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Heterogeneous Impact of Land-Use on Climate Change: Study From a Spatial Perspective

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Studies have shown that land and climate interact in complex ways through multiple biophysical and biogeochemical feedbacks. In this interaction mechanism, the carbon fixation effect among different land-use types and objective conditions among different regions have significant gaps, leading to the heterogeneous impact of land-use on climate change. This study takes temperature change as the observation index to reflect climate change, and analyzes the process of land use type adjustment affecting vegetation cover and climate change. Based on the data of 214 countries from 1990 to 2018, this paper uses the spatial Durbin model with temperature lag to verify the heterogeneous impact of land-use on climate change in two dimensions of land-use type (Agriculture, forestry and their subdivision structure) and region (latitude and land-sea difference). The following conclusions are drawn: 1) The impact of different land-use types on climate change is heterogeneous. The impact of agricultural land on climate change is not significant, but the increase of the forest land proportion will help to restrain the rise of national temperature. 2) The impact of land-use on climate change has regional heterogeneity. There is heterogeneity in the impact on climate change among sample countries of different latitudes. The geographical differences make the mechanism of land-use affecting climate change between island countries and mainland countries also have heterogeneity, mainly in that island countries are not affected by the land-use structure adjustment of neighboring countries. 3) A country's climate change is affected by both its own land-use structure and the land-use structure of neighboring countries, and the latter is more critical. The conclusions in this study provide helpful supplementary evidence for the importance of international climate cooperation and provide a reference for proposing international initiatives to address climate change or establishing an international convention to address climate change.

Keywords: land-use, climate change, heterogeneity, spatial durbin model, latitude

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1 INTRODUCTION

1.1 Literature Review

Global warming is a natural phenomenon that has been widely confirmed by theory and reality. It not only endangers the balance of the natural ecosystem, but also seriously threatens the survival and development of human beings. The available literature indicates that land and climate interact in complex ways through multiple biophysical and biogeochemical feedbacks at different temporal and spatial scales. This inevitably leads to an important academic question worthy of discussion: does the difference of land use types affect the mechanism of its impact on climate change? And what impact will land use type adjustment have on climate change? Given that no observational information is available on how historical land-use structure changes affect global and regional climate, simulation experiments are generally used to estimate the contribution of anthropogenic land cover changes to global warming, including the biogeochemical and biophysical effects of land affecting climate (Byrne and O'gorman, 2013; Sejas et al., 2014; Wallace and Joshi, 2018; Allen et al., 2019). The biogeochemical effect of land on climate refers specifically to the process of regulating the carbon cycle due to net carbon dioxide emissions (Avitabile et al., 2016), while the biophysical effect of land on climate is mainly reflected in the influence of surface characteristics such as surface albedo and surface roughness on ground temperature, humidity, wind speed and evapotranspiration (Ipcc et al., 2013; Forzieri et al., 2017). Another crucial potential feedback from land to climate has to do with the decay of permafrost. After climate warming leads to the decay of glacial permafrost, the released carbon dioxide or methane will cause additional greenhouse effects (Mcguire et al., 2018). However, the extent of this feedback is still uncertain and controversial. The impact of land surface changes on the local and regional climate can be as significant as the impact of increasing greenhouse gas emissions (Berckmans et al., 2019).

The path of land-use affecting climate change has been supported by many empirical studies. Agricultural management, agroforestry, and the resulting surface changes alter the global carbon cycle and surface albedo, altering the Earth's radiative balance. This makes land-use change the second human source of climate change after burning fossil fuels (Li F. et al., 2021; Yang et al., 2021). Gries et al. (2019) study shows a significant positive long-term equilibrium relationship between land-use change and air temperature series, while there is an opposite short-term effect, i.e., land-use change can lead to global warming, but the rising temperature will reduce land-use change. Researchers discussed the current three research challenges of land-use and land-cover change in providing continuous and reliable time-series data, considering overall and structural changes of land-use and managing land allocation; they also proposed the direction for improving the analysis on the terrestrial biosphere models (Prestele et al., 2017; Tong and Liu, 2020). Parks et al. (2020) indicates that previous evaluations of climate connectivity underestimate climate change exposure because they do not account for human impacts. Human land-uses reduce climate connectivity across North America. Cho and Mccarl, (2021) found that human land-uses increase resistance to movement or alter movement routes and thus influence climate connectivity across North America. Nong et al. (2021) used satellite remote sensing and household survey data to research changes in coastal agricultural land-use in response to climate change in Vietnam. After evaluating more than 7,000 research results, the Intergovernmental Panel on Climate Change (IPCC) has confirmed that regional climate change can be inhibited or enhanced through changes in land cover status and land-use structure, but this is also affected by factors such as seasonal and geographical distribution (Ipcc et al., 2018).

Forest and agricultural land are the main factors in the path of land-use affecting climate change, so they have become the focus of previous researches and reflect a certain degree of heterogeneity. According to the 2030 mitigation measures pledged by countries in the Paris Agreement, the reduction of deforestation and forest carbon sequestration, soil carbon sequestration, agricultural management, and bioenergy are explicitly mentioned because of the critical impact of land cover and land-use structure on climate change. A large number of studies have shown that deforestation will cause surface and atmospheric temperature rise, and afforestation is conducive to surface and atmospheric temperature drops. Lejeune et al. (2018) found that historical deforestation increased extreme hot temperatures in high and middle latitudes. Studies in Africa, South America, and Southeast Asia have found that deforestation can reduce evapotranspiration and increase surface temperature (Lejeune et al., 2015; Spracklen and Garcia-Carreras, 2015; Boone et al., 2016; Hartley et al., 2016; Klein et al., 2017; Toelle et al., 2017; Wu et al., 2017). Examples of West Africa, China, the Sahara Desert, and the Australian Desert have confirmed the effect of large-scale afforestation on reducing surface temperature (Abiodun et al., 2012; Ma et al., 2013; Kemena et al., 2018; Haque and Rashid, 2019). Arora and Montenegro, (2011) combined large-scale afforestation with climate change scenarios and found that tropical afforestation is more conducive to cooling climate than temperate afforestation. These results indicate that the mechanism of land-use structure influencing climate change has regional heterogeneity due to latitude differences. Azadi et al. (2021) discussed the relationship between climate change and agricultural land conversion based on the data of countries in different income groups, and they found that agricultural land area in high-income countries is decreasing, but carbon dioxide emissions are increasing, while in low-income countries, agricultural land area has increased and carbon dioxide emissions have decreased (Solana, 2020). Therefore, non-agricultural land conversion may be one of the driving factors of climate change, and land-use conversion is an essential source of carbon dioxide emissions. It is consistent with the results concluded by the United Nations Environment Programme (UNEP) that Agricultural Land-use Change (ALC) can increase CO_2 emissions by disturbing soils and vegetation, and deforestation is the primary driver, in particular when agriculture is taken up (Kanter et al., 2013).

It is worth noting that the impact of land-use on climate change has spillover effect and spatial correlation. Abiodun et al. (2012) found that deforestation sometimes did not lead to local temperature increase but would lead to temperature increase in neighboring countries, indicating a spatial correlation between the impacts of deforestation and land-use structure change on climate. IPCC also mentioned that some studies have shown that changes in land cover or water available for irrigation will affect the climate in areas hundreds of kilometers downwind, indicating that the impact of land on climate change has a trans-regional spillover effect (Ipcc et al., 2018).

1.2 Research Motivation and Hypothesis

Based on the literature review, it is not difficult to find that the existing research on the mechanism of land-use and climate change mostly takes individual countries or regions as the research object. The representativeness and rationality of sample selection need to be discussed, and the robustness and generalization of the corresponding analysis conclusions can be further optimized (Lehner et al., 2018; Lopez et al., 2018; Tabari and Willems, 2018). In order to make up for this deficiency, this study not only expands the sample value range but also focuses on testing whether there is regional heterogeneity in the impact of land-use on climate change. Suppose the test confirms the existence of regional heterogeneity in the impact of land-use on climate change. In that case, it can confirm the deficiency of the conclusions of existing literature based on the analysis of individual sample country or region.

Firstly, different types of land-use may influence the biogeochemical effects of land on climate change. The land is considered to have a significant impact on climate change and the greenhouse effect, including through the carbon sequestration of plants attached to the land (Li et al., 2020), carbon dioxide release through respiration by plants, animals, and microorganisms (Collalti et al., 2020), and greenhouse gases released permafrost temperatures rise (Brentrup et al., 2021). Land-use type and land-use structure are key factors affecting climate change and the greenhouse effect (Dirmeyer et al., 2010). Intuitively, it is easy to understand that different land cover types, such as forest and farmland, are different in the carbon dioxide emission and absorption mode; their impact on the carbon cycle and seasonal characteristics of climate change are also different (Searchinger et al., 2018). Fujita et al. (2019) distinguishes six land-use categories in Japan and projects future trends of each land-use type under alternative climate and population change scenarios. This study attempts to explore the mechanism of land use type adjustment affecting temperature change and climate change by affecting atmospheric carbon cycle. Among them, land use type adjustment is the driving factor, and land use type adjustment will change vegetation structure and eventually affect atmospheric carbon cycle. Atmospheric carbon cycle is the key factor affecting temperature change, and temperature change is an important observation index reflecting climate change. Different land-use types, such as agricultural land and forest land, or arable land and agricultural land attached with permanent perennial crops, natural forest, and planted forest felled regularly, may have different efficiency and seasonal characteristics of carbon dioxide absorption and emission, which may lead to heterogeneity of land-use impact on climate change. Thus, we propose the first research hypothesis:

H1: The impacts of different land-use types on climate change are heterogeneous.

Secondly, the differences in geographical distribution, latitude, climate zone, and water cycle environment may also lead to the heterogeneity of the biophysical effects of land on climate. From the climate perspective, there are different temperature zones in the world, such as those in high latitudes, middle latitudes, and low latitudes. Countries with different temperature zones also have vast differences in geographical environment, land development degree, and vegetation distribution (Zhu et al., 2021), so it is likely to produce regional heterogeneity in the interaction mechanism between land and climate. The biophysical effects of land on climate are different due to the surface albedo (Dong et al., 2021), surface roughness (Li and Bo, 2019), atmospheric humidity (Byrne and O'gorman, 2018), wind speed (Jeong and Sushama, 2019), and evapotranspiration (Zhang et al., 2019). The geographical distribution characteristics, latitude and the climatic zone characteristics, the distribution of rivers and lakes, and the location from the coastline of different regions may affect the size and direction of the biophysical effects. Therefore, we put forward the second research hypothesis:

H2: There is regional heterogeneity in the impact of land-use on climate change.

In addition, the spatial correlation between land-use and climate change also deserves attention. Considering that the natural boundary of climate zones does not coincide with the national boundary lines, and the cross-border interaction between land and climate is almost inevitable (Hedlund et al., 2018; Benzie and Persson, 2019), it is natural to think that a country's change in climate is affected not only by its own land-use structure but also by the land-use types of surrounding areas. Therefore, from the perspective of the boundary of the actual national border, there should be cross-regional spatial effects caused by land and climate interaction. Suppose the impact of land-use on climate change is heterogeneous due to the differences in land-use types and regional distribution. In that case, we cannot help but think about the conclusions of examining the impact of land-use on climate change from a more macro perspective transcends the existing national and regional boundaries. Considering the spatial Durbin model used in this study, it is helpful to study the spatial correlation of land impact on climate change. Therefore, we propose the third research hypothesis:

H3: The impact of land-use on climate change is spatially correlated.

It is conceivable that if the difference of land-use types causes the heterogeneity of land impact on climate change, the adjustment of land-use structure may substantially impact climate change. Therefore, land-use planning can also be an effective means to deal with climate change and the greenhouse effect. The existence or otherwise of regional heterogeneity is related to whether the national experience can be used for reference and promotion without distinction. It has essential reference values for strengthening the international coordination on climate change.

The 26th United Nations climate change conference will be held in Glasgow, United Kingdom, from November 1 to 12, 2021. Countries worldwide will discuss cooperation to increase climate action, build climate resilience and reduce carbon emissions to deal with global climate change. The study on the transnational impact of land-use and climate change can provide a valuable reference for putting forward international initiatives to deal with climate change or formulating international conventions to deal with climate change.

The paper is structured as follows: the first section is the introduction. Based on the introduction of empirical facts and the summary of existing literature, the core question of this study is put forward, that is, whether there is heterogeneity in the impact mechanism of land on climate change due to different land-use types and regions. The second section presents the data and methods for the research. This part mainly includes the selection of key indicators and descriptive statistical analysis, and the introduction of the main research methods. **Sections 3** and **4** build econometric models and conduct empirical analysis to examine the main research objectives of this paper. The fifth section outlines the research summary and implications.

2 DATA AND METHODS

2.1 Methodological Steps

The specific research objectives of this paper are mainly reflected in the following aspects. First, based on extensive sample data, this paper attempts to confirm that there is heterogeneity in the impact of different land-use types on climate change. In this study, land-use types are grouped into agricultural land (AL) and forest land (FL) to investigate the impact heterogeneity of different land-use types on climate change. Agricultural land is further divided into arable land (AraL), land under permanent crops (PCL), and land under permanent meadows and pastures (PMPL), and forest land is subdivided into naturally regenerating forest land (NRFL) and planted forest land (PFL). The specific classification descriptions come from the database of the Food and Agriculture Organization of the United Nations (https://www.fao.org/faostat/zh/#data/RL). Second, the data based on latitude grouping and geographic distribution feature grouping attempts to confirm the regional heterogeneity of land-use impact on climate change. In terms of sample selection, this study analyzes the data of 214 countries around the world. It divides the sample countries into two categories: countries of high, middle, and low latitude and countries of island and continent. On this basis, the regional differences of the effects of land-use on climate change are investigated. Third, the spatial correlation of land-use impact on climate change is confirmed from multiple levels. The spatial correlation of land-use impacts on climate change has been widely confirmed by the benchmark model, the spatial Durbin model, and the models grouped by land-use subcategories as well as sample country types.

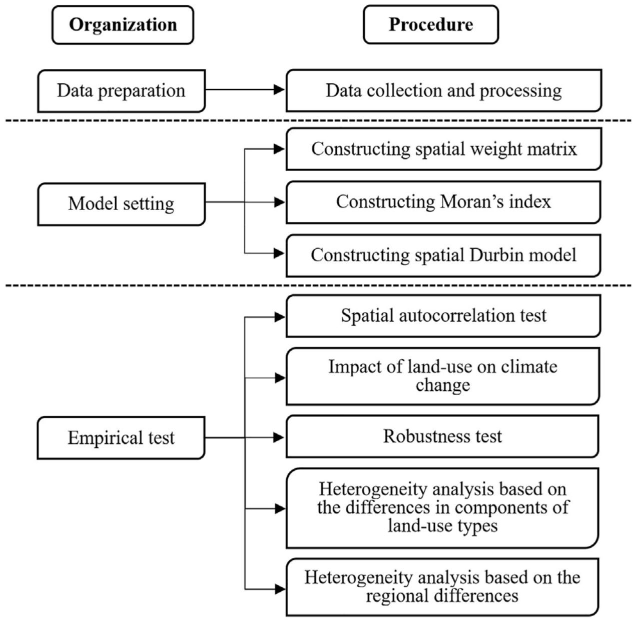

FIGURE 1 | The methodological steps of this paper.

Figure 1 illustrates this research's methodological steps.

2.2 Data Sources

2.2.1 Dependent Variable

In this paper, the temperature anomaly is selected as the dependent variable to represent climate change. Temperature anomaly is one of the important variables used to measure climate change in scientific research, which a large number of climate studies has proved in the past (Huntingford and Cox, 2000; Lee and Ouarda, 2012; Bury et al., 2019). Compared with other variables measuring climate change (such as the absolute value of temperature), temperature anomaly has several advantages. One is the comparability of data. If the ordinary absolute value index is used to measure climate change, due to the differences of original geographical environment in various regions, there will be a false spatial spillover effect in spatial econometrics, and this error is difficult to be eliminated by control variables. The second is the availability of data. Climate change research is one of the critical points of environmental research. In the past, many kinds of indicators have been used to explain, such as temperature, precipitation, haze, and air pressure, but the temperature is always the main factor and has generally recognized data sources. Given a large number of national research samples in this paper, it is not easy to find an appropriate and complete variable to explain climate change, and the temperature anomaly meets these conditions.

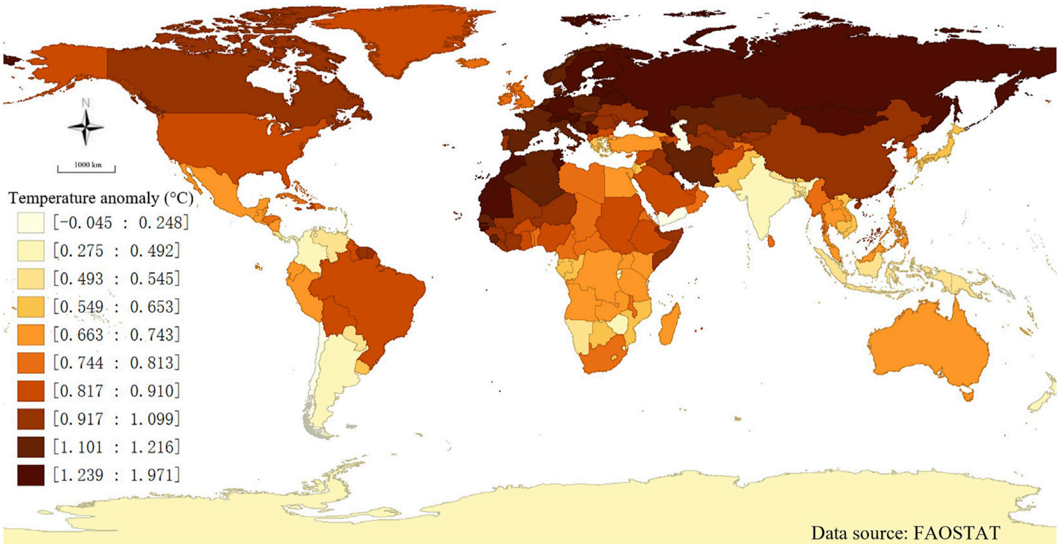

FIGURE 2 | Average temperature anomalies from 1990 to 2018.

The time and space dimensions are 1990–2018 and 214 countries, respectively, and they are the same for the following independent variables and control variables. The temperature anomaly data, published by the Food and Agriculture Organization Corporate Statistical Database (FAOSTAT), are updated annually according to the national average land surface temperature change statistics. The data currently released cover the period from 1961 to 2020. Statistical data of monthly, seasonal, and annual mean temperature anomalies, i.e., the baseline climatological temperature changes corresponding to the period from 1951 to 1980, can be obtained. The standard deviation of the temperature change of the reference method can also be obtained. These data are based on the public GISTEMP data, i.e., the Global Surface Temperature Change data released by the National Aeronautics and Space Administration Goddard Institute for Space Studies (NASA-GISS). The GISS Surface Temperature Analysis (GISTEMP) is an estimate of global surface temperature change. Graphs and tables are updated around the middle of every month using current data files from NOAA GHCN v4 (meteorological stations) and ERSST v5 (ocean areas). These updated files incorporate reports for the previous month and also late reports and corrections for earlier months. The temperature anomaly data are from FAOSTAT, and there is no missing or artificial supplement. **Figure 2** shows the annual average temperature anomalies of countries worldwide from 1990 to 2018 using the GeoDa software. In **Figure 2**, according to the decile method, the color depth is used to represent the distribution of temperature anomalies. The darker the color is, the greater the temperature change is. It can be seen that the temperature rise in northwest Africa, Europe and northern Asia is large, while that in southern Africa, South America and southern Asia is small.

2.2.2 Independent Variables

In this paper, the proportion of different land-use in different countries is selected as the independent variable. Because of large area differences among countries, simply using the absolute value of land-use area can lead to strong data discrete trend and large heteroscedasticity, which is not in line with the overall goal of this paper to analyze the heterogeneity of land-use types. Therefore, this paper selects the ratio of land-use types to the total area of the country to represent land-use, making the comparison among countries more scientific and reasonable. The specific independent variables are the proportion of agricultural area, which can be decomposed into the proportion of arable land, the proportion of permanent crops, and the proportion of meadows and pasture land; as well as the proportion of forest area, which can be decomposed into the proportion of natural forest and the proportion of planted forest. The land-use area data comes from the United Nations Food and Agriculture Organization, with no missing and artificial supplements.

2.2.3 Control Variables

In this paper, six control variables are selected to control the social factors that affect climate except for land-use. They are GDP per land (100 USD/ha), population per land (1000 P/ha), capital stock per land (10 USD/ha), industrial added value as a percentage of GDP (%), CO2 emission per land (0.1 MM tons/ha) and energy consumption per land (quad Btu/ha). The above variables are ratios, and the reasons for selection are the same as those for independent variables. In addition, the first-order lag variable of temperature anomaly (°C) is controlled to exclude the lag effect caused by the previous year's temperature. The above data are obtained from PWT10.0, United States Energy Information (EIA), and

TABLE 1 | Variable data source.

Variable	Abbr	Source
Temperature change (temperature anomalies)	Temchan	FAOSTAT
The proportion of agricultural land	AL	FAOSTAT
The proportion of arable land	AraL	FAOSTAT
The proportion of land under permanent crops	PCL	FAOSTAT
The proportion of land under permanent meadows and pastures	PMPL	FAOSTAT
The proportion of forest land	FL	FAOSTAT
The proportion of naturally regenerating forest land	NRFL	FAOSTAT
The proportion of planted Forest land	PFL	FAOSTAT
GDP per land	GDP	PWT10.0
Population per land	Pop	PWT10.0
Capital stock per land	Cap	PWT10.0
Industrial added value/GDP per land	Indus	World Bank
Total CO2 emissions per land	CO2	World Bank
Total energy consumption per land	Energy	EIA

TABLE 2 | Descriptive statistics.

Variable	Unit	Mean	Max	Min	Std
Temchan	°C	0.780	3.039	−1.371	0.569
AL	prop	0.373	0.854	0.002	0.221
AraL	prop	0.134	0.726	0	0.133
PCL	prop	0.048	0.666	0	0.091
PMPL	prop	0.190	0.832	0	0.187
FL	prop	0.332	0.985	0	0.251
NRFL	prop	0.302	0.984	0	0.248
PFL	prop	0.029	0.335	0	0.056
GDP	100USD/ha	4.299	725.485	0	29.803
Pop	p/ha	1.747	81.205	0.001	4.953
Cap	10USD/ha	1.534	294.825	0	12.127
Indus	prop	26.791	213.690	0	15.434
CO2	MM tones/10ha	1.712	344.252	0	15.357
Energy	quad Btu/ha	0.280	52.773	0	2.360

World Bank Database. A few missing data are supplemented by interpolation (Liu et al., 2019; Tapver, 2019; Zawadzki, 2020; Li et al., 2021a; Li et al., 2021b; Li et al., 2022a).

Table 1 lists the data sources of the major variables involved in this study. **Table 2** shows the descriptive statistics of major variables in the study.

2.3 Modelling Procedures

A panel data model is suitable for the analysis of correlations between observed samples in different periods (Li T et al., 2021; Li et al., 2021c; Li et al., 2021d; Li et al., 2022b). In this study, it is helpful to investigate the mechanism of land-use affecting climate change in 214 sample countries over for 40 years. The First Law of Geography, according to Waldo Tobler, (1970), is "everything is related to everything else, but near things are more related than distant things". Climate change in adjacent areas is inherently related, and the change of land-use structure in a particular area may directly or indirectly affect the climate change in neighboring areas. Therefore, it is necessary to study the possible spatial spillover effects of land-use on climate change using the spatial panel model (Zhong and Li, 2020).

The first step is to test the spatial correlation of temperature changes. The most popular method to measure spatial autocorrelation is Moran's I:

$$I = \frac{\Sigma_{i=1}^{n}\Sigma_{j=1}^{n} w_{ij}\left(x_i - \bar{x}\right)\left(x_j - \bar{x}\right)}{S^2 \Sigma_{i=1}^{n}\Sigma_{j=1}^{n} w_{ij}} \# \quad (1)$$

Where, S^2 is the sample variance. w_{ij} is the element (i, j) of spatial weight matrix, and $\Sigma_{i=1}^{n}\Sigma_{j=1}^{n} w_{ij}$ is the sum of all spatial weights.

In the second step, to compare with the spatial panel model, a fixed panel data model without spatial effect is established:

$$TemChan_{it} = \alpha_0 + \alpha_1 TemChan_{i,t-1} + \alpha_2 AL_{it} + \alpha_3 FL_{it} + \alpha X_{it} + \pi_i + \varepsilon_{it} \# \quad (2)$$

In **Eq. 2**, the dependent variable $TemChan_{it}$ represents annual temperature change; the independent variables AL_{it} and FL_{it} represent the proportion of agricultural land and the proportion of forest land; X_{it} represents the six control variables adopted, including GDP per land, population per land, capital stock per land, the proportion of industrial added value in GDP, total CO2 emissions per land, and total energy consumption per land. The formula can be used to reflect the impact of land-use structure on climate change without spatial effect. α_1 represents the lag effect of the temperature change in the last year on the temperature change in the current period (Jia et al., 2021); α_2 and α_3 respectively describe the impact of agricultural land and the forest land on temperature change. Ordinal fixed-effect panel regression can reveal what conclusions will be obtained without considering the impact of sample surrounding countries on local countries. In addition, more importantly, by comparing the goodness of fitting of empirical results with and without spatial effect, this paper can better judge the optimal option of the model.

According to IPCC and other literature (Abiodun et al., 2012; Maimaitiyiming et al., 2014; Ipcc et al., 2018; Sayyadi et al., 2019), land-use in neighboring countries may also affect climate change in their own countries. Spatial Durbin model (SDM) is a combined extension of spatial lag and spatial error term model, which can be established by adding corresponding constraints to spatial lag model and spatial error model. In fact, SDM is a spatial lag model (SAR) enhanced by adding spatial lag variables. This is highly consistent with the spatial autocorrelation of variables in this paper, and we can get more effective conclusions. Therefore, In the third step, to demonstrate whether there is spillover and spatial correlation between land-use and climate change, this paper introduces the weighted term of the spatial weighting matrix of each variable as the explanatory variable and establishes a spatial Durbin model:

$$\begin{aligned} TemChan_{it} = \beta_0 + \beta_1 TemChan_{i,t-1} + \beta_2 \sum_{j \neq i}^{n} WTemChan_{it} \\ + \beta_3 \sum_{j \neq i}^{n} WAL_{it} + \beta_4 \sum_{j \neq i}^{n} WFL_{it} + \beta_5 AL_{it} + \beta_6 FL_{it} \\ + \beta X_{it} + \pi_i + \varepsilon_{it}\# \end{aligned} \tag{3}$$

In **Eq. 3**, $\Sigma_{j \neq i}^{n} W$ is the spatial weighting matrix. In this paper, the Inverse Distance Spatial Weighting Matrix is adopted to calculate the spatial weight (Getis and Aldstadt, 2004), that is, the linear distance between each other is calculated according to the longitude and latitude coordinates of the geographic center of each country, and based on dimensionless processing, the reciprocal is taken as the weight. If the linear distance between the geographic centers of the two sample countries is more than 20, then the weight is assigned to 0, that is, the two sample countries are identified as non-neighborhood relationship (the distance threshold is adjusted in the robustness test later). The meanings of other variables in **Eq. 3** are the same as those in **Eq. 2**. This equation can be used to reflect the influence of land-use structure on climate change when spatial effects are included. According to spatial econometric theory, α_1 represents the lag effect of the temperature change in last year on the temperature change in the current period; β_2 represents the spatial spillover intensity and direction of temperature change in surrounding countries; β_3 and β_4, respectively describe the intensity and direction of the impact of agriculture land and forest land in surrounding countries on local temperature change; β_5 and β_6 respectively describe the intensity and direction of the impact of agriculture land and forest land in local on temperature change.

After that, the robustness test, component heterogeneity and regional heterogeneity test are carried out by using the model of **Eq. 3**. In the robustness test, we adjust the bandwidth and type of W, which is described in 3.3 Robustness Test. In the component heterogeneity test, we adjusted the variables AL and FL in **Eq. 3** to more subdivided land-use types.

In the regional heterogeneity test, we only change the number of regression samples. In **Section 4**, the sample countries are categorized into high latitude group (111 countries with geographic center latitude higher than 60), middle latitude group (75 countries with geographic center latitude between 30 and 60), and low latitude group (28 countries with geographic center latitude lower than 30). The samples are also divided into island countries (45 island countries) and mainland countries (169 countries other than island countries) according to whether they are islands.

From the temperature change indicator in the third row of **Table 3**, we can see the heterogeneity of temperature change among samples. After grouping by latitude, the average temperature change of high latitude sample countries is 0.568°C; the average temperature change of middle latitude sample countries is 0.908°C, and that of low latitude sample countries is 0.747°C. In terms of land-sea difference, the average temperature change of island countries is 0.612°C, while that of non-island continent countries is 0.825°C.

After grouping by latitude, it shows significant differences in land-use structure of sample countries in different groups in **Table 3**. Taking agricultural land as an example, the proportion of agricultural land in high-latitude countries is 24.8%, that in mid-latitude countries is 45.1%, and that in low-latitude countries is 35.2%. In terms of forest land, the proportion of forest land in high-latitude countries, mid-latitude countries and low-latitude countries is 42.8%, 26.9% and 35.0%, respectively. Generally speaking, high latitudes are cold, low latitudes are prone to drought, and middle latitudes are more suitable for crop growth. There are large coniferous forests and hot spot rain forests in high and low latitudes, respectively, which are the areas where natural forests are concentrated.

Considering that there is significant heterogeneity in the degree of climate change and the type of land-use in the sample countries after grouping, it is necessary to investigate whether there is inter-group heterogeneity in the mechanism of land-use impact on climate change.

3 HETEROGENEITY ANALYSIS BASED ON THE DIFFERENCES OF LAND-USE TYPES

3.1 Spatial Autocorrelation Test of Temperature Change

Before analyzing the spatial effect of land-use on climate change, it is necessary to verify whether there is spatial autocorrelation of climate change in each sample country. In this paper, according to **Eq. 1**, the GeoDa software (GeoDa is a free software package that conducts spatial data analysis, geo-visualization, spatial autocorrelation, and spatial modeling) is used to establish the spatial weighting matrix based on the longitude and latitude distance (Anselin et al., 2006), and Moran's I test (Moran's I is a measure of spatial autocorrelation developed by Patrick Alfred Pierce Moran) is used to investigate the annual temperature change of all samples based on the distance spatial weight index (Moran, 1950; Li et al., 2007). The corresponding test results are shown in **Figure 3**, where the range bandwidth in the model is selected from 0–20.

As can be seen from **Figure 3**, the spatial distribution of temperature changes in 214 countries over the past years is not random, but shows significant spatial correlation on the whole, and temperature changes have strong spatial dependence. The results show that the global Moran's I values are all positive, between 0.236 and 0.615, and the Z-values are between 7.69 and 20.88, both of which pass the 1% significance test. Therefore, the spatial distribution of the temperature change levels has a

TABLE 3 | Variable grouping statistics.

Variable	Items	High latitude	Middle latitude	Low latitude	Island countries	Mainland countries
N	-	812	2,175	3,219	1,305	4,901
Temchan	Mean	0.568	0.908	0.747	0.612	0.825
	Std	0.532	0.681	0.466	0.417	0.595
AL	Mean	0.248	0.451	0.352	0.317	0.388
	Std	0.175	0.215	0.215	0.210	0.221
AraL	Mean	0.063	0.181	0.120	0.111	0.140
	Std	0.061	0.132	0.136	0.112	0.137
PCL	Mean	0.112	0.031	0.043	0.109	0.031
	Std	0.184	0.050	0.066	0.135	0.065
PMPL	Mean	0.072	0.238	0.188	0.096	0.215
	Std	0.082	0.210	0.176	0.148	0.188
FL	Mean	0.428	0.269	0.350	0.377	0.320
	Std	0.259	0.212	0.263	0.267	0.246
NRFL	Mean	0.394	0.216	0.337	0.338	0.292
	Std	0.233	0.203	0.262	0.256	0.245
PFL	Mean	0.034	0.051	0.013	0.039	0.026
	Std	0.077	0.071	0.025	0.063	0.054

TABLE 4 | Panel regression results without spatial effect.

Items	Temperature change			
	(1)	(2)	(3)	(4)
AL	0.013 (0.42)	0.043 (1.38)	−0.652***(-3.43)	−0.684***(-3.62)
FL	−0.054**(-2.13)	−0.046*(1.81)	−1.194***(-3.40)	−1.149***(-3.29)
TemChan_lag	0.577***(53.45)	0.569***(52.19)	0.399***(32.38)	0.376***(30.26)
GDP	-	0.003 (1.45)	-	0.001 (0.23)
Pop	-	−0.008***(-2.85)	-	0.141***(7.87)
Cap	-	0.001 (0.23)	-	−0.002 (-0.32)
Indus	-	0.001***(2.92)	-	−0.005***(-4.73)
CO2	-	−0.001 (-0.23)	-	−0.007 (-1.08)
Energy	-	−0.013 (-0.38)	-	−0.055 (-1.18)
Cons	0.362***	0.329***	1.126***	1.042***
FE	No	No	Yes	Yes
N	5,992	5,992	5,992	5,992
R-squared	0.3251	0.3288	0.1492	0.0328

Notes:, **, *** stand for significant levels of 10%, 5% and 1% respectively, and the values in brackets are T-values.*

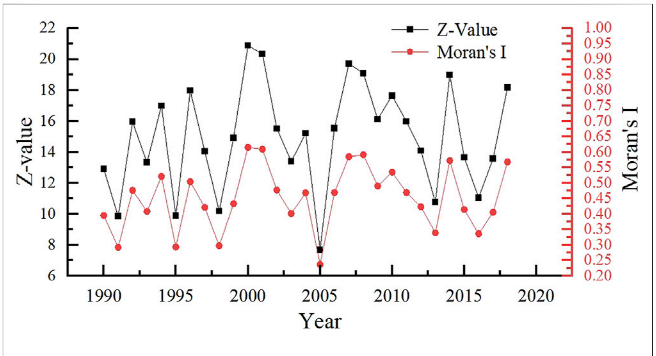

FIGURE 3 | Moran's I and Z-Value evolution of annual temperature change.

significant positive global spatial auto-correlation during the study period, and the temperature change of the local country will be affected by that of its neighboring countries. This analysis conclusion is logical and in line with expectations. It is also consistent with the annual mean temperature anomaly of all countries in the world from 1990 to 2018 shown in **Figure 2**. The division mode of climatic zones does not coincide with the actual national boundaries, and the climate changes in adjacent areas are bound to have a variety of relationships, thus the climate types, direction, and degree of climate change are likely to be related. Based on this, the spatial econometric model can be used for model fitting and analysis after statistical testing.

3.2 Analysis of Benchmark Regression

Table 4 shows the regression results using the benchmark panel model without spatial effect according to **Eq. 2** to test the impact of land-use on climate change. Because all empirical tests in this paper consider the first-order lag factor of temperature change, the actual regression sample is the 28-year data (i.e., 1991-2018) of 214 countries.

According to **Table 4**, it can be found that after adding the lag term TemChan_lag of the dependent variable TemChan, the increase of the proportion of forest land has a significant effect on reducing the national temperature in all the analysis models, but in the analysis results of Columns (3) and (4) that control the individual random effect, the coefficients of the forest land proportion are larger and more significant. Under the condition of not controlling the individual random effect, the coefficients of the agricultural land proportion in Columns (1) and (2) are positive but not significant. If the individual random effect is controlled, the coefficients of agricultural land proportion in Columns (3) and (4) are negative and significant, that is to say, the increase of the proportion of the agricultural land will significantly reduce the temperature level of the country. Therefore, it can be seen that there are significant differences in the impacts of the change of agricultural land and forestry land on climate change, and the impacts of different land-use types on climate change are heterogeneous.

In Columns (1) and (2) without individual random effect control, the lag-term coefficient of the dependent variable $TemChan_{it}$ is larger. In comparison, the coefficient of the agricultural land proportion AL and that of the forest land proportion FL are smaller. After controlling the individual random effect, the coefficients (absolute value) of Al and FL shown in Columns (3) and (4) are larger and significantly enhanced. However, it is worth noting that after controlling the individual random effect, the goodness of fitting R2 of the model will decrease significantly.

In the control variables of **Table 4**, when individual countries are not fixed, that is Column (2), the regression results largely reflect the horizontal comparison between countries. The first-order lag term of temperature change has a significant positive effect on the current temperature change ($\alpha = 0.569$, $p = 0.00$). A country's temperature change depends on various objective conditions. They show strong rigidity in the process of change with time, such as topography, climate zone, and land-sea location. These factors are difficult to quantify and analyze, and the first-order lag of temperature change can well eliminate the influence of these factors. The effect of population density on temperature change is significantly negative ($\alpha = -0.008$, $p = 0.00$). Throughout the world, countries with high development levels usually have high population density. These countries have gradually carried out green economic transformation since modern times, which has played a positive role in climate change. At the same time, climate optimization has also siphoned population migration. The proportion of industrial output value to temperature change is significantly positive ($\alpha = 0.001$, $p = 0.00$). In the horizontal comparison among countries, the development of countries with significant industrial ratios is bound to be accompanied by the emission of a large number of greenhouse gases such as carbon dioxide, which is bound to have a negative impact on the climate. When the individual country is fixed, that is Column (4), the regression results primarily reflect the vertical comparison within the country. The first-order lag of temperature change also has a significant positive impact on the current temperature change ($\alpha = 0.376$, $p = 0.00$), and there is a noticeable time lag effect on the temperature change. The effect of population density on temperature change is significantly positive ($\alpha = 0.141$, $p = 0.00$). At this time, the regression results reflect that the increase of population density within the country will increase local carbon emissions and increase the temperature. The ratio of industrial output value to temperature change is significantly negative ($\alpha = -0.005$, $p = 0.00$). In the development process of a country, the increase in the proportion of industrial output value is often accompanied by industrial upgrading and optimization of resource allocation. More efficient and environmentally friendly technologies are gradually popularized with the progress of the industry, and the climate is improved.

3.3 Analysis of Spatial Durbin Model Regression

Next, according to **Eq. 3**, the regression of the spatial Durbin model is carried out to investigate the spatial correlation of land-use impact on climate change. According to **Table 5**, after adding the spatial weighting matrix, the fitting regression coefficients of $W \times AL$, $W \times FL$ and $W \times Temchan$ which reflect the spatial interaction effect in the four columns are very significant, that is, the impact of land-use on climate change has obvious spatial correlation (Where "W" represents spatial weighting matrix, "AL" represents agricultural land and "FL" represents forestry land). Specifically, $W \times AL$ refers to the proportion of agricultural land in adjacent areas; $W \times FL$ refers to the proportion of forestry land in adjacent areas. In all models, the adjustment of agricultural land proportion in adjacent areas has a more significant impact on local climate change than that of local agricultural land proportion, and the significance is stronger. Similar conclusions exist in the analysis of the proportion of forest land. The impact coefficient of the adjustment of the forest land proportion in adjacent areas represented by $W \times FL$ on the local temperature change is greater than that of the adjustment of the local forest land proportion represented by FL, and the former is more significant.

Further observation shows that the impact of land-use on climate is heterogeneous in land-use types, that is, there are differences between the impact of domestic agricultural land structure adjustment and the impact of forestry land structure adjustment on its own temperature change. The same is true for that of agroforestry structure adjustment in surrounding areas. Specifically, first, in the analysis results shown in Column (4), the impact of agricultural land on climate change is not significant. In contrast, the increase of forestry land will significantly lead to the decrease of temperature (each 1% increase in the proportion of forestry land will reduce the temperature anomaly by 0.326°). This shows that the heterogeneity of the impact of land-use types on climate change exists. Second, the agricultural and forestry land of surrounding countries will significantly reduce domestic temperature. As we mentioned, the flow of carbon dioxide in the atmosphere and the climate change in nature are not bound by human society's national boundaries. The adjustment of land-use structure in neighboring countries will lead to adjusting parameters in land and atmosphere feedback mechanism, affect local carbon dioxide cycle and temperature, and affect

TABLE 5 | The regression results of the spatial Durbin model.

Items	Temperature change			
	(1)	(2)	(3)	(4)
AL	−0.051**(-2.18)	−0.027 (-1.11)	−0.165 (-1.27)	−0.142 (-1.09)
FL	−0.039*(-1.69)	−0.063***(-2.66)	−0.294 (-1.20)	−0.326*(-1.73)
W × AL	−0.460***(-12.59)	−0.491***(-13.44)	−0.976***(-3.54)	−1.018***(-3.68)
W × FL	-0.183***(-6.15)	−0.182***(-6.01)	−0.855**(-2.12)	−0.855**(-2.12)
W × Temchan	0.642***(66.87)	0.650***(67.77)	0.756***(89.86)	0.753***(88.29)
TemChan_lag	0.336***(37.53)	0.328***(36.67)	0.152***(17.56)	0.150***(17.16)
GDP	-	0.002 (1.44)	-	−0.000 (-0.02)
Pop	-	−0.018***(-8.33)	-	0.001 (0.05)
Cap	-	−0.006*(-1.84)	-	0.002 (0.51)
Indus	-	−0.001**(-2.36)	-	−0.002**(-2.40)
CO2	-	0.009**(2.23)	-	0.001 (0.28)
Energy	-	−0.021 (-0.81)	-	−0.016 (-0.52)
FE	No	No	Yes	Yes
N	5,992	5,992	5,992	5,992
R-squared	0.6980	0.7099	0.2142	0.2258

Notes:, **, *** stand for significant levels of 10%, 5% and 1% respectively, and the values in brackets are T-values.*

local climate change. The analysis results in **Table 5** well reflect this phenomenon. Besides, the impact coefficient of the proportion of agricultural land of surrounding countries on the domestic temperature change (the coefficient is negative, the absolute value should be taken for comparison) is always greater than that of the proportion of forestry land of surrounding countries on the domestic temperature change. This indicates that the spatial spillover of land-use to climate change is also heterogeneous due to the difference in land-use types.

In the control variables of **Table 5**, when individual countries are not fixed, that is Column (2), the regression results reflect the horizontal comparison between countries. After considering the spatial effect, the first-order lag of temperature change still plays a significant role in promoting the current temperature change ($\beta = 0.328,\ p = 0.00$), and there is a noticeable time lag effect in the temperature change. The effect of population density on temperature change is significantly negative ($\beta = -0.018,\ p = 0.00$), which is consistent with the regression result without spatial effect, that is, in the horizontal comparison between countries, the temperature rise in areas with high population density is lower, which is related to both green industrial transformation and the orientation of population migration. After considering the spatial effect, the impact of capital stock ($\beta = -0.006,\ p = 0.06$) and industrial output value ($\beta = -0.001,\ p = 0.02$) on temperature change is significantly negative. Local economic development will drive the overall level of the surrounding areas. There is a significant spatial diffusion effect of energy utilization efficiency and innovative green technology. Therefore, the countries around the region have developed at the level of green production. Carbon dioxide plays a significant role in promoting temperature change ($\beta = 0.009,\ p = 0.03$), which is consistent with the nature of greenhouse gases. When the individual country is fixed, that is Column (4), the regression results reflect the vertical comparison within the country. Time lag effect also exists in temperature change ($\beta = 0.150,\ p = 0.03$). The proportion of

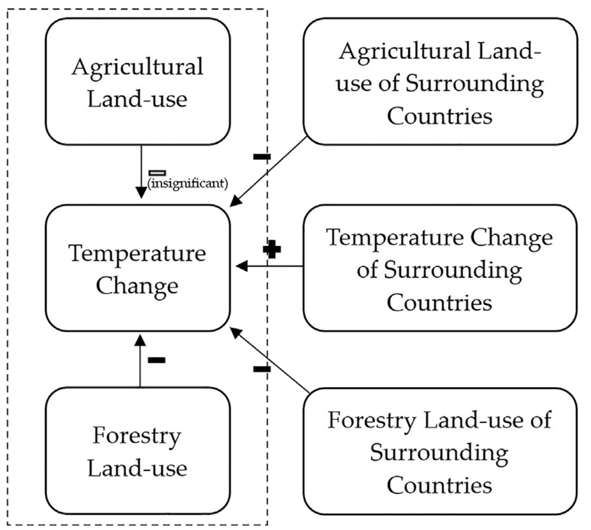

FIGURE 4 | The spatial affecting mechanism of land-use on temperature change.

industrial output value to the current temperature change is significantly negative ($\beta = -0.002,\ p = 0.02$), indicating that the green production capacity of a country gradually increases in the process of industrial development, which is consistent with the regression result without spatial effect.

Compared with the empirical results without spatial effect, the regression results of the spatial Durbin model may be more reliable. First, from the model design perspective, factors affecting climate change, such as carbon dioxide, will flow between different regions, resulting in significant spatial autocorrelation of temperature change at the geographical level. Excluding the spatial effects will lead to the missing variable deviation, and the result may be unreliable. Second, From the perspective of fitting effect, the goodness of fit of the regression results of the spatial Durbin model is much better than

TABLE 6 | Results of robustness test.

A. Results of distance bandwidth adjustment

Items	Temperature change		
	W: 0–20	W: 0–30	W: 0–40
	(1)	(2)	(3)
AL	–0.142 (–1.09)	–0.070 (–0.53)	–0.040 (–0.30)
FL	–0.326*(–1.73)	–0.281*(–1.74)	–0.187 (–0.73)
W × AL	–1.018***(–3.68)	–1.351***(–4.37)	-1.218***(-3.37)
W × FL	–0.855**(–2.12)	–1.116**(–2.45)	–0.567*(–1.75)
W × Temchan	0.753***(88.29)	0.800***(89.97)	0.829***(87.56)
TemChan_lag	0.150***(17.16)	0.119***(13.42)	0.113***(12.25)
GDP	–0.000 (–0.02)	-0.000 (–0.15)	–0.000 (–0.15)
Pop	0.001 (0.05)	-0.014 (–1.14)	–0.025*(-1.80)
Cap	0.002 (0.51)	0.003 (0.72)	0.004 (0.73)
Indus	–0.002**(–2.40)	-0.001**(–1.98)	–0.001*(–1.95)
CO2	0.001 (0.28)	0.001 (0.24)	0.001 (0.30)
Energy	–0.016 (–0.52)	-0.004 (–0.13)	0.002 (0.08)
FE	Yes	Yes	Yes
N	5,992	5,992	5,992
R-squared	0.2258	0.2541	0.2664

B. Results of spatial weighting matrix type adjustment

Items	Temperature change		
	W: 0–20 (contiguity)	W: 0–30 (contiguity)	W: 0–40 (contiguity)
	(4)	(5)	(6)
AL	–0.152 (-1.11)	–0.087 (–0.61)	–0.059 (–0.40)
FL	–0.393*(-1.69)	–0.237*(–1.89)	–0.100 (–0.36)
W × AL	–1.323***(-3.96)	–1.389***(-3.45)	–1.836***(–3.47)
W × FL	–1.312***(-2.71)	-0.977*(–1.69)	–0.411 (–0.55)
W × Temchan	0.743***(79.54)	0.772***(72.68)	0.770***(62.77)
TemChan_lag	0.152***(16.45)	0.129***(13.07)	0.131***(12.42)
GDP	0.000 (0.05)	–0.000 (–0.12)	0.000 (0.10)
Pop	0.003 (0.24)	–0.007 (–0.50)	–0.013 (–0.91)
Cap	0.002 (0.35)	0.003 (0.57)	0.001 (0.26)
Indus	–0.002**(-2.67)	–0.002**(–2.19)	–0.002**(–2.38)
CO2	0.001 (0.13)	0.000 (0.06)	0.001 (0.20)
Energy	–0.009 (-0.28)	–0.001 (–0.03)	0.002 (0.07)
FE	Yes	Yes	Yes
N	5,992	5,992	5,992
R-squared	0.2354	0.2683	0.2759

Notes:, **, *** stand for significant levels of 10%, 5% and 1% respectively, and the values in brackets are T-values.*

the regression results without spatial effect. Third, from the perspective of empirical results, the empirical results in **Table 5** are more reasonable. **Figure 4** comprehensively shows the mechanism of the spatial affecting of land-use on the temperature change, and within the dotted line is the benchmark regression without spatial effect.

3.4 Robustness Test

Based on the spatial correlation test of land-use impact on climate change, the robustness test is carried out to investigate the influence of adjusting the distance bandwidth and the spatial weighting matrix type on the robustness of the analysis conclusion (Su et al., 2021). **Table 6** shows all the empirical estimation results of the robustness test. The specific settings and analysis are described below.

The first is the robustness test of distance bandwidth. For the theoretical model with spatial correlation analysis, the selection of distance bandwidth determines the number of neighboring countries, which may affect the test results of spatial effect. In order to test whether the adjustment of the distance band affects the robustness of the model analysis, the distance bandwidth is expanded from 0–20 to 0–30 and 0–40, respectively, as shown in Columns (1–3) of **Table 6**. At this time, the sample countries will have more neighbors to be included in the spatial matrix. It can be seen that the impact of land-use on climate change is not affected by the setting of distance bandwidth, and the analysis conclusion is robust.

The second is the robustness test of the contiguity spatial weighting matrix. The spatial weighting matrix is the critical parameter of the spatial panel data model. The setting method of

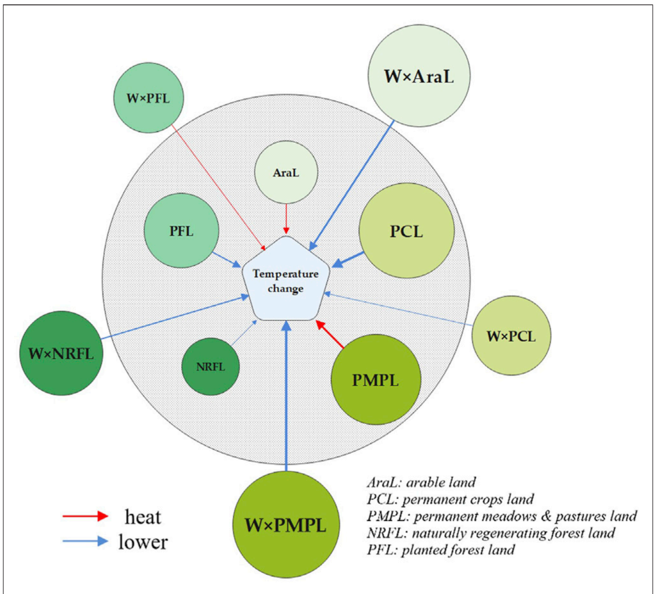

FIGURE 5 | Spatial Durbin regression results of land type subdivision.

spatial weighting matrix may affect the test results of spatial effect. In this part, the contiguity weighting matrix is used for the robustness test. The contiguity spatial weighting means that there is a distance dummy variable, when the distance between two samples is less than the set threshold, the distance dummy variable between them is regarded as a neighbor (i.e., 1); When the distance between them is greater than the set threshold, this distance dummy variable is regarded as not adjacent (i.e., 2). This setting is different from the direct distance calculation between the two countries, but the general idea is the same. The adjusted spatial weighting matrix in combination with different distance band settings is used to investigate the spatial correlation of land-use affecting climate change, and the analysis results are shown in Columns (4–6) of **Table 6**. As can be seen from the test results, adjusting the setting of the spatial weighting matrix does not affect the robustness of the analysis conclusion.

3.5 Additional Analysis: Heterogeneity Based on the Differences in Components of Land-Use Types

Considering that agricultural land can be divided into arable land, land under permanent crops and meadows and pasture land, and forest land can be divided into naturally regenerating forest land and planted forest land, thus we can further investigate the impact of land-use on climate change based on the subdivisions of agricultural and forestry land.

According to **Figure 5**, it can be found that the impact of land-use on climate change is still heterogeneous after land-use types are subdivided in the spatial Durbin model. The size of circles in **Figure 5** is set according to the absolute values of the influence. The red and blue arrows represent the heating and cooling effect, respectively. The increase of arable land proportion (β_{AraL} = 0.033) or meadows and pasture land proportion (β_{PMPL} = 0.121) has a positive effect on temperature rise. In contrast, the increase of land under permanent crops proportion (β_{PCL} = −0.285) or natural forest proportion (β_{NRFL} = −0.028) or planted forest proportion (β_{PFL} = −0.085) has a negative effect on climate change. However, the effect of arable land proportion adjustment or planted forest land proportion adjustment on climate change is not significant. Taking into account the spatial correlation effect, the increase of arable land ($\beta_{W\times AraL}$ = −0.364), meadows and pasture land ($\beta_{W\times PMPL}$ = −0.413), and natural forest land ($\beta_{W\times NRFL}$ = −0.112) in the surrounding areas have a significant inhibitory effect on the local greenhouse effect, while the increase of land under permanent crops ($\beta_{W\times PCL}$ = −0.089) or planted forest land ($\beta_{W\times PFL}$ = 0.082) has no significant effect on the local greenhouse effect. It is worth noting that, in the case of distinguishing the natural forest from the planted forest, the increase of the proportion of planted forest has no significant effect on temperature. The root cause may be that the planted forest needs to occupy certain land resources, which may cause the reduction of agricultural land or natural forest, and may need to support large-scale human activities, so as to produce more carbon emissions in the short term.

4 HETEROGENEITY ANALYSIS BASED ON THE REGIONAL DIFFERENCES

This section examines the regional heterogeneity of the impact of land-use on climate change. The general econometric model heterogeneity analysis usually divides the samples into developed and developing countries (Drissi and Boukhatem, 2020). In this paper, the biogeochemical and biophysical effects of land-use on climate change may be heterogeneous due to regional differences such as latitude, geographical distribution and hydrological characteristics, and the conclusions obtained by case studies of selected sample countries in existing literature may have sample bias due to regional heterogeneity. Next, the spatial Durbin model will be used to test whether there is significant regional heterogeneity in the impact of land-use on climate change.

Figure 6 shows the spatial Durbin model analysis results of the impact of land-use on climate change for the whole sample, high-latitude samples, middle-latitude samples, low-latitude samples, island country samples and mainland country samples based on **Eq. 3**. The part inside the dotted line is land-sea difference, and the part outside the dotted line is latitude difference. The size of pie charts in **Figure 6** is set according to the absolute values of the influence.

Latitude difference will cause the heterogeneous impact of land-use on climate change. Taking the impact of agricultural land proportion on temperature change as an example, the increase of agricultural land proportion in high latitude countries (β_{AL} = −0.120) will significantly inhibit the rise of regional temperature. In contrast, the increase of agricultural land proportion in low latitude countries (β_{AL} = −0.284) and middle latitude countries (β_{AL} = 0.104) has no significant impact on

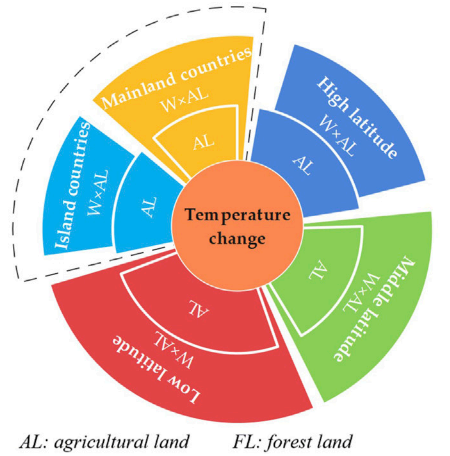

FIGURE 6 | Spatial Durbin regression results for regional heterogeneity analysis.

regional temperature change. Suppose we observe the impact of forest land on climate change. In that case, only the increase of forest land proportion in middle latitude countries ($\beta_{FL} = -0.296$) will significantly inhibit the regional temperature rise. In contrast, the increase of forest land proportion in high latitude sample countries ($\beta_{FL} = -0.025$) and low latitude sample countries ($\beta_{FL} = 0.266$) has no significant impact on the temperature change. Focusing on the impact of the increase in the proportion of agricultural land or forest land in neighboring countries on the temperature change of a country, we can find that the temperature change of high latitude sample countries ($\beta_{W\times AL} = -0.106$, $\beta_{W\times FL} = -0.045$, but no significant) is not affected by the land structure adjustment of surrounding areas. In contrast, the increase in the proportion of agricultural land or forest land in middle ($\beta_{W\times AL} = -0.369$, $\beta_{W\times FL} = -0.319$) and low latitude samples ($\beta_{W\times AL} = -0.629$, $\beta_{W\times FL} = -0.535$) will significantly inhibit the local temperature rise.

There is also heterogeneity in the impact of land-use structure adjustment on climate change in island countries and mainland countries. The increase in the proportion of agricultural land in island countries and mainland countries has no significant impact on the temperature change. However, the increase in the proportion of agricultural land in island countries will inhibit the temperature rise ($\beta_{AL} = -0.071$), while the increase in the proportion of agricultural land in mainland countries will aggravate the temperature rise ($\beta_{AL} = 0.034$). Similarly, the increase of the proportion of forest land in island countries will significantly inhibit the increase of local temperature ($\beta_{FL} = -0.153$). In contrast, the increase of the proportion of forest land in mainland countries will not significantly affect local temperature changes ($\beta_{FL} = 0.034$). If the spatial correlation factor is included, the temperature change of island countries is not affected by the adjustment of land-use structure in the surrounding sample countries ($\beta_{W\times AL} = 0.056$, $\beta_{W\times FL} = -0.030$, but no significant), and the increase of agricultural land proportion or forestry land proportion in the surrounding areas of mainland countries will significantly inhibit the increase of local temperature ($\beta_{W\times AL} = -0.500$, $\beta_{W\times FL} = -0.196$).

5 RESULTS AND DISCUSSION

On the basis of a comprehensive review of existing theories and literature, this paper uses the Moran's I test (**Eq. 1**), benchmark model (**Eq. 2**) and spatial Durbin model (**Eq. 3**) to verify the heterogeneity of land-use impact on climate change in the two dimensions of type and region, based on the data of 214 countries from 1990 to 2018. The following empirical results are drawn: 1) According to the Moran's I test results, we find that the temperature change shows significant spatial correlation, that is, it has a strong spatial dependence. 2) According to the benchmark and spatial Durbin test results, we find there is heterogeneity in the impacts of different land-use types on climate change. On the one hand, the impact of agricultural land on local climate change is small and not significant, but the increase of the proportion of forestry land can significantly inhibit the temperature rise in the local country. On the other hand, the growth of agricultural and forestry land in neighboring countries has significantly inhibited climate change in their own countries, and the inhibitory effect is greater than the change of land structure in their own countries. 3) The component heterogeneity test shows that local proportion of land under permanent crops and naturally regenerating forest land can significantly inhibit temperature changes, while the inhibitory effects of surrounding countries mainly come from arable land, land under permanent meadows and pastures and naturally regenerating forest land. 4) The regional heterogeneity test shows that there is heterogeneity in the impact of land-use on climate change between different latitudes and island and mainland countries.

From the empirical results and analysis, several important findings and implications can be summarized.

First, the impacts of different land-use types on climate change are heterogeneous. The impact of agricultural land on climate change is small and not significant, but the increase of the proportion of forestry land can significantly inhibit the temperature rise in the local country. To some extent, agricultural land comes from the conversion of forest land. The conversion from forest land to agricultural land is actually a carbon emission process because the forest has a much stronger carbon sequestration capacity than farmland. The increase of agricultural land may be from converting non-agricultural land to agricultural land, or from the conversion of forest land. Without understanding the internal conversion mechanism, the data shows that the increase of agricultural land and forest land will inhibit the rise of temperature. In contrast, the inhibitory effect of agricultural land is not significant, and the increase of forest land has a greater inhibitory effect. This conclusion provides experience for the land-use transformation now needed to address climate change.

Second, the impact of land-use on climate change has regional heterogeneity in the dimensions of latitude difference and land-sea difference. In terms of latitude difference, what worth noting is that, as shown in **Table 3**, the proportion of agricultural land in high latitude sample countries, middle latitude sample countries and low latitude sample countries is 24.8%, 45.1% and 35.2%, respectively, of which the proportion of agricultural land in high latitude countries is the lowest and significantly lower than that in the other two groups of sample countries. The proportion of forestry land in high latitude sample countries, middle latitude sample countries and low latitude sample countries is 42.8%, 26.9% and 35.0%, respectively. Among them, the proportion of forestry land in middle latitude sample countries is the lowest and significantly lower than that in the other two groups of sample countries. To a certain extent, this may explain why temperature change is more sensitive to the change of agricultural land proportion in high latitude countries and the change of forestry land proportion in mid latitude countries. After all, they have less basic shares, and their share change has a more noticeable impact on the adjustment of local land-use structure. In terms of land-sea difference, continent countries and neighboring countries share a land climate cycle system. The adjustment of land-use structure caused by the change of the proportion of agricultural land or forest land in neighboring countries will affect this system's multiple biophysical and biogeochemical effects. Logically, island countries have no *de facto* neighbors, even if the geographical distance may be small. After all, it is the sea that borders the island countries. This conclusion provides a reference for the land-use policy of countries in specific regions.

Third, climate change in a country is affected by its own land-use structure and, more importantly, the land-use structure of neighboring countries. This phenomenon is logically reasonable. Temperature and climate change in nature are in an integrated form, and carbon dioxide can freely flow across borders in the atmosphere. Considering that the adjustment of agricultural or forestry land-use within a sample country represents the adjustment of land-use in a single country (which is much smaller than the adjustment of land-use in neighboring countries or regions) represents the whole world. Therefore, it is reasonable that the adjustment of agroforestry land structure in neighboring countries significantly affects the climate change of a country so that the effect exceeds the effect of the adjustment of local land-use structure. This conclusion reinforces the importance of international cooperation on climate and environment.

Admittedly, this study also has several shortcomings. 1) Although the proposed heterogeneous impact of land-use type provides a guideline for agroforestry climate policy, the impact is dependent on the sample data and the mathematical reasoning proof, lacking the in-depth natural science analysis. This issue may limit the long-term validity of the results in the future and merely reflect the facts of what happened in the past. In future research, more datasets should be used to verify its effectiveness. 2) It should be noted that there are some large countries in the sample (such as Russia, the United States, and China), and they almost have no "neighbors" in the model. For a country with a very large area, the distance between its geographical center and its boundary is very far, so few neighbors are at the distance threshold of 0–20. Even at the distance threshold of 0–30 and 0–40, these large countries have few neighbors. Therefore, in the regression of the spatial Durbin model, the impact of land-use in neighboring countries on their own climate change is hardly considered. In fact, this is just in line with the actual situation. When considering the relation of land-use and climate change, countries with a large area have certain particularities. They have a vast territory so that their climate change basically depends on their own characteristics and is not affected by the small neighboring countries. This means that future models should strive to achieve the ability to identify specific samples. 3) The main estimation method of spatial econometric model is MLE (Maximum likelihood estimate), but the large sample theory of MLE needs to be improved. Spatial metrology also requires researchers to set a non-random spatial weight matrix (rather than estimating this matrix based on data), so this spatial weight matrix may not fully reflect the complex relationship between different regions. 4) In the additional analysis, the proportion of subdivided types of land will further decrease (the proportion of arable land must be less than that of agricultural land, while the proportion of natural forest land must be less than that of forest land), and the direction of the transformation of different subdivided types of land is unclear (the increase of planted forest land may be at the cost of occupying wasteland or arable land, or at the cost of occupying natural forest land). Therefore, it is not easy to understand or explain the fitting model results based on the data of subdivided land-use structure change. It is necessary to further clarify the internal mechanism of land-use subdivision type. We plan to examine these issues in the future.

Overall, this study analyzes the impact of land-use on climate change through quantitative methods, and the relevant conclusions can provide a reference for proposing international initiatives to address climate change or establishing an international convention to address climate change. From the perspective of land-use, effective measures should be taken to prevent deforestation and over-exploitation of agricultural land. From the perspective of location differences, countries with different geographical distribution conditions should specify land and climate policies according to local conditions. From the perspective of international climate relations, it is necessary for all countries to abandon the narrow thinking of "zero-sum game" and share more and play more to the inhibitory effect of green land-use on global warming, so as to realize the great ideal of mutual benefit and win-win results.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

SJ, CY, MW, and PF contributed to conception and design of the study. SJ and CY organized the database. SJ and CY performed the statistical analysis. SJ, CY, MW, and PF wrote the first draft of the manuscript. SJ, CY, MW, and PF wrote sections of the manuscript. All authors contributed to manuscript revision, read, and approved the submitted version.

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