Estimating Effects of Spatial Temperature Risk on Rice Yield in Japan Using Climate Records and Prediction from Machine Learning

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1. Introduction

Global warming and extreme weather events have presented new challenges for the agricultural sector worldwide. Japan is no exception, as the country is likely to face significant uncertainties in agricultural production due to these climate conditions. For example, temperature rises may have differential impacts on crop choice, yields, and farm livelihoods in different areas of the country. In recent years, concerns about national food security and sustainable agricultural development have increased. Thus, this study examines the regional effects of weather shocks on agricultural yields, specifically focusing on Japanese rice productivity.

2. Methodology and Data

Temporal data from weather stations and spatial data (e.g., land cover, land use, population density, and DEM) across Japan were collected. An Artificial Neural Network (ANN) with 7-fold cross-validation (70/30) was applied to predict the model. Root Mean Square Error (RSME) was used for model selection and validation. The interpolation of temporal data using Inverse Distance Weighting was used for mapping prediction. The ANN prediction should produce a coherent spatial image, increase prediction resolution (compared to other interpolation methods), reduce bias from noise in the data input, and possess good statistical properties.

The empirical model Fixed Effect Generalized Least Squared (FEGLS) is used to estimate the effect of spatial temperature risk on rice productivity across prefectures in Japan. The formula is described as follows:

$$Y_{jt} = \alpha_j + \delta_t + Temp_{jt} + \epsilon_{jt}$$

3. Results

We build a map of predicted maximum air temperature in August using the model. The predicted temperature shows increasing trends throughout the 1960 to 2000, and 2000 to 2020 periods, which reflects the findings in climate change literature. There is much variance across space in terms of maximum temperature increases. The high-resolution map allows for identifying regions with higher exposure to the risks of increases in the long-run temperature from CO_2 emission. The building climate map is consistently aligned with weather extreme

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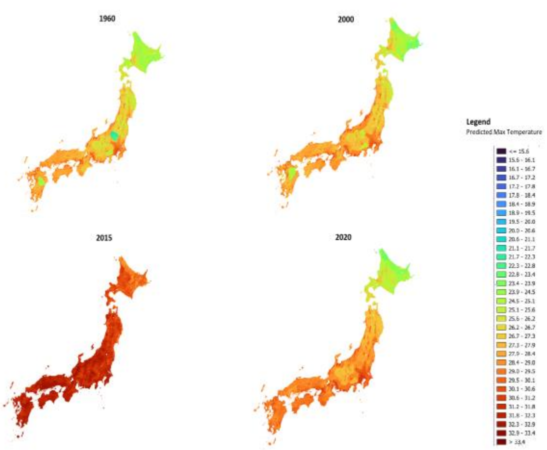
events that have occurred across Japan, such as the cold summer event of 1980 (Murakami, 1982) and the El Niño event of 2015 (Shiozaki and Enomoto, 2020). These events have had a significant impact on the country's rice production. The map also displays a lesser degree of spatial variation within the country in the case of a global extreme weather event such as El Nino in 2015.

Using FEGLS models enable more precise predictions of rice yields from temperature and shocks. In the models, we include year effects from 1960 to 2020 to control for year fixed effects to mitigate the concerns of long-run climate adaptation mechanisms as mentioned above. We use GLS with Fixed Effects to correct the serial correlation issues and heteroskedasticity. Temperature shocks (mean_temp) have negative and significant effects on rice yields per 10a. The magnitude effects vary significantly between models, a 1-degree deviation from mean temperature causes a decrease in 1.39 tons to 0.41 tons per 10 a.

4. Conclusion



	(1) GLS xtgls	(2) GLS RE xtregar	(3) GEE xtgee
mean_temp	-1.39***	-0.50***	
	(0.27)	(0.17)	
total_pre	0.00	0.00**	
	(0.00)	(0.00)	
D.mean_temp			-0.41*
			(0.24)
D.total_pre			0.00***
			(0.00)
1960.year	20.62***		1.73
	(0.69)		(1.36)
1961.year	28.60***		-0.91
	(0.85)		(1.53)
1962.year	32.38***		-2.54*
	(0.96)		(1.40)
1963.year	37.02***		-3.23**
	(2.74)		(1.37)
.... 2021			
_cons	362.29***	442.66***	8.63***
	(4.64)	(7.73)	(1.41)
N	2944	2944	2898

Overall, the building climate map is a powerful tool that has helped researchers and policymakers better understand the complex and dynamic nature of temperature risk in Japan. Its insights and information are critical in guiding the development of effective policies and interventions that can enhance the resilience of Japan's agriculture in the face of climate change.

Reference

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