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多年份反聖嬰事件對東南亞降雨與農業影響之探討：
以芒果為案例

Exploring the Impacts of Multi-Year La Niña Events on
Rainfall and Agriculture in Southeast Asia:
A Case Study of Mango

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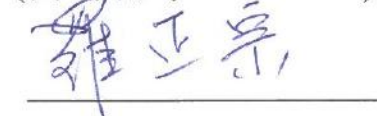
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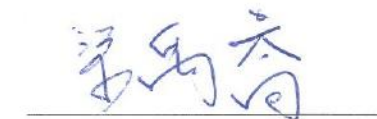

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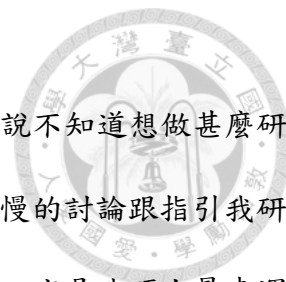


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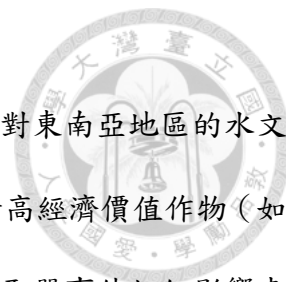
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中文摘要



隨著氣候變遷加劇，多年份反聖嬰事件的頻率與強度已出現變化，對東南亞地區的水文氣候與農業生產構成潛在威脅。然而，其背後的大氣動力機制及對高經濟價值作物（如芒果）的長期影響，迄今仍缺乏明確的理解。本研究探討多年份反聖嬰事件如何影響東南亞的水文氣候，並量化其對台灣芒果產量的影響。研究中利用 NCAR Community Earth System Model Version 2 (CESM2)，氣候模式結合大氣再分析資料與觀測降水資料，分析多年份反聖嬰的降水變化以及動力機制。模擬結果顯示，此類事件呈現第一年偏乾、第二年偏濕的「乾－濕」階段轉換特徵，與太平洋海溫配置及菲律賓氣旋異常有密切關聯。在升溫 2°C 的氣候情境下，模擬結果亦顯示暖化可能改變此種乾濕結構，需進一步評估對農業系統的潛在衝擊。另一方面，本研究亦透過經濟計量模型評估氣候異常對台灣芒果產量的影響。結果顯示，「第一年偏乾、第二年偏濕」的氣候條件對產量產生相反的效果，在假設對數線性關係的情況下，二月降雨量每增加 10 毫米，平均每公頃的芒果產量將減少約 0.5%。綜合農業生理知識推論，花期期間若降雨過多，可能導致授粉受阻，進而造成產量下降。最後，本研究分析 CMIP6 模擬資料中不同暖化情境下，台灣二月降水的變化趨勢。結果指出未來降水偏多的異常機率有上升趨勢，顯示芒果花期所面臨的氣候風險可能進一步加劇，需及早規劃調適對策。本研究結合氣候模擬與經濟分析，深入探討多年份反聖嬰事件下東亞地區「乾濕循環」的動態驅動機制，並量化其對芒果產業的衝擊。研究成果有助於提升對農業部門在當前與未來氣候變異下脆弱性的理解，亦可作為制定農業調適策略的重要科學依據。

關鍵字：反聖嬰現象、芒果、雨量、氣候變遷

ABSTRACT



As climate change intensifies, the frequency and strength of multi-year La Niña events have shifted, increasing potential threats to the climate and agricultural production across Southeast Asia. However, the underlying climate dynamics and their long-term impacts on high-value crops, such as mangoes, remain poorly understood. This study investigates how multi-year La Niña events influence atmospheric processes and rainfall in Southeast Asia and quantifies their effects on Taiwan's mango yields. The NCAR Community Earth System Model Version 2 (CESM2) climate model combined with atmospheric reanalysis dataset and observed rainfall data are used to explore the dynamic mechanisms behind these events. Results reveal a distinct "dry-wet" phase transition, characterized by drier conditions in the first year and wetter conditions in the second. This precipitation pattern is associated with Pacific sea surface temperature patterns and the development of the Philippine Sea anomalous cyclone (PSCC). Further model simulations under a +2°C warming scenario suggest that such dry-wet structures may intensify under future climate conditions, with important implications for agricultural systems. Additionally, a panel data model is applied to assess the effects of climate anomalies on mango yields in Taiwan. The analysis shows that drier conditions in the first year of a multi-year La Niña tend to increase yields, while wetter conditions in the second year may result in excessive rainfall during flowering, which can disrupt pollination and lower productivity. To quantify this effect, we estimate that assuming a log-linear relationship within the observed range, a 10 mm increase in February precipitation is associated with an average reduction of approximately 0.5% in mango yield per hectare. Finally, projections based on CMIP6 simulations indicate an increased likelihood of positive precipitation anomalies across Taiwan in February under future warming scenarios. This points to rising climate risks during the mango flowering period and highlights the need for proactive adaptation strategies. By integrating climate modeling and economic analysis, this study reveals the dynamic drivers

behind the dry–wet cycles associated with multi-year La Niña events in Southeast Asia and quantifies their impacts on Taiwan’s mango industry. The findings provide a scientific foundation for understanding agricultural vulnerability under both current and future climate extremes and support the formulation of targeted adaptation strategies.



Keywords: La Niña, Mango, Precipitation, Climate change

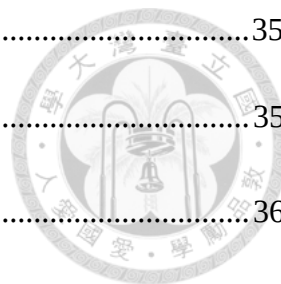
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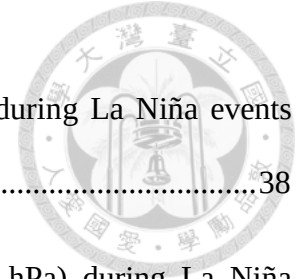


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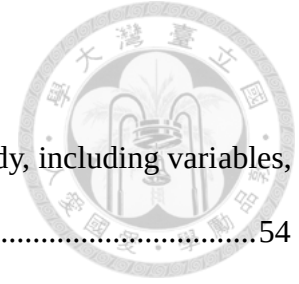


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Chapter 1 Introduction

1.1 ENSO Shifts and the Rising Risk of Multi-Year La Niña Events

As climate change intensifies, the frequency and severity of extreme weather events have also increased. Among these, the El Niño–Southern Oscillation (ENSO) stands out due to its pivotal role in modulating global climate and substantially influencing weather patterns and economic activities worldwide (Liu et al., 2023). Recent observations suggest that ENSO dynamics may be undergoing fundamental shifts, characterized by heightened variability and prolonged event durations (Lu et al., 2025). A prominent example is the rare occurrence of three consecutive La Niña years from 2020 to 2022, which highlights potential changes in ENSO behavior under climate change. Supporting this concern, Geng et al. (2023) demonstrate a strong multi-model consensus: 15 out of 20 CMIP6 models (75%) project a significant increase in the frequency of multi-year La Niña events under greenhouse warming.

In addition, paleo-ENSO reconstructions reveal a long-term trend toward greater persistence. Lu et al. (2025) report that the ratio of multi-year to single-year ENSO events has increased fivefold over the past 7,000 years, with multi-year La Niña events occurring more frequently than El Niño events. These findings raise serious concerns about the far-reaching implications of an increasingly persistent La Niña pattern. Among the sectors most affected by such climatic changes, agriculture is especially vulnerable due to its dependence on stable hydroclimate conditions. The Southeast Asia–Pacific region, a vital hub for global agricultural production and economic activity, faces significant exposure to climate-related disruptions (Panda, 2021). Consecutive La Niña events may intensify anomalies and lead to prolonged disruptions in agricultural production (Okumura et al., 2017; Anderson et al., 2022). Such extremes are already seen as serious threats to food security (FAO, 2025).

Although the broader impacts of ENSO on agriculture have been studied extensively, the specific effects of consecutive La Niña events on crop production in Southeast Asia remain poorly understood. A more context-specific understanding of these impacts is crucial for designing evidence-based strategies that enhance agricultural resilience and food security under intensifying climate variability.

1.2 Sensitive Agricultural Products: Mango

Every year, over one million hectares of mangoes are cultivated across eight countries in East and Southeast Asia, including China, Indonesia, the Philippines, Thailand, Vietnam, Taiwan, Cambodia, and Myanmar, yielding a total production of more than 10 million metric tons (FAO, 2023). In 2023, the mango industry in Taiwan generated an estimated NT\$8.95 billion in production value (農業部農糧署, 2023), making it the country's fourth most valuable fruit crop and a key contributor to agricultural exports. In Taiwan, mango cultivation predominantly relies on improved cultivars, with the Irwin mango being the most prominent representative (陳, 2012; 黃和劉, 1998).

According to a technical report by the Tainan District Agricultural Research and Extension Station (Tainan DARES), approximately 93% of Taiwan's mango cultivation area is concentrated in the southern regions of Tainan, Kaohsiung, and Pingtung (石, 2021). In these areas, flowering typically begins from December to January in Pingtung, from January to February in Kaohsiung, and from February to March in Tainan. Most orchards reach their peak flowering stage between early and mid-February (石, 2021; 李等人, 2011; 農業部農業知識入口網, 2023).

February, which coincides with the peak blooming period in major production areas, is a critical phenological window for improved mango cultivars. During this time, floral bud

differentiation, pollen development, and pollination occur, all of which substantially affect fruit set outcomes. (劉等人, 2022; 農業部農業知識入口網, 2023). According to data from the Tainan DARES and the National Science and Technology Center for Disaster Reduction (NCDR), cold surges and prolonged rainfall are the most frequent meteorological hazards during the flowering season (January to March). Unfavorable weather conditions during this period can reduce pollen viability, suppress pollinator activity, and induce floral organ decay or panicle drop. These stressors often result in incomplete pollination or increased incidence of parthenocarpic fruit, ultimately compromising yield (簡, 2020; 石, 2021; 劉等人, 2022; 農業部農業知識入口網, 2023).

Therefore, this study identifies February as the focal month for examining the potential influence of multi-year La Niña events on mango production. Although existing literature has examined the impact of La Niña on Southeast Asian winter climate, few studies have specifically addressed whether multi-year La Niña episodes systematically alter February weather patterns in mango-producing regions. However, this gap in the literature underscores the need to quantify the meteorological changes induced by prolonged La Niña conditions and their implications for yield stability. Accordingly, this study aims to assess the impact of multi-year La Niña events on February weather conditions and, by extension, on mango yields, in order to provide science-based recommendations for climate adaptation in agriculture.

As a regionally important fruit crop, mango production is not only vital to local farmer livelihoods but also tied to broader economic stability and international supply chains. Clarifying how persistent climate anomalies—such as multi-year La Niña events—affect mango yields is therefore critical to supporting long-term agricultural resilience. This

strategic importance underscores the rationale for selecting mango as a focal crop to assess climate-induced risks and guide adaptive responses in sensitive subtropical agroecosystems.



1.3 Research Aims and Objectives

Building on the aforementioned climatic concerns and crop-specific vulnerabilities, this study aims to integrate climate science with agricultural economic impact analysis by examining how multi-year La Niña events influence precipitation patterns in Taiwan, southeastern China, and Southeast Asia. It also investigates the associated atmospheric dynamics that drive these anomalies. Furthermore, it evaluates the impact of precipitation anomalies on local crop yields.

We apply a refined panel data model, primarily based on Liu et al. (2023), while also drawing methodological inspiration from the non-linear panel framework of Burke et al. (2015), which models climate impacts on productivity using temperature and precipitation anomalies, to quantify agricultural production losses associated with multi-year La Niña events. By integrating time-series meteorological data and regional crop yield records, the model enables analysis across both temporal and spatial dimensions. This integration facilitates the simulation of changes in agricultural output under climate conditions influenced by multi-year La Niña events, enabling a more precise assessment of economic impacts.

Overall, this study seeks to generate a comprehensive understanding the effects of multi-year La Niña events on agriculture, including meteorological variables, crop yields, and economic factors. The findings will contribute empirical evidence to support research and inform policy decisions aimed at mitigating climate risks in the agricultural sector.

Chapter 2 Data and Methods



2.1 Meteorological Datasets

2.1.1 Regional-Scale Climate Datasets for East and Southeast Asia

In support of the regional-scale climate–agriculture analysis, this study incorporates a combination of reanalysis and observational precipitation datasets (Table.1). These data are used to analyze precipitation anomalies associated with multi-year La Niña events, examine large-scale atmospheric dynamics, and validate the consistency of model outputs.

The ERA5-Land monthly dataset, offering total precipitation (mm/day) and 2-meter temperature (K) at 0.1° resolution (Muñoz Sabater, 2019), enables detailed temporal analysis of weather variability during critical phenological stages, particularly mango flowering.

Complementing the high-resolution ERA5-Land data, the monthly-averaged ERA5 dataset (Hersbach et al., 2023) captures large-scale variables such as wind components (m/s), Specific humidity (kg/kg), and Q_1 from 1000 to 100 hPa at 0.25° resolution. These variables are essential for diagnosing the broader atmospheric mechanisms linked to La Niña anomalies.

Among these variables, the apparent heat source (Q_1) is particularly valuable. Derived from the thermodynamic energy equation, Q_1 represents the net diabatic heating of the atmospheric column and is expressed as:

$$Q_1 = c_p \frac{\partial T}{\partial t} - c_p (\omega \sigma - V \cdot \nabla T)$$

where T is temperature, ω is the vertical pressure velocity, σ denotes static stability, V is the horizontal wind vector, and ∇T is the horizontal temperature gradient. This formulation separates the local heating tendency from advective processes, enabling a

more detailed interpretation of diabatic contributions to tropical convection. Both ERA5 and ERA5-Land datasets cover the period from 1950 to 2023.



2.1.2 High-Resolution Climate Datasets for Taiwan

To support localized assessments of agricultural impacts and climate–economic interactions in Taiwan, this study utilizes two high-resolution datasets: one based on observed meteorological station data and the other derived from statistically downscaled global climate model projections (Table.1).

The TCCIP Gridded Observation Dataset (Version 2.8) provides monthly mean precipitation (mm/day) and average temperature (°C) at a spatial resolution of $0.05^{\circ} \times 0.05^{\circ}$ from 1960 to 2023. Developed by the Taiwan Climate Change Projection Information and Adaptation Knowledge Platform (TCCIP), this dataset integrates long-term station observations compiled from multiple government agencies (Lin et al., 2022). Precipitation data are gridded through a multi-step process involving Latent Gaussian Variable (LGV) transformation, Empirical Orthogonal Function (EOF) decomposition, and Natural Neighbor Interpolation (Watson, 1994). The dataset includes cross-validated uncertainty estimates derived from leave-one-out procedures and accounts for spatial error variation due to topographic complexity and station density, enabling robust historical analysis of climate–agriculture relationships across Taiwan (楊等人, 2024).

To assess future precipitation changes under global warming scenarios, this study incorporates the AR6 Bias-Corrected and Statistically Downscaled Monthly Mean Precipitation (mm/day) Dataset. Produced by TCCIP (Lin et al., 2022), this dataset downscales CMIP6 daily outputs to a $0.05^{\circ} \times 0.05^{\circ}$ resolution using a quantile delta mapping (QDM) approach. The bias correction is based on observational data from 1960 to 2014 and

provides future projections from 2015 to 2100 under four SSP scenarios: SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5 (林等人, 2023).

The downscaling method includes bilinear spatial interpolation, temporal segmentation, moving-window sampling, and precipitation probability correction. These steps collectively preserve rainfall distribution patterns and seasonal variability. As a result, the dataset enables high-resolution evaluation of future precipitation trends in Taiwan and supports regional-scale climate–economic modeling under various warming pathways.

2.2 Agricultural Datasets

To analyze the relationship between climate variability and mango production, this study utilizes county-level data on mango yield per hectare (kg/ha) in Taiwan, covering the period from 1960 to 2023. All data are sourced from the Agricultural Statistics Yearbook, published annually by the Agriculture and Food Agency, Ministry of Agriculture (MOA) (農業部農糧署農業統計年報, 1960–2023).

For the period 1997 to 2023, the data were obtained directly from the MOA’s official agricultural statistics portal (<https://agrstat.moa.gov.tw>). Historical data from 1960 to 1996 were manually compiled from printed volumes of the Agricultural Statistics Yearbook archived at the National Taiwan University Library. Although the access methods, both sources originate from the same official publication series.

To match the spatial resolution of the agricultural data, gridded climate variables were aggregated to the county level. Gridded meteorological datasets introduced in Section 2.1.2 were averaged within each county boundary using area-weighted zonal statistics. Monthly mean precipitation (mm/day) and average temperature (°C) were thus derived for each administrative unit. The administrative boundaries are defined using the “County and City

Administrative Boundary” dataset georeferenced in the TWD97 coordinate system (內政部, 2024). All data were harmonized to match the current administrative divisions as of 2023.

This integration of high-resolution climate data with county-level agricultural statistics enables subnational assessments of the climate impacts on mango production, supporting both historical and forward-looking analyses.

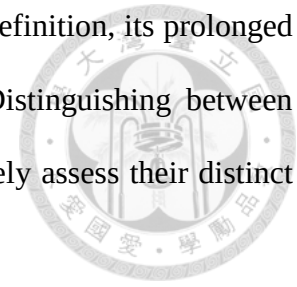
2.3 Identification and Categorization of La Niña Events

This study identifies and classifies La Niña events using the Oceanic Niño Index (ONI), published by the National Oceanic and Atmospheric Administration (NOAA). Events are categorized into single-year and multi-year types. The initial occurrence of a La Niña event is referred to as year (0), with subsequent years labeled as (+1) and (+2).

A single-year La Niña event is defined as one in which the Niño-3.4 index drops below -0.75 standard deviations for at least one month between October of year (0) and February of year (+1), but remains above -0.5 standard deviations from October (+1) to February (+2), indicating that the event does not persist into a second year. Based on this definition, four single-year events are identified from 1950 to 2024: 1965, 1989, 1996, and 2006 (Table 2).

Multi-year La Niña events are classified following the criteria proposed by Okumura et al. (2017). Specifically, these events occur when the Niño-3.4 index falls below -0.75 standard deviations for at least one month between October (0) and February (+1), and remains below -0.5 standard deviations for at least one month between October (+1) and February (+2). Using this definition, nine multi-year events are identified: 1955–56, 1971–72, 1974–75, 1984–85, 1999–2000, 2008–09, 2011–12, 2017–18, and 2021–22 (Table 2).

While the (0) year of a multi-year event satisfies the single-year definition, its prolonged cooling and atmospheric anomalies extend beyond the first year. Distinguishing between single-year and multi-year La Niña events is thus essential to accurately assess their distinct climate and agricultural impacts.



2.4 Econometric model

2.4.1 Panel Data Model

To examine how climate variability influences mango production in Taiwan, this study employs a panel data model. This approach integrates cross-sectional and time-series data to capture spatiotemporal variation and account for unobserved heterogeneity among counties. Considering the long-term span of the dataset and the regional heterogeneity in agro-environmental conditions (e.g., rainfall and temperature patterns), the panel data model offers a suitable framework for capturing both intertemporal trends and spatial disparities.

Panel data models offer several advantages over purely cross-sectional or time-series approaches (Baltagi, 2005; Hsiao, 2003):

1. Control for unobserved individual heterogeneity: Fixed effects eliminate time-invariant differences across counties (e.g., soil quality, geography, policy environment), thereby improving the internal consistency of the estimates.
2. Capture temporal dynamics: The multi-year structure enables incorporation of lagged climate effects and long-term trends, allowing for assessment of persistence and cumulative impacts.
3. Flexible model specification: The model allows inclusion of nonlinear (e.g., squared) and interaction terms, as well as time-varying covariates, which enhance its ability to capture complex climate–agriculture interactions.

According to Baltagi (2008), the general form of a panel data model can be expressed as:

$$y_{it} = \alpha + X'_{it}\beta + u_{it} \quad i = 1, \dots, N; t = 1, \dots, T \quad (1)$$

where y_{it} denotes the dependent variable, mango yield per hectare, for county i at year t ; X_{it} is a $K \times 1$ vector of explanatory variables, including climatic indicators such as precipitation and temperature; β is the vector of parameters to be estimated; and u_{it} is the composite error term encompassing unobserved effects.

Based on how the unobserved effect u_i is treated, the model can be further categorized into:

- Fixed Effects (FE) Model: Assumes that u_i is a fixed, county-specific constant that may be correlated with explanatory variables and therefore must be controlled.
- Random Effects (RE) Model: Assumes that u_i is a random variable uncorrelated with the independent variables and the idiosyncratic error term.

The fixed effects model is generally preferred when the cross-sectional units (e.g., counties) possess persistent, non-random characteristics, such as regional farming practices or climate sensitivity, that are likely correlated with both the dependent and independent variables (Hsiao, 2003). This approach is particularly appropriate for Taiwan, where counties differ in long-standing features such as irrigation systems, crop calendars, and institutional capacity (Lam et al., 2021; Chang, 2002). By controlling for these time-invariant unobserved characteristics, the fixed effects model enhances the internal validity of the estimates.

Panel models have been widely adopted in the climate–economy literature (Dell et al., 2012; Burke et al., 2015; Kahn et al., 2019; Liu et al., 2023). Several influential studies have applied nonlinear panel frameworks using fixed effects models to examine the macroeconomic impacts of temperature and precipitation anomalies (Burke et al., 2015; Kahn

et al., 2019; Liu et al., 2023). More recently, this approach has been extended to study nonlinear ENSO-related impacts under future climate scenarios (Liu et al., 2023). While these studies primarily focus on national-level economic outcomes, our study adapts the framework to a subnational agricultural context. By using county-level data, we aim to generate spatially disaggregated insights to inform localized adaptation strategies and regional agricultural policy.

2.4.2 Empirical Model Design

This study adapts the panel data framework originally proposed by Liu et al. (2023), who examined the relationship between ENSO and national-level GDP growth, and applies it to the context of subnational agricultural production in Taiwan. Because mango is a perennial fruit crop with yield outcomes that are especially sensitive to climatic conditions during the flowering period (typically occurring in February), the model is explicitly designed to assess the impact of February-specific climate anomalies on mango yield.

The dependent variable is the natural logarithm of mango yield per hectare, $\log(y_{it})$, where y_{it} represents the mango yield in county i and year t . The log transformation allows for the interpretation of coefficients in percentage terms and facilitates comparability across regions with different production scales. The explanatory variables include February temperature anomalies (T_{it}) and February precipitation anomalies (P_{it}), along with their squared terms (T_{it}^2 and P_{it}^2), which are included to capture potential nonlinear relationships. These anomalies are calculated relative to the 1960–2023 climatological mean using high-resolution gridded datasets, as described in Section 2.1.2.

To account for unobserved regional heterogeneity, the model includes county fixed effects (μ_i), as well as county-specific linear and quadratic time trends ($\theta_{1i}t + \theta_{2i}t^2$) to

control for long-term structural changes, including but not limited to adjustments in agricultural policy, infrastructure development, and technological advancement.

The final model is specified as follows:

$$\log(y_{it}) = \alpha_1 T_{it} + \alpha_2 T_{it}^2 + \beta_1 P_{it} + \beta_2 P_{it}^2 + \mu_i + \theta_{1i}t + \theta_{2i}t^2 + \varepsilon_{it} \quad (2)$$

This specification enables the quantification of nonlinear climatic effects on crop yield across regions and years, offering a robust empirical basis for understanding climate–agriculture interactions at the subnational level.

Chapter 3 Results



3.1 Precipitation Anomalies in Multi-La Niña Events

We begin our analysis by examining February precipitation anomalies across Southeast Asia during La Niña events, with particular attention to multi-year occurrences. When averaging across all La Niña February months (Fig. 1a), a modest negative precipitation anomaly is observed over Southeast Asia. This dry anomaly is also present, though slightly more pronounced, during multi-year La Niña Februarys (Fig. 1c). However, year-by-year disaggregation reveals a clear contrast: the first year of multi-year La Niña is characterized by suppressed rainfall (Fig. 1d), whereas the second year exhibits increased precipitation (Fig. 1e).

This raises a key question: Why do February rainfall anomalies differ so markedly between the first and second years of multi-year La Niña events, despite both being under the same ENSO phase? To explore this, we further examine atmospheric conditions, including 850hPa moisture flux and diabatic heating anomalies.

3.2 Atmospheric Mechanisms

3.2.1 Influence of Philippine Sea Anomalous Cyclone

We first examine 850 hPa moisture flux anomalies (Fig. 3) and diabatic heating anomalies (Fig. 2) to explore the atmospheric mechanisms associated with the contrasting precipitation patterns between the first and second years of multi-year La Niña events. During the first year, the lower-tropospheric circulation is dominated by enhanced northeasterly winds and reduced moisture flux into Southeast Asia (Fig. 3d), while negative diabatic heating anomalies (Fig. 2d) suggest suppressed convection and enhanced atmospheric stability.

This pattern corresponds to a cyclonic anomaly over the Philippine Sea—here referred to as the Philippine Sea anomalous cyclone (PSCC)—which blocks the northward transport of tropical moisture and enhances the intrusion of dry air into Southeast Asia. In the second year, the PSCC-related anomaly weakens markedly (Fig. 3e), and southerly winds prevail at 850 hPa over the South China Sea, enhancing the northward transport of moisture flux and contributing to positive diabatic heating anomalies (Fig. 2e), indicative of increased convective activity. These thermodynamic and dynamical shifts between the first and second La Niña years suggest a potential mechanism behind the transition from rainfall suppression to enhancement.

3.2.2 Role of the Philippine Sea Anomalous Cyclone

Previous studies have emphasized the importance of regional sea surface temperature (SST) gradients in shaping low-level atmospheric circulation over the Philippine Sea. Wang et al. (2000) showed that the development of the Philippine Sea Anomalous Anticyclone (PSAC) during El Niño winters is driven not only by remote central Pacific warming but also by local SST contrasts within the Philippine Sea region. Specifically, cooler SSTs on the eastern flank of the PSAC suppress convection and increase surface pressure, while relatively warmer SSTs on the western side support convective activity. This east–west SST gradient reinforces boundary-layer divergence and establishes a positive feedback that sustains the anomalous anticyclone.

While originally proposed for anticyclonic anomalies during El Niño, this framework might offer insight into the possible mechanisms behind cyclonic patterns observed during La Niña years. In the first year of multi-year La Niña events, strong central Pacific cooling coincides with a warm western Philippine Sea and a cooler South China Sea (Fig. 4a), forming a reversed SST contrast that favors surface convergence and low-level cyclonic

vorticity—referred to here as the PSCC. This circulation enhances northeasterly wind anomalies and suppresses moisture flux, covering Southeast Asia, the Taiwan region, and adjacent waters to its east (Fig. 3d), contributing to the suppressed rainfall observed in the first La Niña year.

By contrast, in the second year, SST anomalies weaken across the region, and both the Philippine Sea and South China Sea exhibit warmer-than-normal temperatures (Fig. 4b). The diminished SST gradient weakens the thermal forcing necessary for PSCC maintenance, allowing for a reorganization of the circulation and facilitating increased southerly moisture transport and rainfall across Southeast Asia (Fig. 3e).

3.2.3 Prescribed SST experiments in climate model

To assess the influence of SST anomalies in the western and southeastern Pacific on low-level wind anomalies over the Philippine Sea, this study conducted a set of prescribed SST experiments using the atmospheric component of the Community Earth System Model version 2 (CESM2; Danabasoglu et al., 2020). The simulations were configured under the fully prescribed historical (FHIST) setup, with the Community Atmosphere Model version 6 (CAM6) and the finite-volume (FV) dynamical core at approximately 1° horizontal resolution. This configuration is widely used in tropical climate studies and has demonstrated skill in capturing large-scale atmospheric responses to SST forcing.

An Atmospheric Model Intercomparison Project (AMIP) experimental design was adopted, with simulations initialized in January and integrated for 18 months to capture the seasonal transition from La Niña's peak to decay. SST anomalies were derived from ERA5 reanalysis based on nine multi-year La Niña events between 1950 and 2024. Monthly means were composited separately for year (0), year (+1), and year (+2).

Each experiment consisted of two simulation periods:

- First-year La Niña experiment: SST anomalies from January (year 0) to June (year +1).
- Second-year La Niña experiment: SST anomalies from January (year +1) to June (year +2).



The design of CESM2 experiments used in this study is summarized in Table 3. SST forcing fields were generated by superimposing La Niña anomalies onto the monthly climatological mean, with the anomalies detrended using a linear regression method to remove long-term warming signals. A spatial mask was applied to constrain the anomalies to the tropical Pacific (see Fig. 5-7 for the red box region). Each experiment included 20 ensemble members, generated by perturbing the atmospheric initial conditions. Each ensemble member was generated by introducing small, random perturbations to the atmospheric initial conditions at January 1st of the simulation year, following the CESM2 default protocol. The ensemble mean was analyzed to isolate the SST-forced signal from internal variability. Atmospheric responses were diagnosed by subtracting the model's climatological baseline from the SST-forced ensemble mean. Wind anomalies were then analyzed to evaluate the large-scale circulation mechanisms responsible for PSCC development and associated moisture transport.

3.2.4 Analyses in Moisture Transport

Building upon the prescribed SST experiments described in Section 3.2.3, we analyzed atmospheric responses—particularly moisture flux and low-level circulation—under different SST anomaly configurations to better understand the mechanisms driving precipitation asymmetry during multi-year La Niña events. We then further investigated which specific ocean regions' SST anomalies are responsible for these changes in atmospheric circulation. To this end, three sets of experiments were conducted, each isolating SST anomalies in a different ocean region.

In the first experiment, SST anomalies were prescribed over the entire tropical Pacific (120°E–70°W, 30°S–40°N; restricted to the Pacific Ocean; Fig. 5), and simulations were performed for both the first and second years of multi-year La Niña events. In the first-year simulation, the model reproduced a cyclonic anomaly near the Philippines and northeasterly wind anomalies along the East Asian coast, resembling the observed PSCC pattern (Fig. 5a), which suppressed moisture transport into Southeast Asia, and simulated precipitation anomalies revealed widespread drying over Taiwan, southeastern China, and Mainland Southeast Asia. In the second-year simulation, southerly wind anomalies dominated at 850 hPa (Fig. 5b), facilitating enhanced moisture transport from the tropics. Precipitation anomalies indicated above-normal rainfall across Taiwan, southern China, and northern Vietnam (Fig. 5d), forming a southwest–northeast band of increased rainfall. The model outputs for both years closely matched the observational composites (Fig. 3d, e), supporting the reliability of CESM2 in capturing large-scale circulation and precipitation anomalies associated with La Niña events.

In the second experiment, SST anomalies were restricted to the South China Sea and the western North Pacific (100°E–155°E, 5°S–25°N; Fig. 6). This region is characterized by a pronounced SST gradient during the first year of multi-year La Niña events, but such a gradient is largely absent in the second year. The first-year simulation generated a prominent PSCC-like cyclonic anomaly near the Philippine Sea, with strengthened northeasterlies and reduced northward moisture transport (Fig. 6a). Simulated rainfall anomalies (Fig. 6c) showed widespread drying over the South China Sea, Taiwan, and the coastal regions of southeastern China, with the strongest suppression over the Taiwan Strait and northern Luzon. In contrast, the second-year simulation displayed no clear low-level circulation anomalies (Fig. 6b), and precipitation anomalies (Fig. 6d) were spatially weak and near-neutral across most of Southeast Asia, indicating that the absence of regional SST gradients inhibited both

dynamic and convective responses. These results suggest that regional SST gradients play a critical role in triggering and sustaining the PSCC during the first year of multi-year La Niña events.

In the third experiment, SST anomalies were applied only to the central and eastern tropical Pacific (150°E – 155°W , 5°S – 25°N), where negative SST anomalies dominate during La Niña. In both the first and second-year simulations, PSCC did not form. Instead, southwesterly wind anomalies extended northward into southern China and Taiwan (Fig. 7a, b). Simulated rainfall anomalies revealed increased precipitation in both years (Fig. 7c, d), particularly over Southeast Asia and the South China coast. These results imply that remote SST forcing likely plays a dominant role in generating the southwesterly wind anomalies and enhanced rainfall observed during the second year of multi-year La Niña events, even in the absence of regional cyclonic activity.

Synthesizing our results with previous literature, we can summarize the atmospheric mechanisms underlying multi-year La Niña events. In the first year (Fig. 8a), central Pacific cooling strengthens southeasterly winds, triggering a Gill-type atmospheric response (Gill, 1980) that alters tropical circulation and facilitates the northward redistribution of warm water. This tropical forcing can induce a downstream Rossby wave response, contributing to the development of a cyclonic anomaly near Japan (Matsuno, 1966). This anomaly, in combination with the northeast monsoon, transports cold air southward into the South China Sea, thereby cooling the region and enhancing the temperature contrast with the warmer western Pacific. The resulting zonal thermal gradient promotes the formation of the PSCC, which alters low-level water vapor transport, suppresses convection, and contributes to reduced rainfall across Southeast Asia.

In the second year (Fig. 8b), SST cooling in the equatorial Pacific weakens and becomes more zonally uniform, leading to the disappearance of the cyclonic anomaly. As a result, the

PSCC does not form. Instead, remote SST forcing from the central and eastern Pacific emerges as the dominant driver of southwesterly wind anomalies, which transport tropical moisture into Southeast Asia. This shift in circulation enhances convective activity and contributes to increased rainfall during the second year of multi-year La Niña events.

3.2.5 Warmer SST experiments

To further assess how atmospheric circulation may respond to multi-year La Niña events under future warming conditions, we conducted an AMIP-style experiment incorporating uniform ocean surface warming. The experimental setup followed the procedure described in Section 3.2.3, with one key modification: a uniform +2°C warming increment was applied to the SST climatology, resulting in a warmed baseline upon which La Niña anomalies were superimposed. Atmospheric CO₂ concentration was set to 560 ppm, representing a moderate warming scenario. The SST anomaly masks were identical to those used in Experiment 2 and Experiment 3 of Section 3.2.4. Each simulation was integrated for 18 months, starting from January of the initial year.

To isolate warming-induced atmospheric responses, we compared the historical simulations with their +2°C counterparts by differencing the two. Specifically:

- Figure 9a, c shows the difference between the historical (Figure 7a, c) and +2°C first-year simulations, both using the SST mask in Experiment 2.
- Figure 9b, d presents the difference for the second year, derived from simulations in Experiment 3 (Figure 8b, d).

This differencing approach reveals how future warming may alter atmospheric circulation and precipitation patterns during multi-year La Niña events. In the first year, northeasterly wind anomalies intensified under the +2°C warming scenario (Fig. 9a),

suggesting a possible strengthening of the East Asian winter monsoon. This was accompanied by a reduction in precipitation across Southeast Asia (Fig. 9c), indicating that warming may amplify dry-season conditions during the early phase of multi-year La Niña events.

In contrast, in the second year, precipitation increased compared to the historical simulation (Fig. 9d), despite only modest changes in wind fields (Fig. 9b). The increased precipitation is likely attributable to higher atmospheric moisture content under warming, which amplifies convective responses even without stronger dynamic forcing.

These findings suggest that future warming may amplify the interannual contrast of rainfall associated with multi-year La Niña events—intensifying dry anomalies during the first year and enhancing wet conditions in the second year. This increase in hydrological extremes could exacerbate both drought and flood risks across Southeast Asia. Therefore, incorporating projected climate responses into adaptation planning and climate-resilient agricultural strategies is essential for mitigating future climate impacts.

3.3 Assessing the Climate Impact on Agricultural Products

3.3.1 Panel Regression Results

This section presents the empirical results of the panel data model constructed in Section 2.4 (see Equation (2)), is applied to panel data on mango yield, February temperature, and precipitation from 1960 to 2023 across 17 counties in Taiwan (Section 2.2). The analysis investigates the effects of climate anomalies in February, a critical period for mango development on yield. As shown in Table 4, the estimated coefficient α_1 for February temperature anomalies (T_{it}) in the fixed effects model is 0.0013 ($p = 0.908$), and the coefficient α_2 for its squared term (T_{it}^2) is -0.007 ($p = 0.171$); neither is statistically

significant. These results suggest that February temperature anomalies have no statistically significant linear or nonlinear effect on mango yield within the observed range.

In contrast, the coefficient β_1 for February precipitation anomalies (P_{it}) is -0.0005 , statistically significant at the 5% level ($p = 0.042$). This may be due to increased pollen washout during the flowering stage caused by excessive rainfall, which can disrupt pollination and reduce fruit development (劉等人, 2022; 簡, 2020). The estimated coefficient β_2 for the squared term for precipitation (P_{it}^2) is not statistically significant ($p = 0.270$), indicating limited evidence of nonlinear precipitation effects.

The model explains approximately 51% of the variation in mango yield ($R^2 = 0.511$; adjusted $R^2 = 0.480$). The overall F-statistic of 16.44 ($p < 0.0001$) indicates joint significance of the explanatory variables. However, the Durbin–Watson statistic is 1.143, which is below the threshold of 2 and indicates potential positive autocorrelation in the residuals. This may affect the precision of coefficient estimates. A more detailed discussion of the model’s structural robustness and specification sensitivity is provided in Section 4.3.

3.3.2 Visualizing Regional Yield Responses

To further examine spatial differences in mango yield responses to February climate anomalies, this section visualizes the relationships between precipitation and temperature anomalies and the logarithm of mango yield per hectare (Figure 10). Each data point represents a county-level observation, categorized by geographic location into southern and northern Taiwan based on the Zhuoshui River boundary. The southern region includes the primary mango-producing counties, namely Tainan, Kaohsiung, and Pingtung. In contrast, the northern region encompasses counties with lower production intensity, serving as a basis for agro-climatic comparison.

To illustrate potential effects of ENSO-related climate variability, Figure 10 also includes composite markers for multi-year La Niña events. Red and blue dots represent the average precipitation anomaly and corresponding log-yield value for the first year (+1) and second year (+2) of each La Niña episode, calculated as county-level means. These markers are intended to highlight ENSO-phase influences within the broader distribution of climate-yield observations.

The black solid curves represent second-order polynomial regressions fitted to the entire sample. A 95% confidence band, estimated using a bootstrap procedure with 1000 resampled datasets, is displayed as a shaded region. For each bootstrap iteration, the polynomial regression was re-estimated and the standard deviation of predicted values at each x was calculated. The confidence band is defined as:

$$\hat{y}(x) \pm 1.96 \cdot \sigma(x)$$

To aid interpretation, we vertically shifted the fitted curve to pass through the observed sample mean (denoted as “Data Mean”) so that modeled relationships could be visually compared with empirical yield levels.

Figure 10a shows a negative association between precipitation anomalies and mango yield, consistent with the regression result reported in Section 3.3.1. Most second-year La Niña data points (blue) fall within the range of positive precipitation anomalies and are associated with lower yields, whereas first-year points (red) tend to cluster around moderate or negative precipitation anomalies and correspond to relatively higher yield levels. These results support the hypothesis that ENSO-induced February precipitation shifts contribute to year-to-year variability in mango productivity, potentially through changes in environmental conditions that affect flowering and fruit development.

To provide a more concrete interpretation of this relationship, assuming a log-linear response within the observed range, a 10 mm increase in February precipitation is associated with an average reduction of approximately 0.5% in mango yield per hectare.

Figure 10b depicts the association between February temperature anomalies and mango yield. Although the regression results do not indicate a statistically significant temperature effect, the visual suggests that second-year La Niña points (blue) tend to cluster in the lower temperature range, in contrast to those from the first year (red). While these observations are not directly associated with consistent yield reductions, the potential risks associated with temperatures should not be overlooked, particularly for other temperature-sensitive crops or when anticipating phenological changes under future climate variability.

Together, these visualizations complement the regression analysis by revealing regional disparities and event-based climatic influences, enhancing our understanding of mango yield variability in a changing climate.

3.4 Rainfall Projections from Fully Coupled CMIP6 Models

Given the significant negative relationship between February precipitation and mango yield established in Section 3.3, it is essential to assess how rainfall may evolve under future warming conditions. To this end, we analyzed February precipitation projections using the statistically downscaled CMIP6 dataset from TCCIP introduced in Section 2. The dataset provides precipitation projections for four Shared Socioeconomic Pathways (SSP1_2.6, SSP2_4.5, SSP3_7.0, and SSP5_8.5) covering the period from 2015 to 2100, along with a historical simulation from 1960 to 2014.

The results (Fig. 11) show that February precipitation is projected to increase across all future scenarios compared to the historical baseline (black line). This trend is consistently observed under both moderate and high-emissions scenarios, indicating a robust shift toward

wetter conditions during the critical flowering stage of mango production. These projections are consistent with the atmospheric mechanisms discussed in Section 3.2.4, where warming enhances moisture availability and alters circulation patterns, particularly during multi-year La Niña events. The expected increase in February rainfall could amplify the risks of pollen washout and yield loss. These findings underscore the urgency of incorporating climate projections into crop planning, regional adaptation strategies, and the design of resilient agricultural systems under future climate variability.

To further quantify the potential agricultural risks associated with future precipitation anomalies, we applied the fixed-effects panel regression model developed in Section 2.4.2 to estimate mango yield responses under different CMIP6 scenarios. Specifically, we used the February mean precipitation anomaly values derived from the statistically downscaled CMIP6 simulations (SSP1–2.6, SSP2–4.5, SSP3–7.0, and SSP5–8.5), and input them into the regression equation to obtain predicted log mango yields per hectare.

The results are presented in Figure 12, which plots the mean February precipitation anomaly (x-axis) against the predicted mango yield response (y-axis) for each scenario. The historical baseline (black) shows the highest yield outcome, while all future scenarios exhibit lower yield predictions due to increased precipitation. Notably, the SSP5–8.5 scenario, which projects the highest rainfall anomaly, corresponds to the most substantial reduction in predicted yield. This pattern aligns with our earlier findings that excessive February precipitation during the mango flowering stage can lead to pollen washout and fruit-setting failure.

These projections suggest that yield risks may persist even under moderate emission pathways such as SSP2–4.5, due to shifts in sub-seasonal precipitation patterns.

Chapter 4 Discussion

4.1 Limitations and Uncertainty of Climate Datasets Used

This study utilizes multiple climate datasets to assess the potential impacts of precipitation anomalies on mango production in Taiwan, including ERA5-Land, ERA5 monthly average data, the Gridded Observation Dataset, and the AR6 statistically downscaled climate projections released by TCCIP. Although these datasets offer long temporal coverage and wide spatial resolution, their quality, physical consistency, and spatial representativeness remain subject to several limitations.

This study primarily uses ERA5-land reanalysis precipitation data to calculate precipitation anomalies. The dataset, produced by ECMWF, provides high temporal resolution and consistent global coverage, and is widely used in large-scale climate variability analyses. However, previous research has noted that ERA5 or ERA5-Land exhibits considerable uncertainty in simulating precipitation in regions with complex terrain, such as Southeast Asia, South Asia, and Pacific island chains. Reported biases include underestimation of rainfall intensity and potential spatial displacement of orographic rainfall (Jiang et al., 2021; Muñoz-Sabater et al., 2021). These limitations may introduce uncertainty in assessing climate-related impacts, particularly under extreme precipitation conditions.

To evaluate the applicability of ERA5 precipitation data in the study area, this study further introduces the Global Precipitation Climatology Project (GPCP) observational precipitation dataset to assess the reliability of ERA5-derived precipitation. GPCP, led by NOAA, integrates ground station observations and multiple satellite products (e.g., SSM/I, GPI, OLR), and provides monthly average precipitation data from 1979 to 2023 with a spatial resolution of $2.5^{\circ} \times 2.5^{\circ}$ (Adler et al., 2003). Although its resolution is relatively coarse, the dataset is known for its temporal stability and global consistency, and is widely used in

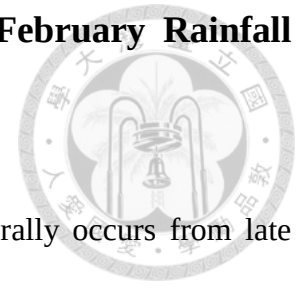
climate variability research and model evaluation. In this study, interannual precipitation trends from GPCP are generally consistent with those from ERA5 (Fig. 12), and thus GPCP serves as a useful supplementary dataset to validate ERA5-derived anomalies.

In addition, this study employs the TCCIP Gridded Observation Dataset (Lin et al., 2022), which provides monthly precipitation at $0.05^\circ \times 0.05^\circ$ resolution and is suitable for regional-scale analysis. This dataset integrates station records from the Central Weather Administration, Water Resources Agency, and Taiwan Forestry Research Institute since 1960. It applies Latent Gaussian Variable (LGV) modeling, Empirical Orthogonal Function (EOF) decomposition, and Natural Neighbor Interpolation to reconstruct gridded data. According to the dataset's official uncertainty report (楊等人, 2024), larger errors may occur in mountainous or high-rainfall areas. Main sources of uncertainty include: (1) limitations in statistical model parameterization, (2) estimation errors caused by distance and elevation differences during gap-filling, and (3) gridding bias due to observation density and terrain variation. These factors may affect the accuracy of monthly precipitation anomaly estimates, particularly in southern mountainous areas such as Pingtung and Kaohsiung.

This study also utilizes the AR6 statistically downscaled precipitation projections released by TCCIP to assess future climate risks. This dataset is adjusted using Quantile Mapping (QM) and Quantile Delta Mapping (QDM) methods (林等人, 2023), which improve the simulation performance of CMIP6 models in Taiwan and enhance their representation of monthly rainfall extremes. However, due to the absence of dynamical downscaling (e.g., through WRF or regional atmospheric models), its ability to represent short-duration and terrain-induced rainfall remains limited. As a result, it may underestimate the effects of typhoons or convective rainfall during mango flowering and pollination stages.

4.2 Limitations Related to Mango Phenology and Regional Variation

4.2.1 Regional Differences in Flowering Timing and February Rainfall Sensitivity



As discussed in Section 1.2, mango flowering in Taiwan generally occurs from late winter to early spring, but the actual flowering timeline varies significantly by regions. In southern areas such as Tainan, Kaohsiung, and Pingtung, peak flowering usually occurs in February. However, local variations exist. For example, mango trees in Pingtung often begin flowering as early as December of the previous year, with blooming continuing through February. In contrast, central and northern regions experience delayed flowering due to cooler temperatures (農業部農業知識入口網, 2024). While official phenological records in the north are limited, observational data from the Taipei Botanical Garden show that mango flowering in northern Taiwan generally takes place from late March to early April (台北植物園, 2025), more than a month later than in the south. Therefore, although this study uses February as the reference month for analyzing climate anomalies during multi-year La Niña events, this time window may not fully capture the actual flowering periods across all production regions. If rainfall anomalies occur outside of the sensitive flowering stage, it may introduce bias into the estimated yield impacts.

To address potential bias stemming from regional phenological differences, this study applies the nonlinear fixed effects model separately to southern (Table 6) and northern (Table 5) Taiwan, and illustrates their respective rainfall–yield relationships in Figure 13. In the figure, orange and green dots represent county-level observations in the south and north, respectively, while the fitted curves depict the response patterns of mango yield to February precipitation anomalies.

The results suggest that the negative impact of excess rainfall is more pronounced in southern Taiwan. As shown in Table 5, the coefficient for the linear rainfall term in the south

is -0.00141 and statistically significant at the 5% level ($p = 0.031$), while the corresponding coefficient in the north is -0.0003 and not statistically significant ($p = 0.385$). Moreover, the fitted curve for the south shows a clearer downward slope under positive rainfall anomalies, while the curve for the north appears relatively flat. These findings suggest that mango yield in southern regions is more sensitive to February rainfall variability, particularly under wetter-than-average conditions.

This heightened sensitivity is likely due to the fact that February coincides with the peak reproductive phase in the south, making mango flowers more vulnerable to excess rainfall during this period. In contrast, the delayed flowering in the north reduces exposure to climate anomalies in February. These results confirm that the yield response to February precipitation is significantly stronger in the south, highlighting the need for targeted risk assessment and adaptation strategies in key southern production zones.

Another important limitation lies in the temporal mismatch between climate indicators and the actual phenological stages of mango development. This study finds that February temperature anomalies are not significantly associated with mango yield, which may be due to the fact that the low-temperature stimulus required for floral induction occurs earlier in the season—typically between December and January. According to Tainan DARES, mango trees in southern Taiwan require a period of low temperatures below approximately 15°C prior to floral bud differentiation, which promotes bud awakening and inflorescence development (張, 2017). Therefore, focusing solely on temperature variations in February may overlook this critical phenological window, potentially explaining the lack of significant temperature effects in the regression model. Incorporating daily minimum temperature data for December and January in future analyses could help more accurately assess the role of early-season cold conditions in mango flowering and subsequent yield outcomes.

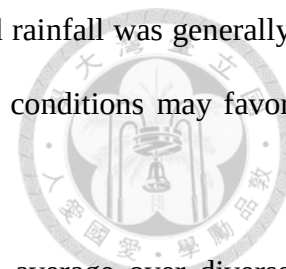
4.2.2 Localized Yield Patterns and Limitations of Spatial Aggregation

At the spatial level, the agricultural data used in this study are only available at the county level. Although the Zhuoshui River is used to delineate northern and southern samples, the model cannot capture intra-county variability in climate conditions or farm management practices. Due to data limitations, this study cannot estimate separate models for individual counties such as Tainan or Pingtung. Moreover, even within a single county, such as Tainan (e.g., Yujing, Nanhua and Nansi) or Kaohsiung (e.g., Liouguei, Qishan and Meinong), flowering periods and cultivation strategies may differ. Some areas adopt early flowering management practices, which may lead to mismatches between climate anomalies and sensitive phenological stages (劉等人, 1988; 簡, 2020). Failure to account for these differences limits the model's capacity to diagnose regional risk.

To enhance the identification of intra-regional climate risks, this study conducted an additional analysis focusing on the highest-yielding mango-producing townships in three major southern regions—Tainan, Kaohsiung, and Pingtung. The selected representative townships are Yujing and Nansi in Tainan, Liouguei in Kaohsiung, and Fangliao in Pingtung. According to the Agricultural Statistics Yearbook published by the Ministry of Agriculture (1997–2023), these four townships are the leading mango-producing areas within their respective counties and are thus highly representative. Since township-level mango production data are only available starting from 1997, the period of analysis in this section is limited to 1997–2023.

It is worth noting that when using county-level data (Section 3.3), this study identified a near-linear negative relationship between February precipitation anomalies and mango yield per hectare—that is, as precipitation anomalies decreased, mango yields tended to increase (see Fig. 10a). However, when township-level data were used, a clear nonlinear pattern

emerged (Fig. 14; Table 7). The results not only showed that increased rainfall was generally associated with lower yields, but also suggested that moderately dry conditions may favor mango fruiting, whereas extreme drought may negatively affect yields.

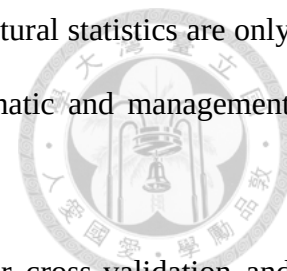


This difference may stem from the fact that county-level data average over diverse climate conditions and farm management practices across multiple townships, thereby smoothing or masking potential nonlinear responses. At the township level, the spatial alignment between climate data and actual agricultural activities is more precise, allowing local microclimates and management heterogeneity to be more accurately reflected and nonlinear patterns to emerge. For example, while moderately dry conditions can reduce disease risks and support flowering, excessive drought has been suggested to pose risks to mango production, though the specific mechanisms may vary across regions and conditions. As this study specifically focuses on yield reduction under excessive rainfall, such negative effects are more pronounced at the township level. These results indicate that improving spatial resolution helps reveal critical thresholds and nonlinear responses to climate risks.

In addition, Fig. 14 marks the township-level average values during the first year (red dots) and second year (blue dots) of multi-year La Niña events. It can be observed that yields during the second year (+2), under relatively wetter conditions, are generally lower than in the first year, supporting the hypothesis that second-year La Niña events disrupt mango flowering and pollination.

Furthermore, potential sources of uncertainty arise from mismatches between the temporal and spatial resolutions of climate and agricultural data. While climate anomalies are calculated on a monthly basis, mango's sensitive phases such as flowering and pollination often fluctuate on a weekly scale. If extreme events occur at the beginning or end of the month, they may not align with the actual phenological windows, potentially leading to

biased estimates. In addition, climate data are gridded, whereas agricultural statistics are only available at the county level, making it difficult to reflect microclimatic and management variation within townships, even after spatial averaging.



In summary, although this study employs multiple datasets for cross-validation and aligns the analysis window with the representative flowering period, structural uncertainties remain due to the limited resolution and construction of available data sources. In particular, the mismatch between spatial and temporal scales may obscure critical climate impacts on mango development. Future improvements, such as incorporating grid-level or township-level yield and phenology observations alongside high-resolution meteorological data, would help align climate variables with sensitive growth stages. These enhancements would improve the precision of climate risk assessments and support more localized agricultural adaptation strategies.

4.3 Limitations of the Economic Model

While the panel data model provides a flexible and empirically grounded framework for analyzing interactions between regional climate and agricultural outcomes, and has been widely applied in climate–economy research, the model employed in this study entails several limitations that merit close attention.

In particular, as emphasized by Newell et al. (2021), there is no theoretically prescribed functional form for the relationship between temperature and economic outcomes, and researchers often rely on empirical assumptions regarding variable selection, model structure, and trend controls. Their study systematically evaluates over 800 model specifications and demonstrates that a wide variety of functional forms—including those excluding temperature altogether—can yield statistically indistinguishable out-of-sample performance. This implies that estimated coefficients in climate–economy models, including those based on temperature

anomalies, are highly sensitive to modeling choices, raising concerns about inference robustness.

These findings suggest caution in interpreting estimates from any single model and underscore the importance of accounting for model selection uncertainty. Although this study adopts a nonlinear fixed effects framework commonly used in the literature, the results should be interpreted with caution, as model structure may influence both the magnitude and direction of estimated climate impacts.

To examine the robustness of our model, we conducted a stability test by modifying the baseline fixed effects model introduced in Section 2.4.2. Specifically (see Equation (2)), we estimated three alternative models in which county-level time trends, including both linear and quadratic terms ($\theta_{1i}t$ and $\theta_{2i}t^2$), were either partially or fully excluded:

- Model 1: excluded the linear term ($\theta_{1i}t$) only. (table 8)
- Model 2: excluded the quadratic ($\theta_{2i}t^2$) term only. (table 9)
- Model 3: excluded both linear and quadratic terms ($\theta_{1i}t$ and $\theta_{2i}t^2$). (table 10)

As shown in the comparison in table 11, removing either component resulted in a substantial reduction in explanatory power. The adjusted R^2 declined from 0.480 in the baseline model to 0.393 when only one trend component was included, and further dropped to 0.257 when both were excluded. Meanwhile, AIC and BIC values increased considerably, indicating poorer model fit.

In addition, the significance levels of the precipitation terms varied across model specifications. In the baseline model, the linear precipitation term was statistically significant at the 5% level. However, when only one of the time trend components was included, either the linear term or the quadratic term, both precipitation coefficients lost statistical

significance. In contrast, in the most restrictive specification, which excluded both time trend terms, the quadratic precipitation term became statistically significant ($p = 0.019$), while the linear term remained insignificant. These findings indicate that the estimated effects of rainfall on mango yield are sensitive to how temporal trends are modeled, and may not remain stable across different assumptions.

Moreover, the model treats temperature and precipitation as independent variables, without accounting for possible physical interactions between them. In reality, higher temperatures can influence precipitation through thermodynamic processes such as increased evaporation and atmospheric moisture capacity, which may enhance convective rainfall under certain conditions. Conversely, in some cases, high temperatures may be associated with dry, subsiding air masses that suppress precipitation. These opposing mechanisms may partially explain the sensitivity of rainfall coefficients and the lack of a consistent temperature effect. Future analyses incorporating the physical co-dependence of climate variables may improve the explanatory power and realism of agricultural impact models.

In addition to interactions between climatic variables, this study does not account for the phenomenon of alternate bearing in mango production (Fig. 15). Mango trees are highly prone to biennial bearing cycles, in which a year of abundant fruit production is often followed by a sharp decline in flowering or even a complete absence of flowering in the subsequent year (陳, 2012). This physiological pattern is closely related to internal hormonal levels and carbohydrate storage within the tree. If such endogenous interannual cycles are not incorporated into the model, there is a risk of misattributing yield fluctuations driven by the tree's own flowering rhythm to external climatic variables, resulting in biased estimates. Future research may consider filtering out or controlling for this cyclical effect to improve the model's ability to account for physiological variation inherent to the crop.

Overall, these results underscore the importance of recognizing that regression estimates are conditional on specific modeling assumptions. Although the current model is consistent with established literature, its results should be interpreted with caution. Future research should be mindful of structural uncertainty in model specification and aim to improve the robustness of climate impact assessments through careful sensitivity analysis and transparent model design.

Chapter 5 Conclusions

5.1 Summary of Key Findings

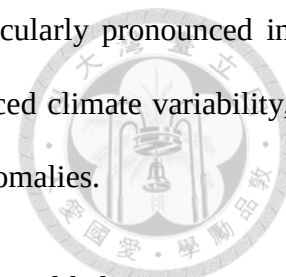


This study investigates how multi-year La Niña events influence both regional climate and agricultural production in Southeast Asia, with a particular focus on February precipitation patterns and mango yield in Taiwan. Through an integrated analysis that combines climate diagnostics, CESM2 prescribed-SST simulations, and a panel data model, several key findings emerge. First, the results reveal a consistent dry–wet transition across multi-year La Niña events. While overall February precipitation anomalies appear modest when averaged across all events (Fig. 1a), a clear year-by-year contrast is observed: the first year of multi-year La Niña events is typically associated with reduced rainfall (Fig. 1d), whereas the second year tends to exhibit increased precipitation in Southeast Asia (Fig. 1e). This interannual asymmetry is closely tied to changes in low-level circulation, particularly the presence or absence of the PSCC, which modulates regional moisture transport and convective activity.

Second, the CESM2 experiments show that spatial patterns of SST anomalies contribute to the development of distinct atmospheric responses. In the first year, SST cooling in the South China Sea and western North Pacific supports the formation of the PSCC and dry northeasterly flow into Southeast Asia. In contrast, second-year events are more strongly influenced by central Pacific SST anomalies, which promote southwesterly moisture intrusion even in the absence of a PSCC.

Third, panel regression results suggest a nonlinear relationship between February climate anomalies and mango yield growth, with precipitation having a more consistent and significant effect than temperature. Assuming a log-linear relationship within the observed range, a 10 mm increase in February precipitation is associated with an average reduction of

approximately 0.5% in mango yield per hectare. This effect is particularly pronounced in southern Taiwan, where flowering coincides with peak La Niña-induced climate variability, making mango production especially vulnerable to seasonal rainfall anomalies.



Finally, future projections based on CMIP6 models indicate a likely increase in February precipitation under warming scenarios. This projected wetting trend during the mango flowering period could heighten the risk of pollination failure and yield loss, underscoring the need to account for seasonal rainfall patterns in long-term agricultural adaptation planning.

Together, these findings highlight the complex interactions between multi-year La Niña events, atmospheric circulation anomalies, and crop-specific climate sensitivities. They underscore the importance of integrating physical climate diagnostics with econometric modeling to capture both the mechanisms and consequences of climate variability. More broadly, this research demonstrates the value of interdisciplinary approaches in revealing hidden vulnerabilities in perennial crop systems—vulnerabilities that may intensify under future climate change. By linking seasonal-scale precipitation anomalies with phenologically sensitive stages of crop development, this study provides actionable insights for climate-informed agricultural planning in Taiwan and beyond.

5.2 Future Research Directions

Building on the findings of this study, future research should place greater emphasis on connecting climate risk assessments with stakeholder-oriented adaptation strategies. While our results highlight the climate sensitivity of mango production under multi-year La Niña conditions, the practical effectiveness of mitigation and adaptation measures ultimately depends on their relevance to local decision-makers. Collaborative efforts involving farmers,

agricultural extension officers, local governments, and agricultural cooperatives are essential to co-develop solutions such as resilient crop varieties, adjustments to irrigation and fertilization schedules during flowering, and the integration of seasonal climate forecasts into farm-level decision support systems. Incorporating stakeholder knowledge and needs can help bridge the gap between scientific analysis and actionable risk management.

In addition, the panel data model developed in this study offers a transferable framework for analyzing climate impacts on crop production. Although the current model is designed for mango production in Taiwan, its structure is suitable for other crops that exhibit strong responses to sub-seasonal hydro-climate fluctuations. Future applications could explore its relevance to crops such as rice, tea, or vegetables, especially in regions affected by similar precipitation or temperature variability. To improve the reliability of this framework, future research should incorporate crop-specific phenology, farming practices, and high-resolution yield data. Using finer-scale climate projections and spatially disaggregated agricultural statistics would further enhance model accuracy and policy relevance. Extending this modeling framework to other regions and crop types would contribute to a more comprehensive understanding of agricultural vulnerability and inform the development of more targeted climate adaptation strategies.

FIGURES

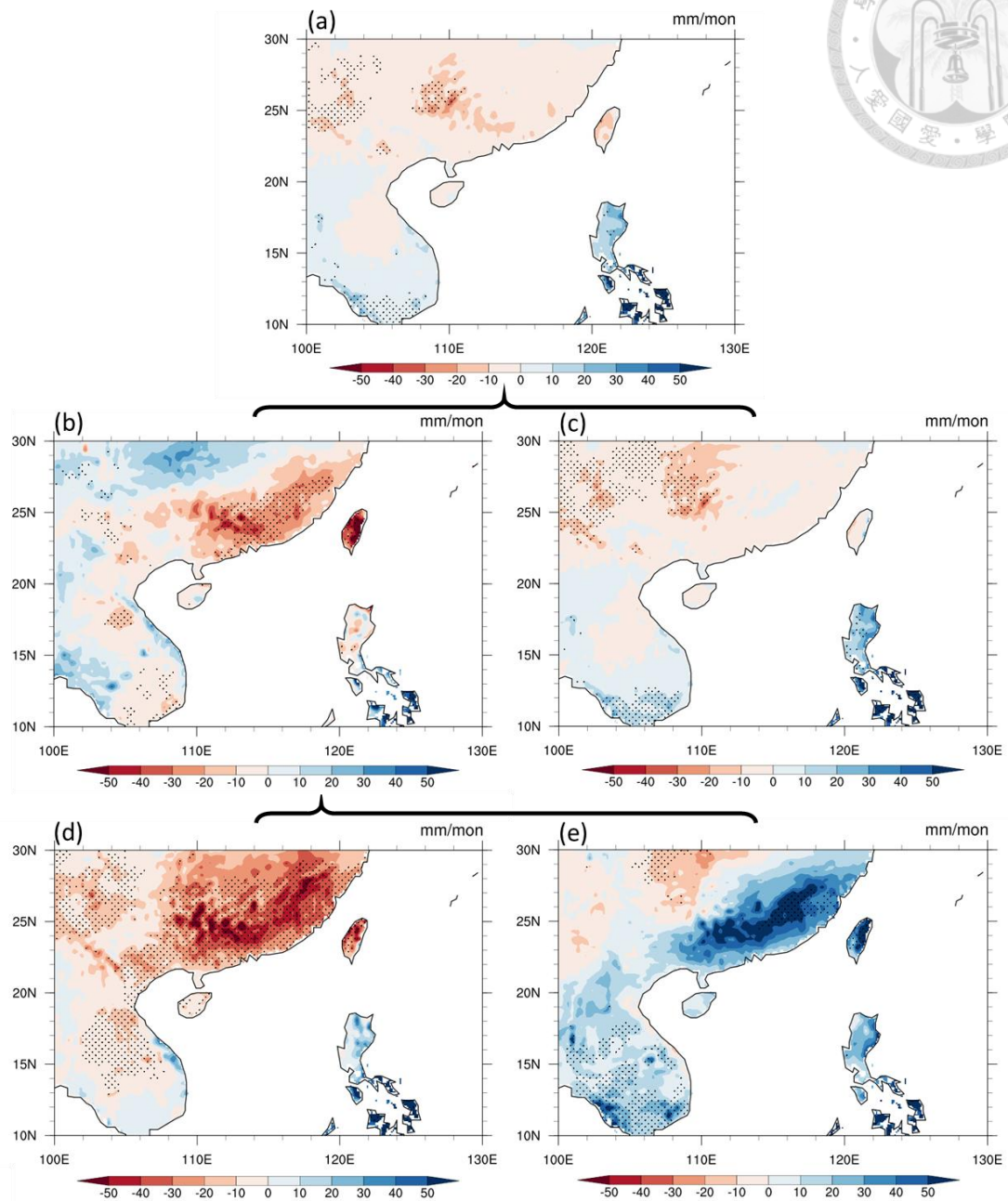


Figure 1. February mean total precipitation anomalies (mm/mon) during La Niña events (1950–2023). Subfigures show: (a) average of all La Niña years, (b) average of single-year La Niña events, (c) average of multi-year La Niña events, (d) average of the first year of multi-year events, and (e) average of the second year of multi-year events. Dots indicate grid cells where anomalies are statistically significant ($p < 0.05$).

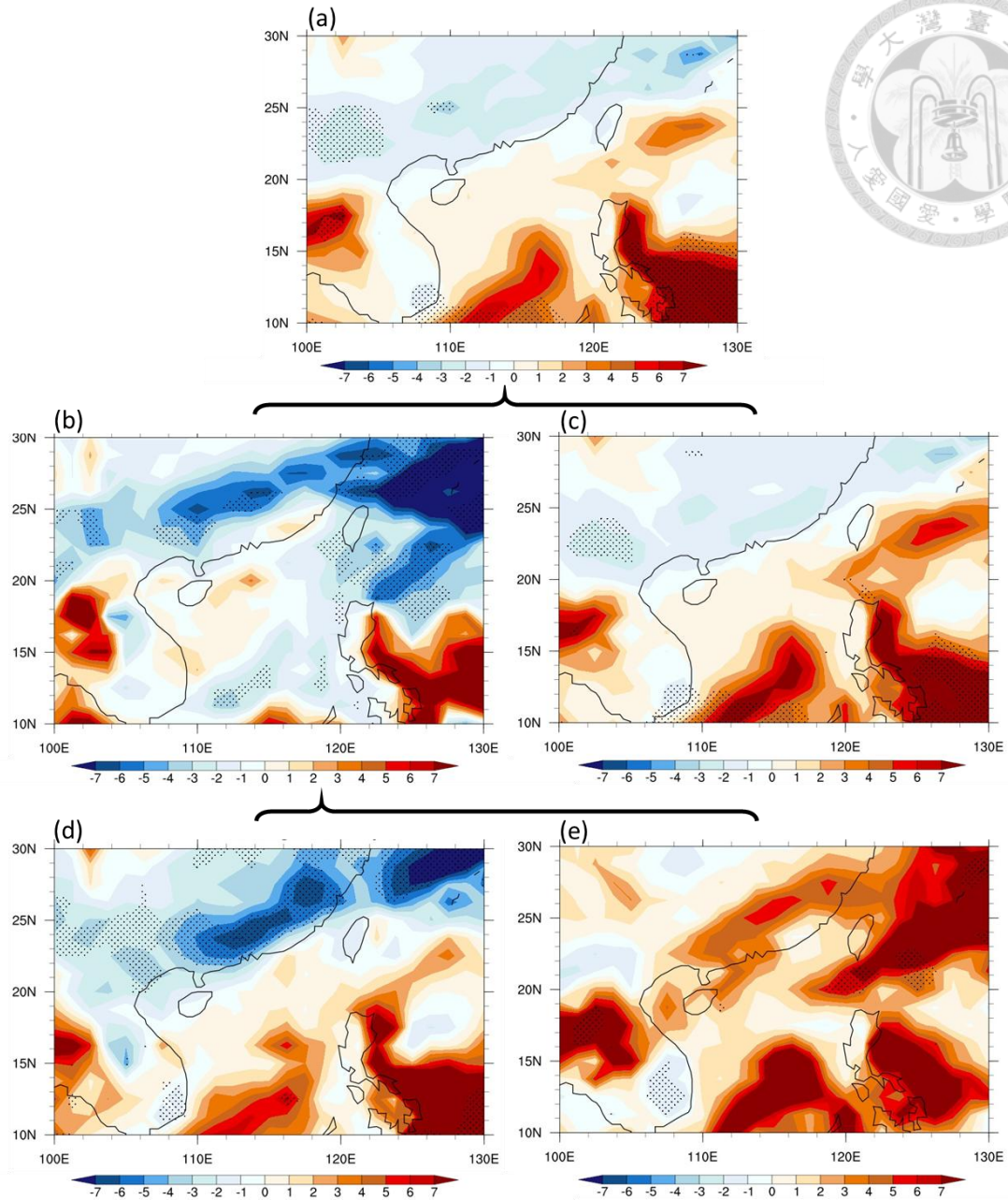


Figure 2. February vertical absolute heating anomalies (1000–100 hPa) during La Niña events (1950–2023). Subfigures show: (a) average of all La Niña years, (b) average of single-year La Niña events, (c) average of multi-year La Niña events, (d) average of the first year of multi-year events, and (e) average of the second year of multi-year events. Dots indicate grid cells where anomalies are statistically significant ($p < 0.05$).

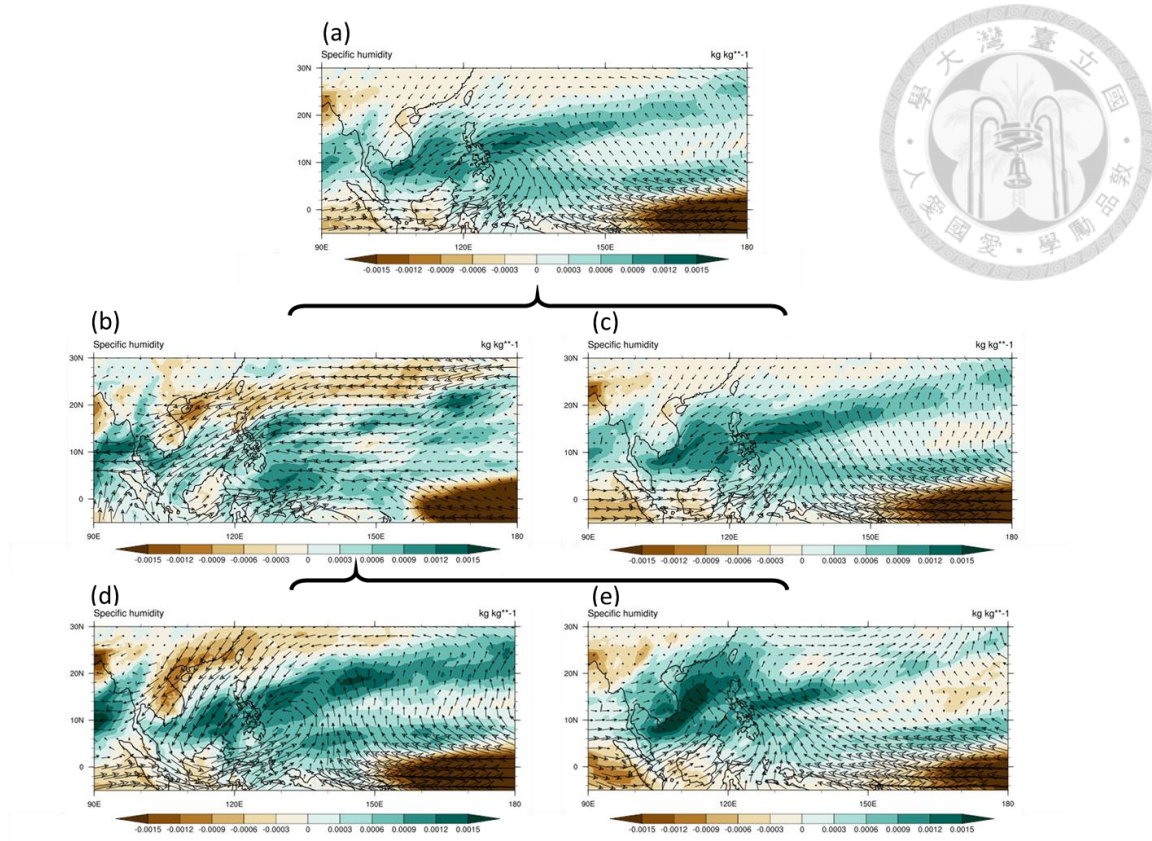


Figure 3. February moisture flux and specific humidity anomalies (kg/kg) during La Niña events (1950–2023). Subfigures show: (a) average of all La Niña years, (b) average of single-year La Niña events, (c) average of multi-year La Niña events, (d) average of the first year of multi-year events, and (e) average of the second year of multi-year events. Dots indicate grid cells with statistically significant anomalies.

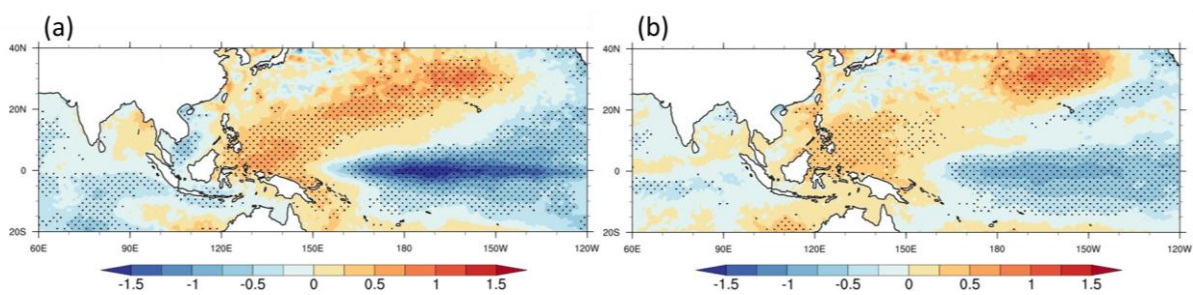


Figure 4. February sea surface temperature anomalies (K) during La Niña events (1950–2023). Subfigures show: (a) average of the first year of multi-year events and (b) average of the second year of multi-year events. Dots indicate grid cells with statistically significant anomalies ($p < 0.05$).

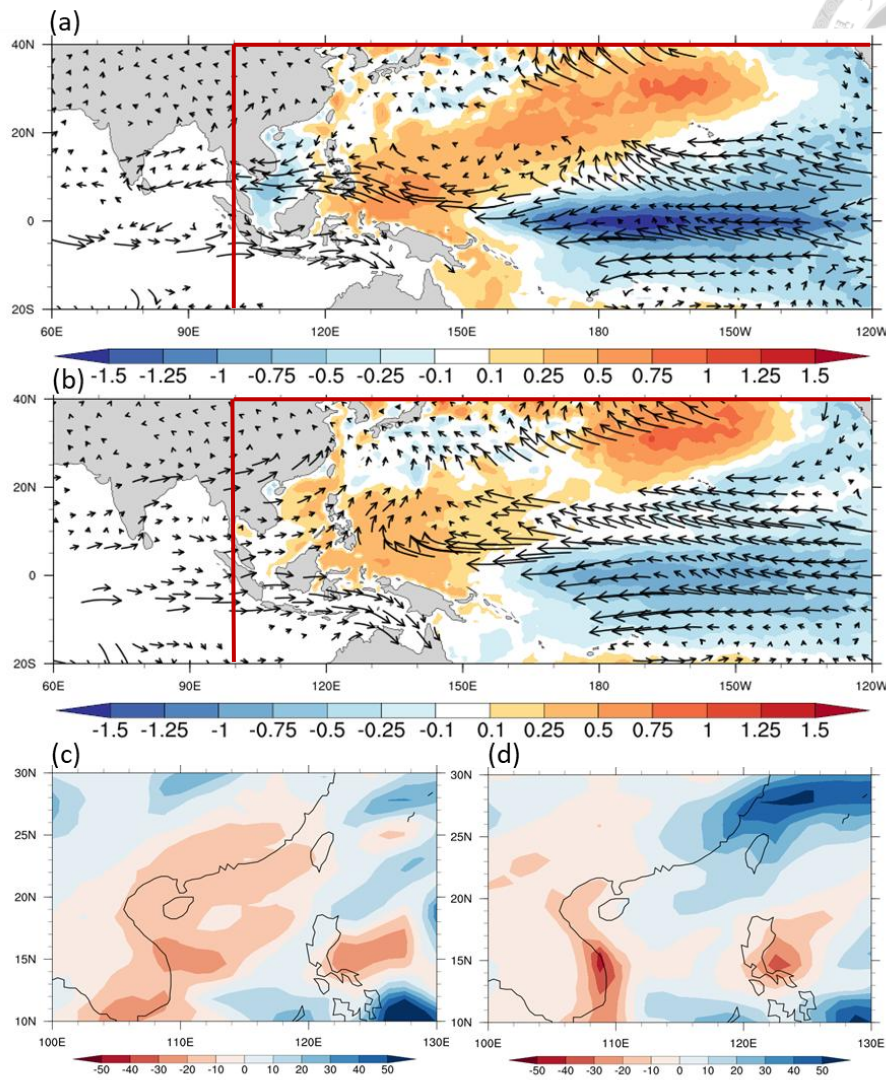


Figure 5. CESM2-simulated anomalies for multi-year La Niña events using full SST forcing. Moisture flux anomalies during the (a) first and (b) second La Niña years are shown, limited to regions that are statistically significant ($p < 0.05$). Shading represents the prescribed February sea surface temperature (SST) anomalies, derived from the ERA5 composite mean of nine historical La Niña events (Fig. 4) and used as boundary conditions in the AMIP-style simulation (first 18 months). Simulated precipitation anomalies for the (c) first and (d) second La Niña years are also shown. All anomalies are calculated relative to the February climatology of the CESM2 simulation. The red box indicates the spatial mask applied to constrain the SST anomalies over the Pacific.

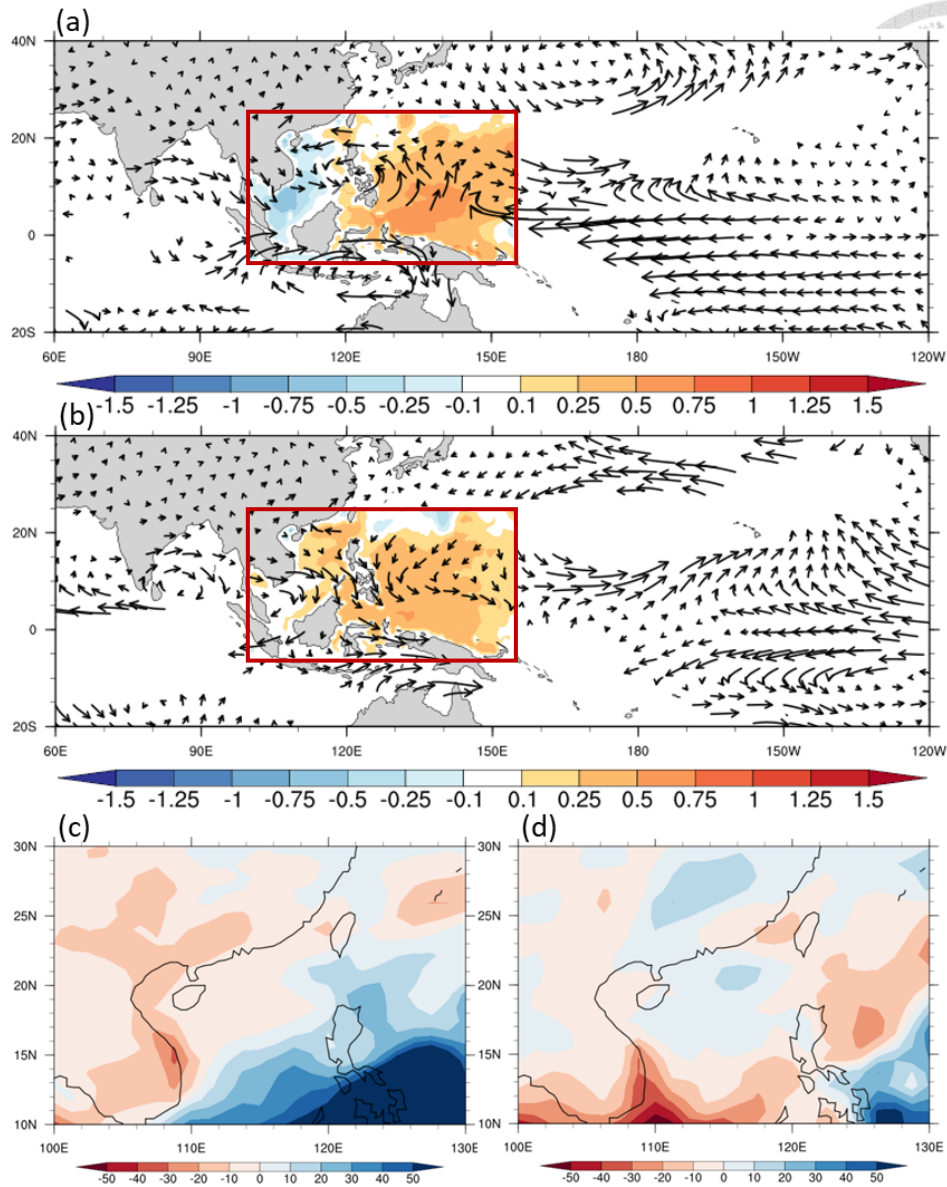


Figure 6. CESM2-simulated anomalies using modified SST forcing over the South China Sea. Moisture flux anomalies during the (a) first and (b) second La Niña years are shown, limited to regions that are statistically significant ($p < 0.05$). Shading represents the prescribed February sea surface temperature (SST) anomalies, which are spatially restricted to the South China Sea and the western North Pacific (100°E–155°E, 5°S–25°N (Red box)), based on the ERA5 composite of nine historical La Niña events (Fig. 4). Simulated precipitation anomalies for the (c) first and (d) second La Niña years are also shown. All anomalies are calculated relative to the February climatology of the CESM2 simulation.

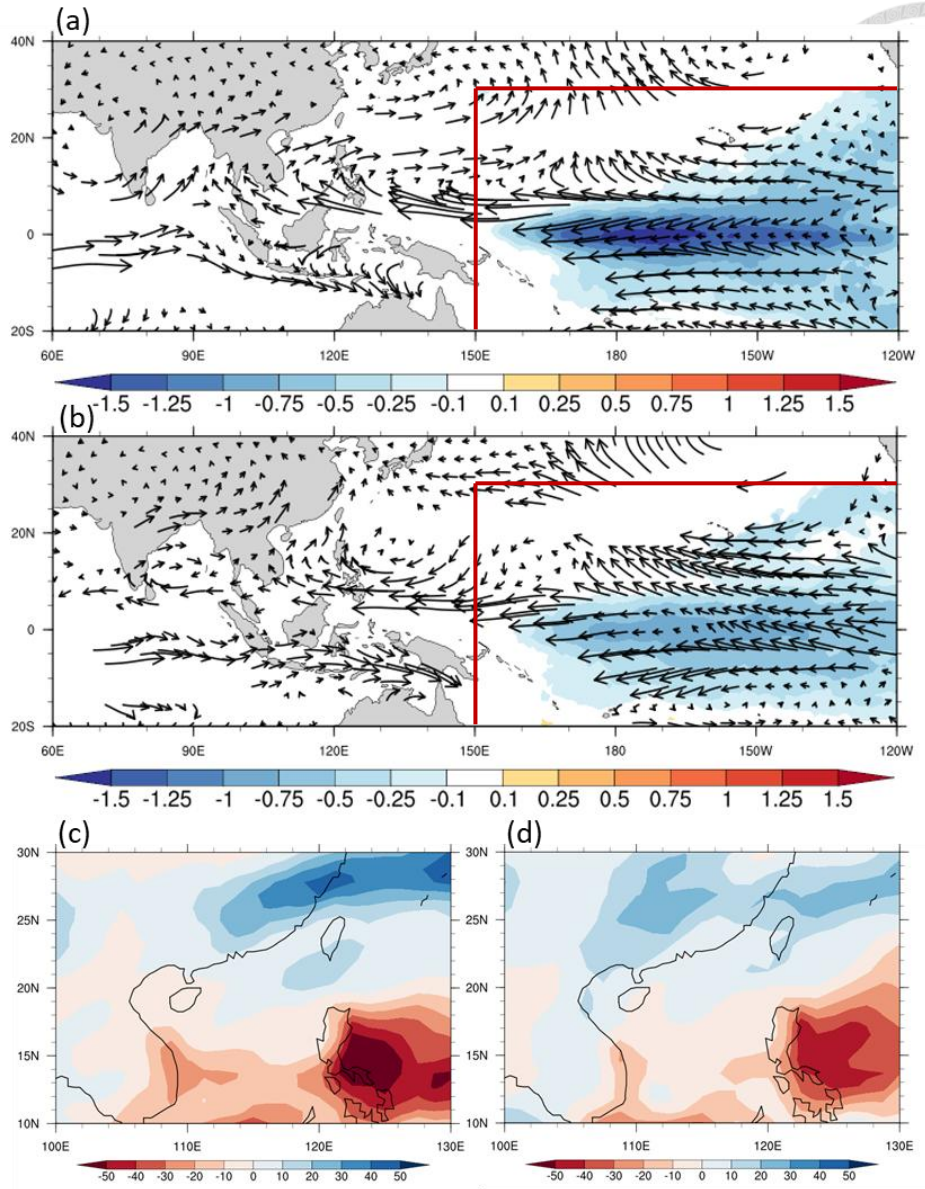


Figure 7. CESM2-simulated anomalies using SST forcing limited to the eastern-central Pacific. Moisture flux anomalies during the (a) first and (b) second La Niña years are shown, limited to regions that are statistically significant ($p < 0.05$). Shading represents the prescribed February sea surface temperature (SST) anomalies, applied only over the eastern and central Pacific (150°E–155°W, 5°S–25°N (Red box)) and limited to areas with negative SST departures, based on the ERA5 composite of nine historical La Niña events (Fig. 4). Simulated precipitation anomalies for the (c) first and (d) second La Niña years are also shown. All anomalies are calculated relative to the February climatology of the CESM2 simulation.

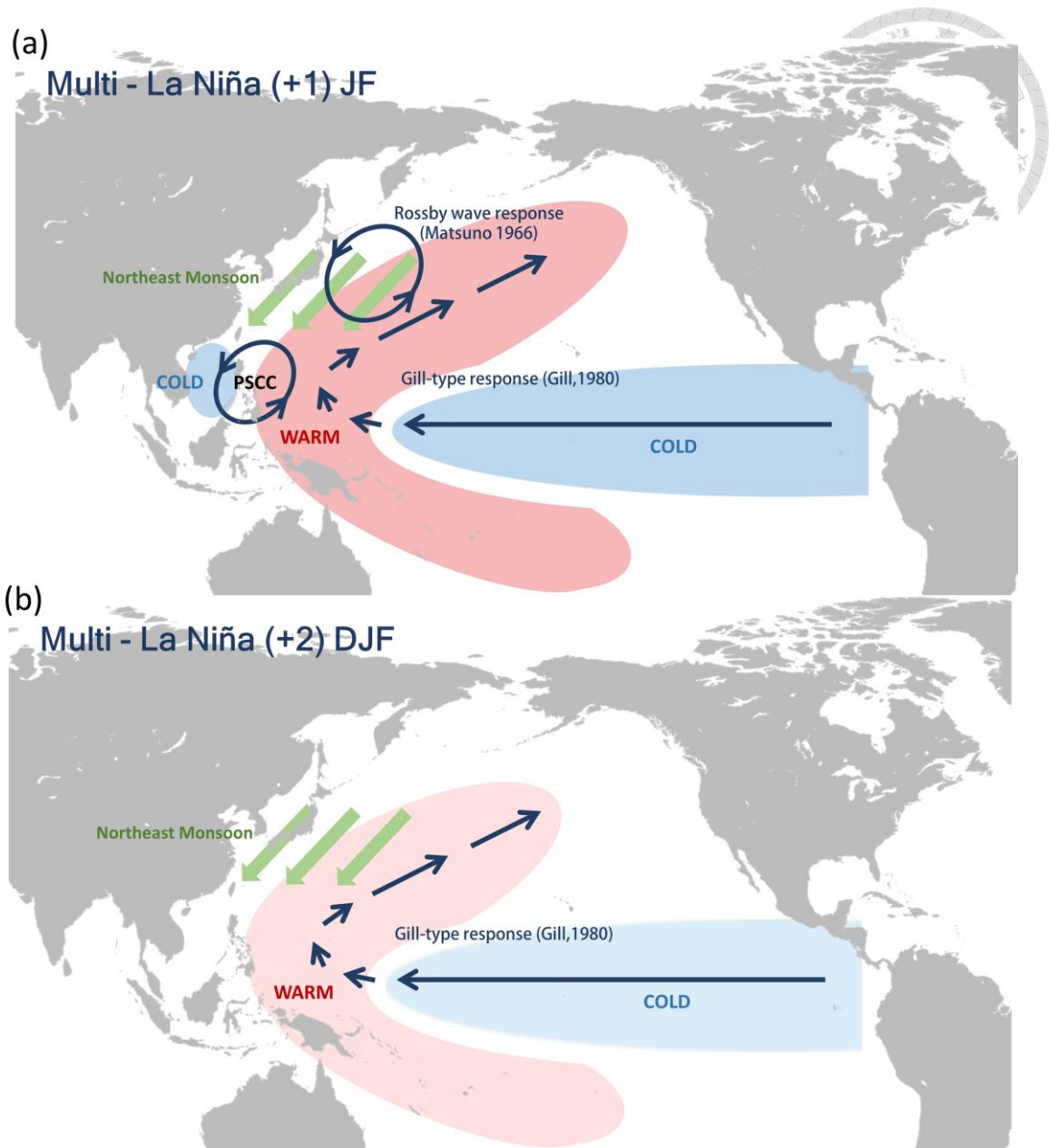


Figure 8. Schematic of PSCC-related air–sea interactions during multi-year La Niña events. (a) In the first winter of a multi-year La Niña event (+1 DJF), cold SST anomalies in the central and eastern Pacific induce a Gill-type atmospheric response and support the development of the PSCC, along with enhanced northeast monsoon and a Rossby wave train toward East Asia. (b) In the second winter (+2 DJF), the PSCC weakens despite persistent warm SST anomalies in the western Pacific, and the Rossby wave response becomes less pronounced, indicating a weakened coupling and reduced influence on Southeast Asia.

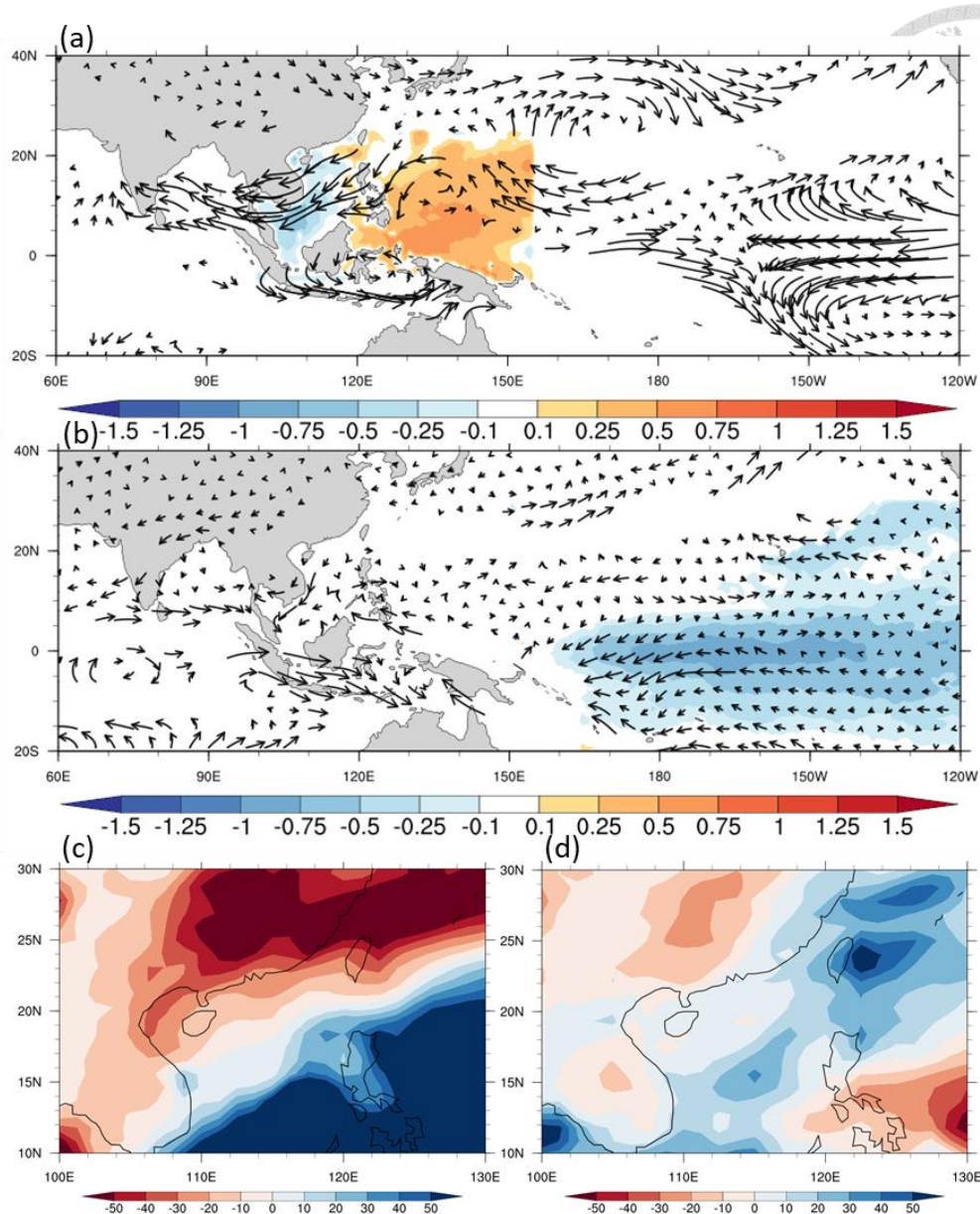


Figure 9. AMIP-simulated February anomalies under a +2°C warming scenario. All anomalies are computed as the difference between the +2°C warming simulations ($\text{CO}_2 = 560$ ppm) and their corresponding historical simulations, in order to isolate warming-induced atmospheric responses. Panels (a) and (b) show moisture flux anomalies (vectors), overlaid on the prescribed February SST anomalies (shading, °C) used as boundary forcing in the +2°C simulations. Panel (a) shows the result of the +2°C Year 1 simulation minus the historical simulation shown in Fig. 6a, using SST forcing restricted to the eastern and central Pacific (150°E–155°W, 5°S–25°N). Panel (b) shows the result of the +2°C Year 2 simulation

minus Fig. 7b, using SST forcing over the South China Sea and the western North Pacific (100°E–155°E, 5°S–25°N). The SST anomalies are based on the ERA5 composite of nine historical La Niña events (see Fig. 4). Only statistically significant areas of moisture flux anomalies are shown ($p < 0.05$). Panels (c) and (d) display simulated precipitation anomalies (mm/month) for the (c) first and (d) second La Niña years. Panel (c) shows the difference between the +2°C simulation and the historical simulation in Fig. 6c. Panel (d) shows the difference between the +2°C simulation and Fig. 7d. All precipitation anomalies are calculated relative to the February climatology of the CESM2 AMIP simulation.

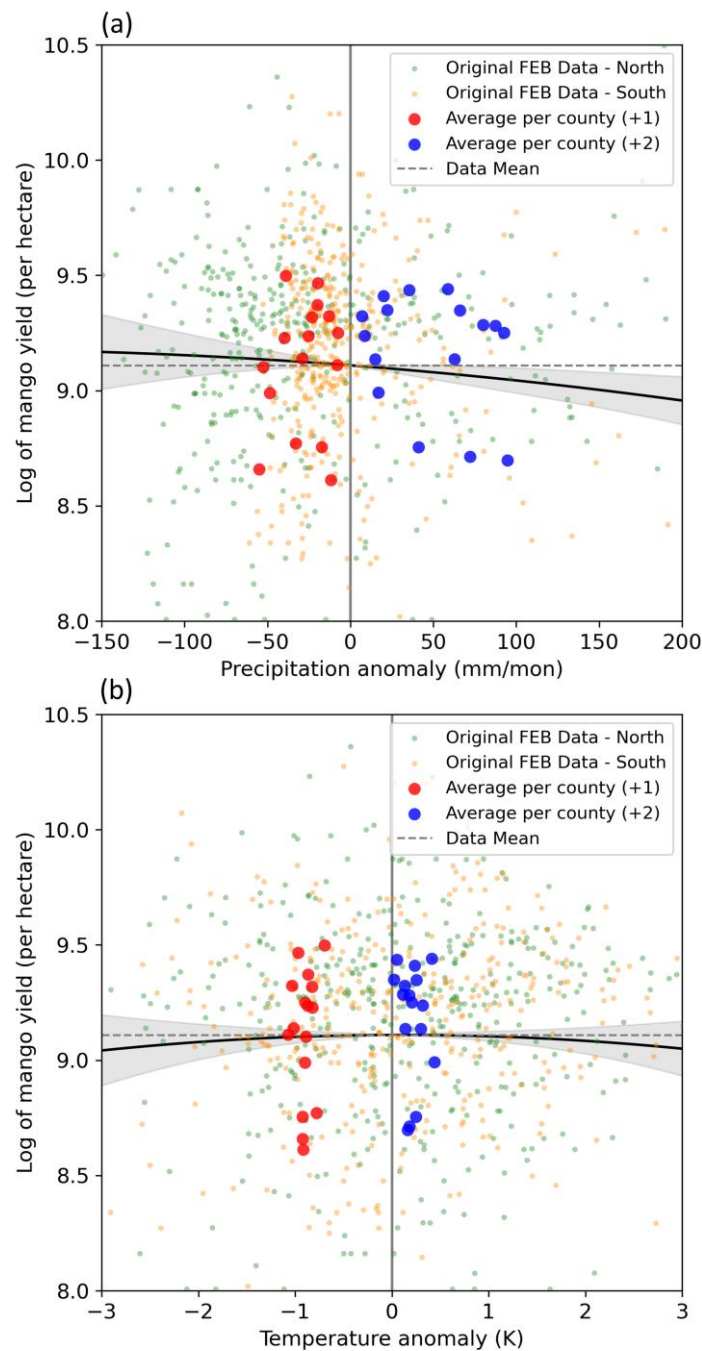


Figure 10. Nonlinear relationships between February (a) precipitation (b) temperature and mango yield per hectare (log-transformed). Each dot represents a county-level observation, with green and orange points indicating northern and southern Taiwan, respectively, divided geographically by the Zhuoshui River. Red and blue circles represent the average conditions during the first (+1) and second (+2) years of multi-year La Niña events, computed as the mean precipitation or temperature anomaly and the mean log-transformed yield across

counties in each event year. Black solid lines indicate second-order polynomial regressions fitted to the full sample (both northern and southern counties). Shaded gray bands show 95% bootstrap confidence intervals, calculated from 1000 resampled datasets using the standard deviation of predicted values at each anomaly level. For visual interpretability, the fitted regression curves are vertically shifted to pass through the observed data mean (“Data Mean”), allowing direct comparison between modeled trends and empirical yield levels.

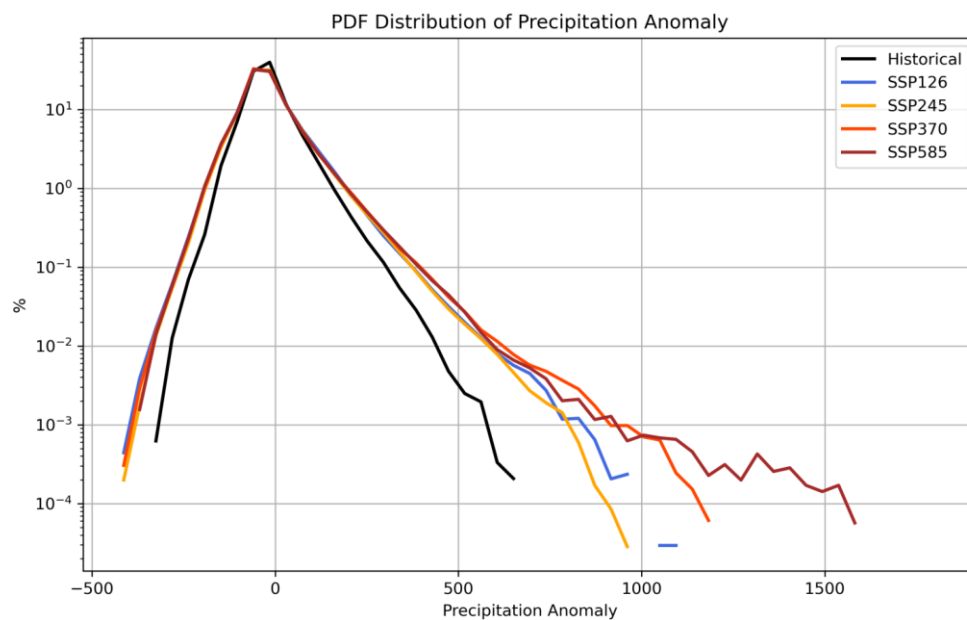


Figure 11. Probability density function (PDF) of February rainfall anomalies (mm/mon) under different CMIP6 scenarios. The black line represents the historical scenario, while colored lines indicate future projections for SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5. The y-axis is on a logarithmic scale.

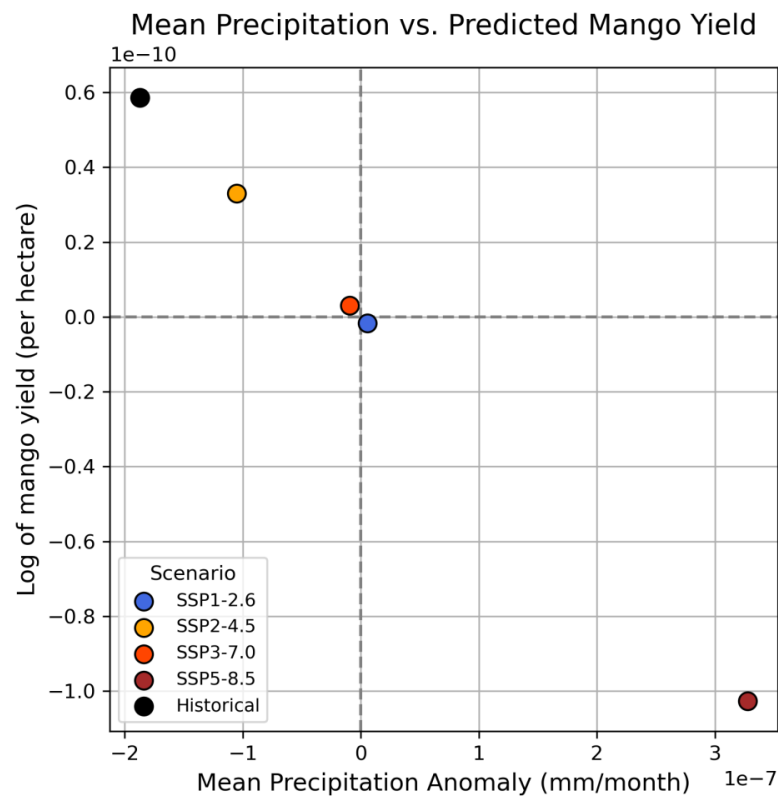


Figure 12. Relationship between February mean precipitation anomaly and predicted mango yield (log-transformed) under historical and four CMIP6 future scenarios (SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5). Yield responses are calculated using the fixed-effects panel regression model described in Section 2.4.2. Historical average (black) shows the highest predicted yield, while higher-emission scenarios (e.g., SSP5-8.5) are associated with increased rainfall and lower yields.

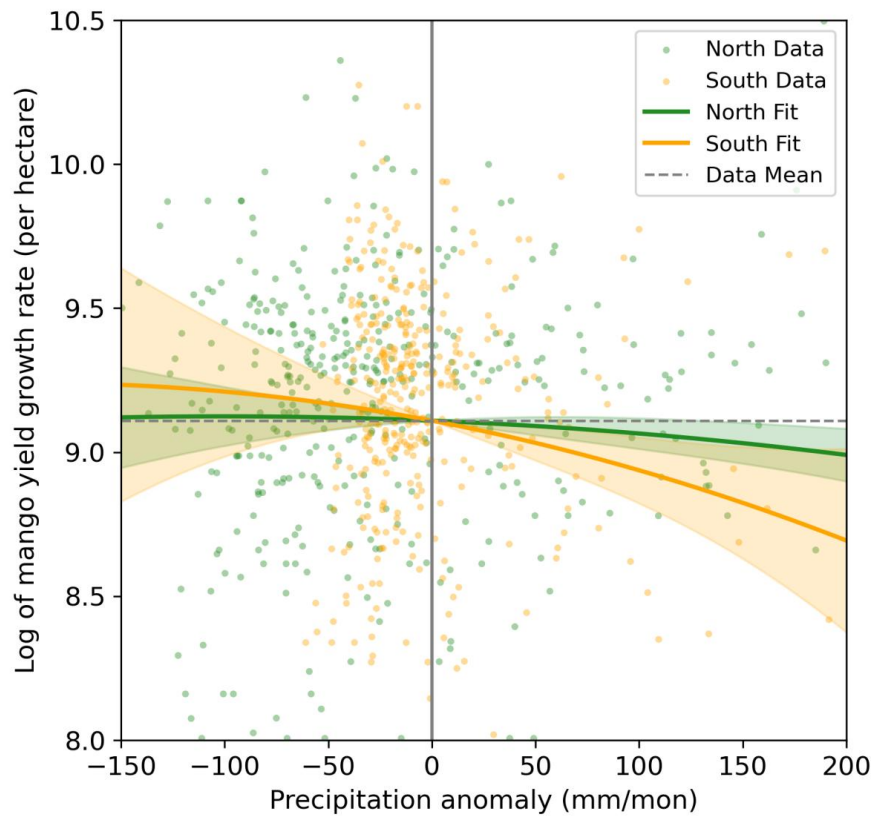


Figure 13. Nonlinear relationships between February precipitation and mango yield per hectare (log-transformed). Each dot represents a county-level observation, with green and orange points indicating northern and southern Taiwan, respectively, divided geographically by the Zhuoshui River. Green (Orange) solid lines indicate second-order polynomial regressions fitted to the northern (southern) counties. Shaded bands show 95% bootstrap confidence intervals, calculated from 1000 resampled datasets using the standard deviation of predicted values at each anomaly level. For visual interpretability, the fitted regression curves are vertically shifted to pass through the observed data mean (“Data Mean”), allowing direct comparison between modeled trends and empirical yield levels.

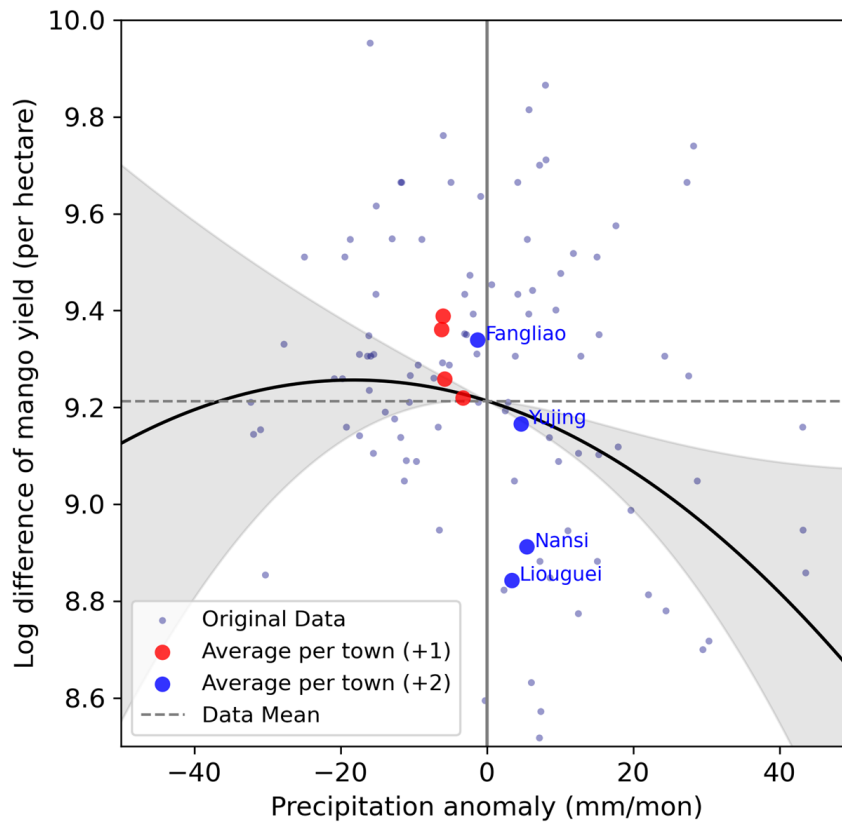


Figure 14. Nonlinear relationship between February precipitation anomaly and the log-transformed mango yield per hectare, based on township-level data (1997-2023). Each dot represents a township-level observation in Nansi, Yujing, Liouguei and Fangliao, with blue and red circles indicating the average precipitation anomaly and mean yield for each township during the first (+1) and second (+2) La Niña year, respectively. Several townships are labeled for reference. The black solid line represents a second-order polynomial regression fitted to the full sample, with the shaded gray band denoting the 95% bootstrap confidence interval based on 1000 resampled datasets. The regression curve is vertically shifted to pass through the sample mean (dashed line), allowing direct comparison between modeled and observed yields. The visual pattern suggests that moderate drying may be associated with slightly improved yields, but excessive dryness or wetness tends to lower yields.

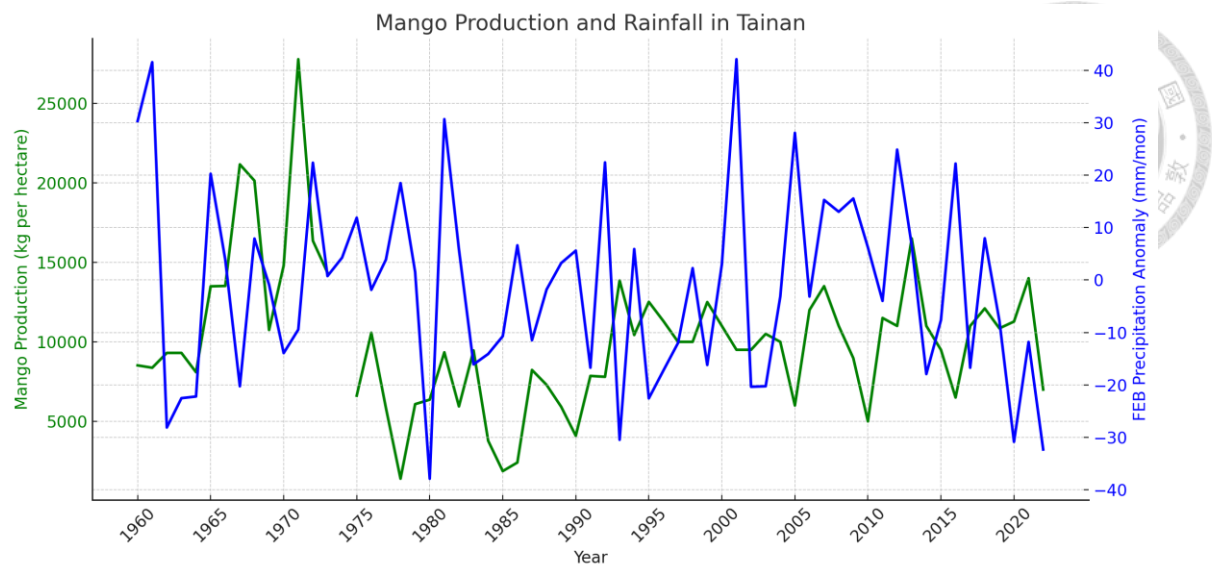


Figure 15. Mango Yield and February Rainfall Anomalies in Nansi and Yujing (1960–2023). This figure shows average mango yield (kg/ha, green line, left y-axis) and February rainfall anomalies (mm/month, blue line, right y-axis) from 1960 to 2023. Yield data for 1960–1996 are based on Tainan County due to the lack of township-level records; data from 1997 onward are averaged from Nansi and Yujing districts. Rainfall anomalies are based on the February average from the two districts.

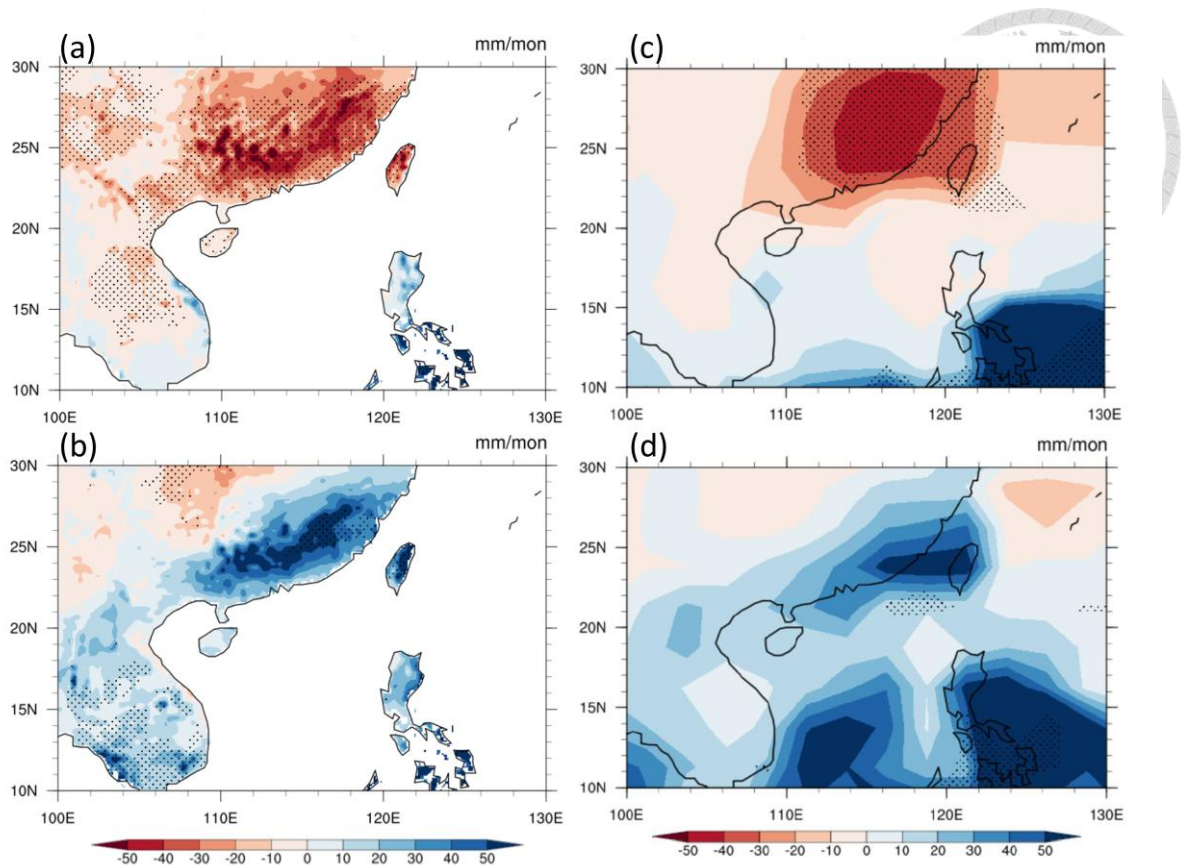


Figure 16. Comparison of February precipitation anomalies between ERA5 and GPCP datasets. The figure compares February mean precipitation anomalies (mm/month) during multi-year La Niña events, based on (a, b) ERA5-land reanalysis and (c, d) GPCP observations. Subfigures show: (a, c) anomalies in the first La Niña year and (b, d) anomalies in the second La Niña year. Dots indicate grid cells with statistically significant anomalies ($p < 0.05$).

TABLES

Data set	Variables	Resolution	Citation	Time
GPCP	Total precipitation (mm/day)	2.5°×2.5°	Adler et al., 2003	1979-2023
ERA5-Land monthly averaged data	Temperature (K)	0.1°×0.1°	Muñoz-Sabater, 2019	1950-2023
ERA5 monthly averaged data	U-component of wind, V-component of wind (m/s)	0.25° x 0.25°	Hersbach et al., 2023	
	Sea surface temperature (K)			
	Vertical velocity (Pa/s)			
	Temperature (K)			
	Specific humidity (kg/kg)			
Ministry of Agriculture	Mango unit production (kg/ha)	17 Counties (Taiwan)	Ministry of Agriculture, 1960-2023	1960-2023
TCCIP Gridded Monthly Observational Data	Precipitation (mm)	0.05°×0.05° (Taiwan)	Lin, et al., 2022	
	Temperature (°C)			
TCCIP Statistically Downscaled Monthly Data from AR6	Precipitation (mm)			
	Temperature (°C)			

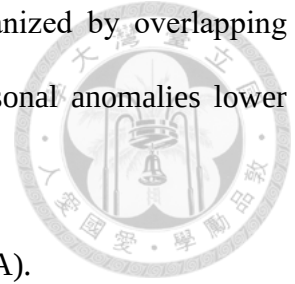
Table 1. Summary of climate and agricultural datasets used in this study, including variables, resolution, time range, and data sources.

Single La Niña events												
YEAR	DJF	JFM	FMA	MAM	AMJ	MJJ	JJA	JAS	ASO	SON	OND	NDJ
1965	-0.6	-0.3	-0.1	0.2	0.5	0.8	1.2	1.5	1.9	2.0	2.0	1.7
1989	-1.7	-1.4	-1.1	-0.8	-0.6	-0.4	-0.3	-0.3	-0.2	-0.2	-0.2	-0.1
1996	-0.9	-0.8	-0.6	-0.4	-0.3	-0.3	-0.3	-0.3	-0.4	-0.4	-0.4	-0.5
2006	-0.9	-0.8	-0.6	-0.4	-0.1	0.0	0.1	0.3	0.5	0.8	0.9	0.9
Multi La Niña events												
YEAR	DJF	JFM	FMA	MAM	AMJ	MJJ	JJA	JAS	ASO	SON	OND	NDJ
1955	-0.7	-0.6	-0.7	-0.8	-0.8	-0.7	-0.7	-0.7	-1.1	-1.4	-1.7	-1.5
1956	-1.1	-0.8	-0.6	-0.5	-0.5	-0.5	-0.6	-0.6	-0.5	-0.4	-0.4	-0.4
1971	-1.4	-1.4	-1.1	-0.8	-0.7	-0.7	-0.8	-0.8	-0.8	-0.9	-1.0	-0.9
1972	-0.7	-0.4	0.1	0.4	0.7	0.9	1.1	1.4	1.6	1.8	2.1	2.1
1974	-1.8	-1.6	-1.2	-1.0	-0.9	-0.8	-0.5	-0.4	-0.4	-0.6	-0.8	-0.6
1975	-0.5	-0.6	-0.7	-0.7	-0.8	-1.0	-1.1	-1.2	-1.4	-1.4	-1.6	-1.7
1984	-0.6	-0.4	-0.3	-0.4	-0.5	-0.4	-0.3	-0.2	-0.2	-0.6	-0.9	-1.1
1985	-0.1	-0.8	-0.8	-0.8	-0.8	-0.6	-0.5	-0.5	-0.4	-0.3	-0.3	-0.4
1999	-1.5	-1.3	-1.1	-1.0	-1.0	-1.0	-1.1	-1.1	-1.2	-1.3	-1.5	-1.7
2000	-1.7	-1.4	-1.1	-0.8	-0.7	-0.6	-0.6	-0.5	-0.5	-0.6	-0.7	-0.7
2008	-1.6	-1.5	-1.3	-1.0	-0.8	-0.6	-0.4	-0.2	-0.2	-0.4	-0.6	-0.7
2009	-0.8	-0.8	-0.6	-0.3	0.0	0.3	0.5	0.6	0.7	1.0	1.4	1.6
2011	-1.4	-1.2	-0.9	-0.7	-0.6	-0.4	-0.5	-0.6	-0.8	-1.0	-1.1	-1.0
2012	-0.9	-0.7	-0.6	-0.5	-0.3	0.0	0.2	0.4	0.4	0.3	0.1	-0.2
2017	-0.3	-0.2	0.1	0.2	0.3	0.3	0.1	-0.1	-0.4	-0.7	-0.8	-1.0
2018	-0.9	-0.9	-0.7	-0.5	-0.2	0.0	0.1	0.2	0.5	0.8	0.9	0.8
2021	-1.0	0.9	-0.8	-0.7	-0.5	-0.4	-0.4	-0.5	-0.7	-0.8	-1.0	-1.0
2022	-1.0	-0.9	-1.0	-1.1	-1.0	-0.9	-0.8	-0.9	-1.0	-1.0	-0.9	-0.8

Table 2. Oceanic Niño Index (ONI) values based on NINO3.4 SST anomalies during La Niña events (1950–2023). Monthly sea surface temperature anomalies (°C) in the NINO3.4 region are shown for identified La Niña years during 1950–2023. Event years are classified into single-year and multi-year La Niña episodes based on the criterion defined in Section 2.3, where the ONI is calculated as the three-month running mean of NINO3.4 anomalies. Periods

where ONI remains below -0.5°C are highlighted. Values are organized by overlapping three-month seasons (e.g., DJF, JFM, etc.). Red entries indicate seasonal anomalies lower than -0.5°C .

Data source: National Oceanic and Atmospheric Administration (NOAA).



Experiment Name	Base Case (Year)	SST Pattern	Period	Mask SSTA Region	Members
Climatology	1950–2014	F2000	2 year	F2000 All SST	2
Multi-La Niña (+1) Pacific Ocean	2000–2001	CESM2 Historical 1950-2014	18 mon	120°E–70°W, 30°S–40°N; restricted to the Pacific Ocean (Fig. 5)	20
Multi-La Niña (+2) Pacific Ocean				100°E–155°E, 5°S–25°N; restricted to the South China Sea and the western North Pacific	
Multi-La Niña (+1) South China Sea and the western North Pacific				150°E–155°W, 5°S–25°N; restricted to where negative SST departures dominate during La Niña. (Fig. 7)	
Multi-La Niña (+2) South China Sea and the western North Pacific					
Multi-La Niña (+1) negative SST in central and eastern tropical Pacific					
Multi-La Niña (+2) negative SST in central and eastern tropical Pacific					
Climatology+2K	2000–2001	CESM2 Historical 1950-2014	2 year	F2000 All SST	10
Multi-La Niña (+1) South China Sea and the western North Pacific+2K			18 mon	100°E–155°E, 5°S–25°N; restricted to the South China Sea and the western North Pacific. (Fig. 9a)	10
Multi-La Niña (+2) negative SST in central and eastern tropical Pacific+2K				150°E–155°W, 5°S–25°N; restricted to regions with dominant negative SST anomalies during La Niña. (Fig. 9b)	

Table 3. Summary of CESM2 Experiment Designs.

This table presents the experimental setup used in this study, including the base case period, sea surface temperature (SST) forcing patterns, simulation periods, and regional SST anomaly masks. Climatology experiments are based on either the F2000 or FHIST forcing,

while multi-year La Niña experiments simulate SST anomalies in specified ocean regions with different intensity phases and warming conditions. Each configuration includes the number of ensemble members used. The SST anomaly masks are applied to isolate the spatial extent of climate signals associated with La Niña events, as detailed in corresponding figures.

Variable	Coefficient	Std. Error	t-value	P-value	95% CI Lower	95% CI Upper
T_{it}	0.0013	0.011	-0.115	0.908	-0.024	0.021
T_{it}^2	-0.007	0.005	1.370	0.171	-0.003	0.017
P_{it}	-0.0005**	0.000	-2.036	0.042	-0.001	-1.97e-05
P_{it}^2	-1.074e-06	9.72e-07	-1.105	0.270	-2.98e-06	8.35e-07
Model Summary:						
R-squared				0.511		
Adjusted R-squared				0.480		
F-statistic				16.44 (p = 4.70e-91)		
No. of observations				837		
Log-Likelihood				-361.33		
AIC				824.7		
BIC				1066		
Durbin-Watson				1.143		

Table 4. Estimated coefficients from the fixed effects panel regression model evaluating the nonlinear impacts of February climate anomalies on log-transformed mango yield per hectare across 17 counties in Taiwan (1960–2023). The estimated model is specified as: $\log(y_{it}) = \alpha_1 T_{it} + \alpha_2 T_{it}^2 + \beta_1 P_{it} + \beta_2 P_{it}^2 + \mu_i + \theta_{1i}t + \theta_{2i}t^2 + \varepsilon_{it}$ where y_{it} is mango yield per hectare in county i and year t ; T_{it} and P_{it} denote February temperature and precipitation anomalies; μ_i represents county fixed effects; and $\theta_{1i}t + \theta_{2i}t^2$ are county-specific time trends. The table reports coefficients, standard errors, t-values, p-values, and 95% confidence intervals. County fixed effects and time trend coefficients are omitted for brevity. Model diagnostics are shown in the upper panel.

Variable	Coefficient	Std. Error	t-value	P-value	95% CI Lower	95% CI Upper
T_{it}	0.002	0.018	-0.113	0.910	-0.037	0.033
T_{it}^2	-0.0083	0.008	1.038	0.300	-0.007	0.024
P_{it}	-0.0003	0.000	-0.869	0.385	-0.001	0.000
P_{it}^2	-1.484e-06	1.17e-06	-1.265	0.206	-3.79e-06	8.21e-07
Model Summary:						
R-squared				0.480		
Adjusted R-squared				0.445		
F-statistic				13.52 (p = 4.91e-44)		
No. of observations				454		
Log-Likelihood				-256.64		
AIC				573.3		
BIC				696.8		
Durbin-Watson				1.095		

Table 5. Estimated coefficients from the fixed effects panel regression model applied to northern Taiwan only, with counties defined as north of the Zhuoshui River. The model estimates the nonlinear impacts of February temperature and precipitation anomalies on log-transformed mango yield per hectare over the period 1960–2023. The model specification follows: $\log(y_{it}) = \alpha_1 T_{it} + \alpha_2 T_{it}^2 + \beta_1 P_{it} + \beta_2 P_{it}^2 + \mu_i + \theta_{1i}t + \theta_{2i}t^2 + \varepsilon_{it}$ where y_{it} is mango yield per hectare in county i and year t ; T_{it} and P_{it} denote February temperature and precipitation anomalies; μ_i represents county fixed effects; and $\theta_{1i}t + \theta_{2i}t^2$ are county-specific time trends. The table reports coefficients, standard errors, t-values, p-values, and 95% confidence intervals. County fixed effects and time trend coefficients are omitted for brevity. Model diagnostics are shown in the upper panel.

Variable	Coefficient	Std. Error	t-value	P-value	95% CI Lower	95% CI Upper
T_{it}	0.0013	0.013	0.098	0.922	-0.025	0.027
T_{it}^2	-0.0057	0.006	0.944	0.346	-0.006	0.018
P_{it}	-0.0014**	0.001	-2.164	0.031	-0.003	-0.000
P_{it}^2	-3.576e-06	3.87e-06	-0.924	0.356	-1.12e-05	4.03e-06
Model Summary:						
R-squared				0.584		
Adjusted R-squared				0.556		
F-statistic				20.91 (p = 4.57e-54)		
No. of observations				383		
Log-Likelihood				-71.962		
AIC				193.93		
BIC				292.6		
Durbin-Watson				1.205		

Table 6. Estimated coefficients from the fixed effects panel regression model applied to southern Taiwan only, with counties defined as south of the Zhuoshui River. The model estimates the nonlinear impacts of February temperature and precipitation anomalies on log-transformed mango yield per hectare over the period 1960–2023. The model specification follows: $\log(y_{it}) = \alpha_1 T_{it} + \alpha_2 T_{it}^2 + \beta_1 P_{it} + \beta_2 P_{it}^2 + \mu_i + \theta_{1i}t + \theta_{2i}t^2 + \varepsilon_{it}$ where y_{it} is mango yield per hectare in county i and year t ; T_{it} and P_{it} denote February temperature and precipitation anomalies; μ_i represents county fixed effects; and $\theta_{1i}t + \theta_{2i}t^2$ are county-specific time trends. The table reports coefficients, standard errors, t-values, p-values, and 95% confidence intervals. County fixed effects and time trend coefficients are omitted for brevity. Model diagnostics are shown in the upper panel.

Variable	Coefficient	Std. Error	t-value	P-value	95% CI Lower	95% CI Upper
T_{it}	-0.057	0.124	-0.461	0.646	-0.303	0.189
T_{it}^2	-0.061	0.255	-0.240	0.811	-0.569	0.446
P_{it}	-0.0047	0.002	-2.179	0.032	-0.009	-0.000
P_{it}^2	-0.001	8.15e-05	-1.589	0.116	-0.000	3.25e-05
Model Summary:						
R-squared				0.122		
Adjusted R-squared				0.026		
F-statistic				1.269		
No. of observations				63		
Log-Likelihood				-42.664		
AIC				99.33		
BIC				114.2		
Durbin-Watson				0.951		

Table 7. Estimated coefficients from the fixed effects panel regression model applied to Nansi, Yujing, Liouguei and Fangliao districts only. The model estimates the nonlinear impacts of February temperature and precipitation anomalies on log-transformed mango yield per hectare over the period 1997–2023. The model specification follows: $\log(y_{it}) = \alpha_1 T_{it} + \alpha_2 T_{it}^2 + \beta_1 P_{it} + \beta_2 P_{it}^2 + \mu_i + \theta_{1i}t + \theta_{2i}t^2 + \varepsilon_{it}$ where y_{it} is mango yield per hectare in county i and year t ; T_{it} and P_{it} denote February temperature and precipitation anomalies; μ_i represents county fixed effects; and $\theta_{1i}t + \theta_{2i}t^2$ are county-specific time trends. The table reports coefficients, standard errors, t-values, p-values, and 95% confidence intervals. County fixed effects and time trend coefficients are omitted for brevity. Model diagnostics are shown in the upper panel.

Variable	Coefficient	Std. Error	t-value	P-value	95% CI Lower	95% CI Upper
T_{it}	-0.00235	0.013	1.960	0.050	-3.62e-05	0.051
T_{it}^2	-0.00018	0.006	0.301	0.764	-0.010	0.014
P_{it}	3.593e-05	0.000	0.116	0.908	-0.001	-0.001
P_{it}^2	-2.676e-06	1.14e-06	-2.354	0.019	-4.91e-06	-4.44e-07
Model Summary:						
R-squared				0.274		
Adjusted R-squared				0.257		
F-statistic				16.19 (p = 4.95e-45)		
No. of observations				837		
Log-Likelihood				-527.09		
AIC				1094		
BIC				1189		
Durbin-Watson				0.840		

Table 8. Estimated coefficients from the fixed effects panel regression model excluding both linear and quadratic time trend terms, used to assess model stability. The model estimates the nonlinear impacts of February climate anomalies on log-transformed mango yield per hectare across 17 counties in Taiwan (1960–2023). The estimated model is specified as: $\log(y_{it}) = \alpha_1 T_{it} + \alpha_2 T_{it}^2 + \beta_1 P_{it} + \beta_2 P_{it}^2 + \mu_i + \varepsilon_{it}$. This specification omits county-specific linear and quadratic time trends ($\theta_{1i}t + \theta_{2i}t^2$) to evaluate the sensitivity of estimated coefficients to structural assumptions about long-term regional change. The table reports coefficient estimates, standard errors, t-values, p-values, and 95% confidence intervals. County fixed effects are included but omitted from display. Model diagnostics are shown in the upper panel.

Variable	Coefficient	Std. Error	t-value	P-value	95% CI Lower	95% CI Upper
T_{it}	-0.0001	0.012	0.009	0.993	-0.024	0.024
T_{it}^2	-0.0024	0.005	0.447	0.655	-0.008	0.013
P_{it}	-0.0003	0.000	-1.094	0.274	-0.001	-0.000
P_{it}^2	-1.55e-06	1.05e-06	-1.482	0.139	-3.6e-06	-5.03e-07
Model Summary:						
R-squared				0.418		
Adjusted R-squared				0.393		
F-statistic				16.46 (p = 4.97e-72)		
No. of observations				837		
Log-Likelihood				-434.09		
AIC				940.2		
BIC				1110		
Durbin-Watson				0.995		

Table 9. Estimated coefficients from the fixed effects panel regression model excluding only the linear county-specific time trend term ($\theta_{1i}t$), while retaining the quadratic time trend ($\theta_{2i}t^2$). The model is applied to log-transformed mango yield data from 17 counties in Taiwan (1960–2023), assessing the nonlinear effects of February temperature and precipitation anomalies. The estimated model is specified as: $\log(y_{it}) = \alpha_1 T_{it} + \alpha_2 T_{it}^2 + \beta_1 P_{it} + \beta_2 P_{it}^2 + \mu_i + \theta_{2i}t^2 + \varepsilon_{it}$. This specification tests whether excluding linear time trends affects the magnitude and significance of estimated climate impacts. All coefficient estimates, standard errors, and model diagnostics are reported below; county fixed effects are included but not shown.

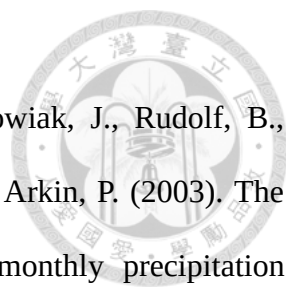
Variable	Coefficient	Std. Error	t-value	P-value	95% CI Lower	95% CI Upper
T_{it}	-9.993e-05	0.012	0.008	0.993	-0.024	0.024
T_{it}^2	-0.0024	0.005	0.447	0.655	-0.008	0.013
P_{it}	-0.0003	0.000	-1.094	0.274	-0.001	-0.000
P_{it}^2	-1.549e-06	1.05e-06	-1.482	0.139	-3.6e-06	-5.03e-07
Model Summary:						
R-squared				0.418		
Adjusted R-squared				0.393		
F-statistic				16.46 (p = 4.87e-72)		
No. of observations				837		
Log-Likelihood				-434.07		
AIC				940.1		
BIC				1110		
Durbin-Watson				0.995		

Table 10. Estimated coefficients from the fixed effects panel regression model excluding only the quadratic county-specific time trend term ($\theta_{2i}t^2$), while retaining the linear time trend ($\theta_{1i}t$). The model assesses the nonlinear influence of February climate anomalies on log-transformed mango yield across 17 counties in Taiwan (1960–2023). The estimated model is specified as: $\log(y_{it}) = \alpha_1 T_{it} + \alpha_2 T_{it}^2 + \beta_1 P_{it} + \beta_2 P_{it}^2 + \mu_i + \theta_{1i}t + \varepsilon_{it}$. This specification isolates the role of quadratic time trends in capturing structural temporal changes and evaluates the robustness of climate coefficients. Reported statistics include regression coefficients, standard errors, t-values, p-values, and 95% confidence intervals. Model summary diagnostics are provided; fixed effects are omitted for brevity.

Model	R^2	$Adj. R^2$	AIC	BIC	$\beta_1 (P_{it})$	$\beta_2 (P_{it})$
baseline	0.511	0.480	824.7	1066	significant ($p = 0.042$)	not significant
Excluding $\theta_{1i}t$ ($\theta_{2i}t^2$)	0.418	0.393	940.2	1110	not significant	not significant
Excluding $\theta_{2i}t^2$ ($\theta_{1i}t$)	0.418	0.393	940.1	1110	not significant	not significant
Excluding $\theta_{1i}t + \theta_{2i}t^2$	0.274	0.257	1094	1189	not significant	significant ($p = 0.019$)

Table 11. Model comparison table summarizing fit statistics and precipitation term significance across four fixed effects panel regression specifications. Each model varies in the inclusion of county-specific linear ($\theta_{1i}t$) and quadratic ($\theta_{2i}t^2$) time trends. Metrics include R^2 , adjusted R^2 , AIC, BIC, and the p-values for β_1 and β_2 .

REFERENCE

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- Adler, R. F., Huffman, G. J., Chang, A., Ferraro, R., Xie, P., Janowiak, J., Rudolf, B., Schneider, U., Curtis, S., Bolvin, D., Gruber, A., Susskind, J., & Arkin, P. (2003). The version 2 Global Precipitation Climatology Project (GPCP) monthly precipitation analysis (1979–present). *Journal of Hydrometeorology*, 4(6), 1147–1167. [https://doi.org/10.1175/1525-7541\(2003\)004<1147:TVGPCP>2.0.CO;2](https://doi.org/10.1175/1525-7541(2003)004<1147:TVGPCP>2.0.CO;2)
- Anderson, W., Cook, B. I., Slinski, K., Schwarzwald, K., McNally, A., & Funk, C. (2023). Multiyear La Niña events and multiseason drought in the Horn of Africa. *Journal of Hydrometeorology*, 24(1), 119–131. <https://doi.org/10.1175/JHM-D-22-0043.1>
- Baltagi, B. H. (2005). *Econometric analysis of panel data* (3rd ed.). John Wiley & Sons.
- Burke, M., Hsiang, S. M., & Miguel, E. (2015). Global non-linear effect of temperature on economic production. *Nature*, 527(7577), 235–239. <https://doi.org/10.1038/nature15725>
- Chang, C.-C. (2002). The potential impact of climate change on Taiwan's agriculture. *Agricultural Economics*, 27(1), 51–64. [https://doi.org/10.1016/S0169-5150\(01\)00060-3](https://doi.org/10.1016/S0169-5150(01)00060-3)
- Danabasoglu, G., Lamarque, J.-F., Bacmeister, J., Bailey, D. A., DuVivier, A. K., Garcia, R., ... & Strand, W. G. (2020). The Community Earth System Model version 2 (CESM2). *Journal of Advances in Modeling Earth Systems*, 12(2), e2019MS001916. <https://doi.org/10.1029/2019MS001916>
- Dell, M., Jones, B. F., & Olken, B. A. (2012). Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics*, 4(3), 66–95. <https://doi.org/10.1257/mac.4.3.66>
- FAO. (2023). *Crops and livestock products: Mangoes, guavas and mangosteens – Area harvested and production*. FAOSTAT. <https://www.fao.org/faostat/en/#data/QC>
- FAO. (2025). *La Niña: Anticipatory Action and Response Plan, January 2025 update – Mitigating the expected impacts of La Niña-induced climate extremes on agriculture and*

- food security*. Food and Agriculture Organization of the United Nations.
<https://openknowledge.fao.org/handle/20.500.14283/cd4047en>
- Geng, T., Jia, F., Cai, W., Wu, L., Gan, B., Jing, Z., Li, S., & McPhaden, M. J. (2023). Increased occurrences of consecutive La Niña events under global warming. *Nature*, 619, 774–781. <https://doi.org/10.1038/s41586-023-06380-5>
- Gill, A. E. (1980). Some simple solutions for heat-induced tropical circulation. *Quarterly Journal of the Royal Meteorological Society*, 106(449), 447–462.
<https://doi.org/10.1002/qj.49710644905>
- Hersbach, H., Bell, B., Berrisford, P., Biavati, G., Horányi, A., Muñoz Sabater, J., Nicolas, J., Peubey, C., Radu, R., Rozum, I., Schepers, D., Simmons, A., Soci, C., Dee, D., & Thépaut, J.-N. (2023). ERA5 hourly data on single levels from 1940 to present. Copernicus Climate Change Service (C3S) Climate Data Store (CDS).
<https://doi.org/10.24381/cds.adbb2d47>
- Hsiao, C. (2003). *Analysis of panel data* (2nd ed.). Cambridge University Press.
<https://doi.org/10.6342/NTU202001691>
- Jiang, Q., Li, W., Fan, Z., He, X., Sun, W., Chen, S., Wen, J., Gao, J., & Wang, J. (2021). Evaluation of the ERA5 reanalysis precipitation dataset over Chinese Mainland. *Journal of Hydrology*, 595, 125660. <https://doi.org/10.1016/j.jhydrol.2020.125660>
- Kahn, M. E., Mohaddes, K., Ng, R. N. C., Pesaran, M. H., Raissi, M., & Yang, J.-C. (2021). Long-term macroeconomic effects of climate change: A cross-country analysis. *Energy Economics*, 104, 105624. <https://doi.org/10.1016/j.eneco.2021.105624>
- Lam, W.-F., Tang, C.-P., & Tang, S.-K. (2021). Bureaucratising co-production: Institutional adaptation of irrigation associations in Taiwan. *Water Alternatives*, 14(2), 435–452.
water-alternatives.org

- Lam, W.-F., Tang, C.-P., & Tang, S.-K. (2021). Bureaucratising co-production: Institutional adaptation of irrigation associations in Taiwan. *Water Alternatives*, 14(2), 435–452. Retrieved from <http://www.water-alternatives.org>
- Lin, L.-Y., Lin, C.-T., Chen, Y.-M., Cheng, C.-T., Li, H.-C., & Chen, W.-B. (2022). The Taiwan Climate Change Projection Information and Adaptation Knowledge Platform: A Decade of Climate Research. *Water*, 14(3), 358. <https://dx.doi.org/10.3390/w14030358>
- Liu, Y., Cai, W., Lin, X., Li, Z., & Zhang, Y. (2023). Nonlinear El Niño impacts on the global economy under climate change. *Nature Communications*, 14, 5887. <https://doi.org/10.1038/s41467-023-41667-1>
- Lu, Z., Schultze, A., Carré, M., Brierley, C., Hopcroft, P. O., Zhao, D., Zheng, M., Braconnot, P., Yin, Q., Jungclaus, J. H., Shi, X., Yang, H., & Zhang, Q. (2025). Increased frequency of multi-year El Niño–Southern Oscillation events across the Holocene. *Nature Geoscience*, 18, 337–343. <https://doi.org/10.1038/s41561-025-01368-w>
- Matsuno, T. (1966). Quasi-geostrophic motions in the equatorial area. *Journal of the Meteorological Society of Japan. Ser. II*, 44(1), 25–43. https://doi.org/10.2151/jmsj1965.44.1_25
- Muñoz-Sabater, J. (2019). ERA5-Land hourly data from 1950 to present. Copernicus Climate Change Service (C3S) Climate Data Store (CDS). <https://doi.org/10.18739/A2RX93G07>
- Muñoz-Sabater, J., Dutra, E., Agustí-Panareda, A., Albergel, C., Arduini, G., Balsamo, G., ... & Vogt, J. (2021). ERA5-Land: A state-of-the-art global reanalysis dataset for land applications. *Journal of Climate*, 34(23), 9051–9071. <https://doi.org/10.1175/JCLI-D-20-0500.1>

- Newell, R. G., Prest, B. C., & Sexton, S. E. (2021). The GDP-temperature relationship: Implications for climate change damages. *Journal of Environmental Economics and Management*, 108, 102445. <https://doi.org/10.1016/j.jeem.2021.102445>
- NOAA Climate Prediction Center. (n.d.). *Oceanic Niño Index (ONI)* version 5. National Weather Service. Retrieved May 30, 2025, from https://origin.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ONI_v5.php
- Okumura, Y. M., DiNezio, P., & Deser, C. (2017). Evolving impacts of multiyear La Niña events on atmospheric circulation and U.S. drought. *Geophysical Research Letters*, 44(22), 11614–11623. <https://doi.org/10.1002/2017GL075034>
- Panda, A. (2021). *Climate change and agricultural insurance in the Asia and Pacific region* (Asian Development Outlook 2021 Update Background Paper). Asian Development Bank. <https://www.adb.org/sites/default/files/institutional-document/731791/adou2021bp-climate-change-agri-insurance-asia-pacific.pdf>
- Wang, B., Wu, R., & Fu, X. (2000). Pacific–East Asian teleconnection: How does ENSO affect East Asian climate? *Journal of Climate*, 13(9), 1517–1536. [https://doi.org/10.1175/1520-0442\(2000\)013<1517:PEATHD>2.0.CO;2](https://doi.org/10.1175/1520-0442(2000)013<1517:PEATHD>2.0.CO;2)
- Watson D. (1994). Nngridr: An implementation of natural neighbor interpolation., Dave Watson Publiser, Claremont, Australia, 170pp.
- 陳盟松 (2012)。芒果隔年結果原因之探討。收錄於台中區農業改良場 (編)，101 年度專題討論專集 (頁 299 – 302)。台中區農業改良場。
- 黃和炎、劉銘峰 (1998)。《芒果》。台南區農業改良場特刊第 3 號。農業部。取自 <https://book.tndais.gov.tw/Brochure/pub3-3.htm> (查詢日期：2025 年 6 月 3 日)
- 簡榮成 (2020)。《農業氣象災害對芒果產量之影響與調適策略》(碩士論文)。國立臺灣大學農業經濟學研究所。 <https://hdl.handle.net/11296/c226kx>

李雪如、陳思如、周國隆、李承翰（2011）。《行政院農業委員會高雄區農業改良場 100 年度科技計畫研究報告》。台北市：行政院農業委員會高雄區農業改良場。

林修立、童裕翔、王俊寓、林士堯（2023 年 1 月 1 日）。AR6 統計降尺度雨量資料生產履歷（第 1.0 版）。臺灣氣候變遷推估資訊與調適知識平台。取自 https://tccip.ncdr.nat.gov.tw/upload/data_profile/20220718101540.pdf

林業試驗所台北植物園（2025）。芒果－開花情報。林業試驗所。取自 https://tpbg.tfri.gov.tw/FlowersContent.php?ID=4100&edM=4&edY=2025&pn=1&stM=01&stY=2025&utm_source=chatgpt.com

劉玫婷、李欣輯、徐永衡、陳永明（2022）。〈2022 年 1~2 月農作物寒害暨雨害損失調查紀實〉。《災害防救電子報》，203 期。國家災害防救科技中心。取自 <https://www.ncdr.nat.gov.tw/>

劉銘峰、張明聰、黃和炎（1988）。提前或延後芒果產期需技術。收錄於台南區農業改良場（編），*良技術專刊 園藝-1 (No.45)*。台南區農業改良場。取自：
<https://book.tndais.gov.tw/Brochure/tech45.htm>

內政部（2024 年 12 月 24 日）。《直轄市、縣市界線（TWD97 經緯度）－SHP 格式》〔資料集〕。內政部開放資料平台。
<https://data.moi.gov.tw/MoiOD/System/DownloadFile.aspx?DATA=72874C55-884D-4CEA-B7D6-F60B0BE85AB0>

農業部農糧署（1960-2023）。59-112 年農業統計年報。取自 <https://agrstat.coa.gov.tw/>

農業部農糧署（2024）。《縣市作物查詢系統》。取自農情報告資訊網：
https://agr.afa.gov.tw/afa/afa_frame.jsp（查詢日期：2025 年 6 月 2 日）

農業部農業知識入口網（2023）。芒果生態－生育週期。取自
<https://kmweb.moa.gov.tw/subject/subject.php?id=10690>

農業部農業知識入口網 (2024)。花果生育習性－芒果主題館。農業部。取自

<https://kmweb.moa.gov.tw/subject/subject.php?id=10692>

石佩玉 (2021)。《農作物防減災與生產調適：芒果》。台南區農業改良場技術專刊 110-1

號。台南：農業部台南區農業改良場。

楊承道，王俊寓，林士堯 (2024 年 1 月 12 日)。網格化觀測雨量 V2 版資料生產履歷

(第 4.1.1 版)。臺灣氣候變遷推估資訊與調適知識平台。取自

https://tccip.ncdr.nat.gov.tw/upload/data_profile/20220706104221.pdf

張錦興 (2017)。芒果產期調節研究發展與產業調適。臺中區農業改良場特刊，131-140

<https://www.airitilibrary.com/Article/Detail?DocID=P20131108002-201712-201805150>

014-201805150014-131-140

