Unveiling Climate–Land Use and Land Cover Interactions on the Kerch Peninsula Using Structural Equation Modeling

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Abstract: This paper examines the effects of climatic factors, specifically temperature and precipitation, on land use and land cover (LULC) on the Kerch Peninsula using structural equation modeling (SEM). The Normalized Difference Vegetation Index (NDVI) was used as a mediator in the model to accurately assess the impact of climate change on vegetation and subsequent LULC dynamics. The results indicate that temperature exerts a significant negative influence on LULC in the early periods, inducing stress on vegetation and leading to land degradation. However, this influence diminishes over time, possibly due to ecosystem adaptation and the implementation of resilient land management practices. In contrast, the impact of precipitation on LULC, which is initially minimal, increases significantly, highlighting the need for improved water resource management and adaptation measures to mitigate the negative effects of excessive moisture. The NDVI plays a crucial mediating role, reflecting the health and density of vegetation in response to climatic variables. An analysis of lagged effects shows that both precipitation and temperature exert delayed effects on LULC, underscoring the complexity of water dynamics and ecosystem responses to climatic conditions. These results have important practical implications for land resource management and climate adaptation strategies. Understanding the nuanced interactions between climatic factors and LULC can inform the development of resilient agricultural systems, optimized water management practices, and effective land use planning. Future research should focus on refining models to incorporate nonlinear interactions, improving data accuracy, and expanding the geographic scope to generalize findings. This study highlights the importance of continuous monitoring and adaptive management to develop sustainable land management practices that can withstand the challenges of climate change.

Keywords: climate change; land use and land cover; NDVI; structural equation modeling SEM; climate adaptation

1. Introduction

LULC dynamics represent a crucial element of environmental studies, as they illustrate the interplay between human activities and the natural environment [1,2]. Changes in LULC can have significant impacts on climate, hydrological processes, biodiversity and the quality of life of populations. Such changes are frequently attributable to a multitude of natural and anthropogenic factors, including urbanization, agriculture, deforestation, and the restoration of natural landscapes. Consequently, monitoring and analyzing LULC dynamics is of paramount importance for the sustainable management of natural resources and spatial planning [3,4].

Climatic parameters such as temperature and precipitation play a determinating role in LULC change. These factors directly influence the physiological and phenological aspects
of vegetation, determining its distribution, seasonality, and productivity [5]. For instance, alterations in precipitation patterns can result in notable alterations in vegetation density and type, which subsequently influence local and regional ecosystems. Temperature anomalies, such as prolonged periods of drought or excessive precipitation, can cause significant environmental impacts, including soil erosion, reduced biodiversity, and landscape degradation [6].

Ecological indicators such as the Normalized Difference Vegetation Index (NDVI) have a wide range of applications for assessing vegetation condition and dynamics. The NDVI represents a valuable instrument for the monitoring of photosynthetic activity and vegetation health over extensive geographical areas [7,8]. This index permits the evaluation of spatial and temporal alterations in vegetation cover, which is of particular significance for the identification of areas subjected to environmental stress, such as drought, fire, or anthropogenic impacts. The use of the NDVI in combination with remotely sensed data can produce detailed maps of vegetation cover and analyze long-term trends in LULC change [9–11]. It is of great importance to understand the influence of climate drivers and LULC on ecosystems in order to develop effective adaptation and mitigation strategies. For instance, an understanding of the impact of changes in precipitation and temperature on vegetation distribution can inform the development of more resilient agricultural systems and conservation measures [12]. Furthermore, such knowledge is essential for the planning of sustainable urban development, including the management of water resources, the protection of soil, and the conservation of biodiversity [13].

The current research employs the NDVI to investigate the responses of vegetation to climate anomalies, thereby confirming the utility of this indicator in assessing the resilience and vulnerability of different landscapes to climate stresses. For instance, research conducted on the Huang-Huai-Hai Plain [4] has demonstrated a correlation between extreme rainfall and NDVI fluctuations. This evidence suggests that intense rainfall events can affect vegetation health and, consequently, land cover. Such studies demonstrate that extreme rainfall events can lead to significant changes in vegetation density and type, with direct impacts on local ecosystems and land use. Additionally, studies conducted in vulnerable karst areas in southwest China have demonstrated that NDVI changes are related to both climatic changes and anthropogenic factors, including large-scale construction projects [3]. These studies demonstrate the intricate interrelationship between natural and anthropogenic factors in influencing land cover patterns. In karst areas, where soils and ecosystems are particularly sensitive to change, the impact of human activities can exacerbate the effects of climate change, leading to landscape degradation and reduced biodiversity.

Furthermore, remote sensing has become an indispensable tool for the continuous monitoring of these changes. It provides spatial and temporal data that permit the monitoring of the impact of both gradual climate change and sudden environmental events on LULC dynamics [1,9]. This technological approach significantly enhances the capacity to develop more precise and efficacious strategies to mitigate the effects of climate change on terrestrial ecosystems. Remotely sensed data provide highly accurate vegetation maps, assess environmental stress, and analyze long-term trends in land cover change [14–16].

The integration of remotely sensed data with the NDVI enables the identification of changes in vegetation, the anticipation of potential risks, and the formulation of adaptation strategies. For instance, these techniques can be employed to monitor droughts, predict agricultural yields, and assess the impact of natural disasters. Due to their high spatial and temporal resolutions, satellite data provide continuous observations of land cover, which is of particular importance in the context of a rapidly changing climate.

The interaction between climate parameters and LULC mediated by the NDVI is a complex and multidimensional process. While the influence of individual climatic factors such as land surface temperature (LST) and precipitation on LULC is increasingly being addressed in various studies, comprehensive analyses integrating these data with the NDVI in different ecosystems remain scarce. A significant challenge is to accurately quantify...
these influences, given the variability in spatial and temporal data and the indirect nature of the NDVI as an indicator of vegetation health.

For instance, studies conducted in Vadodara, Gujarat [6], and in the Saiss Plain [10] examine the relationships between LST, the NDVI, and LULC in detail. However, they also highlight significant difficulties in understanding the subtle impacts of microclimatic changes on the NDVI and, consequently, on LULC. These studies demonstrate that alterations in land surface temperature and precipitation can exert considerable influence on the distribution and condition of vegetation. However, the acquisition of high-resolution data, encompassing both spatial and temporal dimensions, is essential for the comprehensive comprehension of these processes.

In addition, methods such as Observation Minus Reanalysis, applied in south India [17], demonstrate innovative approaches to study these interactions but also highlight the need for methodological improvements to better interpret the dynamic interactions between climate parameters and LULC. For example, the Observation Minus Reanalysis method is a widely used technique to assess the impact of land use change and urbanization on the climate by comparing observed data with reanalysis data. Studies have shown that its trends can be influenced by multidecadal variability differences between station observations and reanalysis data, leading to inconsistent estimates of urbanization effects [18,19]. These methods permit the identification of discrepancies between observations and modeled data, thereby providing an opportunity for more in-depth analyses of climate forcing. However, their application requires further development to account for local and regional specificities.

These deficiencies underscore the pressing necessity for the development of enhanced analytical techniques that can integrate climate data, the NDVI, and LULC assessments to provide more predictive insights into the way these factors interact over time. The development of such methodologies is of critical importance for informing strategies for sustainable land management and climate change adaptation. New approaches must consider not only macroclimatic parameters but also localized microclimatic conditions that can significantly influence vegetation health and distribution.

Climate change, and in particular changes in temperature and precipitation levels, plays a determining role in influencing the nature of LULC at a given site. Numerous studies have highlighted the complex relationship between climatic factors and changes in LULC and emphasized the significant influence they can have on each other [5,11,20,21].

Temperature is one of the most important climatic factors that can directly influence LULC dynamics. A change in temperature can result in a change in the type and pattern of vegetation, which in turn affects the land management approaches employed. For instance, an increase in temperature can prompt alterations in farming practices and influence land cover types, such as agricultural land or pastures [22]. Furthermore, temperature fluctuations can influence the distribution of vegetation, and the decisions made regarding land use in the context of forestry or conservation activities.

Precipitation is also an important climatic factor and plays a significant role in the formation and distribution of LULCs. Differences in precipitation can directly affect the availability of water, which in turn influences land use, such as the choice of irrigation methods or the fulfillment of water consumption objectives. Modifications in precipitation patterns can result in alterations to the distribution of land cover types. This can be exemplified by the transformation of wetlands or grasslands, which are dependent on water availability, into other land cover classes.

Empirical evidence indicates that the interaction between temperature and precipitation can have a synergistic effect on LULC changes. For instance, an increase in temperature accompanied by alterations in precipitation patterns may result in alterations to land cover types, which could subsequently affect agricultural productivity or the natural distribution of vegetation. These combined impacts underscore the intricate relationship between climate variables and LULC dynamics [23].
It is also important to consider the influence of climate parameters on the NDVI, which can reflect changes in LULC. For instance, studies have indicated that NDVI alterations in the eastern coastal regions of China from 1982 to 2019 are predominantly associated with accelerated warming, in addition to augmented precipitation and solar radiation [8]. Additionally, Wang [24] determined that the primary drivers of NDVI change in China are climate change and droughts. The increase in the NDVI was associated with an increase in precipitation, particularly in arid and semi-arid regions, while temperature influenced vegetation growth throughout the country. A similar study was conducted in the Mt. Everest reserve and surrounding areas [25], which revealed that the primary factor influencing NDVI changes is rainfall, particularly in regions with high grazing pressure. A study conducted in the Indian state of Jharkhand demonstrated that the NDVI is more responsive to temperature fluctuations than to precipitation and soil moisture [26]. It can be observed that temperature has a more significant effect on plant growth, particularly during the summer months.

Authors also believe that structural equation modeling (SEM) should be considered as a potential method for investigating interactions between climate parameters, the NDVI and LULC. SEM is a widely utilized analytical technique in various scientific disciplines for the investigation of intricate interactions between diverse variables. For instance, Ramanathan [27] employed SEM to examine the interplay between environmental regulation, innovation, and output in the UK manufacturing sector. The findings indicated that the implementation of environmental regulation had a considerable impact on the country’s economic growth. In the work of Aboelmaged [28], SEM was employed to assess the direct and indirect effects of environmental innovation, nature focus, and supplier interactions on hotel operations in the UAE. Another illustrative example of the application of SEM is the study of the impact of environmental consciousness on competitive advantage through intellectual capital management. This study identified a more pronounced non-direct effect of environmental consciousness, which was primarily mediated by competitive advantage through intellectual capital [29].

The incorporation of climate data, the NDVI, and LULC into this study using SEM offers several advantages over similar studies. Conventional approaches frequently fail to consider the intricate interrelationships between variables. For instance, studies frequently consider only direct effects, as evidenced by Pettorelli [13], who examined the direct effects of precipitation and temperature on vegetation and the interaction of microclimatic effects on the NDVI and LULC [12]. However, these studies do not address the diversity of influences on different time scales and the dynamism between them, nor do they consider the possibility of indirect effects. The present study attempts to improve existing approaches to gain a deeper understanding of the complexity of interactions between climate, vegetation, and land use and land cover (LULC) using a more holistic approach. In particular, the use of the NDVI as a mediator reveals indirect climatic influences on LULC through vegetation health, which represents a level of system complexity that may have previously been overlooked.

2. Materials and Methods

2.1. Research Area

The Kerch Peninsula, situated in the eastern sector of the Crimean Peninsula and separated from it by the Akmonai Isthmus, is a region with a rich historical background and diverse natural complexes. The peninsula is bordered by the Black Sea, the Sea of Azov and the Kerch Strait. Its longest axis extends from north to east for approximately 90 km and from north to south for approximately 54 km, and its total area is approximately 3000 km² (Figure 1).
The peninsula’s relief is predominantly characterized by steppe hills, which can be divided into two distinct parts: a relatively gentle south-western section and a hillier north-eastern region. From a geological perspective, the Kerch Peninsula is situated within the Kerch-Taman fold belt, which is characterized by the prevalence of sedimentary rocks that exceed 5 km in thickness. The region exhibits a high level of seismic activity, comparable to that observed in the mountainous systems of the Caucasus and the Crimean Mountains. This seismic activity is associated with the deformation of young geological formations, the occurrence of mud volcanoes, and crustal movements.

The climate of the Kerch Peninsula can be characterized as temperate continental, with pronounced aridity features. The mean annual temperature, as determined by long-term observations, is approximately 11 °C. Winters are relatively mild, although temperatures can drop significantly, and thaws may occur. The absolute minimum temperature is recorded at around −25 °C to −27 °C. In summer, temperatures typically reach 35 °C to 40 °C. The mean annual precipitation is 459 mm, with the highest levels occurring during the winter and early spring months.

The peninsula is characterized by a paucity of permanent watercourses—a consequence of the low precipitation levels. The water resources are predominantly represented by rivers and streams, which exhibit low water availability. The autumn and winter floods are weak. The principal lakes are of marine origin and are situated on the coast. A considerable number of lakes contain therapeutic muds, which, because of pollution and desalination in recent years, have experienced a significant reduction in their reserves.
The soil cover of the Kerch Peninsula is constituted by a complex mosaic of different soil types, including southern chernozems, saline and carbonate soils, dark chestnut soils, saline soils, solonetz and solonchaks, which are present to varying degrees. These soils require special protection, as the active anthropogenic transformation of the land has resulted in the degradation of the soil cover, which has a detrimental impact on the state of the soil resources.

The semi-soil vegetation is primarily comprised of steppe and semi-steppe communities. In this area, cereal and herbaceous steppes are the most prevalent, with a diverse flora comprising species such as wattle, thyme, sage, wormwood, and others. Solonchak plants, including glasswort and marsh-rosemary, are found along the shores of saline lakes and estuaries. The forest vegetation is predominantly located in ravines and gullies, where oak, maple, elm, and other tree species flourish.

2.2. Structural Equation Modeling

Structural equation modeling is a statistical approach that combines aspects of multiple regression and factor analysis to investigate complex interactions between observed and latent variables [30]. SEM is a commonly utilized approach in ecological research, enabling researchers to investigate the effects of variables on one another through direct, indirect, and mediator interactions [31]. This approach allows for the simultaneous analysis of multiple interaction pathways between variables, rendering it an invaluable tool in the study of dynamic interactions within natural systems [32,33].

In the context of studying LULC, SEM allows us to investigate how variables such as temperature and humidity—for example, how they affect the distribution of LULC classes in the study area. Furthermore, it offers the possibility of studying how this impact may increase or decrease as it passes through different mediating variables. An illustrative example is the NDVI, which reflects vegetation health and density. The NDVI is a quantitative measure of vegetation cover that may be affected by changing climatic conditions, thereby influencing LULC.

The fundamental tenet of SEM is the model, which is comprised of two components: a measurement model and a structural model. The measurement model serves to relate the observed data to the latent constructs, thereby ensuring that the latent variables are represented by the observed data. Mathematically, this can be represented as follows:

\[ x = \lambda x \xi + \delta \]

where \( x \) is the vector of observed variables, \( \lambda x \) is the matrix of factor loadings, \( \xi \) is the latent variable, and \( \delta \) is the vector of measurement errors.

Consequently, the structural model that defines the relationships between the latent variables can be expressed as follows:

\[ \eta = B\eta + \Gamma\xi + \zeta \]

where \( \eta \) is the vector of dependent latent variables, \( B \) and \( \Gamma \) are the matrices of coefficients representing the relationships between latent variables and between exogenous and endogenous latent variables, respectively, and \( \zeta \) is the vector of errors.

To construct the SEM model, this study employed a set of variables that can be classified into two distinct groups: latent and exogenous. In this case, the latent variable was LULC, while the exogenous variables—that is, those that exert a direct influence on the latent variable—were climate variables and the NDVI. The SEM model was comprised of four layers, each of which estimated specific types of interactions between variables (Figure 2).
The objective of the measurement layer was to ascertain the influence of climate variables (temperature and precipitation) and the NDVI on LULC at the current time point $T_n$. In this context, the variable LULC is dependent on the variables $Prec_{T_n}$, $Temp_{T_n}$ and $NDVI_{T_n}$, and the direct effect on it is measured.

The second layer was an autoregressive layer, whose objective was to ascertain the extent of the impact of LULC between successive time steps. In this layer, $LULC_{T_n}$ is dependent on previous LULC states, such that $LULC_{T_{n-1}}$ affects $LULC_{T_{n-1}}$, $LULC_{T_{n-2}}$ affects $LULC_{T_{n-2}}$, and so on.

The lag effects layer addressed the impact of climate variables and the NDVI from preceding periods on the present state of $LULC_{T_n}$. This layer is crucial for enhancing our comprehension of the long-term influence of climate on LULC.

The fourth layer, the mediator layer, identified the mediating effect of climate variables on LULC through the NDVI. This implies that climatic changes can initially affect the vegetation state, and subsequently, these changes in vegetation can affect LULC.

2.3. Data Description

This study employed a diverse array of datasets sourced from various sources to conduct a comprehensive analysis of the impact of climatic factors on LULC changes (Figure 3).
extending back to 1984. This methodology enabled the creation of a long-term NDVI time series, which is critical for studying changes in vegetation and their relationship to climatic factors. The use of GEE also permitted the preprocessing of the data, including the masking of clouds.

LULC data were obtained by classifying Landsat satellite data using a convolutional neural network for the Kerch Peninsula [35,36]. The set represents five time steps, each including the spatial location of eight different LULC classes specific to the Kerch Peninsula. These steps are 1990–1994, 1995–1999, 2000–2004, 2005–2009 and 2010–2014.

Figure 3. Spatial and temporal distribution of variables used in this study.

Climate data, including temperature and precipitation information, were obtained from the ERA5 dataset provided by the European Centre for Medium-Term Weather Forecasts (ECMWF). The data were downloaded using the Google Earth Engine (GEE) platform, resulting in a high-quality climate data time series with a spatial resolution of 0.25 degrees and a time step of one hour. The ERA5 dataset [34] provides detailed meteorological data, which allows for the spatial and temporal variations in climate factors to be analyzed.

The NDVI was derived from Landsat satellite data. Landsat data, accessible via the Google Earth Engine platform, offer high spatial resolution (30 m) and temporal coverage extending back to 1984. This methodology enabled the creation of a long-term NDVI time
series, which is critical for studying changes in vegetation and their relationship to climatic factors. The use of GEE also permitted the preprocessing of the data, including the masking of clouds.

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2.4. Study Design

In the initial stage, the geoTIFF data were collated into a single raster stack (Figure 4). The data were then extracted and converted into a comma-separated-values (CSV) format for subsequent processing. The GDAL and Rasterio libraries were employed for this undertaking, facilitating the expeditious processing and conversion of geospatial data. Subsequently, the data were converted into CSV format and loaded into a Pandas DataFrame, where they were subjected to a thorough examination for accuracy and completeness. To reduce the amount of data to an acceptable level for analysis and to avoid overfitting the model later, a random sampling of 5% of the total data was carried out. This approach reduced the computational burden of the analysis while maintaining the representativeness of the sample. A standard scaling method, implemented via the scikit-learn library, was employed to normalize the data. The scaling process enabled the data to be unified on a single scale, thereby enhancing the quality and stability of subsequent analyses.

A structural model incorporating both measurement and regression pathways was developed for the analysis. The model accounted for both direct and indirect effects of temperature and precipitation on LULC, as well as their influence on the NDVI. Additionally, the model incorporated autoregressive pathways to account for the temporal dynamics of LULC. The model was then fitted and trained on the scaled data using the “semopy” library [37]. The fitting results included the estimation of model parameters and the calculation of statistical measures of the quality of the model fit.

Figure 4. General scheme of research.
Statistical indicators, including coefficient values, their significance, and overall model quality indices, were calculated and interpreted to assess the fit of the model to real data. These indicators enabled the confirmation or refutation of hypotheses regarding the influence of climatic factors on LULC through the NDVI.

3. Results

3.1. Configuration of the Model Structure

The model structure was configured in a comprehensive manner to analyze the influence of climatic factors on the NDVI and LULC. The model incorporated measurement components, interaction pathways, and autoregressive pathways to account for temporal dynamics. The model accounted for the influence of the LULC metrics at each time step associated with the respective values of the NDVI, temperature, and precipitation, thus allowing the direct influence of these climatic factors on LULC to be accounted for. Furthermore, interactions between temperature and precipitation were incorporated into the model to ascertain their collective impact on the NDVI and, consequently, on LULC. The incorporation of regression pathways permitted the impact of preceding values of the NDVI, temperature, and precipitation on the current LULC values to be quantified, which was crucial for elucidating temporal alterations and their cumulative effects. The autoregressive pathways were employed to model the effect of LULC at the previous stage on LULC values at the current stage. This allowed for the temporal consistency and dynamics of LULC changes to be accounted for.

3.2. Modeling Results

The analysis of the influence of climatic parameters on LULC changes on the Kerch Peninsula using structural equation modeling allowed us not only to assess the direct effect of temperature and precipitation on LULC but also to trace their cumulative and indirect effects when the NDVI was used as a mediator (Figure 5).

![Figure 5](image_url)

Figure 5. A structural equation model was constructed to examine the impact of climate on land use and land cover (LULC) from 1990 to 2014. This diagram illustrates the direct, lagged, and mediated effects of temperature and precipitation on LULCC through the NDVI across five time steps. It highlights the evolving influence of climatic variables on vegetation health and land cover dynamics. The time periods considered are as follows: T₀ (1990–1994), T₁ (1995–1999), T₂ (2000–2004), T₃ (2005–2009), and T₄ (2010–2014).
The results indicate a significant direct influence of climatic factors on LULC during the same period. For instance, in the period $T_1$, the effect of temperature on LULC was $-0.61$, indicating a significant interaction. This implies that areas with higher atmospheric temperatures are more likely to be areas without vegetation cover, such as urbanized areas or barren land. This is largely due to the characteristic manifestation of vegetation stress.

In contrast to temperature, the direct influence of precipitation is weakly pronounced and shows only insignificant negative values, except for $T_1$, where the value is $-0.02$, and $T_2$, where the value is $-0.01$. It is also noteworthy that the direct effect of precipitation on LULC increased threefold over time, from $-0.02$ in $T_1$ to $-0.07$ in $T_4$. However, the level of this influence remains relatively low. Conversely, the growth of the direct influence of temperature on LULC is observed to diminish over time. Consequently, during the $T_1$ period, the level of its influence was $-0.61$, and by the $T_3$ period, its impact decreased to $-0.03$. However, in the $T_4$ period, it began to have a positive impact, albeit very weakly.

It is also noteworthy that the NDVI serves as a mediator of climate impacts on LULC. As evidenced by the modeling results, its role can be quite significant. This is evidenced by its strong negative impact in the period. However, its role is significantly diminished over time. The direct influence of climate on LULC can be expressed in the fact that at high temperatures, significant levels of precipitation falling on the territory can contribute to various negative processes for the natural environment. These include soil erosion and salinization, which in turn lead to changes in land use. Previously, some areas could be used for agriculture; however, the climate impacts can lead to their reformatting for anthropogenic development or withdrawal from economic turnover. It is also important to highlight the occurrence of extreme climatic conditions, particularly in relation to air temperature, which is particularly acute in the context of the Kerch Peninsula. Consequently, during the summer months, elevated temperatures facilitate the ignition and spread of extensive fires involving dry grass, which has a detrimental impact on this region. Similarly, critical levels of precipitation can also lead to the same consequences, which, with rare periodicity, lead to flooding in the eastern part of the peninsula, especially in the city of Kerch.

The lag effect is more pronounced in the influence of climatic parameters on LULC. For instance, the impact of precipitation is more pronounced in this case than the direct impact in the initial time periods. For instance, during period $T_1$, the impact of precipitation is positive and equal to 0.28, whereas during period $T_2$, the impact is negative, indicating excessive moisture, which may result in flooding and soil erosion. It is also possible to trace the dynamics of change in atmospheric air temperature, which decreased from 0.40 $^\circ$C in $T_1$ to 0.23 $^\circ$C in $T_4$. This may reflect the adaptation of ecosystems to significant temperature impacts or a shift to more heat-tolerant crops or plant species in the agricultural sector. The biennial lag has a less pronounced effect on LULC than the direct effect, although it is still more pronounced. As with rainfall, the lag effect of temperature is also significant, but this decreases over time.

It is also important to note the role of the NDVI as a mediator of the influence of climatic factors on LULC. The results indicate that the role of the NDVI is increasing over time. It is likely that the impact of climate change is shifting from direct to indirect effects through other environmental factors.

The results obtained demonstrate the complexity and multifaceted nature of the interaction between climate and LULC. This interaction is expressed both in the direct influence of temperature and precipitation levels in the initial periods and in the indirect impact through mediators that enhance their direct impact.

3.3. Models’ Performance

The accuracy of the SEM performance was evaluated using several metrics that assess the adequacy and performance of the model for assessing the impact of climate variables on LULC (Table 1).
Table 1. Accuracy performance of the SEM model.

<table>
<thead>
<tr>
<th>Metric</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Degrees of Freedom (DoF)</td>
<td>114</td>
</tr>
<tr>
<td>Chi-Square ($\chi^2$)</td>
<td>1469.508</td>
</tr>
<tr>
<td>CFI</td>
<td>0.997</td>
</tr>
<tr>
<td>TLI</td>
<td>0.996</td>
</tr>
<tr>
<td>GFI</td>
<td>0.996</td>
</tr>
<tr>
<td>AGFI</td>
<td>0.996</td>
</tr>
<tr>
<td>NFI</td>
<td>0.996</td>
</tr>
<tr>
<td>RMSEA</td>
<td>0.027</td>
</tr>
<tr>
<td>AIC</td>
<td>43.816</td>
</tr>
<tr>
<td>BIC</td>
<td>212.809</td>
</tr>
<tr>
<td>LogLik</td>
<td>0.0917</td>
</tr>
</tbody>
</table>

A review of the presented table of accuracy metrics reveals that the values of the chi-square statistic and the degrees of freedom index are relatively low, indicating a high degree of ability of the model to analyze the data. The values of CFI, TLI, GFI, and AGFI are also close to 1, indicating that the model has been well-tuned and is able to understand the structure and relationships of the data. Consequently, the results of the accuracy tests indicate that the model represents the relationship between climate variables and LULC with a high degree of accuracy.

Furthermore, several significant patterns can be discerned. Firstly, the proximity of CFI, TLI, GFI and AGFI values to 1 indicates not only an excellent model fit to the data but also that the model is capable of adequately accounting for the complex interactions between climate variables and changes in LULC. This suggests that the model can capture both the direct and indirect effects of climatic factors, such as temperature and precipitation, on vegetation and land use.

Secondly, the low RMSEA value indicates that the model exhibits minimal deviations from a perfect fit, which is of particular importance in predicting and managing changes in ecosystems. This value also indicates that the model is robust to minor alterations in the data, thereby establishing its reliability as a tool for long-term forecasting.

The AIC and BIC information criteria, along with LogLik, indicate that the selected model is the optimal choice among a multitude of potential models. The low values of these criteria indicate that the model not only fits the data accurately but also minimizes complexity by avoiding overfitting.

4. Discussion

One of the most significant climatic factors influencing LULC changes is temperature. In our study, we observed a negative effect of temperature on LULC at the beginning of the study period. For example, in the time interval $T_1$ (1995–1999), the effect of temperature on LULC was $-0.61$. The data indicate that elevated temperatures have the potential to create stressful conditions for vegetation, which in turn can lead to changes in land use patterns. High temperatures can induce stress in vegetation, which is manifested by a reduction in photosynthetic activity, a decrease in biomass, and a deterioration in overall vegetation health. This can result in the conversion of previously vegetated areas to urban or agricultural land. Such changes typically occur in response to unfavorable climatic conditions, where plants are unable to adapt to extreme temperatures, leading to their degradation or death. Nevertheless, our study also indicated that the impact of temperature on LULC diminishes over time. For instance, by period $T_3$ (2005–2009), the effect of temperature had decreased to $-0.03$, and in the period of $T_4$ (2010–2014), temperature began to have a weak positive effect on LULC. This weakening effect of
temperature may be indicative of several potential explanations. Firstly, ecosystems may have developed tolerance to high temperatures because of adaptation to changing climatic conditions. Secondly, alterations in land use practices, such as the transition to more sustainable agricultural techniques or the cultivation of heat-tolerant crops, may have diminished the detrimental impact of temperature on LULC.

The impact of precipitation on LULC was less pronounced than that of temperature, yet it increased over time. At the outset of the study period in \( T_1 \) (1995–1999), the impact of precipitation on LULC was minimal, with a value of \(-0.02\). This suggests that precipitation exerted a minimal direct effect on LULC during this period. However, as time progressed, the influence of precipitation on LULC increased. During the period, By the end of the study period in \( T_4 \) (2010–2014), the figure reached \(-0.07\). Although the magnitude of this impact remains relatively low, the pronounced increase in the impact of precipitation on LULC necessitates a comprehensive analysis. Potential explanations for the observed increase in the impact of precipitation on LULC may be related to changes in water management practices and improvements in farming practices. Improvements in irrigation and water conservation practices may have reduced the dependence of agricultural land on natural rainfall, which in turn reduced its direct impact on LULC. For instance, the implementation of drip irrigation and other contemporary water management systems enables more effective utilization of available water resources, thereby mitigating the adverse effects of deficit or excess rainfall. Furthermore, enhancements in agronomic practices, such as the cultivation of more drought-tolerance or moisture-loving crops contingent on climatic conditions, may have contributed to a reduction in the vulnerability of agricultural land to fluctuations in rainfall. These measures may have served to mitigate the negative effects of climate change, thereby contributing to more stable and sustainable land use.

The NDVI was found to be a significant mediator of the relationship between climatic factors and LULC. The NDVI, as an indicator of photosynthetic activity and vegetation health, permits the assessment of the impact of temperature and precipitation on vegetation conditions, which in turn affects LULC. The effect of the NDVI on LULC was found to be significant at the outset of the study period. For instance, during the period \( T_1 \) (1995–1999), the NDVI exhibited a pronounced negative influence on LULC. This suggests that alterations in vegetation resulting from climatic influences exerted a considerable influence on land use. The presence of high NDVI values during this period is indicative of healthy vegetation. Conversely, a decline in the NDVI suggests vegetation degradation, which may be attributed to extreme climatic conditions such as drought or excessive rainfall. The impact of the NDVI on LULC exhibited a declining trend over time. In the period, the impact of \( T_4 \) (2010–2014) became less pronounced. This decline may be indicative of a shift in the role of vegetation in response to climate change. It is possible that ecosystems have adapted to changing conditions, or that land use practices have changed in a way that mitigates the effects of climatic factors on vegetation. The mechanisms through which the NDVI affects LULC are numerous and diverse. Firstly, the NDVI is a direct reflection of the condition of vegetation, which is determined by climatic conditions. The presence of high NDVI values is indicative of dense and healthy vegetation, which may favor the development of agricultural land and forested areas. Conversely, low NDVI values indicate vegetation degradation, which can result in the conversion of land to urbanized or barren areas. Secondly, alterations in the NDVI can be correlated with modifications in the composition of vegetation types. For instance, increases in temperature and alterations in precipitation patterns can facilitate alterations in vegetation types, such as transitions from forests to savannahs or from farmland to deserts. These alterations in vegetation, as reflected by the NDVI, exert an influence on land use patterns. Furthermore, the NDVI can influence LULC through alterations in land use practices. For instance, regions exhibiting a high NDVI may be utilized for intensive agriculture, whereas regions exhibiting a low NDVI may be destined for urbanization or remain unused. Furthermore, the implementation of sustainable agricultural practices and enhanced land management techniques can facilitate the maintenance of a high NDVI, which, in turn, has a beneficial impact on LULC.
The analysis of lag effects demonstrated that the impact of precipitation on LULC can manifest with a temporal lag. For example, during period $T_1$ (1995–1999), a positive effect of precipitation was observed, which may indicate favorable conditions for vegetation growth. However, in period $T_2$ (2000–2004), the influence of precipitation became negative. This change may be attributed to the presence of excess moisture, which can lead to the occurrence of flooding and soil erosion. Excessive precipitation can result in flooding, which can damage agricultural land and other land uses. Furthermore, it can contribute to soil erosion, which reduces soil fertility and leads to land degradation. Furthermore, the dynamics of temperature effects also demonstrate the presence of lag effects. During period $T_1$, temperature exhibited a pronounced negative effect on LULC, which may be attributed to vegetation stress and deterioration of vegetation. However, the effect of temperature exhibited a temporal change. During the period of $T_3$ (2005–2009), the effect became less pronounced. By $T_4$ (2010–2014), the effect exhibited a weak positive trend. This shift may be indicative of a gradual adaptation of ecosystems to higher temperatures. Potential explanations for ecosystem adaptation include alterations in vegetation species composition, the development of heat-tolerant crops, and enhanced land use practices. For instance, more sustainable agricultural practices, such as the cultivation of drought-tolerant crops or the implementation of optimized water use, may have been implemented in response to elevated temperatures. Furthermore, natural ecosystems may have adapted to new climatic conditions by changing their species composition and structural characteristics.

Our study also demonstrated that these climatic factors could interact with one another, either enhancing or mitigating their individual effects on LULC. The interaction of temperature and precipitation creates conditions that can both favor the development of vegetation and lead to its degradation. For instance, moderate temperatures in conjunction with sufficient precipitation can facilitate the growth of crops and natural vegetation. This, in turn, has a positive effect on agricultural productivity and regional biodiversity. In our analysis, such interactions were particularly evident during periods with favorable climatic conditions, when high agricultural productivity coincided with optimal levels of temperature and precipitation. Conversely, temperature and precipitation extremes can amplify each other’s adverse effects. For instance, elevated temperatures in conjunction with excessive precipitation can give rise to unfavorable processes such as soil erosion and flooding. This effect was evident during the periods $T_1$ and $T_2$, when the negative effects of precipitation were exacerbated by high temperatures, resulting in land degradation and reduced productivity. Precipitation more than the capacity of the soil to absorb it can result in the leaching of nutrients from the soil, which in turn reduces soil fertility and may necessitate a change in land use. Furthermore, temperature and precipitation interactions can have a synergistic effect on vegetation distribution. For instance, during periods of high temperatures and low precipitation, a decline in the NDVI may be observed, indicating that vegetation cover is deteriorating and land is shifting toward more drought-tolerant vegetation types or toward urbanized areas. Such changes have been observed in more recent periods, during which vegetation has adapted to changing climatic conditions, resulting in alterations to vegetation types and structure.

The objective of our study was to examine the strengths and limitations of SEM, despite its advantages. First and foremost, SEM is predicated on the assumption of linear relationships between variables. Nevertheless, it is possible that the interactions between climatic factors and LULC may not be linear. For instance, the impact of extreme climatic events (such as droughts or floods) on vegetation and land use may not be linear. The utilization of linear models may result in the simplification of genuine processes and the loss of crucial information regarding intricate interactions. Furthermore, SEM is highly susceptible to the quality and completeness of input data, which initially precluded the use of the entire dataset and subsequently led to its reduction to 5% due to model retraining. The reduction of the dataset permitted an increase in the accuracy of the results to an acceptable level. Furthermore, it is crucial to select and define variables correctly when utilizing SEM. In this study, the variables were selected based on the available data and
literature. Nevertheless, the incorporation of supplementary data into the presented model would enhance its accuracy, thereby facilitating a more comprehensive comprehension of the factors influencing LULC.

The findings of this study have significant practical implications, particularly in the context of land management and adaptation to climate change. First and foremost, the relationships between climate variables and LULC that have been identified in this study can be utilized to optimize land management practices. For instance, data indicating that elevated temperatures can result in land degradation can be employed to devise adaptation strategies, such as the adoption of heat-tolerant crops or the implementation of techniques that mitigate the effects of temperature stress on plants. Furthermore, given the increasing impact of rainfall on LULC, the introduction of improved water management systems such as drip irrigation is recommended. Such systems can reduce the negative impacts of excess rainfall and improve the resilience of agricultural systems to climate change. To mitigate the adverse effects of climate extremes on land use, it is imperative to develop and implement measures to prevent soil erosion and to manage flooding. For instance, the establishment of greenbelts and afforestation can serve to mitigate soil erosion, while the construction of water retention structures can help to prevent flooding. Furthermore, these measures can facilitate the improvement of vegetation and the NDVI.

5. Conclusions

This study employed an SEM to investigate the intricate interrelationships between climatic factors (temperature and precipitation) and LULC dynamics on the Kerch Peninsula. Furthermore, the NDVI was employed as a mediator to enhance comprehension of the impact of climate change on vegetation health and subsequent LULC alterations.

The results of our analysis indicate that temperature had a significant negative effect on LULC during the 1990s, leading to vegetation stress and land degradation. Initially, elevated temperatures resulted in considerable vegetation stress and land degradation, with a pronounced negative impact during $T_1$. However, over time, the effect of temperature decreased and became slightly positive in $T_4$, suggesting the potential for ecosystem adaptation and the adoption of sustainable land management practices.

Conversely, the impact of precipitation on LULC, which was initially minimal, increased markedly over the course of the study. This underscores the significance of efficacious water management. The implementation of improved irrigation techniques and sustainable agricultural practices is of paramount importance for the mitigation of the adverse effects of excess rainfall, such as soil erosion and flooding.

The NDVI acts as a mediator, reflecting the condition and density of vegetation in response to climatic forcing. The considerable negative impact of precipitation on LULC, observed during the initial observation period, diminished over time, indicating the evolving nature of vegetation cover and land use practices adapting to climatic variability. A lag effect analysis indicates that both precipitation and temperature exert delayed effects on LULC. The positive lag effect of precipitation in $T_1$, which transitions to a negative effect in $T_2$, highlights the complexity of water dynamics. The observed reduction in the lag effect of temperature suggests the possibility of ecosystem acclimatization or shifts towards species that are more heat tolerant.

Specific patterns of local ecosystem adaptation have been identified for the Kerch Peninsula. The achieved results indicated that vegetation in this region demonstrates a relatively rapid adaptation to temperature changes. This may be attributed to the historically elevated level of climatic stress in this region, which has resulted in the evolution of climate-resistant plant species. Furthermore, the impact of precipitation on vegetation recovery was observed to increase markedly toward the conclusion of the study period, thereby substantiating the necessity for long-term monitoring of climatic conditions and their influence.

These findings have significant implications for the practical implementation of land management and climate adaptation strategies. An understanding of the complex relation-
ships between climate variables and LULC dynamics can inform the design of resilient agricultural systems, optimized water management practices, and effective land use planning. The necessity of implementing adaptive land use management practices to mitigate the adverse effects of temperature on vegetation is a principal conclusion of our study. Moreover, the significance of efficacious water management strategies to enhance the resilience of local ecosystems is emphasized.

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