

Article

Analysis of the Characteristics and Causes of Land Degradation and Development in Coastal China (1982–2015)

Ya Huang ¹, Guiping Li ¹, Yong Zhao ², Jing Yang ¹ and Yanping Li ^{1,*}

¹ College of Oceanography, Hohai University, Nanjing 210098, China; hygccw@hhu.edu.cn (Y.H.)

² State Key Laboratory of Simulation and Regulation of Water Cycle in River Catchment, China Institute of Water Resources and Hydropower Research, Beijing 100038, China

* Correspondence: yanping.li@hhu.edu.cn

Abstract: Land degradation and development (LDD) is one of the important ecological issues in coastal China. This study analyzed the temporal and spatial changes of the LDD process in coastal China from 1982 to 2015 using the LDD index constructed from normalized NDVI and GPP data. The study also quantitatively evaluated the relative contributions of climate and human factors to LDD and explored their impact on LDD. The study's findings indicate that coastal regions in China experienced a marked increase in land development during the study period, with 62.47% of the regions displaying a growth trend and only 7.03% exhibiting signs of land degradation. The impact of climate change on the change in LDD processes was limited, while human activities were the main driving force, with their impact becoming increasingly apparent over time. Human activities were the dominant contributor to the change in LDD in most regions, accounting for over 60% of the change. Fast urbanization led to a notable decrease in cropland, wetland, shrub, and grassland, with a substantial proportion of the affected cropland transformed into impervious surfaces, accounting for 91.31% of the total cropland conversion. These findings deepen our understanding of the LDD process and its driving factors in coastal China, providing valuable insights for developing effective policy interventions and implementing successful land restoration plans in the region.

Keywords: land degradation and development; coastal China; human activities; climate change



Citation: Huang, Y.; Li, G.; Zhao, Y.; Yang, J.; Li, Y. Analysis of the Characteristics and Causes of Land Degradation and Development in Coastal China (1982–2015). *Remote Sens.* **2023**, *15*, 2249. <https://doi.org/10.3390/rs15092249>

Academic Editor: Sandra Eckert

Received: 11 February 2023

Revised: 20 April 2023

Accepted: 23 April 2023

Published: 24 April 2023



Copyright: © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Land degradation is a persistent and severe environmental problem that occurs at regional and global scales and is characterized by soil erosion, desertification, and vegetation degradation [1]. It has resulted in numerous environmental and social problems, such as biodiversity loss, dust storms, and food and water security [2–4]. On the contrary, land development, characterized by vegetation recovery, increased land ecosystem productivity and coverage, has a beneficial impact on ecological conservation and the advancement of sustainable social and economic growth [5]. However, the complex interactions between various factors contributing to the process of land degradation and development (LDD) not only depend on the interaction between different physical, chemical, and biological factors in the soil, but also involve the impact of human activities and climate change [6,7]. Furthermore, LDD is characterized by local compounding factors. Therefore, the main driving factors of LDD, such as climate change and human activities [8,9], have attracted the attention of the scientific community [10–13].

Coastal areas with a high degree of urbanization and dense populations [14] are highly vulnerable to the impacts of natural and human-induced environmental issues at the local, regional, and global levels [15]. In recent decades, urbanization, industrialization, and population expansion in coastal areas have led to global land use and land coverage (LULC) alterations, significantly affecting the coastal ecosystem [16]. The overdevelopment of land and urbanization have been recognized as primary drivers of land degradation in

coastal regions, particularly coastal wetlands, significantly impairing their roles as carbon and nitrogen sinks [17,18]. In addition to the human impact, climate variables such as temperature, precipitation, and soil moisture are also frequently regarded as key driving factors in the LDD processes [19,20].

The coastal regions of China span across tropical, subtropical, and temperate zones, encompassing approximately 13.6% of China's total land area and being the regions with the highest economic development and population density [21]. Since the reform and opening in 1978, coastal China's social and economic development has been huge in world history with unprecedented speed and scale. However, fast industrialization and urbanization, excessive land reclamation, and unreasonable natural resource development have brought huge pressure to coastal China regarding soil, biological resources, natural environment, and ecological systems. In recent decades, China's coastal region have experienced fast and less-regulated development, with widespread land reclamation activities leading to land degradation, which has become a major environmental concern restricting the eco-friendly development of the coastal areas [22]. From 1979 to 2014, the area of coastal wetlands reclamation reached 11,163 km², causing massive coastline changes [23,24]. During this process, LDD has caused serious disturbances in the coastal environment and ecological system, degrading many coastal wetland ecological functions [23,25]. To support the rapid financial growth and urban expansion, a significant portion of high-quality agricultural land and city water bodies have been converted into urban construction land [26,27].

Many studies have evaluated the LDD in specific areas based on observations and remote sensing products, although often using a single normalized vegetation index [19,28]. However, the Normalized Difference Vegetation Index (NDVI) has limitations and may not accurately capture substantial changes in vegetation [29]. Thus, a single NDVI index may not fully reflect the dynamic changes in biological mass and ecological power in a specific area, leading to strong uncertainty in evaluating LDD dynamics. To address this issue, some studies have attempted to combine NDVI with other parameters (such as gross primary productivity, sun-induced chlorophyll fluorescence, and net primary productivity) to construct new composite indices for evaluating LDD [12,29–31]. Among these, the LDDI index based on NDVI and Gross primary productivity (GPP) can comprehensively reflect the terrestrial ecosystem's vegetation coverage, productivity, and biomass, allowing for the accurate and rapid detection of changes in the LDD process across diverse spatial and temporal scales. Kang et al. [12] conducted a similar analysis of China's LDD process using an LDD index but failed to perform a quantitative analysis of the factors influencing LDD. In addition, their study focused on the entire country's LDD process at a coarse resolution (10 km) and did not carry out a detailed analysis or discussion of different regions.

Monitoring and analyzing the LDD processes in coastal areas is of great importance for decision-makers and stakeholders to implement effective policy measures for the sustainable management and utilization of natural resources. Therefore, this study aims to examine the spatial and temporal variations in LDD by evaluating the vegetation coverage and primary productivity of coastal land ecosystems. Additionally, the study employs analytical methods such as residual analysis, land transfer analysis, and trend analysis to investigate the impact of human and climate factors on LDD. The study quantitatively evaluates the influence of human and climate factors on LDD in different regions and explores the possible relationship between extreme precipitation, extreme temperature, land use change, and the LDD process. Section 2 outlines the study area, data sources, and methods, while Section 3 presents the main findings. Finally, Sections 4 and 5 provide a comprehensive discussion and conclusion, respectively.

2. Materials and Methods

2.1. Study Area

The coastal areas studied in this research comprise 12 provincial administrative regions of China: Jiangsu (JS), Hainan (HN), Guangxi (GX), Liaoning (LN), Fujian (FJ), Guangdong (GD), Shandong (SD), Tianjin (TJ), Taiwan (TW), Zhejiang (ZJ), Shanghai (SH), and Hebei

(HB) (excluding some islands and the Hong Kong and Macau Special Administrative Regions due to lack of data). Among these regions, the metropolitan regions in China, such as the Pearl River Delta (PRD), Bohai Sea, and Yangtze River Delta (YRD), are among the most dynamic and fast-growing regions in the country [32]. The research area spans a total land area of 496,342.5 km², extending from northeast to southwest for approximately 2967 km and reaching a maximum width of approximately 550 km from east to west. About 43% of the population lives in China's coastal areas, and the GDP of coastal provinces accounts for about 60% of the country's total [33]. The predominant landform types in Coastal China are hills and plains, with a significant concentration of plains in the north and hills in the south. The LULC types in the study area are predominantly composed of forests and croplands, exhibiting a distribution with croplands in the north and forests in the south, divided by Jiaxing City in Zhejiang Province (Figure 1). In recent decades, due to urbanization, swift economic expansion, and overexploitation of land, China's coastal areas have experienced severe ecological destruction and environmental deterioration [34–36].

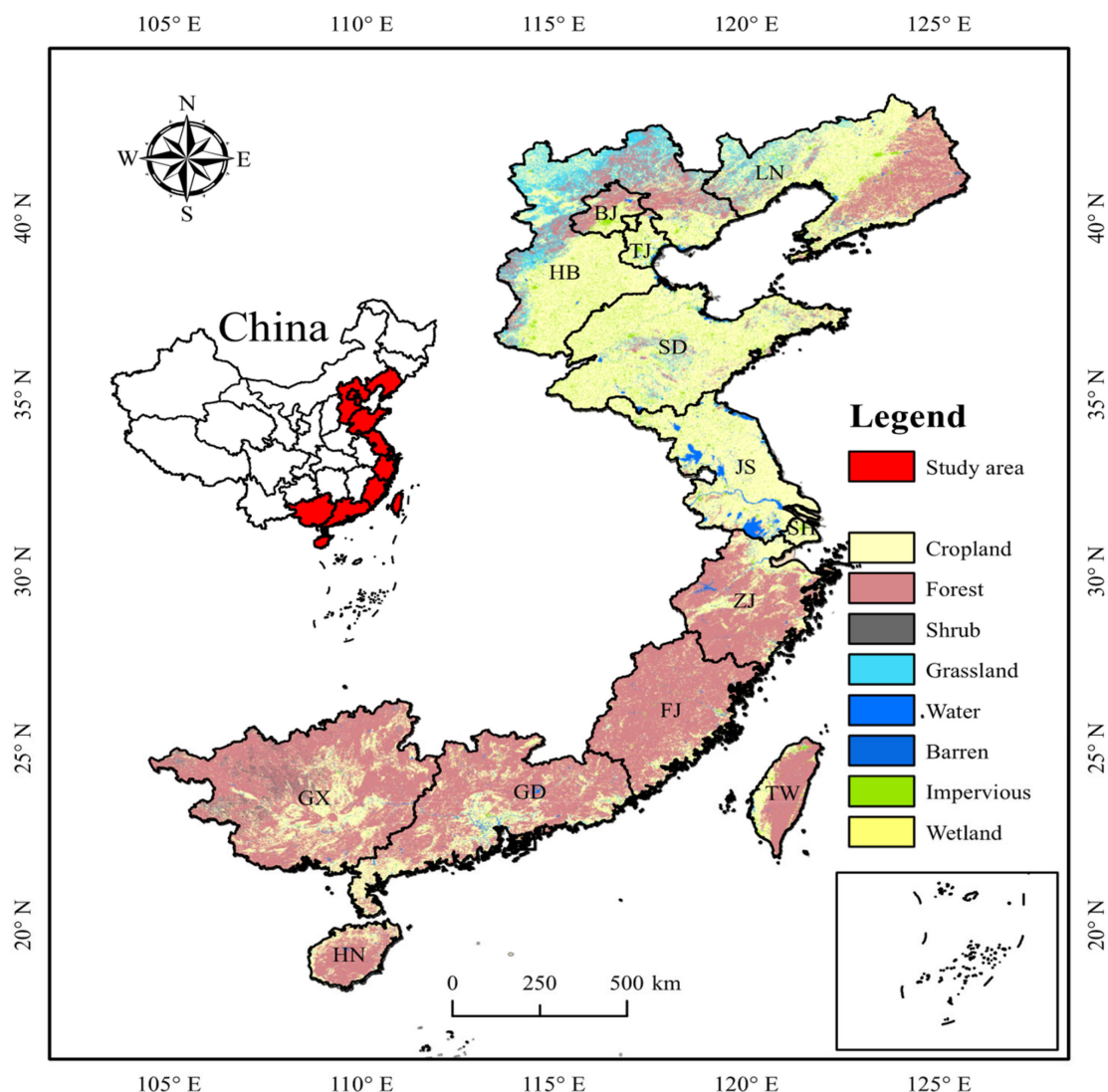


Figure 1. Geographical location and LULC types of the study region in 1985.

2.2. Datasets

This study utilized various datasets, including NDVI, GPP, temperature, precipitation, and LULC. The NDVI values were obtained from the GIMMS-NDVI 3g.v1 dataset with a temporal resolution of 15 days and a spatial resolution of 8 km from 1982 to 2015. This dataset is derived from the data collected by the Advanced Very High-Resolution

Radiometer (AVHRR) satellite of the National Oceanic and Atmospheric Administration (NOAA) and has been widely used in various research fields, including agriculture, forestry, and ecology [37]. The GPP values were obtained from a GPP dataset with a spatial resolution of 0.05° and a temporal resolution of 8 days for 1982–2017, which was generated by Zheng et al. [38] using the revised EC-LUE model. The annual mean temperature and precipitation data with a 1 km resolution for 1982–2015 were obtained from the National Tibetan Plateau Data Center. This dataset was generated using the Delta method to downscale the CRU climate dataset and the high-resolution global climate dataset published by WorldClim [39]. The observed temperature and precipitation data from the CN05 dataset [40] with a resolution of $0.5^\circ \times 0.5^\circ$ from 1982 to 2015 was utilized to calculate climate indices. The LULC dataset for China from 1985 to 2021 developed by Yang et al. [41] has a 30 m horizontal resolution and will be used to analyze the transformation of nine land types (e.g., cropland, forest, shrub, grassland, water, snow and ice, barren, impervious, and wetland) in coastal China. All of the data mentioned above from 1982 to 2015 were preprocessed by projection transformation, clipping, resampling, and other methods, then converted to a raster data type with a uniform resolution of 1 km.

2.3. Methods

2.3.1. Land Degradation and Development Index (LDDI)

To calculate LDDI, it is necessary to process the original NDVI and GPP data. Firstly, the maximum NDVI value is extracted from the GIMMS-NDVI 3g.v1 dataset for each half-month. Next, the half-month data is converted into monthly data, and the NDVI values for 12 months are averaged to obtain the annual NDVI data. The original GPP data consists of 46 files per year, with daily averages from 1 to 45. To obtain the annual GPP data, the daily data from 1 to 45 is multiplied by 8 days, and the last data point is multiplied by 5 or 6 days, depending on leap year conditions. Finally, all the data is summed to obtain the total annual GPP. After processing the original NDVI and GPP data, NDVI and GPP are normalized using the following equation:

$$NNDVI = \frac{NDVI - NDVI_{\min}}{NDVI_{\max} - NDVI_{\min}} \quad (1)$$

$$NGPP = \frac{GPP - GPP_{\min}}{GPP_{\max} - GPP_{\min}} \quad (2)$$

where $NGPP$ and $NNDVI$ represent the normalized values of GPP and $NDVI$, respectively. $NGPP_{\min}$ and $NDVI_{\min}$ represent the minimum values of GPP and $NDVI$, respectively, while $NGPP_{\max}$ and $NDVI_{\max}$ represent the maximum values of GPP and $NDVI$, respectively. In the normalization process, the maximum and minimum values of $NDVI$ and GPP are the maximum (small) values in the time series of the study period. Then, $LDDI$ is calculated based on the Euclidean distance method using the normalized $NDVI$ and GPP values [12,42].

$$LDDI = \sqrt{(NNDVI - NNDVI_{\min})^2 + (NGPP - NGPP_{\min})^2} \quad (3)$$

Since both $NNDVI_{\min}$ and $NGPP_{\min}$ are 0 after normalization, $LDDI$ can be simplified as:

$$LDDI = \sqrt{NNDVI^2 + NGPP^2} \quad (4)$$

2.3.2. Trend and Change-Point Detection Methods

This study used various methods to analyze the trends and change points in the LDD process in coastal areas. First, the nonparametric Mann–Kendall (M-K) test was applied to assess the trend of the LDDI index. The M-K test is widely used and effective for analyzing

trends in time series data, particularly in hydrology and meteorology [43,44]. The M-K test is given as follows:

$$Z = \begin{cases} \frac{S-1}{\sqrt{\text{Var}(S)}} & S > 0 \\ 0 & S = 0 \\ \frac{S+1}{\sqrt{\text{Var}(S)}} & S < 0 \end{cases} \quad (5)$$

where statistic S can be calculated as:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sgn}(x_j - x_i) \quad (6)$$

where x_i and x_j are the observations at the i th and j th moments, respectively, and n is the length of the series. When $x_j - x_i$ is greater than, equal to or less than 0, $\text{sgn}(x_j - x_i)$ equals 1, 0, or -1 , respectively. The statistic Z can measure the trend, with $Z > 0$ and $Z < 0$ indicating increasing and decreasing trends, respectively. A significance level of 0.05 was considered in this study, where $Z > 1.96$ and $Z < -1.96$ indicate significant increasing and decreasing trends, respectively. Additionally, the Theil–Sen slope [45] was used to calculate the robust trend rate of the LDDI, which can eliminate the impact of missing data or anomalies on the trend test. The slope is estimated by:

$$\beta = \text{Median} \left[\frac{(x_j - x_i)}{(j - i)}, \forall j > i \right] \quad (7)$$

where β is the estimate of the slope of the trend; x_i and x_j are the observations at the i -th and j -th moments, respectively. Through the Sen median trend analysis and the Z statistic from the M-K test, the LDD process in coastal areas was divided into five categories (as seen in Table S1) [12,46].

In addition, this study used a Bayesian ensemble algorithm (BEAST) for change-point detection [47]. For a given time series, BEAST outputs a model capturing the seasonality of the data, the long-term trend, as well as the probability and location of breakpoints in the trend. Briefly, BEAST combines several models into an average model (Bayesian model average) instead of relying on a single model to detect changes in time series. It allows for estimating the probability of abrupt changes at any given time, unlike other change point algorithms that simply identify whether a change point is present. Compared with traditional change-point detection methods (e.g., sliding t -test, M-K test), BEAST can not only determine the time points of change points, but also calculates the likelihood of multiple change points occurring at multiple time points. Zhao et al. [47] provided the mathematical details of BEAST, which was run using the “Rbeast” package in R [48,49].

2.3.3. Residual Trend Analysis and Corresponding Quantitative Analysis

A multivariate linear regression model was employed to analyze the effects of precipitation and temperature on the LDD process at each pixel. By examining the multivariate regression residuals, we were able to deduce the impacts of human and climate factors on the LDD process, as well as their relative contributions. The calculation formula is as follows:

$$LDDI_{CC} = C_1 \times T + C_2 \times P + A \quad (8)$$

$$LDDI_{HA} = LDDI_{obs} - LDDI_{CC} \quad (9)$$

where $LDDI_{CC}$ and $LDDI_{obs}$ are the predicted and observed values of LDDI, respectively (dimensionless). P and T are the normalized values of precipitation and temperature, respectively. C_1 and C_2 represent the regression coefficients, and A is a constant. The $LDDI_{HA}$ (i.e., residuals) represents the portion of the $LDDI_{CC}$ dependent variable that is

not significantly impacted by the explanatory factors (T and P) and can be considered as the part of the LDD affected by human factors.

To determine the trend of $LDDI_{HA}$, a linear regression model was utilized, and the $LDDI_{HA}$ was classified into five categories based on the classification of Tian et al. [50] (Table S2). Over time, an increase in the $LDDI_{HA}$ indicates the intensification of human activity, whereas a decrease indicates a decline in human activity. Furthermore, the relative contribution rates of climate and human factors to the change of LDD in coastal China were calculated according to Table 1 [51].

Table 1. Calculation criteria for relative contribution rate of driving factors in LDD process changes.

Slope ($LDDI_{obs}$) ^a	Driving Factors	Standard of Calculation		Contribution Rate	
		Slope ($LDDI_{CC}$) ^b	Slope ($LDDI_{HA}$) ^c	Climate (CC)	Human (HA)
>0	CC&HA	>0	>0	$\frac{slope(LDDI_{CC})}{slope(LDDI_{obs})}$	$\frac{slope(LDDI_{HA})}{slope(LDDI_{obs})}$
	CC	>0	<0	100	0
	HA	<0	>0	0	100
<0	CC&HA	<0	<0	$\frac{slope(LDDI_{CC})}{slope(LDDI_{obs})}$	$\frac{slope(LDDI_{HA})}{slope(LDDI_{obs})}$
	CC	<0	>0	100	0
	HA	>0	<0	0	100

Notes: “a” represents the slope of LDDI from remote sensing, “b” represents the slope of LDDI from binary regression predictions, and “c” represents the slope of the $LDDI_{HA}$. All slopes were calculated using linear trend method.

2.3.4. Indices of Climatic Extremes

To further analyze the relationship between temperature, precipitation, and LDDI, this study selected 24 extreme climate indices recommended by ETCCDI [52–54] to describe extreme temperature and precipitation. Table 2 shows the selected extreme climate indices, which can describe the specific frequency, amplitude, and duration of extreme precipitation and temperature events in the study area, such as the maximum 1-day precipitation ($Rx1day$), the number of heavy precipitation days ($R25mm$), and summer days (SU) (days with maximum temperature exceeding 25 °C). Firstly, 14 temperature extremes and 10 precipitation extremes indices are calculated from the CN05 observation dataset based on Table 2. Then, the M-K test and Theil–Sen slope are used to analyze the variation trend of the selected extreme climate indices from 1982 to 2015. Finally, the Pearson correlation coefficient is used to analyze the relationship between LDDI and extreme climate indices.

Table 2. Extreme climate indices used in this study.

ID	Index	Definition	Unit
1	FD ^a	Annual count when TN(daily minimum) < 0 °C	days
2	SU25 ^a	Annual count when TX(daily maximum) > 25 °C	days
3	TR20 ^a	Annual count when TN(daily minimum) > 20 °C	days
4	TXx ^a	Monthly maximum value of daily maximum temperature	°C
5	TNx ^a	Monthly maximum value of daily minimum temperature	°C
6	TXn ^a	Monthly minimum value of daily maximum temperature	°C
7	TNn ^a	Monthly minimum value of daily minimum temperature	°C
8	TN10p ^a	Percentage of days when TN < 10th percentile	days
9	TX10p ^a	Percentage of days when TX < 10th percentile	days
10	TN90p ^a	Percentage of days when TN > 90th percentile	days
11	TX90p ^a	Percentage of days when TX > 90th percentile	days
12	WSDI ^a	Annual count of days with at least 6 consecutive days when TX > 90th percentile	days
13	CSDI ^a	Annual count of days with at least 6 consecutive days when TN < 10th percentile	days
14	DTR ^a	Monthly mean difference between TX and TN	°C
15	Rx1day ^b	Monthly maximum 1-day precipitation	mm
16	Rx5day ^b	Monthly maximum consecutive 5-day precipitation	mm

Table 2. Cont.

ID	Index	Definition	Unit
17	SDII ^b	Annual total precipitation divided by the number of wet days (defined as PRCP $\geq$ 1.0 mm) in the year	mm/day
18	R10 ^b	Annual count of days when PRCP $\geq$ 10 mm	days
19	R20 ^b	Annual count of days when PRCP $\geq$ 20 mm	days
20	CDD ^b	Maximum number of consecutive days with RR < 1 mm	days
21	CWD ^b	Maximum number of consecutive days with RR $\geq$ 1 mm	days
22	R95p ^b	Annual total PRCP when RR > 95th percentile	mm
23	R99p ^b	Annual total PRCP when RR > 99th percentile	mm
24	PRCPTOT ^b	Annual total PRCP in wet days (RR $\geq$ 1 mm)	mm

Note: ^a Indices of temperature extremes; ^b Indices of precipitation extremes.

2.3.5. Land Transition Change

The transition matrix is an effective tool for analyzing changes in LULC, which can quantify the transition trajectory of each LULC type [55]. Additionally, to quantitatively analyze the changes in LULC types over different periods, this study also calculates the total area and change rate of different LULC types. The calculation formula is as follows:

$$A = \sum_{i=1}^{n-1} |a_{i+1} - a_i| \quad (10)$$

$$p = \frac{1}{n-1} \sum_{i=1}^{n-1} |a_{i+1} - a_i| \quad (11)$$

where a_i is the LULC type of specific year; i and n are the total number of years in the analyzed period.

3. Results

3.1. Spatial Patterns and Long-Term Trends for LDD and Climate

Figure 2a shows that the LDDI values across the study area exhibit significant spatial heterogeneity across different provinces, with higher values in the south and lower values in the north. Specifically, southern provinces (GX, GD, HN, FJ, ZJ, TW) generally have LDDI values ranging from 0.7 to 1.3, while northern provinces (JS, SD, SH, HB, TJ, LN) have LDDI values ranging from 0.3 to 0.7. This pattern accurately reflects the higher vegetation greenness and productivity in southern regions compared to northern regions, as seen in Figures S1 and S2. Between 1982 and 2015, most of the study area experienced land development (Figure 2b). Approximately 62.47% of the areas exhibited significant ($p < 0.05$) trends in land development, while only 5.01% showed no significant trend. Additionally, only 7.03% of the areas experienced land degradation processes, with the YRD, PRD, the northern region of TW, and the northeast region of LN experiencing significant land degradation processes. The climatic conditions in the study area manifest a warm and humid trend, characterized by a noteworthy temperature increase in most regions (Figure 2c). The trend in precipitation variation is not significant, but there has been an overall increase in most regions, except for certain areas in GX, GD, and LN, which showed a downward trend (Figure 2d).

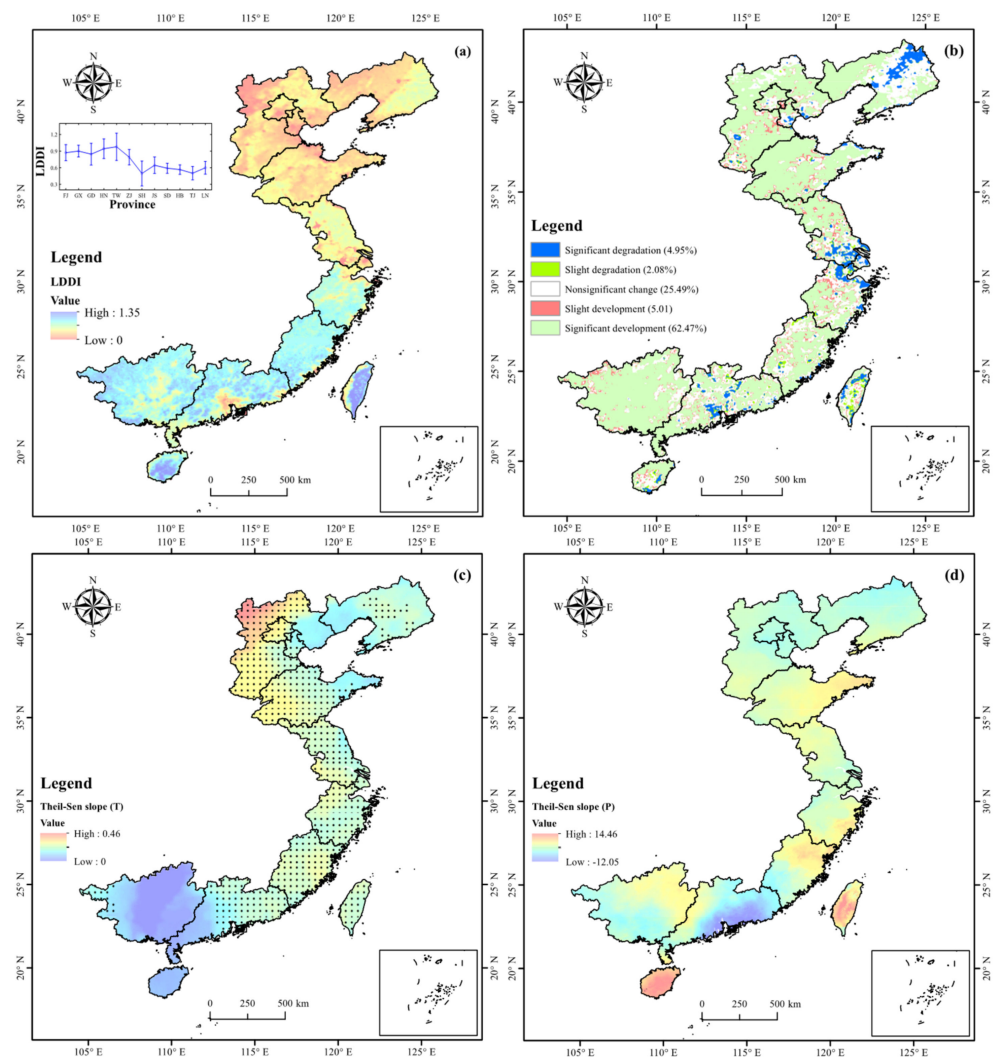


Figure 2. Temporal evolution of LDD processes in Coastal China from 1985 to 2015. (a) Spatial distribution of LDDI multi-year mean values (the built-in subgraph shows the LDDI of each province); (b) Theil–Sen slope of LDDI; (c) Theil–Sen slope of temperature; (d) Theil–Sen slope of precipitation. The black dots denote data points that have achieved statistical significance at a level of 0.05.

3.2. Links between LDDI, Climatic, and Anthropogenic Factors

As shown in Figure 3a, temperature positively impacts LDDI in most of the study area except for the western region of GX, the eastern region of GD, FJ, and the eastern region of LN. Similarly, precipitation positively impacts LDDI in areas other than the PRD, YRD, and TW (Figure 3b). However, the observed and fitted results in the relationship between LDDI and climate factors exhibit a low correlation coefficient of less than 0.3 in general, and the overall relationship fails to pass the significance test (Figure 3c). Nevertheless, despite the overall lack of significance in the regression relationship between LDDI and climate factors, some areas, particularly in the northern region of the study area, including SD, HB, northern JS, and eastern LN, exhibit a significant relationship ($p < 0.01$). In addition, some pixel-scale regions in southern provinces, such as GX, GD, FJ, ZJ, and HN, also show this significant relationship.

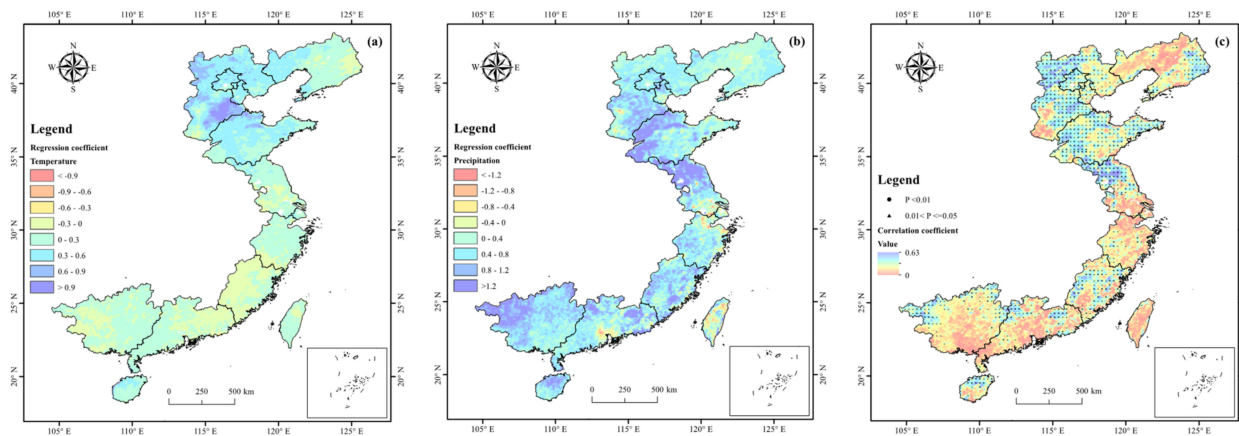


Figure 3. The correlation between climate factors and LDDI in coastal China. (a) The regression coefficient of temperature; (b) the regression coefficient of precipitation; and (c) the significance level. The black dots denote data points that have achieved statistical significance at a level of 0.05.

The trend of $LDDI_{HA}$ indicates the degree to which human activities have impacted the LDD process. Spatially, the $LDDI_{HA}$ trend increased throughout the study period, indicating that the influence of human activities on the LDD process was becoming increasingly significant (Figure 4a). However, even under similar natural environmental conditions, the $LDDI_{HA}$ trends of different provinces showed significant differences, and the spatial heterogeneity of the $LDDI_{HA}$ trend was strong. Among them, the $LDDI_{HA}$ trend in GX was the strongest, indicating that the LDD process in this area was most affected by human activities relative to climate factors. Approximately 55.48% of the entire study area was affected by increasing human activities, of which about 8.92% had a significantly increasing $LDDI_{HA}$ trend ($p < 0.01$). In 4.29% of the areas, the influence of human activities on LDD decreased, mainly distributed in the YRD, PRD, and Northeast LN. Additionally, about 38.23% of the areas showed no significant change in the $LDDI_{HA}$ trend, mainly distributed in FJ, JS, and TW.

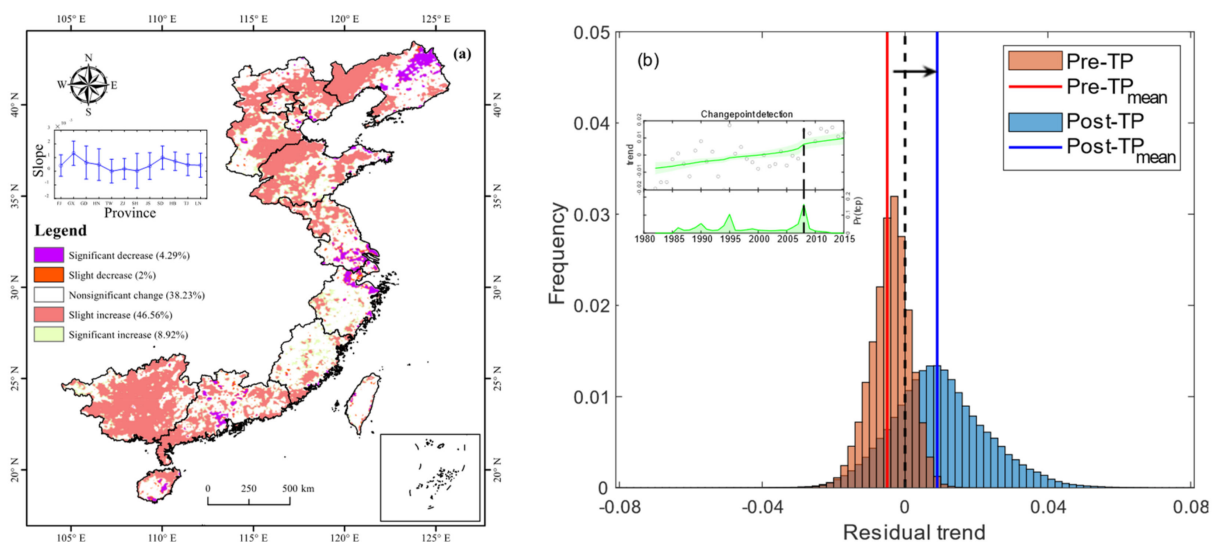


Figure 4. Temporal and spatial variation characteristics of $LDDI_{HA}$. (a) Spatial distribution of $LDDI_{HA}$ trends (the built-in subgraph shows the $LDDI_{HA}$ trend of each province); (b) histograms of $LDDI_{HA}$ in different periods (the built-in subgraph indicates the trend of region-average $LDDI_{HA}$; the scatter is the $LDDI_{HA}$ of region-average for each year from 1982 to 2015; the black arrows indicate transition direction; the red and blue lines indicate the multi-year average $LDDI_{HA}$ values of the study region in Pre-TP and in Post-TP, respectively).

To gain a deeper understanding of the variations in $LDDI_{HA}$ during different periods, this study examined the turning points (TPs) in the $LDDI_{HA}$ time series. The analysis using BEAST showed that the average $LDDI_{HA}$ in the entire study area increased significantly ($p < 0.01$) during the study period, with a TP around 2008 (probability = 0.24). Accordingly, the $LDDI_{HA}$ before (Pre-TP, red line) and after (Post-TP, blue line) the TP were calculated, respectively (Figure 4b). A marked contrast between the two periods before and after the TP is evident. Before the TP, the average $LDDI_{HA}$ value was mainly less than zero. However, after the TP, the average $LDDI_{HA}$ of the whole region increased from -0.04 to 0.01 , indicating that the influence of human activities on LDD in Post-TP is more significant than in Pre-TP.

3.3. Contribution of Human Activities and Climate Change to LDD

As shown in Figure 5a, human factors have a stronger impact on the changes in the LDD process than climate change factors. In most regions, human activities are responsible for over 60% of the alterations in LDD. Among them, the highest contribution of human activities to the changes in LDD is in GX (85.31%), followed by LN (81.3%) and TJ (79.3%), and the lowest is in FJ (50.73%). To further quantitatively analyze the impact of human factors and climate change on the LDD process, the LDD process is divided into eight types (Table S3). As shown in Figure 5b, the LDD process affected by human activities accounts for about 25.76% of the study area. Specifically, the majority of the LDD process in the study area (about 21.61% of the total study area) is attributed to land development, concentrated in the east of GX, HB, and the west of GD and LN. On the other hand, the distribution of land degradation is limited to only 4.15% and can be found in fragmented areas, including the PRD, YRD, and northeast of LN. The LDD process affected only by climate change accounts for about 7.42% of the study area, with land development and land degradation accounting for 7.38% and 0.04%, respectively. The LDD process affected by the joint impact of climate and human factors accounts for 30.94% of the study area, with the majority attributed to land development (30.64%) and mainly distributed in FJ, northern JS, SD, and HB. Although 30.94% of the LDD process is affected by the joint impact of climate and human factors, human factors are the primary factor affecting this LDD type (Figure 5a). At the same time, about 4.56% of the study area experienced natural degradation or development, and about 31.31% showed no significant change.

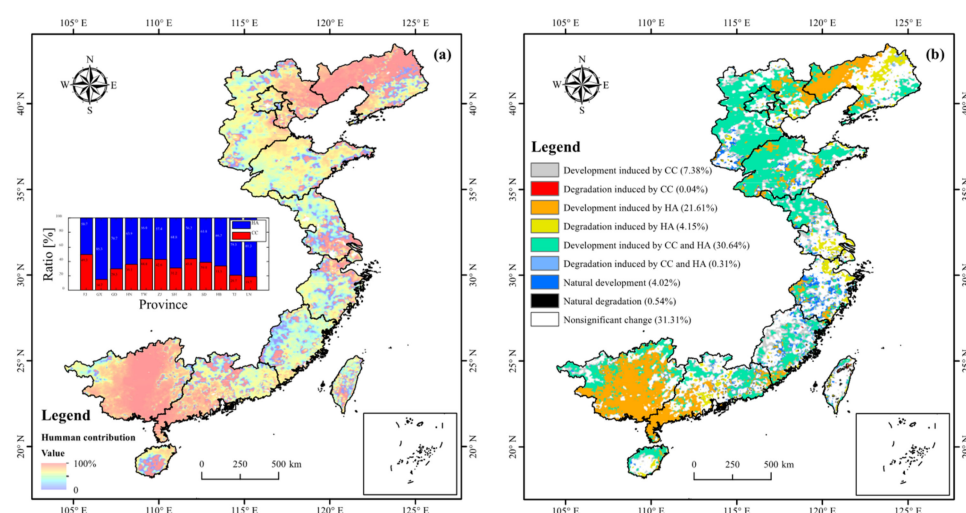


Figure 5. Effects of human activities on LDD processes. (a) The spatial distribution of human contributions, the bar chart displaying the contribution rate (unit: %) of human activities (HA) and climate change (CC) to the LDD process in each province. The red and blue bars represent CC and HA, respectively; (b) the LDD types impacted by HA and CC.

4. Discussion

4.1. Impacts of Climate Factors on the LDD Processes

This study used multiple linear regression to investigate the impact of climate factors (temperature and precipitation) on the LDD process at the pixel scale in coastal areas. Most areas, except for the northern coastal areas, exhibited a non-significant positive relationship between precipitation and temperature and the LDD process, which is consistent with previous studies [12]. The northern coastal region is dominated by cropland, while the southern coastal region is dominated by forest, which accounts for 84.5% of the total area. Therefore, changes in rainfall significantly impact the growth of natural vegetation and crops in these regions due to moisture conditions. The significance level of the multiple regression model indicates that the relationship between the LDDI in the northern coastal region and climate factors is significant at the pixel scale ($1 \text{ km} \times 1 \text{ km}$), indicating that this region is more vulnerable to the effects of climate change (Figure 3c). By analyzing the Pearson correlation between region-average LDDI and extreme temperature indices, significant negative correlations were found between LDDI and FD, TN10p, TX10p, CSDI, and DTR. On the other hand, significant positive correlations were observed between LDDI and TR, TN90p, and TX90p. Except for DTR and TX90p, all other extreme temperature indices show a significant relationship with LDDI, passing the significance test at 0.01 (Table S4). Among the eight extreme temperature indices that display a significant relationship with LDDI, TN10p and TN90p reign supreme with the highest Pearson correlation coefficients with LDDI, reaching -0.63 and 0.63 , respectively. The next most remarkable correlation is with FD, boasting a Pearson correlation coefficient of -0.52 with LDDI. The Pearson correlation coefficient between DTR and LDDI is the smallest, with a value of -0.35 . Moreover, LDDI displays a significant relationship with some extreme precipitation indices, such as SDII, R10, and R95p, which were significantly positively correlated (Table S5). Among all extreme precipitation indices that exhibit a significant relationship with LDDI, R10 stands tall with the highest Pearson correlation coefficient with LDDI at 0.46 , followed by R95p, which holds a Pearson correlation coefficient of 0.44 with LDDI. The smallest correlation is with SDII, displaying a Pearson correlation coefficient of 0.41 .

Figure 6 shows significant trends in the most extreme temperature and precipitation indices in China's coastal region from 1982 to 2015. Overall, the intensity and frequency of extreme climatic events in China's coastal region have increased. The trend in temperature change is particularly noticeable, as nearly all extreme temperature indices, except for TXx, showed a significant upward trend at the 0.01 or 0.05 significance level. Combining the Pearson correlation coefficients between LDDI and extreme climate (temperature and precipitation) indices, it is evident that climate warming has a significant positive impact on LDDI. Moreover, the increase in precipitation intensity also has a significant positive impact on LDDI. It is widely accepted that global warming significantly impacts terrestrial ecosystems. Climate change can worsen land degradation through higher temperatures, evaporation rates, intense precipitation, drought, frequent floods, and increased soil salinity [56,57]. For example, extreme drought increases vegetation thermal and water stress, limiting the growth of natural vegetation and crops and leading to the degradation of farmlands, grasslands, and forests [4,58]. Additionally, climate change can exacerbate soil erosion, intensifying land degradation. The north of the coastal regions comprises many croplands, with their surface soil easily threatened by wind and water erosion [4,58]. High temperatures and strong winds caused by climate change dry the soil and exacerbate wind erosion [59]. Meanwhile, short-term heavy rain increases water erosion [60], reducing soil fertility [61], and thus harming the biomass of terrestrial ecosystems [62]. Higher temperatures can also accelerate the decomposition rate of organic matter in the soil, altering the soil's water nutrient balance and storage capacity, and changing the soil's microbial populations [63,64]. Moreover, higher temperatures increase evaporation, increasing cropland irrigation requirements in the research area. Irrigation water evaporation often results in high salt content in surface soils, making the land unsuitable for crop cultivation [65,66]. Previous studies have indicated that climate change is likely to increase soil salinization

in arid and semi-arid regions, as well as coastal areas [67]. Furthermore, as more extreme events are expected in the future, previously productive and stable ecosystems may become unstable, and their ability to absorb carbon dioxide may decline, further exacerbating climate change and land degradation [68]. Therefore, it is crucial to develop appropriate mitigation policies for maintaining the soil functioning of fragile ecosystems.

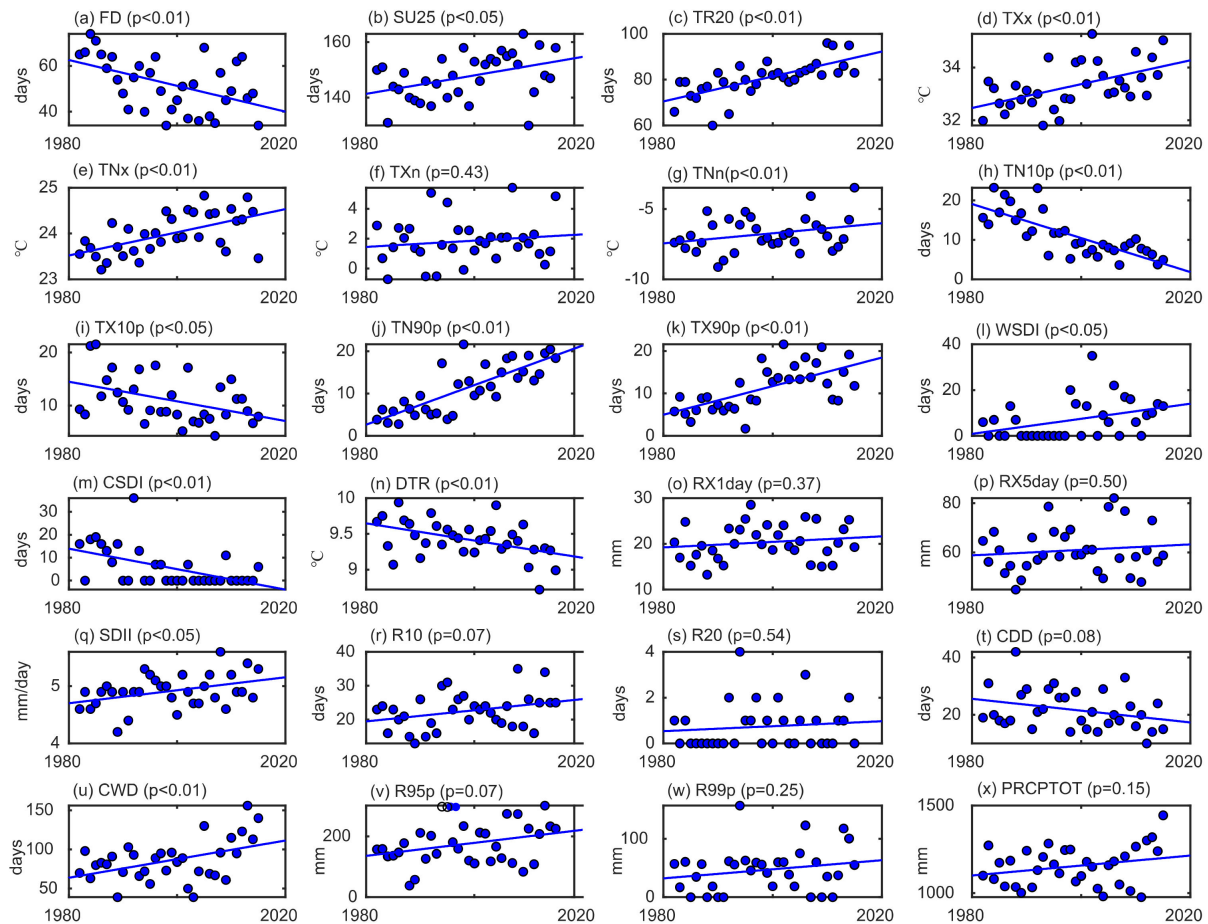


Figure 6. Variation trend of extreme climate indices. (a–n) Represent extreme temperature, and (o–x) represents extreme precipitation indices; The scatter plot displays the extreme climatic index value for each year, while the blue line represents the fitted trend line; the p -value indicates the significance level of the changing trend, with smaller values indicating higher significance.

4.2. Impacts of Human Activities on the LDD Processes

According to the residual analysis, human factors mainly contribute to the LDD changes in coastal China compared to climate factors. Human activities, such as economic development, ecological restoration plans, and urbanization, usually significantly impact the LDD process. As shown in Figure 7, over the past 35 years, the study area has witnessed varying expansions in impervious, water, and forest areas ($p < 0.01$). The impervious area expanded from 5.26 million ha in 1985 to 11.99 million ha in 2015, an increase of 127.93%, far exceeding that of other land types. Water and forest areas also experienced 30.76% and 3.53% growth, respectively. In contrast to the rapid expansion of impervious areas, wetland, shrub, grassland, barren, and cropland trends showed significant decreases ($p < 0.01$). For example, croplands have decreased by 13.2% (7.81 million ha) since 1985, while barren areas decreased by 64.34% (0.13 million ha), wetland areas decreased by 95.08% (444.42 ha), grassland areas decreased by 21.28% (1.22 million ha), and shrub areas decreased by 46.54% (0.49 million ha).

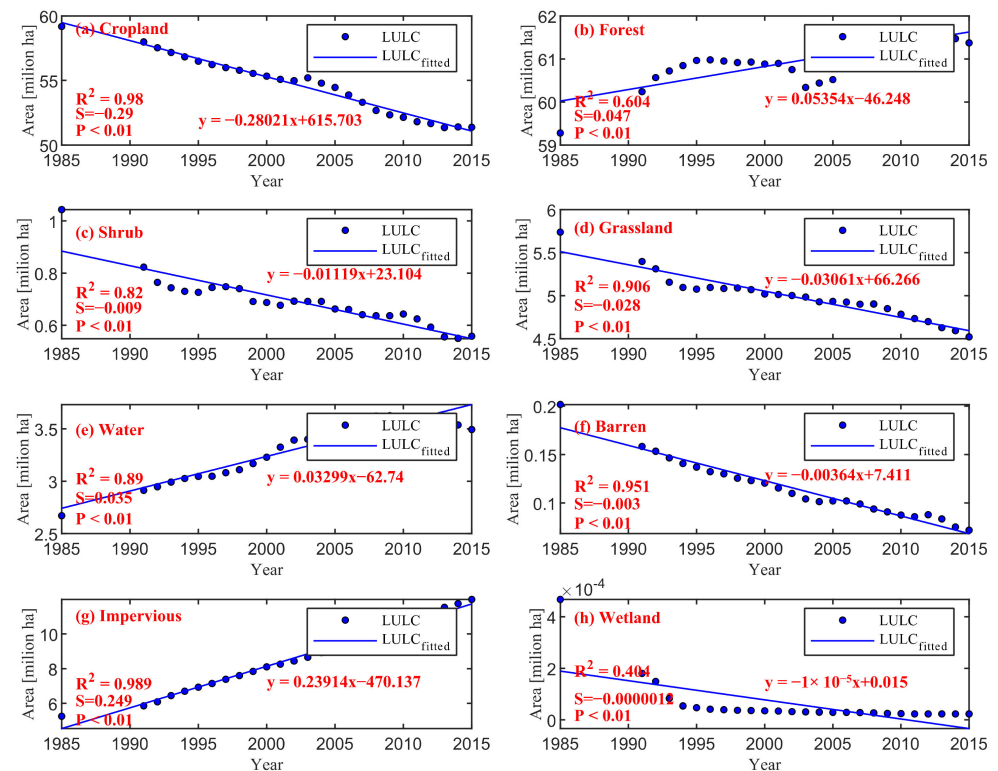


Figure 7. Temporal changes in the area of different LULC types in Coastal China from 1985 to 2015.

Rapid urbanization, particularly in eastern China, has had various direct or indirect impacts on land development in recent decades, with the most prominent issue being the loss of substantial amounts of fertile farmland due to conversion for construction purposes [27]. Among all LULC types, cropland, forest, and impervious surfaces account for 63.21% of the total area in the study area (Figure 8). Figure 8 shows that among all LULC types, the cropland, forest, and impervious land development areas account for 63.21% of the total study area. Additionally, except for barren, water, and wetland, the land development areas of all other LULC types occupy more than 50% of their respective areas, indicating that land development plays a dominant role in the LDD process for most LULC types (Figure S3). Since the reform and opening policy in 1978, China has made significant progress in industrialization and urbanization [69]. According to the China National Bureau of Statistics, the urbanization rate rose from 17.9% in 1978 to 59.6% in 2018, with an average annual increase of 1% [70]. In this context, the LULC has encountered intense pressure and challenges, leading to an imbalanced structure and increased competition among its types [71]. During this period, China has implemented a large number of sustainability programs, such as the “Soil and Water Conservation Program”, “Converting Cropland to Forest Project”, “National Land Consolidation Program”, and “Natural Forest Conservation Program” (Table S6). In particular, since the early 20th century, the Chinese government has invested heavily in implementing numerous nationwide sustainability programs, which have greatly changed land use patterns and improved vegetation coverage, ultimately contributing to land development [72–74]. In the study, the $LDDI_{HA}$ trends have continued to rise, especially after 2008, and this change is closely related to the widespread sustainability programs implemented in China since 2000.

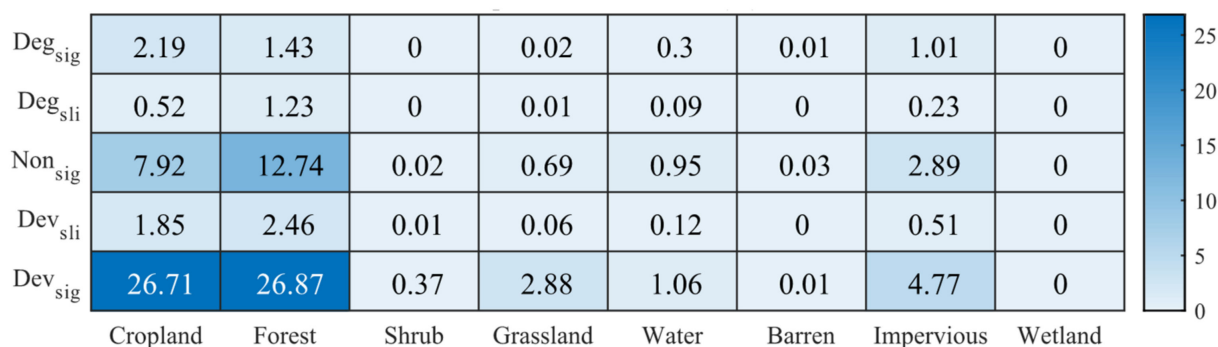


Figure 8. The proportion of different LDD change types in the study area. Deg and Dev represent land degradation and land development, respectively. Sig, Sli, and Non_{sig} represent LDD changes with significant, slight, and no changes. Values less than 0.00001 are represented as 0.

Coastal urbanization has resulted in the conversion of vast areas of farmland and natural spaces, causing land degradation of cropland, forest, grassland, and water bodies [36,75–77]. Among all land use and land cover (LULC) types, cropland, impervious, and forest have undergone the most significant transfer changes in each subregion. Cropland has the highest loss rate (63.24%), followed by forest (16.72%) and grassland (12.5%), as shown in Table S7 and Figure S4. The main transfer direction of cropland is to impervious (53.97%) and forest (29.43%), and 91.31% of the land transferred to impervious comes from cropland. The source of land transferred to forest is also mainly cropland (64.98%), followed by grassland (23.85%). The main land source for the transfer into cropland is forest (70.08%) and grassland (21.7%). Meanwhile, artificial afforestation (54.64%) is also a major factor in the loss of grassland. The changes in water area and wetland area are usually closely related to land reclamation and urban expansion, especially in regions such as the YRD and the PRD, which are strongly impacted by human activities. All of these reflect the unprecedented urbanization process in China and the government’s implementation of various green ecological restoration projects [74].

4.3. Limitations and Future Work

This study aims to analyze the change characteristics of LDD in China’s coastal areas and the corresponding influencing factors using the LDDI index, constructed from NDVI and GPP data, which are openly accessible through existing remote sensing products. However, the study has several limitations and shortcomings that may affect the interpretation of the results. Firstly, analyzing the spatial variability of LDD requires high-resolution datasets, but the length, quality, and accuracy of the data used in this study were limited. Furthermore, the LDDI index may not fully capture the detailed spatial variations in mountainous regions with complex terrains due to the limited resolution and uncertainty of the NDVI and GPP data. Secondly, the dynamic process of LDD is complex and multifaceted, requiring consideration of multiple dimensions such as climate, society, economy, and environment. Understanding the complex relationships between these factors is essential to formulate effective strategies to mitigate land degradation and promote sustainable land use practices. However, in this study, only precipitation and temperature were considered as climate factors, and other climatic elements such as wind and soil moisture that could affect LDD were omitted. Although the impact of temperature, precipitation, and some human factors on LDD was analyzed, it may not fully explain the detailed land degradation and development in coastal China. Despite these limitations, this study enhances our understanding of the factors behind the spatiotemporal changes in LDD in coastal China and sets a foundation for similar research in other coastal regions. Future studies should focus on researching additional factors that may influence the dynamic process of LDD and utilize more accurate, multi-source, high-resolution datasets, and mathematical models

that consider physical processes to investigate the response mechanisms of LDD changes to climate and human factors.

5. Conclusions

In this study, we analyzed the temporal-spatial variation of land development and degradation in China's coastal region from 1982 to 2015, using the LDDI index based on NDVI and GPP data and the residual analysis method. In addition, we quantitatively evaluated the relative contribution of the main driving factors to LDD and explored the impacts of climate and human factors. Our key findings are as follows:

- (1) During the study period, the primary LDD process observed in China's coastal region was land development, with 62.47% of the area exhibiting significant changes in land development trends. In contrast, land degradation processes were observed in only 7.03% of the region, mainly concentrated in the YRD, north of TW, PRD, and northeast LN.
- (2) Compared to climate change factors, human activities have a stronger impact on the changes in the LDD process. During the study period, the contribution of human activities to the LDD process became increasingly evident, with their contribution to LDD changes exceeding 60% in most regions. About 25.76% of the study area was significantly impacted by human activities, with approximately 21.61% of the land mainly affected by land development. In comparison, land degradation accounted for only 4.15% of the total area, fragmented and distributed in the PRD, YRD, and northeastern LN.
- (3) In most land types, land development dominates the LDD process, with land development areas of croplands, forests, and impervious regions accounting for 63.21% of the total study area. Significant expansion trends ($p < 0.01$) were observed in impervious, water, and forest regions within the study region, while wetlands, shrubs, grasslands, barren land, and croplands showed significant decreases ($p < 0.01$). Over the past few decades, China's coastal region has experienced rapid urbanization, significantly converting arable land into construction land. Between 1985 and 2015, cropland area decreased by 13.2% (7.81 million ha), primarily converting into impervious and forest land. Notably, 91.31% of the converted impervious land originated from cropland.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/rs15092249/s1>, Table S1: LDD processes in coastal China; Table S2: The change in effects of human activities on LDD; Table S3: Classification standard of LDD types; Table S4: Pearson correlation coefficients between LDDI and different extreme temperature indices; Table S5: Pearson correlation coefficients between LDDI and different extreme precipitation indices; Table S6: Summary of the planned timeframe, aims, and objectives of major Chinese sustainability programs; Table S7: Ratio (%) of land cover conversions from 1985 to 2015; Figure S1: Multi-year average of normalized NDVI values; Figure S2: Multi-year average of normalized GPP values; Figure S3: The proportion of different LDD change types among different LULC types; Figure S4: Heat map of the ratio (%) of LULC types transfer out and transfer in different provinces.

Author Contributions: Conceptualization, Y.L.; methodology and data curation, Y.H. and J.Y.; writing—original draft preparation, Y.H.; writing—review and editing, Y.H. and G.L.; visualization and supervision, Y.Z. and Y.L. All authors have read and agreed to the published version of the manuscript.

Funding: The study was funded by the Open Research Fund of State Key Laboratory of Simulation and Regulation of Water Cycle in River Basin (IWHR-SKL-KF202204), the Jiangsu Funding Program for Excellent Postdoctoral Talent (2022ZB147), the Key Scientific and Technological Project of the Ministry of Water Resources, P.R.C. (SKS-2022001), the Systematic Project of Guangxi Key Laboratory of Disaster Prevention and Engineering Safety (2022ZDK026) and TianHe Qingsuo Project special fund project in the field of climate, meteorology and ocean.

Data Availability Statement: All of the data used in this study are freely available and can be obtained from the following sources: The GPP dataset is available at <https://doi.org/10.6084/m9.figshare.8942336.v3> (accessed on 1 March 2023). The Land Use and Land Cover data can be obtained from Xin Huang (xhuang@whu.edu.cn) or at <https://doi.org/10.5281/zenodo.5816591> (accessed on 1 March 2023). Precipitation, temperature, and NDVI datasets were obtained from the Big Earth Data Platform for Three Poles at <http://poles.tpdac.ac.cn/> (accessed on 1 March 2023).

Acknowledgments: The authors gratefully acknowledge the National Tibetan Plateau Data Center (<https://data.tpdac.ac.cn/home>) and the Resources and Environmental Sciences and Data Center, Chinese Academy of Sciences (<https://www.resdc.cn/>).

Conflicts of Interest: The authors declare no conflict of interest.

References

- Chappell, A.; Baldock, J.; Sanderman, J. The global significance of omitting soil erosion from soil organic carbon cycling schemes. *Nat. Clim. Change* **2016**, *6*, 187–191. [\[CrossRef\]](#)
- Pacheco, F.-A.-L.; Fernandes, L.-F.-S.; Junior, R.-F.-V.; Valera, C.-A.; Pissarra, T.-C.-T. Land degradation: Multiple environmental consequences and routes to neutrality. *Curr. Opin. Environ. Sci. Health* **2018**, *5*, 79–86. [\[CrossRef\]](#)
- Bastin, J.; Finegold, Y.; Garcia, C.; Mollicone, D.; Rezende, M.; Routh, D.; Zohner, C.-M.; Crowther, T.-W. The global tree restoration potential. *Science* **2019**, *365*, 76–79. [\[CrossRef\]](#)
- Hermans, K.; McLeman, R. Climate change, drought, land degradation and migration: Exploring the linkages. *Curr. Opin. Environ. Sustain.* **2021**, *50*, 236–244. [\[CrossRef\]](#)
- Kust, G.; Andreeva, O.; Cowie, A. Land Degradation Neutrality: Concept development, practical applications and assessment. *J. Environ. Manag.* **2017**, *195*, 16–24. [\[CrossRef\]](#)
- Brevik, E.-C.; Cerdà, A.; Mataix-Solera, J.; Pereg, L.; Quinton, J.-N.; Six, J.; Van Oost, K. The interdisciplinary nature of SOIL. *Soil* **2015**, *1*, 117–129. [\[CrossRef\]](#)
- Parras Alcántara, L.; Díaz Jaimes, L.; Lozano García, B. Management effects on soil organic carbon stock in Mediterranean open rangelands—Treeless grasslands. *Land Degrad. Dev.* **2015**, *26*, 22–34. [\[CrossRef\]](#)
- Reeves, M.-C.; Baggett, L.-S. A remote sensing protocol for identifying rangelands with degraded productive capacity. *Ecol. Indic.* **2014**, *43*, 172–182. [\[CrossRef\]](#)
- Sun, B.; Li, Z.-Y.; Gao, W.-T.; Zhang, Y.-Y.; Gao, Z.-H.; Song, Z.-L.; Qin, P.-Y.; Tian, X. Identification and assessment of the factors driving vegetation degradation/regeneration in drylands using synthetic high spatiotemporal remote sensing Data—A case study in Zhenglanqi, Inner Mongolia, China. *Ecol. Indic.* **2019**, *107*, 105614. [\[CrossRef\]](#)
- Xu, G.; Zhang, H.-F.; Chen, B.-Z.; Zhang, H.-R.; Innes, J.-L.; Wang, G.-Y.; Yan, J.-W.; Zheng, Y.-H.; Zhu, Z.-C.; Myneni, R.-B. Changes in vegetation growth dynamics and relations with climate over China’s landmass from 1982 to 2011. *Remote Sens.* **2014**, *6*, 3263–3283. [\[CrossRef\]](#)
- Liu, Y.-L.; Lei, H.-M. Responses of natural vegetation dynamics to climate drivers in China from 1982 to 2011. *Remote Sens.* **2015**, *7*, 10243–10268. [\[CrossRef\]](#)
- Kang, J.-F.; Zhang, Y.-N.; Biswas, A. Land Degradation and Development Processes and Their Response to Climate Change and Human Activity in China from 1982 to 2015. *Remote Sens.* **2021**, *13*, 3516. [\[CrossRef\]](#)
- Li, H.; Yang, X.-H.; Zhang, K.-B. Understanding global land degradation processes interacted with complex biophysics and socioeconomics from the perspective of the Normalized Difference Vegetation Index (1982–2015). *Glob. Planet. Change* **2021**, *198*, 103431. [\[CrossRef\]](#)
- Cohen, J.-E.; Small, C.; Mellinger, A.; Gallup, J.; Sachs, J. Estimates of coastal populations. *Science* **1997**, *278*, 1209–1213. [\[CrossRef\]](#)
- de Andrade, M.-M.-N.; Szlafsztein, C.-F.; Souza-Filho, P.-W.-M.; Dos Reis Araújo, A.; Gomes, M.-K.-T. A socioeconomic and natural vulnerability index for oil spills in an Amazonian harbor: A case study using GIS and remote sensing. *J. Environ. Manag.* **2010**, *91*, 1972–1980. [\[CrossRef\]](#)
- Davidson, N.-C. How much wetland has the world lost? Long-term and recent trends in global wetland area. *Mar. Freshw. Res.* **2014**, *65*, 934–941. [\[CrossRef\]](#)
- Kirwan, M.-L.; Megonigal, J.-P. Tidal wetland stability in the face of human impacts and sea-level rise. *Nature* **2013**, *504*, 53–60. [\[CrossRef\]](#)
- Hong, C.; Burney, J.-A.; Pongratz, J.; Nabel, J.-E.-M.-S.; Mueller, N.-D.; Jackson, R.-B.; Davis, S.-J. Global and regional drivers of land-use emissions in 1961–2017. *Nature* **2021**, *589*, 554–561. [\[CrossRef\]](#)
- Ibrahim, Y.-Z.; Balzter, H.; Kaduk, J.; Tucker, C.-J. Land degradation assessment using residual trend analysis of GIMMS NDVI3g, soil moisture and rainfall in Sub-Saharan West Africa from 1982 to 2012. *Remote Sens.* **2015**, *7*, 5471–5494. [\[CrossRef\]](#)
- Li, Z.; Chen, Y.-N.; Li, W.-H.; Deng, H.-J.; Fang, G.-H. Potential impacts of climate change on vegetation dynamics in Central Asia. *J. Geophys. Res. Atmos.* **2015**, *120*, 12345–12356. [\[CrossRef\]](#)
- He, Q.; Bertness, M.-D.; Bruno, J.-F.; Li, B.; Chen, G.; Coverdale, T.-C.; Altieri, A.-H.; Bai, J.; Sun, T.; Pennings, S.-C. Economic development and coastal ecosystem change in China. *Sci. Rep.* **2014**, *4*, 5995. [\[CrossRef\]](#) [\[PubMed\]](#)

22. Liu, Y.-B.; Hou, X.-Y.; Li, X.-W.; Song, B.-Y.; Wang, C. Assessing and predicting changes in ecosystem service values based on land use/cover change in the Bohai Rim coastal zone. *Ecol. Indic.* **2020**, *111*, 106004. [\[CrossRef\]](#)
23. Tian, B.; Wu, W.-T.; Yang, Z.-Q.; Zhou, Y.-X. Drivers, trends, and potential impacts of long-term coastal reclamation in China from 1985 to 2010. *Estuar. Coast. Shelf Sci.* **2016**, *170*, 83–90. [\[CrossRef\]](#)
24. Xu, N.; Gao, Z.-Q.; Ning, J.-C. Analysis of the characteristics and causes of coastline variation in the Bohai Rim (1980–2010). *Environ. Earth Sci.* **2016**, *75*, 719. [\[CrossRef\]](#)
25. Wang, W.; Liu, H.; Li, Y.-Q.; Su, J.-L. Development and management of land reclamation in China. *Ocean Coast. Manag.* **2014**, *102*, 415–425. [\[CrossRef\]](#)
26. Li, Y.-F.; Shi, Y.-L.; Zhu, X.-D.; Cao, H.-H.; Yu, T. Coastal wetland loss and environmental change due to rapid urban expansion in Lianyungang, Jiangsu, China. *Reg. Environ. Change* **2014**, *14*, 1175–1188. [\[CrossRef\]](#)
27. Li, Y.-H.; Li, Y.-R.; Westlund, H.; Liu, Y.-S. Urban–rural transformation in relation to cultivated land conversion in China: Implications for optimizing land use and balanced regional development. *Land Use Policy* **2015**, *47*, 218–224. [\[CrossRef\]](#)
28. He, C.-Y.; Tian, J.; Gao, B.; Zhao, Y.-Y. Differentiating climate- and human-induced drivers of grassland degradation in the Liao River Basin, China. *Environ. Monit. Assess.* **2015**, *187*, 4199. [\[CrossRef\]](#)
29. Camps-Valls, G.; Campos-Taberner, M.; Moreno-Martínez, Á.; Walther, S.; Duveiller, G.; Cescatti, A.; Mahecha, M.-D.; Muñoz-Mari, J.; García-Haro, F.-J.; Guanter, L. A unified vegetation index for quantifying the terrestrial biosphere. *Sci. Adv.* **2021**, *7*, c7447. [\[CrossRef\]](#)
30. Badgley, G.; Field, C.-B.; Berry, J.-A. Canopy near-infrared reflectance and terrestrial photosynthesis. *Sci. Adv.* **2017**, *3*, e1602244. [\[CrossRef\]](#)
31. Sur, K.; Chauhan, P. Dynamic trend of land degradation/restoration along Indira Gandhi Canal command area in Jaisalmer District, Rajasthan, India: A case study. *Environ. Earth Sci.* **2019**, *78*, 472. [\[CrossRef\]](#)
32. Wang, X.-G.; Yan, F.-Q.; Su, F.-Z. Changes in coastline and coastal reclamation in the three most developed areas of China, 1980–2018. *Ocean Coast. Manag.* **2021**, *204*, 105542. [\[CrossRef\]](#)
33. China National Bureau of Statistics. *China Statistical Yearbook 2016*; China Statistics Press: Beijing, China, 2016. (In Chinese)
34. Huang, C.-C.; Zhang, M.-L.; Zou, J.; Zhu, A.-X.; Chen, X.; Mi, Y.; Wang, Y.-H.; Yang, H.; Li, Y.-M. Changes in land use, climate and the environment during a period of rapid economic development in Jiangsu Province, China. *Sci. Total Environ.* **2015**, *536*, 173–181. [\[CrossRef\]](#)
35. Yirsaw, E.; Wu, W.; Temesgen, H.; Bekele, B. Effect of temporal land use/land cover changes on ecosystem services value in coastal area of China: The case of Su-Xi-Chang region. *Appl. Ecol. Environ. Res.* **2016**, *14*, 409–422. [\[CrossRef\]](#)
36. Meng, W.-Q.; Hu, B.-B.; He, M.-X.; Liu, B.-Q.; Mo, X.-Q.; Li, H.-Y.; Wang, Z.-L.; Zhang, Y. Temporal-spatial variations and driving factors analysis of coastal reclamation in China. *Estuar. Coast. Shelf Sci.* **2017**, *191*, 39–49. [\[CrossRef\]](#)
37. Tucker, C.-J.; Pinzon, J.-E.; Brown, M.-E.; Slayback, D.-A.; Pak, E.-W.; Mahoney, R.; Vermote, E.-F.; El Saleous, N. An extended AVHRR 8-km NDVI dataset compatible with MODIS and SPOT vegetation NDVI data. *Int. J. Remote Sens.* **2005**, *26*, 4485–4498. [\[CrossRef\]](#)
38. Yuan, W.-P.; Liu, S.-G.; Yu, G.-R.; Bonnefond, J.; Chen, J.-Q.; Davis, K.; Desai, A.-R.; Goldstein, A.-H.; Gianelle, D.; Rossi, F. Global estimates of evapotranspiration and gross primary production based on MODIS and global meteorology data. *Remote Sens. Environ.* **2010**, *114*, 1416–1431. [\[CrossRef\]](#)
39. Peng, S.-Z.; Ding, Y.-X.; Wen, Z.-M.; Chen, Y.-M.; Cao, Y.; Ren, J.-Y. Spatiotemporal change and trend analysis of potential evapotranspiration over the Loess Plateau of China during 2011–2100. *Agric. For. Meteorol.* **2017**, *233*, 183–194. [\[CrossRef\]](#)
40. Wu, J.; Gao, X.-J. A gridded daily observation dataset over China region and comparison with the other datasets. *Chin. J. Geophys.* **2013**, *56*, 1102–1111. (In Chinese)
41. Yang, J.; Huang, X. The 30 m annual land cover dataset and its dynamics in China from 1990 to 2019. *Earth Syst. Sci. Data* **2021**, *13*, 3907–3925. [\[CrossRef\]](#)
42. Mesquita, D.-P.; Gomes, J.-P.; Junior, A.-H.-S.; Nobre, J.-S. Euclidean distance estimation in incomplete datasets. *Neurocomputing* **2017**, *248*, 11–18. [\[CrossRef\]](#)
43. Alexander, L.-V.; Zhang, X.; Peterson, T.-C.; Caesar, J.; Gleason, B.; Klein Tank, A.-M.-G.; Haylock, M.; Collins, D.; Trewin, B.; Rahimzadeh, F.; et al. Global observed changes in daily climate extremes of temperature and precipitation. *J. Geophys. Res. Atmos.* **2006**, *111*, 1042–1063. [\[CrossRef\]](#)
44. Capra, A.; Consoli, S.; Scicolone, B. Long-Term Climatic Variability in Calabria and Effects on Drought and Agrometeorological Parameters. *Water Resour. Manag.* **2013**, *27*, 601–617. [\[CrossRef\]](#)
45. Sen, P.-K. Estimates of the Regression Coefficient Based on Kendall's Tau. *J. Am. Stat. Assoc.* **1968**, *63*, 1379–1389. [\[CrossRef\]](#)
46. Jiang, W.-G.; Yuan, L.-H.; Wang, W.-J.; Cao, R.; Zhang, Y.-F.; Shen, W.-M. Spatio-temporal analysis of vegetation variation in the Yellow River Basin. *Ecol. Indic.* **2015**, *51*, 117–126. [\[CrossRef\]](#)
47. Zhao, K.-G.; Wulder, M.-A.; Hu, T.-X.; Bright, R.; Wu, Q.-S.; Qin, H.-M.; Li, Y.; Toman, E.; Mallick, B.; Zhang, X.-S. Detecting change-point, trend, and seasonality in satellite time series data to track abrupt changes and nonlinear dynamics: A Bayesian ensemble algorithm. *Remote Sens. Environ.* **2019**, *232*, 111181. [\[CrossRef\]](#)
48. R Core Team. *R: A Language and Environment for Statistical Computing*; R Foundation for Statistical Computing: Vienna, Austria, 2021.

49. Li, Y.; Hu, T.; Zhang, X.; Zhao, K.; Dongarra, J.; Moler, C. Rbeast: Bayesian Change-Point Detection and Time Series Decomposition, R Package Version 0.9.7. 2023. Available online: <https://cran.r-project.org/web/packages/Rbeast/Rbeast.pdf> (accessed on 22 January 2023).
50. Tian, H.-J.; Cao, C.-X.; Chen, W.; Bao, S.-N.; Yang, B.; Myneni, R.-B. Response of vegetation activity dynamic to climatic change and ecological restoration programs in Inner Mongolia from 2000 to 2012. *Ecol. Eng.* **2015**, *82*, 276–289. [[CrossRef](#)]
51. Sun, W.-Y.; Song, X.-Y.; Mu, X.-M.; Gao, P.; Wang, F.; Zhao, G.-J. Spatiotemporal vegetation cover variations associated with climate change and ecological restoration in the Loess Plateau. *Agric. For. Meteorol.* **2015**, *209–210*, 87–99. [[CrossRef](#)]
52. Ali, S.; Eum, H.; Cho, J.; Dan, L.; Khan, F.; Dairaku, K.; Shrestha, M.-L.; Hwang, S.; Nasim, W.; Khan, I.-A. Assessment of climate extremes in future projections downscaled by multiple statistical downscaling methods over Pakistan. *Atmos. Res.* **2019**, *222*, 114–133. [[CrossRef](#)]
53. Coppola, E.; Nogherotto, R.; Ciarlo, J.-M.; Giorgi, F.; van Meijgaard, E.; Kadyrov, N.; Iles, C.; Corre, L.; Sandstad, M.; Somot, S. Assessment of the European climate projections as simulated by the large EURO-CORDEX regional and global climate model ensemble. *J. Geophys. Res.-Atmos.* **2021**, *126*, e2019JD032356. [[CrossRef](#)]
54. Ge, F.; Zhu, S.; Luo, H.; Zhi, X.; Wang, H. Future changes in precipitation extremes over Southeast Asia: Insights from CMIP6 multi-model ensemble. *Environ. Res. Lett.* **2021**, *16*, 24013. [[CrossRef](#)]
55. Sang, X.; Guo, Q.-Z.; Wu, X.-X.; Fu, Y.; Xie, T.-Y.; He, C.-W.; Zang, J.-L. Intensity and stationarity analysis of land use change based on CART algorithm. *Sci. Rep.* **2019**, *9*, 12279. [[CrossRef](#)]
56. Scholes, R.; Montanarella, L.; Brainich, A.; Barger, N.; Ten Brink, B.; Cantele, M.; Erasmus, B.; Fisher, J.; Gardner, T.; Holland, T.-G. *Summary for policymakers of the assessment report on land degradation and restoration of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services*; Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES): Bonn, Germany, 2018.
57. Shukla, P.-R.; Skea, J.; Calvo Buendia, E.; Masson-Delmotte, V.; Pörtner, H.-O.; Roberts, D.-C.; Zhai, P.; Slade, R.; Connors, S.; Van Diemen, R. *Climate Change and Land: An IPCC Special Report on Climate Change, Desertification, Land Degradation, Sustainable Land Management, Food Security, and Greenhouse Gas Fluxes in Terrestrial Ecosystems*; Intergovernmental Panel on Climate Change (IPCC): Geneva, Switzerland, 2019.
58. Zhao, A.-Z.; Zhang, A.-B.; Liu, J.-H.; Feng, L.-L.; Zhao, Y.-L. Assessing the effects of drought and “Grain for Green” Program on vegetation dynamics in China’s Loess Plateau from 2000 to 2014. *Catena* **2019**, *175*, 446–455. [[CrossRef](#)]
59. Green, J.-K.; Seneviratne, S.-I.; Berg, A.-M.; Findell, K.-L.; Hagemann, S.; Lawrence, D.-M.; Gentile, P. Large influence of soil moisture on long-term terrestrial carbon uptake. *Nature* **2019**, *565*, 476–479. [[CrossRef](#)]
60. Borrelli, P.; Robinson, D.-A.; Panagos, P.; Lugato, E.; Yang, J.-E.; Alewell, C.; Wuepper, D.; Montanarella, L.; Ballabio, C. Land use and climate change impacts on global soil erosion by water (2015–2070). *Proc. Natl. Acad. Sci. USA* **2020**, *117*, 21994–22001. [[CrossRef](#)]
61. Li, J.-Y.; Ma, X.-F.; Zhang, C. Predicting the spatiotemporal variation in soil wind erosion across Central Asia in response to climate change in the 21st century. *Sci. Total Environ.* **2020**, *709*, 136060. [[CrossRef](#)]
62. Sulaeman, D.; Westhoff, T. The Causes and Effects of Soil Erosion, and How to Prevent It. 2020. Available online: <https://www.wri.org/insights/causes-and-effects-soil-erosion-and-how-prevent-it> (accessed on 7 February 2020).
63. Singh, B.-P.; Cowie, A.-L.; Chan, K.-Y. *Soil Health and Climate Change*; Springer: Berlin/Heidelberg, Germany, 2011.
64. Burgers, A. *Soil Biology*; Elsevier: Amsterdam, The Netherlands, 2012.
65. Nadeem, H.; Ahmad, F. *Soil-Plant and Microbial Interaction in Improving Salt Stress*; Springer: Berlin/Heidelberg, Germany, 2019.
66. Zurlani, H.-A.; Mikhailova, E.-A.; Post, C.-J.; Schlautman, M.-A.; Elhawej, A.-R. A review of Libyan soil databases for use within an ecosystem services framework. *Land* **2019**, *8*, 82. [[CrossRef](#)]
67. Corwin, D.-L. Climate change impacts on soil salinity in agricultural areas. *Eur. J. Soil Sci.* **2021**, *2*, 842–862. [[CrossRef](#)]
68. Vlek, P.; Khamzina, A.; Tamene, L. *Land Degradation and the Sustainable Development Goals: Threats and Potential Remedies*; International Center for Tropical Agriculture (CIAT): Nairobi, Kenya, 2017.
69. Long, H.-L.; Liu, Y.-S. Rural restructuring in China. *J. Rural Stud.* **2016**, *47*, 387–391. [[CrossRef](#)]
70. China National Bureau of Statistics. *China Statistical Yearbook 2019*; China Statistics Press: Beijing, China, 2019. (In Chinese)
71. Zhou, D.; Xu, J.-C.; Lin, Z.-L. Conflict or coordination? Assessing land use multi-functionalization using production-living-ecology analysis. *Sci. Total Environ.* **2017**, *577*, 136–147. [[CrossRef](#)]
72. Li, K.-M.; Feng, M.-M.; Biswas, A.; Su, H.-H.; Niu, Y.-L.; Cao, J.-J. Driving factors and future prediction of land use and cover change based on satellite remote sensing data by the LCM model: A case study from Gansu province, China. *Sensors* **2020**, *20*, 2757. [[CrossRef](#)] [[PubMed](#)]
73. Li, K.-M.; Cao, J.-J.; Adamowski, J.-F.; Biswas, A.; Zhou, J.-J.; Liu, Y.-J.; Zhang, Y.-K.; Liu, C.-F.; Dong, X.-G.; Qin, Y.-L. Assessing the effects of ecological engineering on spatiotemporal dynamics of carbon storage from 2000 to 2016 in the Loess Plateau area using the InVEST model: A case study in Huining County, China. *Environ. Dev.* **2021**, *39*, 100641. [[CrossRef](#)]
74. Bryan, B.-A.; Gao, L.; Ye, Y.; Sun, X.; Connor, J.-D.; Crossman, N.-D.; Stafford-Smith, M.; Wu, J.; He, C.; Yu, D.; et al. China’s response to a national land-system sustainability emergency. *Nature* **2018**, *559*, 193–204. [[CrossRef](#)] [[PubMed](#)]
75. Fu, Y.-C.; Li, J.-F.; Weng, Q.-H.; Zheng, Q.-M.; Li, L.; Dai, S.; Guo, B.-Y. Characterizing the spatial pattern of annual urban growth by using time series Landsat imagery. *Sci. Total Environ.* **2019**, *666*, 274–284. [[CrossRef](#)] [[PubMed](#)]

-
76. Wang, K.; Li, Z.-Y.; Zhang, J.-J.; Wu, X.; Jia, M.; Wu, L. Built-up land expansion and its impacts on optimizing green infrastructure networks in a resource-dependent city. *Sustain. Cities Soc.* **2020**, *55*, 102026. [[CrossRef](#)]
 77. Li, C.-L.; Liu, M.; Hu, Y.-M.; Zhou, R.; Wu, W.; Huang, N. Evaluating the runoff storage supply-demand structure of green infrastructure for urban flood management. *J. Clean. Prod.* **2021**, *280*, 124420. [[CrossRef](#)]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.