A Systematic Review of Key Spatial Econometric Models for Assessing Climate Change Impacts on Agriculture

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A Systematic Review of Key Spatial Econometric Models for Assessing Climate Change Impacts on Agriculture

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Abstract

This paper explores the limitations of traditional econometric models, such as the Ricardian and profit approaches, in accurately quantifying the impacts of climate change on agriculture. While these models offer valuable insights, they often neglect spatial dependencies, heterogeneity, and spillover effects. We argue that spatial econometrics provides a more comprehensive and robust approach to analyzing climate change impacts. By explicitly incorporating spatial relationships between agricultural units, spatial econometric models capture the influence of factors such as proximity to markets, resource sharing, information diffusion, and spatial correlation of climatic variables. We review pioneering studies employing spatial econometric models, including SAR, SEM, SLX, SARAR and SDM, which reveal significant discrepancies between spatial and non-spatial estimations. These studies demonstrate that neglecting spatial dependence can lead to biased estimations and inaccurate predictions of climate change impacts. Moreover, the incorporation of spatial effects often results in smaller marginal effects of climate variables, suggesting that traditional non-spatial models may overestimate negative consequences. This paper contributes to the ongoing research on climate change impacts on agriculture by highlighting the significance of spatial econometrics and emphasizing its potential to inform robust and effective adaptation strategies.

Keywords: Climate change, econometrics approaches, agriculture, adaptation, spatial econometrics.
JEL: Q15, Q51, Q54, R12.

1 Introduction

Introduction Climate change, a global challenge threatening food security and economic development [IPCC, 2023], impacts agriculture heterogeneously [Desmet and Rossi-Hansberg, 2024]. Regions like the MENA, already facing aridity, are experiencing significant climate shifts, with notable variations across countries [Amouzay et al., 2023]. Economies heavily reliant on agriculture, a sector sensitive to temperature fluctuations and extreme weather events, are more vulnerable than those dominated by industry or services [IPCC, 2023]. The impact of climate change on agriculture is spatially differentiated, with more severe consequences at equatorial latitudes compared to higher latitudes [Desmet and Rossi-Hansberg, 2024].

The economic evaluation of climate change impacts on agriculture is a complex field requiring methodologies adapted to available data, study objectives, and regional specificities. Econometric approaches, developed to overcome the limitations of agronomic methods, have significantly advanced in recent decades. These models aim to capture farmers' behavioral responses to climate change [Blanc and Reilly, 2017]. Two economic models are widely recognized: the Ricardian model [Mendelsohn et al., 1994], relying on cross-sectional regressions of agricultural land prices, and the production function model [Deschênes and Greenstone, 2007], based on panel data analysis of agricultural profits. These models allow for evaluating both short- and long-term impacts of climate change on agriculture [Blanc and Reilly, 2017]. However, conventional econometric approaches, such as the Ricardian model [Mendelsohn et al., 1994] and the profit function model [Deschênes and Greenstone, 2007], have limitations that can lead to biased estimates, particularly due to the neglect of spatial autocorrelation and spillover effects of climate change impacts on agriculture [Chatzopoulos and Lippert, 2016; Schlenker et al., 2006]. For example, Schlenker et al. [2006] revealed a negative impact of climate change on US agriculture. By rigorously correcting for spatial error correlation in their data, the authors estimated an annual loss of $5.3 to $5.4 billion for non-irrigated and non-urban areas. This finding contradicts the conclusions of Mendelsohn et al. [1994], who predicted positive effects. This major difference underscores that the effects of climate change are not geographically isolated. Omitting this spatial interdependence, leads to an underestimation, or even a complete reversal, of the actual impact [Schlenker et al., 2006]. Therefore, the use of spatial econometric models is crucial for obtaining reliable estimates and effectively informing adaptation policies, as erroneous conclusions can lead to inefficient and costly strategies.

Spatial econometrics, which accounts for specific spatial effects and interactions among geographical units of climate and agricultural variables, offers a promising alternative to overcome these limitations. The presence of spatial autocorrelation, where neighboring observations influence each other or share an unobserved phenomenon, necessitates specific tools in econometrics. This approach provides a variety of models capable of considering these spatial interactions, starting with a prior definition of the neighborhood relationships among geographical entities [Anselin, 2013]. Consequently, these spatial models allow for a better understanding of causal relationships and provide more accurate estimates of the impacts of climate change on agriculture [Lippert et al., 2009; Schlenker et al., 2006]. In particular, spatial panel models enable the simultaneous consideration of spatial autocorrelation and individual heterogeneity, offering essential tools for decomposing local effects and spillover effects [Chen et al., 2016; Dall'Erba and Domínguez, 2016; Vaitkeviciute et al., 2019].

This paper aims to present a state-of-the-art review of the literature on spatial models used to study the impact of climate change on agriculture and demonstrate how methodological advancements in spatial econometrics have been introduced in this field. We emphasize that this is not an exhaustive review; rather, the objective is to highlight the major contributions to spatial models and their methodological advancements. Our literature reviews deviate from those provided by Auffhammer [2018]; Carter et al. [2018]; Hsiang [2016]; Kolstad and Moore [2020]; Ortiz-Bobea [2021]; Su and Chen [2022], which primarily focus on conventional econometric approaches, without specifically delving into the use of spatial models. Our main objective is to fill this gap by summarizing studies that explicitly incorporate spatial autocorrelation in spatial models to investigate the impacts of climate change on agriculture. This literature review draws upon scholarly articles indexed in *Scopus* and *Web of Science (WOS)* and examines pioneering studies employing spatial econometric models, including SAR, SEM, SLX, SARAR and SDM, published over the past 20 years. This study contributes to a better understanding of these phenomena by providing an overview of spatial methodological tools and their potential for informing adaptation policies in the agricultural sector.

The remainder of this paper is organized as follows. In section 2, we examine a brief overview of conventional econometric approaches for estimating the impact of climate change on agriculture. In section 3, we review state-of-the-art spatial econometric models and justify their relevance for research in this field. Conclusions are presented in section 4.

2 Ricardian and Profit Approaches: A Brief Overview

This section provides a brief overview of the Ricardian and profit approaches, two econometric models widely used to assess the economic impacts of climate change on agriculture. While these approaches offer valuable insights, they also present limitations, which are discussed below.

2.1 Ricardian Approach: Cross-Sectional Model

The Ricardian approach, based on the work of Ricardo [1817], posits that agricultural land rent reflects the present value of future income streams derived from agricultural production. Mendelsohn et al. [1994] pioneered the empirical application of this approach, utilizing the hedonic price method to assess the influence of climate variables: Temperature ($temp_i$) and Precipitation ($prec_i$) and their squares ($prec_i^2$) and ($temp_i^2$), Soil Quality (S_i), and Socioeconomic Variables (Z_i) on Agricultural Land Prices (V_i). β_i ($i = 0, ..., 4$), δ and θ represent a vector of unknown parameters to be estimated.

The Ricardian model can be expressed in different forms, with the semi-logarithmic form being the most common [Vaitkeviciute et al., 2019] :

$$ln\,(V_i) = \beta_0 + \beta_1 prec_i + \beta_2 + \beta_3 prec_i^2 + \beta_4 temp_i^2 + S_i\delta + Z_i\theta + \varepsilon_i \tag{1}$$

The Ricardian approach offers the advantage of incorporating all available adaptation options in the data sample [Mendelsohn et al., 1996]. It assumes that farmers maximize their profits and choose the land allocation that generates the highest revenue. Initially applied in the United States [Mendelsohn et al., 1994], the Ricardian model investigates the direct impacts of environmental factors, including climate, on land value [Rosen, 1974]. It has been applied in approximately 50 countries [Mendelsohn and Massetti, 2017], demonstrating the beneficial effects of warm spring and autumn temperatures but the detrimental effects of hotter summer and winter temperatures [Massetti and Mendelsohn, 2011; Van Passel et al., 2017].

Despite its usefulness in assessing the impact of climate change on agriculture, the Ricardian approach faces several limitations. It is notably susceptible to omitted variable bias [Deschênes and Greenstone, 2007], including the increasing capitalization of agricultural land prices by non-agricultural influences [Hardie et al., 2001; Livanis et al., 2006; Plantinga et al., 2002] and preferences for milder climates Albouy et al. [2016]. Furthermore, it relies on restrictive assumptions regarding price invariance in response to supply changes [Cline, 1996], which underestimates losses and overestimates gains [Cline, 1996]. The approach also neglects adaptation costs and incomplete knowledge of climate change [Kelly et al., 2005; Quiggin and Horowitz, 1999; Reilly et al., 1996] and omits farmers' adaptation strategies [Mendelsohn and Dinar, 2009]. For instance, the irrigation variable is often disregarded, hindering the capture of its influence on agricultural land values [Cline, 1996; Darwin, 1999; Schlenker et al., 2005]. Finally, the endogenous nature of adaptation measures [Chatzopoulos and Lippert, 2015] and the spatial aggregation of data [Fezzi and Bateman, 2015; Timmins, 2006] can bias estimates.

2.2 Profit Approach: Panel Data Model

Proposed by Deschênes and Greenstone [2007], the profit approach utilizes panel data to estimate the impact of meteorological fluctuations on agricultural profits, addressing concerns about omitted variable bias and misspecification inherent in the Ricardian approach. This approach examines the effects of climate change on annual profit, revenu or production, rather than land values, acknowledging that weather conditions can have a short-term impact on agricultural production and expenses.

The profit approach model (Equation 2) incorporates county-level fixed effects to control for unobservable (α_i), time-invariant factors and year or state-level fixed effects to account for common annual variations across counties (γ_t). It investigates the influence of annual weather conditions (W_{it}) on agricultural profits (y_{it}), while controlling for time-varying factors (X_{it}).

$$y_{it} = \alpha_i + \gamma_t + \sum_i \theta_i f_i(W_{it}) + X_{it}\beta + \varepsilon_{it} \tag{2}$$

Panel data models, although widely used to study the impact of climate change on agriculture, have limitations [Blanc and Reilly, 2017]. Including fixed effects is not sufficient to eliminate omitted variable bias, as time-varying confounding factors can be correlated with weather anomalies [Auffhammer et al., 2013; Nugroho et al., 2023]. Using different time scales for agricultural and meteorological variables can also bias results [Blanc and Reilly, 2017], and aggregating meteorological variables to the annual scale can mask seasonal effects. The approach by Deschênes and Greenstone [2007] raises questions about the role of stocks used by farmers to mitigate the effects of unusual economic and weather conditions [Ortiz-Bobea, 2021]. Carter et al. [2018] highlights the risk of multicollinearity, estimation bias in case of response heterogeneity, and model selection challenges related to the frequency of weather data. Furthermore, panel models are sensitive to measurement errors, which can be particularly problematic in regions with scarce or poor-quality data [Auffhammer, 2018]. Spatial interpolation of weather data introduces measurement errors [Auffhammer et al., 2013]. The presence of measurement errors, often extending beyond geographical boundaries, is due to spatial correlation of errors [Chen et al., 2016; Fisher et al., 2012], explained by different data scales and aggregation processes [Vaitkeviciute et al., 2019]. It is thus crucial to consider spatial autocorrelation in the study of the impact of climate change on agriculture, prompting the exploration of spatial econometrics.

3 Spatial Econometrics and Climate Change Impacts on Agriculture

This section underscores the critical role of spatial econometrics in gaining a deeper understanding of climate change impacts on agriculture. We first explore The importance of considering spatial effects (3.1), followed by a comprehensive review of pioneering studies that have employed spatial econometric models to analyze the effects of climate change on agriculture (3.2).

3.1 The Importance of Spatial Effects in Agriculture and Climate Change

The deep intertwining of the concepts of space and agriculture was highlighted as early as the 19^{th} century by Von Thünen [1826], who underscored the crucial importance of the spatial dimension in agricultural economics. This spatial dimension is fundamental to understanding the impacts of climate change on agriculture, as the effects of climate change are not uniformly distributed, varying significantly from region to region [Desmet and Rossi-Hansberg, 2024].

This importance of spatial effects is reinforced by several key factors. Firstly, significant spatial correlations exist in agricultural data. Neighboring counties often share similar climatic, soil, and irrigation characteristics [Polsky, 2004], leading to spillover effects such as information diffusion among farmers, technology transfer, and the diffusion of public agricultural R&D spending [McCunn and Huffman, 2000]. Furthermore, the evapotranspiration-rain cycle and the sharing of resources such as irrigation water create geographical interconnectedness [Dominguez et al., 2009]. Even seemingly objective data, such as weather measurements, exhibit spatial correlation due to data generation processes and interpolation methods used to create spatially geo-located datasets [Auffhammer et al., 2013]. This spatial autocorrelation poses methodological challenges, as the inherent correlation in data, for example meteorological data, can lead to biased estimates if not properly addressed. Several approaches exist to mitigate this bias, including the use of spatial weighting matrices [Conley, 1999], non-parametric methods, or block bootstrapping. However, caution is warranted with interpolated gridded data, as they can introduce problematic multicollinearity, particularly in panel analyses [Auffhammer et al., 2013].

These spatial dependencies necessitate the integration of spatial effects into econometric models to improve the accuracy and reliability of results, thus avoiding erroneous conclusions [LeSage and Pace, 2009]. Indeed, Chatzopoulos and Lippert [2016] highlights several reasons for integrating spatial effects into the Ricardian model: the econometric advantages, including the reduction of omitted variable bias through spatial lags and improved robustness against unobservable factors; the problems related to data aggregation, which can create artificial spatial dependence and homogenize heterogeneous units; the importance of interactions between landowners, who influence prices based on neighboring transactions, and the lack of information on land characteristics; and finally, the influence of common behaviors in land use, which are difficult to incorporate into the traditional Ricardian model. Although land investments generating external benefits could be captured through spatial lags, data availability and theoretical justification limit their application in the studied context. For a rigorous analysis of these spatial dependencies, spatial econometric models are necessary.

Spatial literature has developed a comprehensive classification of key spatial econometric models, based on three types of spatial interaction [Anselin and Bera, 1998; Arbia and Baltagi, 2008; Elhorst, 2010; Florax et al., 2003; Le Gallo, 2002; LeSage and Pace, 2009]. This classification provides a framework for more accurate modeling and informed decision-making regarding complex economic phenomena within a geographical context. Elhorst [2014] further details spatial models for both cross-sectional and panel data, as well as strategies for selecting the best spatial specification. The introduction of a spatial weight matrix introduces endogeneity, rendering ordinary least squares (OLS) inappropriate; panel models are generally estimated using maximum likelihood [Anselin et al., 2008; Elhorst, 2010].

Table 1 below summarizes some common spatial econometric models used in studies on the impacts of climate change on agriculture, highlighting their specific specifications and interpretations.

Table 1: Spatial models specifications use in climate change impacts on agriculture studies

Model	Specification	Model Interpretation
Spatial Autoregressive Model (SAR)	$Y = \rho WY + X\beta + \varepsilon$	Agricultural output one location is determined jointly with that of neighbors
Spatial Error Model (SEM)	$Y = X\beta + \varepsilon$ and $\varepsilon = \lambda W\varepsilon + u$	Agricultural output one location is determined by the unobserved omitted variables of neighbors. Data measurement errors
Spatial Autoregressive Combined Model (SARAR)	$Y = \rho WY + X\beta + \epsilon$ and $\epsilon = \lambda W\epsilon + u$	A combination of SAR and SEM Models
Spatial Lag X Model (SLX)	$Y = X\beta + WX\gamma + \varepsilon$	Agricultural output variable for one location is determined by the explanatory variables of neighbors
Spatial Durbin Model (SDM)	$Y = \rho WY + X\beta + WX\gamma + \varepsilon$	A combination of SLX and SAR Models

Note: ρ is the spatial autoregressive coefficient, λ the spatial autocorrelation coefficient, γ and β represent a vector of unknown parameters to be estimated. W is a nonnegative $N \times N$ matrix describing the spatial configuration or arrangement of the units in the sample.

3.2 Spatial Models Use in Climate Change Impacts on Agriculture Studies

The growing recognition of the importance of geographic distribution in the influence of climate on agriculture has driven the adoption of econometric methods that integrate spatial dimensions. Spatial econometrics has emerged as a distinct discipline, and its integration into the study of climate change impacts on agriculture is crucial. Ignoring the concept of spatial dependence in this context risks introducing bias.

Incorporating the spatial dimension reveals crucial information that aspatial models fail to capture. Spatial approaches, such as SAR, SEM, SLX, SARAR, and SDM models, enable a better understanding of interactions among farmers—often influenced by geographic or sectoral proximity—interregional interactions, spillover effects, and the spatial heterogeneity of impacts. The importance of these models lies in the distinction between local effects and spillover effects. These effects arise from frequent interactions: the adoption of similar agricultural practices among neighboring farmers [Polsky, 2004], the repercussions of public investments in agricultural R&D on neighboring areas [McCunn and Huffman, 2000], or the sharing of resources such as irrigation water among neighboring regions [Dominguez et al., 2009].

According to Dall'Erba and Domínguez [2016], the literature on spillover effects can be categorized into three groups: studies neglecting these effects by assuming Independently and Identically Distributed (*i.i.d.*) errors [Deschênes and Greenstone, 2007; Mendelsohn et al., 1994]; studies addressing global spillover effects [Chatzopoulos and Lippert, 2015; Dall'Erba and Domínguez, 2016; **?**], captured by SAR or SDM models; and studies focusing on local spillover effects [Dall'Erba and Domínguez, 2016; Ortiz-Bobea, 2015; Polsky, 2004; Zouabi and Peridy, 2015], captured by spatial lagging of explanatory variables (SLX model). However, the use of the SLX model requires caution due to the risk of multicollinearity, particularly with highly correlated climate variables [Vaitkeviciute et al., 2019]. To address this, Vaitkeviciute et al. [2019] advocates for the SEM model, which captures spillover effects through the error term, particularly suitable for aggregated data and situations with spatial autocorrelation in climate data or measurement errors [Chen et al., 2016; Lippert et al., 2009; Schlenker et al., 2006]. Climate data, often derived from unevenly distributed weather stations, can generate spatial autocorrelation and measurement errors exceeding the boundaries of aggregation units. In such cases, the SEM model allows for the analysis of spatially complex links between climate variables and agricultural phenomena [Vaitkeviciute et al., 2019].

This literature review identifies pioneering studies using econometric approaches to quantify the impact of climate change on the agricultural sector, with a particular emphasis on those employing spatial econometric models that integrate elements of farmer adaptation. To this end, we selected studies published over the past 20 years (post-2003), using the Scopus and ISI Web of Science (WoS) databases and employing the following keyword pairs: "climate change," "agriculture," "impact," and "spatial econometrics." This search yielded a total of 2916 articles. Based on titles, we removed articles not employing econometric approaches, leaving 386 articles. Next, we examined the abstracts, eliminating those that did not clearly meet our inclusion criteria (e.g., articles must demonstrate significant methodological advancements compared to conventional econometric models (cross-sectional or panel data models)), reducing the total to 157. Among these, we are particularly interested in studies using spatial models such as SAR, SEM, SLX, SARAR and SDM, to analyze the impact of climate variables on land value, agricultural income, agricultural production, or other economic indicators related to agriculture. Consequently, we removed those that did not meet all defined inclusion criteria after a full read. This search and exclusion process left us with 21 articles. Many articles were eliminated because they were not pioneering or did not improve methodologies for quantifying the value of adaptation, focusing only on the application of econometric models.

The evolution of econometric methods applied to the study of climate change impacts on agriculture is marked by a steady progression towards greater complexity and a better accounting for spatial and temporal interactions. While early analyses primarily relied on cross-sectional approaches, the emergence of spatial panel data models, which will be the focus of the following section, represents a significant advancement, enabling a more nuanced understanding of these interactions.

3.2.1 Spatial Cross-sectional Models Studies

Pioneers in this field, such as Polsky [2004] and Schlenker et al. [2006], initially introduced a spatial component into a Ricardian approach applied to US counties. These studies questioned the suitability of classical Ricardian models for assessing the impact of climate change on agriculture, in particular because of their simplifying assumptions concerning the perfect spatial substitutability of agricultural land, and the temporal constancy of environmental, economic and social conditions [Polsky, 2004]. The studies will then be presented by region, and their results summarized in table 2 below.

United States (U.S) Case Studies

Polsky [2004], for instance, investigated Ricardian climate sensitivities in the Great Plains, explicitly challenging the traditional approach's neglect of spatial and temporal dynamics. Unlike classical Ricardian models, which assume perfect spatial substitutability and constant conditions over time, Polsky [2004] employed a multi-scale spatial econometric approach, integrating six spatial models for each year (1969, 1974, 1978, 1982, 1987, and 1992). A key innovation was the inclusion of spatial lag terms (SAR model) and spatial groupwise heteroscedasticity (GHET) to capture previously omitted effects. Results revealed a complex and dynamic picture of climate change impacts on Great Plains agriculture, contrasting sharply with the more static outcomes of classical Ricardian models. The aggregate increase in land values following an 8% increase in precipitation and growing season length varied considerably over the study period, declining from \$7.5 billion in 1969 to only \$0.7 billion in 1992 (1992 dollars). This rapid decrease reflects imperfect and non-instantaneous adaptation, contradicting Ricardian assumptions. Furthermore, the spatial impact was heterogeneous, exhibiting a northwest-southeast gradient with land value decreases in the northwest and increases in the southeast. This heterogeneity also varied temporally, as illustrated by significant fluctuations in county-level impacts (e.g., fluctuations from +19% to -5% in Kidder County, North Dakota). Finally, the influence of non-climatic factors (inter-county communication, water management, market conditions) underscored the complexity of adaptation and the need to move beyond a simple direct response to climate change. These findings have major implications for adaptation policies, requiring spatially targeted strategies that consider temporal dynamics and integrate the complex socioeconomic factors influencing farmers' adaptive capacity. A uniform, static approach is inadequate; flexible and adaptive interventions are necessary.

Schlenker et al. [2006], separately, estimated the impact of climate change (a 5°C temperature increase and 8% increase in precipitation) on the value of agricultural land in non-irrigated, non-urban US counties. They demonstrated that the spatial distribution of agricultural land, variable across and within counties, significantly impacts model results. This distribution influences not only exogenous variables (such as soil characteristics and climate, averaged over each county's agricultural areas) but also the error term structure. These terms, representing unexplained variations, are not independent across counties; geographically proximate counties likely share unobserved characteristics, leading to spatial autocorrelation in the errors. Neglecting this spatial correlation, according to Schlenker et al. [2006], underestimates the true variance-covariance matrix, leading to an undervaluation of uncertainty and an overestimation of t-statistics, thus inflating the perceived statistical significance of regression coefficients. Consequently, to ensure the validity of hedonic land value coefficient estimates and mitigate overestimation bias, Schlenker et al. [2006]) implemented a two-step procedure involving spatial correlation parameter estimation (SEM model) and the White estimator for heteroscedasticity. They compared specifications with and without state fixed effects, justified by the possibility of unobserved characteristics common to all farms within a state, such as state-specific taxes and unequal incidence of crop subsidies due to differences in farming practices across states. Results from the log-linear hedonic regression, using the standardized Queen contiguity matrix, showed that the inclusion of fixed effects did not reduce the significance level of climatic variables; simultaneously, the spatial correlation parameter remained virtually unchanged with the inclusion of fixed effects, suggesting the presence of spillover effects based on spatial proximity rather than administrative assignment to a specific state. This estimation points to an annual loss of between $5.3 and $5.4 billion—a significant loss directly affecting agricultural land value in non-irrigated, non-urban US counties.

Southwestern US Case Studies

Dall'Erba and Domínguez [2016] analyzed the impact of climate change on farmland values in the Southwestern US (124 counties, 2007 data) using a SDM. This model was chosen over SLX and SAL models due to its superior fit to the data, accounting for spatial autocorrelation. The model revealed positive effects of irrigation and fertilizer (especially in lowlands), and negative indirect effects of subsidies (highlands). The surprising positive impact of extreme weather events, particularly in highlands, suggests farmer adaptation. Significant spatial heterogeneity existed between highland and lowland counties. The SDM showed that irrigation significantly increased land values in both areas, with fertilizers positively affecting lowland values and soil characteristics significantly influencing lowland land values. The lack of a significant negative effect from summer temperatures and the

Table 2: Summary of Spatial Cross-sectional Models Studies

Study	Results	Models
United States Case Studies		
Polsky [2004]	The SAR model explores the influence of neighboring land uses on a county, suggesting a role for information diffusion and interactions between farmers. The GHET examines the impact of omitted factors varying across Ogallala and non-Ogallala aquifer sub-regions, potentially highlighting the influence of unobservable variables such as irrigation-specific regulations.	**SAR** and **Spatial GHET**
Schlenker et al. [2006]	Overestimation of the statistical significance of regression coefficients due to spatial error correlation, biasing the assessment of data variability. A two-step method using a SEM and White's estimator was employed to correct this bias, estimating an annual loss of $5.3to5.4$ billion.	**SEM**
Dall'Erba and Domínguez [2016]	Results show that the SDM model provides the best fit to the data. Irrigation has a significant positive effect on land value, while agricultural subsidies have a negative impact, primarily indirect in high-altitude counties. Indirect effects, particularly concerning fertilizer and soil characteristics, highlight the importance of spatial interactions and spillover effects between neighboring counties.	**SLX**, **SAR** and **SDM**
Druckenmiller and Hsiang [2018]	Analysis of the impact of time-invariant geographic factors (such as soil and climate) on crop productivities in the United States. The study shows that the SFD method offers a robust alternative for identifying causal effects in the presence of unobservable variables.	**Spatial First Differences (SFD)**
Europe Case Studies		
Lippert et al. [2009]	The SEM model yielded unbiased estimates of the marginal effects of climate change on land rent in Germany. The analysis revealed a general increase in land rent except in the east of the country.	**SEM**
Chatzopoulos and Lippert [2016]	Negative direct effects of climate change are often offset by positive indirect effects related to farmer adaptation. The study emphasizes the importance of considering indirect effects to understand the overall impact of climate change on German agriculture.	**SAR-IV**, **SARAR IV** and **Spatial-IV**
Africa Case Studies		
Ward et al. [2014]	In sub-Saharan Africa, SEM models show a higher vulnerability of agricultural yields to climate change, moderating the impact of irrigation but highlighting that of precipitation variability and spillover effects between regions. They thus offer a more cautious risk assessment.	**SEM**

positive impact of extreme weather events suggest farmer adaptation.

Europe Case Studies

Lippert et al. [2009] assessed the impact of climate change on German agriculture using a Ricardian analysis that accounts for spatial autocorrelation and relies on high-resolution climate change projections. Using data from the 1999 agricultural census for 439 German districts, they analyzed the influence of climate variables (temperature and precipitation) on agricultural land prices. To correct for biases stemming from incomplete data (particularly regarding average soil quality) and spatial autocorrelation, they employed a spatial error model (SEM). The analysis revealed a general increase in land rents with rising temperatures and declining spring precipitation, except in eastern Germany. Simulations based on three IPCC scenarios (2011-2040, REMO model) projected an overall increase in land rent equivalent to 5-6% of net German agricultural income. However, losses are possible in the long term if climate change is more severe.

Africa Case Studies

Ward et al. [2014] employed a spatial econometric model, correcting for sample selection bias and spatial autocorrelation, to analyze the impact of climate change on cereal yields in Sub-Saharan Africa. Their analysis, based on a spatial Heckman model, utilized cereal yield data averaged over 1997-2003 (considered representative of the year 2000) from $5' \times 5'$ grid cells, subsequently aggregated to a resolution of $18' \times 18'$. This resulted in a sample of 2653 observations covering most of mainland Sub-Saharan Africa (excluding Madagascar and smaller islands). Climate variables (temperature, diurnal temperature range, precipitation, and coefficient of variation of precipitation) were climatic averages over the period 1960-1990. Results, comparing OLS, Non-spatial Heckit, and spatial Heckit (SEM) models, indicated that a 1°C increase in temperature reduces yields by 6.5%, while a 1% improvement in irrigation increases yields by 4%. Yields also increased with total precipitation and its variability, and decreased with increases in the diurnal temperature range.

While previous cross-sectional spatial studies offer valuable insights, they are inherently limited in their capacity to fully capture the temporal dynamics of climate change impacts on agricultural systems. Deschênes and Greenstone [2007]; Schlenker et al. [2006] recognized the limitations of purely cross-sectional models. Indeed, these models, while incorporating spatial aspects, fail to account for the gradual agricultural adaptations (technological changes, crop diversification) that unfold over time, nor the cumulative effects of climate change on yields and land values. Moreover, their static nature prevents analysis of the complex dynamic interactions between climate, agricultural practices, and land values, obscuring crucial feedback loops and temporal dependencies essential for a comprehensive understanding of the phenomenon [Schlenker et al., 2006].

Studies incorporating temporal aspects to varying degrees (pooled data, time series) have yet to fully grasp these dynamics. For instance, the use of time-series variation by Deschênes and Greenstone [2007], while innovative, assumes homogenous responses to meteorological changes across counties within a state, overlooking potential heterogeneities. Baylis et al. [2011] compared results from spatial models (SAR and SEM with fixed and random effects) to non-spatial panel data models (pooled model, fixed effects, random effects). Significant differences in coefficient estimates underscored the importance of considering spatial effects. The magnitude of climate variable effects (temperature and precipitation) was consistently smaller in spatial models, suggesting that non-spatial models overestimated the climate's impact by neglecting spatial dependencies and spillover effects.

These studies collectively illustrate the necessity of transcending cross-sectional spatial models. They implicitly highlight the limitations of cross-sectional spatial analysis when applied to time-evolving processes. They thus pave the way for the logical next step: spatial panel data models, which fully integrate spatial and temporal dependencies, providing a considerably more complete and precise understanding of how farmers adapt to climate change and the consequential effects on land values and agricultural profits. This is the precise focus of the following section.

3.2.2 Spatial Panel Models Studies

Spatial econometric theory is applied to panel data analysis to account not only for individual heterogeneity but also for existing spatial dependencies [Anselin et al., 2008; Baylis et al., 2011]. Given the importance of localization and the extensive use of panel data in finance, risk management, production economics, environmental economics and, increasingly, development economics, recently developed spatial panel methods have great potential for applied researchers in these fields [Anselin, 2001b; Elhorst, 2003; Elhorst et al., 2010].

To our knowledge, Seo et al. [2008] and Baylis et al. [2011] were among the first studies to utilize spatial panel models to analyze the impact of climate change on agriculture. While the majority of Ricardian studies on agricultural land values rely on cross-sectional data, Massetti and Mendelsohn [2011] advocate for the use of panel data to better capture temporal dynamics. They further highlight the crucial importance of the spatial dimension, as neighboring agricultural practices and climatic conditions influence land values, generating spillover effects. Adequate consideration of these spatial effects can lead to results significantly different from those obtained using non-spatial panel models or ex-post corrections for spatially correlated errors [Baylis et al., 2011; Vaitkeviciute et al., 2019]. The studies will then be presented by region, and their results summarized in tables 3 and 4 below.

U.S Case Studies

[Baylis et al., 2011] extended the analysis of [Schlenker et al., 2005] by formally integrating spatial econometric models—SAR and SEM—with fixed and random effects into a panel data framework. Unlike [Schlenker et al., 2005], who employed only ex-post corrections for spatial correlation, [Baylis et al., 2011] directly modeled spatial dependence, enabling a more rigorous analysis. This approach revealed the importance of considering both direct and indirect spillover effects. Spatial models consistently yielded lower estimates of climate effects (temperature and precipitation) than aspatial models, highlighting an overestimation of impacts in the latter due to the neglect of spatial dependencies. The use of SAR models facilitated the decomposition of the total impact into direct (within a county) and indirect (on neighboring counties) effects, illustrating the spatial propagation of climate variable influence. Even SEM models, addressing spatial correlation through the error term, exhibited significant differences from aspatial models. The calculation of average total, direct, and indirect impacts, following LeSage and Pace [2009], confirmed the influence of spillover effects and demonstrated that their consideration could, in some instances, even increase the estimated overall impact. In conclusion, the [Baylis et al., 2011] study underscores the necessity of explicitly integrating the spatial dimension into panel data models in future research to achieve a precise understanding of climate change impacts on agriculture, avoiding the overestimation resulting from the omission of spatial spillover effects.

More recently, Yun and Gramig [2022] analyzed spatial econometric models and specifications of crop yield response functions to evaluate the empirical alternatives available to researchers. Using county-level corn yield data from the United States (east of the 100th meridian, from 1981 to 2018), they compared 14 competing panel regression models, including spatial models (SEM, SAR, SLX, KKP) and non-spatial models (pooled, fixed effects, random effects). A comparative analysis of prediction performance (in-sample, out-of-sample, and bootstrapped out-of-sample) was conducted. Results show that fixed effects spatial error models (SEM) were the best out-of-sample predictors, outperforming both non-spatial models and the spatial autoregressive model (SAR), which showed poor out-of-sample performance. The inclusion of spatial correlation in the error terms significantly improved predictive capabilities, with important implications for public policies adapting to climate change. The study builds upon extensive prior research on climate impacts on US agriculture, highlighting the underutilization of spatial econometrics in crop yield response functions despite the growing attention to spatial correlation in Ricardian studies.

South American Case Studies

The study by Seo et al. [2008], which analyzed the impact of climate change on South American

Table 3: Summary of Spatial Panel Models Studies

Study	Results	Models
U.S. Case Studies		
Baylis et al. [2011]	Spatial models show lower climate impacts than non-spatial models, revealing an overestimation in the latter due to the absence of spatial dependencies. Analysis of direct and indirect effects confirms the importance of spatial spillovers. Considering these spillovers can even, in some cases, increase the estimate of the overall impact.	**SAR** and **SEM**
Ortiz-Bobea [2015]	The SDM model provides a better estimate of the real impact of climate change by accounting for development pressure on agricultural land, confirming the influence of spatially dependent omitted variables.	**SEM** and **SDM**
Miao et al. [2016]	The study uses a panel data approach that controls for spatial error autocorrelation. This approach yields more efficient estimates and more reliable hypothesis tests, leading to a better understanding of the impact of explanatory variables on corn and soybean yields in rain-fed U.S. regions.	**SEM**
Yun and Gramig [2022]	Comparison of the predictive performance of different models (including spatial and non-spatial models) demonstrates the superiority of models incorporating spatial correlation, particularly SEM, for in-sample, out-of-sample, and bootstrapped predictions. This means these models better predict crop yields, both in the past and future.	**SAR**, **SLX** and **SEM**
South American Case Studies		
Seo et al. [2008]	The study uses models to analyze the impact of climate change on small Andean farmers. Results show that the marginal effects of temperature and precipitation changes are generally smaller when spatial dependence is integrated into the models. The study also highlights the particular vulnerability of Andean countries to climate change.	**SAR** and **SEM**
Asian Case Studies		
Kumar [2011]	Spatial models estimate a significantly less negative impact of climate change on net farm income in India than non-spatial models, correcting an overestimation due to spatial autocorrelation. This difference is illustrated by an estimated annual income decrease of only 3% with the spatial model, compared to 8.4% to 12% with non-spatial models.	**SAR** and **SEM**
Chen et al. [2016]	Spatial error correlation is significant, suggesting that non-spatial models underestimate the real impact of climate change on crop yields in China. Estimates indicate an economic loss of $595 to 858$ million for the corn and soybean sectors during the decade studied.	**SEM**

Table 4: Summary of Spatial Panel Models Studies (Continued)

Study	Results	Models
Europe Case Studies		
Vaitkeviciute et al. [2019]	Marginal warming would benefit European agriculture on average, but Southern countries would be penalized by a temperature increase of only 1°C. Non-marginal climate change would have a clear negative impact, with significant land value decreases in the South and negative impacts in several Central, Eastern, and Western European countries.	**SEM**
Sub-Saharan Africa Case Studies		
Emediegwu et al. [2022]	Accounting for spatial and temporal spillover effects respectively exacerbates the cumulative effect of wet days and attenuates it; local agricultural production is affected by the production of neighboring countries.	**SDM**
MENA Region Case Studies		
Amouzay et al. [2024]	Short-term marginal effects of temperature and precipitation vary across MENA countries. Simulations based on the SSP5 8.5 scenario (2020-2039) predict a significant negative impact on the MENA region's agricultural production index, with an estimated average decrease of -29.1%.	**SEM**
Zouabi and Peridy [2015]	Spatial spillover effects suggest that climate changes in neighboring Tunisian regions affect local agricultural production. The study highlights the importance of spatial autocorrelation in understanding the impact of climate and other factors.	**SAR**, **SEM** and **SDM**
Karahasan and Pinar [2023]	Climate change has a variable effect depending on the region, with a greater impact in the northern and central areas of Turkey. The study highlights the importance of spatial modeling to understand the spatial variability of coefficients and to develop effective policies.	**SAR**, **SEM**
Malaekeh et al. [2024]	Net farm income in Iran is projected to decrease by 8-19% in 2050 and 14-51% in 2080; the distributional impacts of climate change will strongly depend on climate zones and geographic locations; some counties may benefit from climate change; finally, not accounting for spatial spillovers when present leads to a misspecified model.	**SAR** and **SEM**
Amouzay and El Ghini [2024]	FE-SEM analysis reveals a significant impact of meteorological variables on Moroccan agricultural production, as well as the presence of spillover effects between regions, as indicated by a negative and highly significant spatial error autocorrelation coefficient.	**SEM**

agriculture, utilized panel data from surveys of over 2,000 farms across seven countries (Argentina, Uruguay, Chile, Brazil, Venezuela, Ecuador, and Colombia) covering the 2003-2004 agricultural seasons. Seo et al. [2008] compared four econometric models: Ordinary Least Squares (OLS), a fixed-effects panel model, and two spatial models (SAR and SEM). Results revealed that the aspatial models (OLS and fixed effects), by neglecting the spatial correlation of land values, overestimated the impact of climate change. These models, failing to account for spatial dependence, exhibited larger and statistically significant effects of climate change (temperature and precipitation) compared to the spatial models. The estimated climate parameters were higher and statistically significant, indicating an overestimation of climate change's impact on land values. This overestimation stems from the failure to account for the spatial correlation of land values (nearby farms exhibiting similar values). Variations in land values attributed to climate could, in reality, originate from geographic proximity and correlated spatial factors. Incorporating spatial dependence yielded substantially different estimates. The marginal effects of climate change (temperature and precipitation) were significantly lower than in the aspatial models. The elasticities, measuring the sensitivity of land values to climate variations, were also considerably lower, indicating that the true impact of climate change is less pronounced than aspatial models suggest. A slight difference was observed between the SAR and SEM models. For temperature effects, the SEM model showed even lower marginal effects than the SAR model. Conversely, for precipitation effects, the SEM model showed slightly larger effects than the SAR model. This difference underscores the sensitivity of results to the choice of spatial model. Finally, the study tested the robustness of the results using an alternative spatial weights matrix, based on provincial instead of district land values. Although spatial correlation statistics were lower with this new matrix, the marginal effect of temperature was substantially larger (twice as large as in the SAR and SEM models), yet remained twice as small as that of the OLS model. This highlights the importance of spatial weights matrix selection but confirms that spatial models provide more realistic estimates of climate change impact than aspatial models. Based on these findings, Seo et al. [2008] suggested that adaptation, particularly through crop diversification and the adoption of more resilient agricultural practices, might be a more effective and less costly strategy than large-scale mitigation in certain contexts. However, this does not imply that mitigation is unnecessary; both strategies are complementary.

ASIA Case Studies

[Kumar, 2011] examined the impact of climate change on net farm revenue in India using spatial panel data for 271 districts over the period 1966–1986. The analysis incorporated spatial econometric models (SAR and SEM) to correct for the significant spatial autocorrelation detected. Compared to aspatial models, spatial models produced consistently lower estimates of climate change's impact on agricultural income, suggesting that aspatial models overestimated the negative effects. For example, in an illustrative scenario of a temperature increase +2° C and a precipitation increase +7%, the aspatial model estimated an average annual decline of 8.4% in net farm revenue [Kumar and Parikh, 2001] or even 12% according to other studies. In contrast, the preferred spatial model (the spatial error model, with an adjusted R^2 of 0.72 compared to 0.65 for the spatial lag model) estimated an annual decline of only 3%. This result underscores the importance of accounting for spatial effects, with autocorrelation leading to a significant overestimation of negative impacts in aspatial models. The study also showed that the impact varied spatially, with some eastern regions (Bihar, West Bengal, and parts of Karnataka) potentially experiencing less negative impacts than others. The author thus recommended improvements in the dissemination of agricultural information through market forces and local leadership for better adaptation, along with further research on large-scale public adaptation strategies for better integration into national development. However, the study did not offer a precise quantification of the economic impact of the recommended adaptation policies.

[Chen et al., 2016] analyzed the impact of climate change on corn and soybean yields in China. Using a county-level panel dataset (approximately 2570 counties, excluding the Qinghai-Tibet Plateau) covering the period 2001–2009, they estimated spatial error models to account for the significant spatial autocorrelation of error terms, as revealed by statistical tests. Unlike previous studies that omitted this spatial dimension or used only ex-post corrections, this study demonstrates that omitting solar radiation in the models leads to an underestimation of the effect of precipitation. The analysis highlights non-linear relationships (inverted U-shaped) between yields and climate variables, along with the negative impact of extremely high temperatures. Estimates indicate an economic loss of $595–858 million for the corn and soybean sectors during the decade studied. The projections for 2100, based on the *Hadley III* model, predict significant yield declines (3 to 12% for corn and 7 to 19% for soybeans), primarily due to higher temperatures. The authors conclude that more rigorous analyses are needed to inform adaptation policies in China, and their results suggest necessary adaptations depending on projected climate change scenarios.

Europe Case Studies

Vaitkeviciute et al. [2019] investigated the impact of climate change on European agriculture by analyzing the choice of climate variables in Ricardian models and taking into account spatial correlation. Using panel data from the EU Farm Accountancy Data Network (FADN) for the period 2004-2012, aggregated to the FADN regional level (107 regions), the authors tested three hypotheses related to the use of degree-day models. They compared the results of Ricardian models incorporating a spatial error model with random effects (SEM-RE) with those of non-spatial models (pooled OLS, random effects, fixed effects, and a SEM model without random effects) to assess the impact of heterogeneity and spatial autocorrelation. Their analysis revealed the importance of climate variables outside the growing season, highlighting the risk of underestimating the impacts of climate change if these data are omitted. Climate change simulations, based on RCP 2.6 and 8.5 scenarios, indicated heterogeneous impacts on agricultural land values, with potential benefits for northern Europe and losses for southern Europe. Vaitkeviciute et al. [2019] highlighted the need for effective and efficient adaptation policies, particularly within the European Common Agricultural Policy (CAP), promoting the development of climate resilient technologies and varieties and considering climate variability beyond the simple growing season.

Middle East and North Africa (MENA) region Case Studies

Amouzay et al. [2024] investigated the economic impact of climate change on agriculture in the MENA region using a spatial panel econometric approach. Employing data from 20 countries over the period 1991–2018, they explicitly addressed spatial autocorrelation by estimating a fixed-effects spatial error model (FE-SEM) that incorporates spillover effects between neighboring countries. This model revealed a non-linear relationship between agricultural production and meteorological variables (temperature and precipitation), with short-term marginal effects varying across countries. A direct comparison of FE-SEM results with those from a non-spatial (fixed-effects OLS) model demonstrated the spatial model's superiority in terms of estimation precision. Simulations based on the SSP5 8.5 scenario (2020–2039) projected a substantial negative impact on the MENA region's agricultural production index, with an average decline of -29.1%. These findings, supported by analyses of the variability in marginal climate impacts across countries, underscore the need for policymakers to prioritize adaptation strategies, invest in sustainable resource management, and foster international collaboration to mitigate the effects of climate change on agriculture in the region.

Sub-Saharan Africa Case Studies

Emediegwu et al. [2022] studied the economic impact of climate change on agricultural production in sub-Saharan Africa, focusing on pearl millet yields, a major cereal for regional food security. Using panel data from 31 countries over the period 1970-2016, aggregated to the level of main production areas (MPAs), the authors employed a sophisticated spatio-temporal econometric methodology, incorporating a spatial Durbin model (SDM) to capture spatial and temporal correlations in yields and explanatory variables (temperature, wet-day frequency, vapor pressure deficit). Unlike previous studies that often neglected spatial effects in sub-Saharan Africa, this analysis highlights the importance of these effects, showing that local production is influenced by the weather conditions in neighboring areas. The results, robust to multiple sensitivity checks, confirm the significant and contemporaneous impact of local meteorological variables (vapor pressure deficit, wet-day frequency, temperature) on millet yields. For instance, the direct effect of vapor pressure deficit (VPD) on yield is estimated at -0.27 in the non-spatial (NS) model and -0.21 in the SDM model, illustrating the attenuation of the negative VPD effect when spatial effects are integrated. Similarly, the total effect of wet-day frequency (WDF) increases from 0.023 in the NS model to 0.028 in the SDM model, highlighting the amplification of the positive impact when spatial diffusion effects are considered. Projections for 2040-2069, incorporating global climate models (GCMs) under the RCP 8.5 scenario, predict heterogeneous impacts on yields, with potentially substantial declines in certain regions, particularly in sub-Saharan Africa. Emediegwu et al. [2022] concluded by emphasizing the importance of considering the spatial and temporal dimensions of climate change impacts when developing adaptation policies in sub-Saharan Africa, encouraging the development of climate-resilient technologies and crop varieties. The comparison with non-spatial models, illustrated by the quantitative differences in the estimated effects of VPD and WDF, underscores the crucial contribution of spatial modeling for a better understanding and prediction of climate change impacts on the region's agricultural systems.

Consequently, the studies reviewed demonstrate that analyzing the impact of climate change on agriculture necessitates incorporating spatial autocorrelation. Spatial econometric models, unlike their aspatial counterparts, account for the dependence among geographically proximate observations (e.g., the influence of neighboring counties, spillover effects), thereby yielding more accurate and reliable impact estimates. These models explicitly consider regional variations in climate conditions, soil types, and agricultural practices. Ignoring these spatial interactions leads to biased and unrealistic results.

4 Conclusion

This paper explored the complexities of quantifying the impacts of climate change on agriculture, highlighting the limitations of traditional econometric approaches like Ricardian and profit models. While these models provide valuable insights, they fail to adequately capture spatial dependence, heterogeneity, and spillover effects that significantly influence agricultural outcomes.

The emergence of spatial econometrics offers a promising alternative by explicitly incorporating spatial relationships, providing a more nuanced and accurate understanding of climate change impacts. This approach acknowledges that agricultural production, land values, and farmer adaptation strategies are not isolated phenomena but are influenced by the spatial context, including proximity to markets, resource sharing, information diffusion, and the spatial correlation of climatic variables.

Our review of pioneering studies employing spatial econometric models (SAR, SEM, SLX, SARAR and SDM) demonstrates the significance of these approaches. These studies reveal that neglecting spatial dependence can lead to biased estimations and inaccurate predictions of climate change impacts. The incorporation of spatial effects often results in smaller marginal effects of climate variables, suggesting that traditional non-spatial models may overestimate the negative consequences of climate change. Furthermore, these studies highlight the importance of understanding both direct and indirect impacts, including spillover effects, which can influence agricultural practices and land rents.

However, the use of spatial econometrics presents significant methodological challenges. The choice of the spatial weights matrix is crucial and strongly influences the results; inadequate specification can bias estimations. Furthermore, a distinctive characteristic of spatial asymptotics is that they can be approached in two ways: by increasing domain (adding observations at the boundaries, similar to time series asymptotics) or by infill (adding observations within a bounded domain, generating an increasingly dense surface) [Cressie, 2015]. These two approaches are not equivalent, which complicates the interpretation of results [Anselin, 2001a]. The presence of spatial weights necessitates the use of Central Limit Theorems (CLTs) and Laws of Large Numbers (LLNs) for triangular arrays, adding further complexity. Finally, the inherent heteroskedasticity in some spatial models (particularly SAR and SMA) requires robust and more complex estimation methods [Anselin, 2001a].

Despite the methodological complexities related to data availability, model specification, and estimation, the advantages of spatial econometrics—particularly the significant reduction in bias amplification due to spatially correlated omitted variables—outweigh the challenges. While this approach does not completely eliminate bias, it mitigates this amplification effect, leading to more robust estimates [Ortiz-Bobea, 2015]. The insights derived are crucial for developing effective adaptation policies tailored to specific regional contexts. Understanding the spatial nuances of climate change impacts allows policymakers to better guide interventions, allocate resources efficiently, and promote sustainable agricultural practices. However, the inherent limitations of the hedonic approach, including its observational nature and reduced-form specification, must be acknowledged. These limitations, which may overlook major future changes (e.g., increased atmospheric CO2, aquifer depletion) and prevent a detailed analysis of farmer adaptation mechanisms, highlight the need for future research focused on adaptation and data-scarce regions [Ortiz-Bobea and Just, 2013]. The use of bioeconomic models, which integrate biophysical and economic components for a better understanding of complex interactions, could provide more in-depth explanations of climate change impacts on agriculture [Lokonon et al., 2019].

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