0	1125	3080	30371
2	0	801.5	3360	21641
3	4226	8076	14728	218044
4	2863	5473	13699	147760
5	0	346	1380	9335
6	0	903	3820	24391
7	0	175	505	4724
8	100	917	1895	24773
9	0	68	360	1830

The weather and air pollutant variables for the studied area on July to December 2017 were derived from Central Weather Bureau Taiwan database. Weather variables including temperature, relative humidity, precipitation, pressure, wind speed, typhoon. Then, air pollutant variable is SO2. Both data produced by ten weather station which is located nearby the greenhouse's locations (fig.1 draw in green circles).

In order to calculate the growing temperature of *Oncidium*, this study used proposed accumulation temperature method by (Chen and Hsu 2003).The accumulation temperature method divided into two part, first accumulation high temperature difference (ACHT) and accumulation low temperature difference (ACLT). ACHT and ACLT used for calculating the accumulate temperature difference at day and night time, respectively. The day time is start from 07:00 to 15:00, while the night time start from 19:00 to 06:00. The formula of ACHT and ACLT could be seen at equation 1.

$$ACHT\ or\ ACLT = \sum_{i}^{n_i}(T_{hi\ or li} - T_{mb\ or\ lb}) \qquad (1)$$

where, T_{hi} is the day time temperature and $T_{li}$is the night time temperature in the greenhouse. T_{mb} is the maximum temperature threshold while T_{lb} is the minimum temperature threshold that define same as 2003 study by Chen in Taiwan. This study used the same threshold as (Chen and Hsu 2003), 25^0C as the maximum and 22^0C as the minimum. The last n_i is the number of accumulation day and it set as seven days, thus because flower produces in each week.

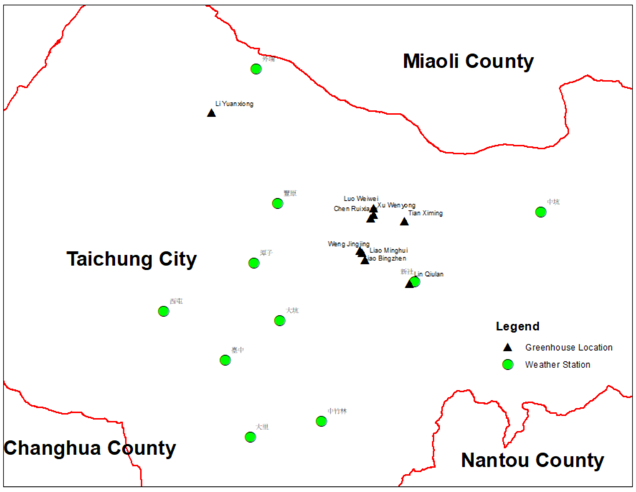

Figure 1. Greenhouses and Weather Stations Location

2.2 Interpolation

Data Interpolation is used to get the weather value for the greenhouse position. Because our greenhouse did not record their own weather data. So, this study uses ten nearby weather station to predict attributed values at greenhouses area using Kriging. Kriging imply the weighting, which assigns more influence to the nearest data points in the interpolation of values for unknown locations. Kriging depends on spatial and statistical relationships to calculate the surface. The two-step process of kriging begins with semi variance estimations and then performs the interpolation. This theory has been discussed by several authors (Cressie 1993; Isaaks and Srivastava 1989; Matheron 1963). Some advantages of this method are the incorporation of variable interdependence and the available error surface output (Legendre and Legendre 1998). The semi variance is generally estimated by the experimental semi variance $(\hat{\gamma}(h))$, which is defined in equation 2 below:

$$\hat{\gamma}(h) = \frac{1}{2N(h)}\sum_{i=1}^{N(h)}\{(z_{x_i} - z_{x_i+h})\}^2 \qquad (2),$$

where, $\hat{\gamma}(h)$ is the semi-variance, z_{x_i} is the value of the measured variation at location of x_i, $N(h)$ is the number of pairs of sample points separated by distance h, and x is the position of samples. Then, the semi-variance model is fitted. The most commonly used models in semi-variance are spherical, exponential and gaussian (Isaaks and Srivastava 1989). After getting the semi-variance estimations then performs the interpolation. Kriging (Krige 1951) is a linear interpolation, which is a process of a theoretical weighted moving average that is defined by equation 3.

$$\hat{Z}(x_0) = \sum_{i=1}^{n} \lambda_i Z(x_i) \quad (3),$$

where $\hat{Z}(x_0)$ is the value to be estimated at the location of x_0, $Z(x_i)$ is the known value at the weather and air pollution stations x_i. Different with other interpolation method (inverse distance weight), the weighting function is calculated based on parameters of semi-variance model. To determine whether the estimation unbiased, the weights sum should equal to one (Eq.4).

$$\sum_{i=1}^{n} \lambda_i = 1 \quad (4)$$

2.3 Spatial panel model

There have been many studies in environmental sciences that use spatio-temporal analysis to help understand phenomena on a spatial plane, over time. This type of analysis could provide valuable information for understanding plant production response to the weather condition by spatial and temporal aspect. Examples of such work include using spatio-temporal analysis to assess whether crop yield and weather have spatial correlation, continuously to the time (Yun et al. 2015), analyzing deforestation in The Brazilian Amazon (Espindola, Pebesma, and Camara 2008), analyzing agricultural economics in climate change application (Baylis, Paulson, and Piras 2011) and studying impact of agricultural economics to climate change (Finucane and Shaffer 1986).

The spatio-temporal method used in this study will now be describe as Spatial Panel Model. Spatial panels can be used for individual intersections or spatial units such as countries, over time. The model may include interactions between the spatial and temporal results. Moreover, spatial panel model contains two spatial autoregressive parameter λ (spatial lag) and ρ (spatial error). For identify the spatial relationship between weather and *Oncidium* production capability comparison analysis, this study utilizes spatial panel estimation approach. Since spatial panel model considered two spatial autoregressive parameters, this model could generate four different models. First, baseline/pooled model (OLS) which does not consider both of spatial autoregressive parameters (λ and ρ equal to 0). Second, spatial lag model (SLM) that dependent variable was related to the nearby dependent variable and other independent variables. This model requires λ is not zero, while ρ is equal to zero. In contrast, the third model spatial error model (SEM) which is the error term correlated with its neighbor error term has conditions λ is zero and ρ is not equal to zero. The spatial error pattern represent that the model ignores several spatial autocorrelation variables. The last model is spatial autoregressive model (SAR) which is includes both of spatial autocorrelations parameters, thus λ and ρ are not equal to zero. The formula for the fixed effect spatial panel model is shown in Equation (5).

$$\begin{aligned} y_{it} &= \sum_{j=1}^{N} \lambda W_{ij} y_{ij} + X_{it}\beta + \mu_i + \varepsilon_{it} \\ \varepsilon_{it} &= \sum_{j=1}^{N} \rho W_{ij} u_{ij} + v_{it} \end{aligned} \quad (5)$$

Where, i is spatial units and t is the time (week). y_{it} is number of flower production in greenhouse i and week t. As mentioned before λ is spatial lag coefficient, ρ is spatial error coefficient and both of them are spatial autoregressive parameters. W_{ij} is spatial neighbor weights matrix, X_{it} is explanatory variables with β as regression parameter. For spatial fixed and random effect is represent by μ_i. Then, the error term is describe by ε_{it}.

To have more general specification Elhorst (2003,2009) examine fixed (FE) and/or random (RE) effects of individual or time on spatial panel model. A fixed effect model examines individual differences in intercepts, assuming the same slopes and constant variance across individual. While random effect model assumes that individual effect is not correlated with any regressors and then estimates error variance specific to groups (or times) (Park 2011). To determine which effect should be applied, the spatial hausman test (Hausman 1978; Mutl and Pfaffermayr 2011) is used. The equation of spatial hausman test is shown at equation 6.

$$H = (\hat{\theta}_{FE} - \hat{\theta}_{RE})^T(\hat{\Sigma}_{FE} - \hat{\Sigma}_{RE})^{-1}(\hat{\theta}_{FE} - \hat{\theta}_{RE}) \qquad (6)$$

Where $\hat{\theta}$ is the estimated coefficient of fixed ($\hat{\theta}_{FE}$)/random ($\hat{\theta}_{RE}$) effect model, $\hat{\Sigma}$ is the variance of estimated coefficient of fixed ($\hat{\Sigma}_{FE}$)/random ($\hat{\Sigma}_{RE}$) effect model. Then, the statistic H is distributed as X^2 distribution. The null hypothesis of hausman test is, "Individual effects are uncorrelated with explanatory variable". If the null is not rejected, a random effect model is favored over its fixed counterpart (Park 2011).

For all data management and estimation process, the recent version of R software (3.5.3) and four R packages were used. The point analysis is adopted with plm packages (Croissant and Millo 2008) and splm packages (Millo and Piras 2012). Function "spml" estimates parameter by maximize likelihood estimation. For panel data model, we change the "model" setting to "random" for random effect, and "within" for fixed effect model. In addition, rgdal packages (Sumner and Hijmans 2019) is used to import the vector dataset and spdep packages (Bivand, Müller, and Reder 2009) was used to create spatial weight matrix.

Table 2. Interpolation Results with Descriptive Statistics

Variable	Explanation	Unit	Min	Mean	Max
ACHT	Accumulation High Temperature Difference	Celcius Degree	-182.9	3.42	105.88
ACLT	Accumulation Low Temperature Difference	Celcius Degree	-188.6	-1.02	90.25
RH	Relative Humidity	%	70.06	82.09	89.77
Pressure	Station Press	hPa	942.7	965.1	1005.2
WS	Wind Speed	m/s	1.19	1.45	2.72
Precipitation	Amount of precipitation happened in each week	mm (the equivalent of one litre of rainfall per metre squared)	0	0.2	1.22
Typhoon	Typhoon happened in study time	yes/no	0	0.22	1
SO2	Sulfur dioxide concentration in weekly average	ppb (parts per billion)	1.88	1.93	2.01
Area	Flower production area in each greenhouses	Ha (Hectare)	0.01	0.4	1.3

3. RESULTS

3.1 Interpolation

The variables for spatial panel model estimation produce by kriging interpolation. The kriging result develop by weekly average of weather and air pollution data in ten weather stations. Then, kriging also produces the weekly average condition in each variable. Table 2 shows the distribution of each variables. ACHT and ACLT obtained by temperature interpolation then calculated using equation 1. The lowest ACHT and ACLT has negative value while the highest have positive value. Relative humidity around greenhouses area is 82.09%, while *Oncidium* is growth in medium dry area (White 2009) that have humidity percentage 75±5. Greenhouses pressure condition is around 965 hPa. The wind speed around greenhouses have 1.45 m/s in average. Moreover, precipitation average is 0.2mm. Typhoon on 2017 around Taichung City occurred in July to August. Lastly, the air pollution variable that is SO2 (Sulfur Dioxide) has average 1.93 ppb in the greenhouses area.

3.2 Spatial panel models

The spatial hausman test gives result that these study models are rejected the null hypothesis. Thus, means individual effects are correlated with explanatory variables then spatial fixed effect is chosen to build spatial panel model. Moreover, spatial fixed effect applied into lag, error and autoregressive model then the model became SLM-FE, SEM-FE and SAR-FE, respectively. The estimation results are given in table 3.

The coefficient of relative humidity (RH), precipitation and typhoon are negative and not statistically significant in the OLS and SEM-FE models. Similar to these models, RH and typhoon also give the same characteristic in SLM-FE although precipitation has positive correlation. In another side, typhoon and precipitation are statistically significant in SARAR-FE with negative and positive correlation, respectively. While, RH give positive and not statistically significant. ACLT has negative sign even though ACHT has positive sign; however, both are statistically significant in each model. For all model wind speed (WS) is negative and statistically significant and area give positive with statistically significant. The air pollutant variable (SO2) has negative and statistically significant to all the models. The performances of all models are compared using AIC and R^2 scores. OLS offers the highest AIC and lowest R^2 compare to other models. Then, the SEM-FE is better than SLM-FE. The SAR-FE model provides the lowest AIC with highest R^2. Thus, it is the best model to explaining the impact of weather and air pollution to flower production in different spatial units.

4. DISCUSSION

In SAR-FE model, only RH is not statistically significant. The coefficient of the spatial lag is positive indicating that neighboring greenhouses tend to display similar patterns in terms of flowers production. In contrast, the coefficient of the error lag is negative suggesting the existence of common unobserved factors not affecting flowers production in neighboring greenhouses. Area as one of the independent variables, give positive correlation and statistically significant with 1% level. That means, the wider of area could provide bigger flower production, here relate1d to (Duan et al. 2015; Ponce et al. 2014)**.** Typhoon and precipitation are connected to flower production. This is intuitive because the week in which typhoon occurs the heavy rainfall will follow. Thus, the heavy rainfall and typhoon could affect to plant damage (P.-H.Lee, Liao, and Yuan 2007) and interfere other weather conditions. Precipitation and RH also give positive correlation this also correlated to (Endres Júnior et al. 2018).

Table 3. Spatial Panel Model Result

Variable	VIF	Model			
		OLS	SAR FE	SEM FE	SLM FE
ACLT	77.1	-76.24***	-21.33*	-13.38*	-53.51***
		(26.26)	(17.23)	(17.05)	(12.29)
ACHT	77.8	93.50**	33.16**	28.05**	55.17***
		(24.84)	(15.64)	(15.16)	(11.81)
RH	2.44	-44.46	3.37	-22.57	-28.32
(%)		(56.44)	(39.46)	(36.09)	(30.14)
Pressure	1.85	72.09***	-27.29*	-1.22	21.78**
(HPa)		(14.77)	(45.06)	(57.15)	(6.75)
Precipitation	1.59	-771.20	146.25*	-343.165	245.44
(mm)		(489.20)	(383.32)	(290.50)	(274.31)
Typhoon	1.49	-116.50	-187.83*	-269.79	-295.55
(yes)		(375.56)	(230.80)	(222.71)	(285.25)
WindSpeed	2.34	-2326.29**	228.74*	-239.46	-880.92**
		(718.173)	(595.96)	(479.27)	(323.48)
SO2	2.13	-1075.71**	-211.33*	-424.51	-662.32**
(ppm)		(378.86)	(243.14)	(206.64)	(200.71)
Area	1.19	2122.12***	2614.3***	2712.5***	2671***
(Ha)		(440.217)	(-236.801)	(-214.479)	(-230.86)
Lag effect			0.85***		-0.20*
			0.02		0.56
Spatial Error effect			-0.75***	-0.446***	
			0.14	0.10	
Log likelihood		-2242.9	-2035.4	-2042.7	-2097.1
AIC		4505.9	4090.9	4103.4	4214.2
R square		0.316	0.87	0.85	0.79
Panel Length		27	27	27	27
Observ		243	243	243	243

Note: * p-value < 10%, ** p-value < 5%, *** p-value < 1%

The sulfur dioxide (SO2) as the air pollutant variable negatively influence flowers production. This is correlated to the flower condition while the high concentration of air pollutant could give damage into sepal of the *Oncidium* (Darley 1960). The damage of the flower could make the production of flower with good quality is decrease. Moreover, the higher production of bad quality flowers tends to give a lower flower production.

5. CONCLUSION

The contribution of this study is spatial panel analysis of weather and air pollutant variable to *Oncidium* production at the nine greenhouses in Taichung, Taiwan. A spatial autoregressive model with fixed effects (SAR-FE) is estimated using maximum likelihood method. In conclusion, flower production responses of weather and air pollutant condition were different among spatial panel models, suggesting that the SAR-FE model could give the best estimation than other models. These results also indicate that a low night temperature can inhibit inflorescence initiation and flowering, even when the day temperature is otherwise conducive for reproductive development but could accelerate the second flower production. In addition, the air pollutant concentration could decrease the flower quality. This study result could suggest the farmer to control the weather condition in greenhouses area.

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