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Data-Driven Forest Cover Change and Its Driving Factors Analysis in Africa

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Forest cover plays an important role in sustaining ecological security to realize Sustainable Development Goals (SDGs). The research target area is composed of the African region which is experiencing unprecedented deforestation based on the data collection from 54 countries and regions between 2000 and 2020. Spatial autocorrelation analysis, global principal component analysis, and geographic detector model have been used as the core research tool. The temporal and spatial patterns of forest cover change in Africa and the driving effects of population growth, economic and trade, social development, arable land expansion, and other factors on forest cover change in different periods have been demonstrated. The findings are as follows: 1) extremely unequal distribution of Africa forest has caused forest area reduction in 20 years. The reduction quantity of forest has been illustrated from strong to weak: Central Africa (strongest), East Africa (higher strong), West Africa (medium), South Africa (higher weak), and North Africa (weakest). However, the forest reduction area in West Africa with the original ratio is the most significant. More than 80% of the forest area reduction in Africa has occurred in 14 countries, just five national forest areas to achieve the net growth, but the increase amount was only 1% of loss amount. 2) The spatial pattern of forest cover change in Africa contracted and clustered gradually, especially after 2012. Algeria was the hotspot cluster of Morocco and Tunisia, forming the increase area of forest cover in North Africa. Zambia, the coldest point, gathers Angola significantly, while the Democratic Republic of the Congo and Tanzania form a significantly reduced forest cover area. 3) Total population, land area, cultivated land, urban population, consumer price index, and birth rate are the main factors influencing the temporal evolution of forest cover change in Africa. It can be divided into four stages to interpret the different explanations and significance of each factor for forest cover change in the study area.

Keywords: data-driven, forest cover change, driving factors, spatio-temporal features, Big Earth Data, environmental modeling

1 INTRODUCTION

Forest is not only one of the important sources of human production and life but also one of the important indicators to maintain ecological security to achieve the Sustainable Development Goals (SDGs) (Glaser, 2012; Giam, 2017; Macdicken, 2015). After human beings frantically plundered forest resources, they gradually realized that large-scale deforestation would cause adverse consequences such as climate change, soil erosion, and biodiversity loss, so the net loss rate of

global forest cover has been slowed down through various appeals and efforts (Barlow et al., 2007; Edwards et al., 2012; Bonan, 2008; Hansen et al., 2013; Harris et al., 2021). However, from 2010 to 2020, Africa's forest cover will be reduced by 3.9 million hectares, surpassing South America, and the net loss rate is the highest in the world (FAO, 2020; Hoang and Kanemoto, 2021). It is expected that Africa will experience large-scale population growth and climate change, and Africa has a typical disturbance-driven ecosystem (Diffenbaugh and Giorgi, 2012; United Nations, Department of Economic and Social Affairs, Population Division, 2017). Once the forests in most areas are affected, the entire ecological environment will become highly vulnerable (Midgley and Bond, 2015; Réjou-Méchain et al., 2021). Analyzing and digging out the main driving factors that affect the changes in forest cover in Africa is essential to promote the protection of global forest protection and help regions achieve Sustainable Development Goals.

Many scholars have conducted research on the relationship between temporal and spatial characteristics based on the changes in forest cover in a specific study area and possible influencing factors, such as cocoa migration and deforestation in West Africa are positively correlated (Ruf et al., 2015), deforestation in Cameroon in relation to food security of poor populations (Gbetnkom, 2009; Pendrill et al., 2019), and road accessibility, agricultural product prices, household income levels, and catchment water balance . are all related to deforestation (Mainardi, 1998; Beckman et al., 2017; Kaimowitz, 1999; Assogba and Zhang, 2018; Mushi et al., 2020; Wilson et al., 2001; A et al., 2004; Garzuglia and Saket, 2003). Research shows that the aforementioned factors can be the root cause of deforestation to a certain extent, which in turn promotes deforestation (farmers, poor populations, animal husbandry, and loggers) to become the main source of deforestation (Gbetnkom, 2009; Afdb and Kouakou, 2010). However, causal attribution of natural and ecosystem system evolution is complicated because exploring forest cover dynamics is being affected by the interaction of many factors such as ecological environment, political, economic, and social factors, and have a wide range of impacts on time and space scales (Geist and Lambin, 2002; Defries et al., 2010; Sandel and Svenning, 2013; Rudel and Roper, 1997; Sannigrahi et al., 2018; Kim and Kim, 2010). Forzieri et al. quantify the vulnerability of European forests to fires, windthrows, and insect outbreaks by random forest (RF) regression (Forzieri et al., 2021). Curtis developed a forest loss classification model, to determine a spatial attribution of forest disturbance, was attributed to commodity production, forestry, shifting agriculture, and wildfire (Curtis et al., 2018; Goodchild and Glennon, 2010). Hoang et al. used remote sensing data and multi-regional input–output models to provide correlation analysis of the spatial pattern of international trade and deforestation (Hoang and Kanemoto, 2021). Beckman used economic models to simulate the reference scenarios of land use in 14 regions around the world to determine the potential impact of policies on relative forest losses (Beckman et al., 2017). DeFries used forest loss data from 2000 to 2005 to estimate the economic, agricultural, and population correlations of 41 countries and found that forest loss was positively correlated

with urban population growth and agricultural exports during this period (Defries et al., 2010).

However, different countries have different social and economic development stages and different forest protection strategies, which may result in significant differences in regional deforestation (Deacon, 1994; Hosonuma et al., 2012; Heitzig et al., 2016). Considering Tobler's first law of geography, severe deforested areas can also be a key driver of deforestation in neighboring areas. Currently, most research in the context of the driving factors of forest cover change has used local decomposition analysis of a few specific factors but do not evolve the spatial heterogeneity of each factor on the intensity of forest cover. This research analysis has mainly evolved the following two aspects: 1) it analyzes the spatial correlation, heterogeneity, and evolution characteristics of the forest cover change pattern in African countries from 2000 to 2020; 2) the 21 driving factors have been opted based on four dimensions of economy, society, and population. The nature of the research analysis is to explore and detect the significant driving factors of forest cover change in different historical periods via geographic detectors and weighted regression geographical models' applications. The research results are intended to provide benchmark for balancing population, economy, and green sustainable development in Africa.

2 STUDY REGION

African area is about 30.2 million square kilometers (land area), accounting for 20.4% of the world's total land area. The plateau (60%) is the major part of the Africa terrain. The elevation is gradually lower from southeast to northwest. The climate factors present high temperature and arid due to the north–south symmetry distributed climate zone in the middle of the African continent (across equator). It is the second largest continent in the world and has the second largest population (about 1.286 billion). Africa is rich in forest resources, accounting for 13.85 percent of the world's forest area (about 51,400 hectares) in 2018 (National Remote Sensing Center of China, 2019). Africa also has one of the fastest growing populations in the world. The Africa's population is growing at an annual rate of 2.3 percent with sub-Saharan Africa in turn growing faster than North Africa. Sub-Saharan Africa is the only region in the world where the number of poor populations is increasing significantly, reaching 2 billion by 2050 (World Bank Group, 2020). The challenge of reducing widespread poverty in Africa can be the core of the continent's development model for improving their living conditions including their increased use of the natural resources around them (Kouakou, 2005). Population growth, the impact of poverty, and the exploitation of natural resources have inevitably restricted and influenced each other. It is difficult to obtain data of individual islands/regions due to the influence of economic development and political situation. Therefore, this study has selected 54 countries and regions in Africa which are represented in **Table 1**, and the population and area of the study area cover more than 99% of the African continent. (**Figure 1**). Refer to World Population Prospects

TABLE 1 | Geographical division of countries in the study area.

Research area	Countries & regions' Name	Datagaps excluded
Eastern Africa	Burundi, Comoros, Djibouti, Eritrea, Ethiopia, Kenya, Madagascar, Malawi, Mauritius, Mozambique, Rwanda, Seychelles, Somalia, South Sudan, Uganda, United Republic of Tanzania, Zambia, and Zimbabwe	Mayotte, Réunion
Middle Africa	Angola, Cameroon, Central African Republic, Chad, Congo, Democratic Republic of the Congo, Equatorial Guinea, Gabon, Sao Tome, and Principe	
Northern Africa	Algeria, Egypt, Libya, Morocco, Sudan, and Tunisia,	Western Sahara
Southern Africa	Botswana, Lesotho, Namibia, South Africa, and Swaziland	
Western Africa	Benin, Burkina Faso, Cabo Verde, Côte d'Ivoire, Gambia, Ghana, Guinea, Guinea-Bissau, Liberia, Mali, Mauritania, Niger, Nigeria, Senegal, Sierra Leone, and Togo	Saint Helena

FIGURE 1 | Map of location and geographical division of the study area. According to UN Department of Economic and Social Affairs World Population Prospects data, the research divisions are divided into East Africa, South Africa, West Africa, North Africa, and Central Africa. Western Sahara, Mayotte, Reunion, and Saint Helena are not including in the study area due to lack of the datasets. The benched map is from the standard Map Service System of the Ministry of Natural Resources of P.R of China. The reviewed map number is GS (2020) 4391.
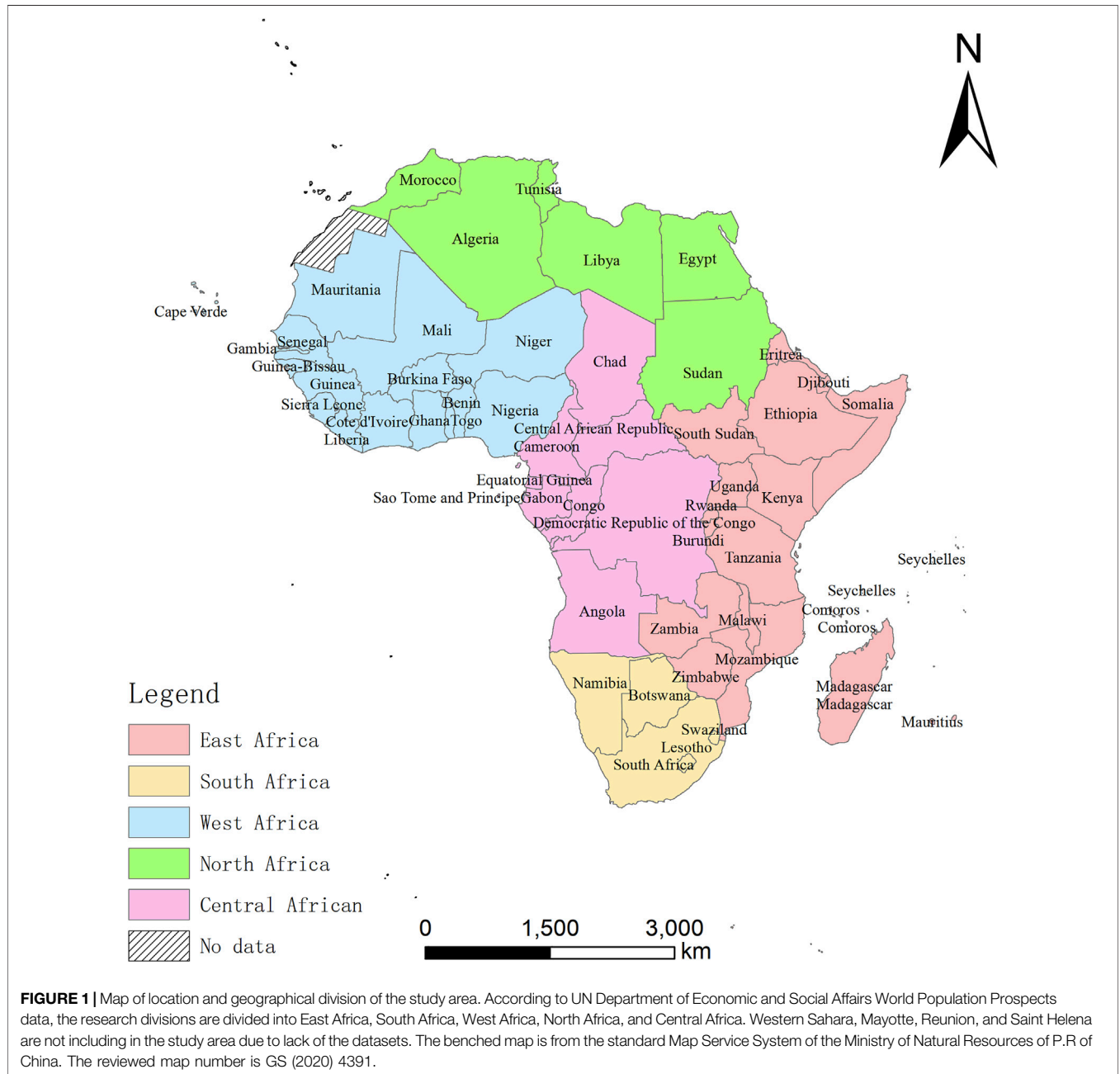
TABLE 2 | Variable description of driving indicators.

Research dimension	Indicators name	Unit	Mean	Standardized deviation	Forcasting
Economic factor	GDP	2010 US$	35901785382.50	75893129242.70	+
	GDP growth	%	2.50	29.91	+
	Foreign direct investment, net inflows	US$	739000886.48	1540164408.52	+
	Foreign direct investment, net inflows	%	4.37	7.82	+
	Goods exports	US$	7420032761.41	15841232780.62	+
	Goods imports	US$	7603241584.23	14153662572.90	+
Social factor	Forest rents	%	4.76	5.54	+
	Net ODA received	%	7.78	9.16	+
	Consumer price index	-	2069.05	35351.53	−
	Unemployment, total	%	8.66	7.05	−
	Access to clean fuels and technologies for cooking	%	26.12	31.61	+
	Compulsory education	Year	7.80	3.29	+
Population factor	Population, total	People	19476448.96	28256604.83	−
	Rural population	People	11628519.60	17045641.91	−
	Urban population	People	7682742.94	12373334.45	−
	Labor force, total	People	7280119.91	10046139.07	−
	Death rate	‰	10.26	3.63	+
	Birth rate	‰	34.84	8.42	−
Natural factor	Land area	Km^2	557709.49	621698.78	+
	Terrestrial protected areas	%	16.18	11.67	+
	Arable land	Hm^2	4067045.04	5830099.69	−

data for the classification of countries and regions (United Nations, Department of Economic and Social Affairs, Population Division, 2019).

3 DATASETS AND METHODOLOGY

3.1 Datasets

Forest cover change has been influenced by multiple factors (Curtis et al., 2018; Geist and Lambin, 2002; FAO, 2015). We selected 21 indicators from four dimensions of those are economy, society, population, and nature as explained variables for analysis. Economic dimension indicators reflect the size of a country's economic development including GDP, GDP growth, foreign direct investment (net inflows), Foreign Direct Investment (net inflows), goods exports, and goods imports. The social dimension reflects the general state of development including forest rents, net ODA received, and consumer price index, unemployment, access to clean fuels and technologies for cooking (% of population) and compulsory education. Population factor indicators reflect the possible consumption of forest resources, including population, total, rural population, urban population, labor force, death rate, and birth rate. The natural dimension index reflects natural resource abundance, land area, terrestrial protected areas (% of total land area), and arable Land. The data cover the period from 2000 to 2020, and the data sources include World Development Indicators (WDI), and it is consistent (**Table 2**) in the Center for International Prospective Studies (CEPII) database (The World Bank, 2021). The number of years of compulsory education is based on UNESCO statistics for 2020 (UNESCO, 2021). Since most of the other population, economic, and social data selected in the subsequent analysis originated from the official statistical

data of the World Bank, the forest cover data of the research area from 2000 to 2018 inevitably refer to "Ag.lnd.frst.k2-Forest Area (SQ.km)" in the WDI dataset. A small part of the missing forest cover data is supplemented via data from FRA 2020 published by FAO and remote-sensing data products (Hansen et al., 2013; Shimada et al., 2014; National Remote Sensing Center of China, 2019; Zhang et al., 2020).

3.2 Spatial Autocorrelation

The purpose of spatial autocorrelation analysis is to analyze whether a certain variable can show a certain spatial correlation and the degree of correlation. Relevant studies indicate that forest distribution will be deeply affected via the Tobler's first law of geography, forest protection, logging, and trade in neighboring countries in terms of the same natural growth environment affected by neighboring regions with a certain spatial autocorrelation (Jha et al., 2016; Kaimowitz et al., 2002). The global Moran's I index can be used to describe the spatial dependence of forest cover, growth, or deforestation in African countries and regions quantitatively (Moran and Ap, 1950). When I∈ (0, 1], the variables become more similar with the shortening of the measured distance, presenting a positive spatial correlation. When I∈ [-1, 0), it indicates that the overall spatial agglomeration is negatively correlated; when I = 0, it indicates that there is no spatial dependence, and the spatial pattern is randomly distributed. The calculation equation is as follows:

$$Moran's\ I = \frac{N}{\sum_{ij} w_{ij}} \frac{\sum_i \sum_j w_{ij}(x_i - \bar{x})}{\sum_i (x_i - \bar{x})^2}, \tag{1}$$

where N is the number of countries along the Belt and Road, I and j represent country numbers, W_{ij} is the spatial weight matrix, X_i is

the forest cover value of country I, and $\bar{x}$ is the average of the research area. The global Moran's I index based on Z scores has been acquired to test its significance, when the | Z | > 1.96, and it indicates that there is spatial autocorrelation with 95% probability. The equation is as follows:

$$Z = \frac{I - E(I)}{\sqrt{v(I)}} \sim N(0, 1), \qquad (2)$$

where E (I) represents the mathematical expectation of global Moran's I, v (I) represents the variance of global Moran's I, and N (0, 1) represents the normal distribution.

For Moran's I value, if Z ≥ 1.96 or ≤ -1.96, it is considered that space has spatial autocorrelation (Moran's I >0 represents positive spatial correlation. The larger the value is, the more significant the spatial correlation is. 0 means spatial negative correlation; the smaller its value is, the greater the spatial difference is; If not, Moran's I = 0 represents that the space is random).

The global Moran's I index can count the significant characteristics of overall agglomeration, while the local indicators of spatial association (LISA) can identify the local characteristics of spatial agglomeration, thus revealing the heterogeneity of local regional spatial association (Anselin, 1995). The LISA index identifies four spatial association types of "high–high cluster," "high–low cluster," "low–high cluster," and "low–low cluster," representing different types of spatial agglomeration patterns.

3.3 Geo-Detector

Geographical Detector is a popular spatial statistical tool developed by the Prof. WangJinfeng team of LREIS, IGNRSS of Chinese Academy of Sciences, based on Excel to measure spatial differentiation and reveal driving factors. By calculating the similarity of the spatial distribution pattern between the independent variable X and dependent variable Y, the geographic detector model detects the explanatory effect intensity of the independent variable on the dependent variable (Wang and Xu, 2017). The geographic detector method was used to analyze the relationship strength of driving factors among the 6 principal component variables obtained from the original 21 variables via global principal component analysis dimension reduction. The main driving factors affecting the formation of the spatial pattern of forest cover change in the study area have been identified in different timescales. The equation is as follows:

$$q = 1 - \frac{\sum_{i=1}^{N} N_i \sigma_i^2}{N \sigma^2}, \qquad (3)$$

where q value is the explanatory degree of the independent variable to the dependent variable, and the larger the q value is, the stronger the explanatory power is. I is the stratification number of the independent variable X and dependent variable Y. The Jenks natural discontinuity point grading method is adopted for stratification to discretize continuous variables. N_i and N are the number of the layer I and countries in the research area, respectively. σ_i^2 and σ^2 are the variances of the layer I and independent variables within the research area, respectively.

3.4 Global Principal Component Analysis

Global principal component analysis (GPCA) is to construct the index system of the three-dimensional time-series data table based on the use of time series and spatial sequence mutual integration, seeking a unified for all cross-section data tables and comparable to simplify subspace. Each data table on which the projection to approximate the best comprehensive effect based on the global data view is constructed.

The indicators to influence forest cover change are very diverse. Human activities are likely to be more rapid and direct, while geographical and climatic factors can also influence over long time series (with the exception of sudden natural disasters, pest disasters, or forest fires). Therefore, the analysis of 20-year time series index data of different countries and regions is constituted into sequential stereoscopic data tables for global principal component analysis. A few of "factors" are deduced from numerous observable "variables" via the analysis of three-dimensional time series data, and the minimum "factors" are used to summarize and explain the largest number of observed facts so as to establish the simplest and most basic conceptual system and reveal the essential relationship between indicators affecting forest cover change.

The steps for extracting principal factors based on global principal component analysis are described as follows:

Step 1. Construct a data table: if n regions are counted and p variables are used to describe, the "global data table" of T years is

$$X = \left[(X1)^{'} (X2)^{'} \ldots (XT)^{'} \right] \in R^{T\,N \times P}. \qquad (4)$$

Step 2. Normalize the elements in the table X by moving the origin of coordinates to the data center and compress and transform them to eliminate dimensional influence.

$$x_{ij}^t = \frac{\left(x_{ij}^t - x_j \right)}{S_j}, \quad (i = 1, 2, \cdots, n; j = 1, 2, \cdots, p); \qquad (5)$$

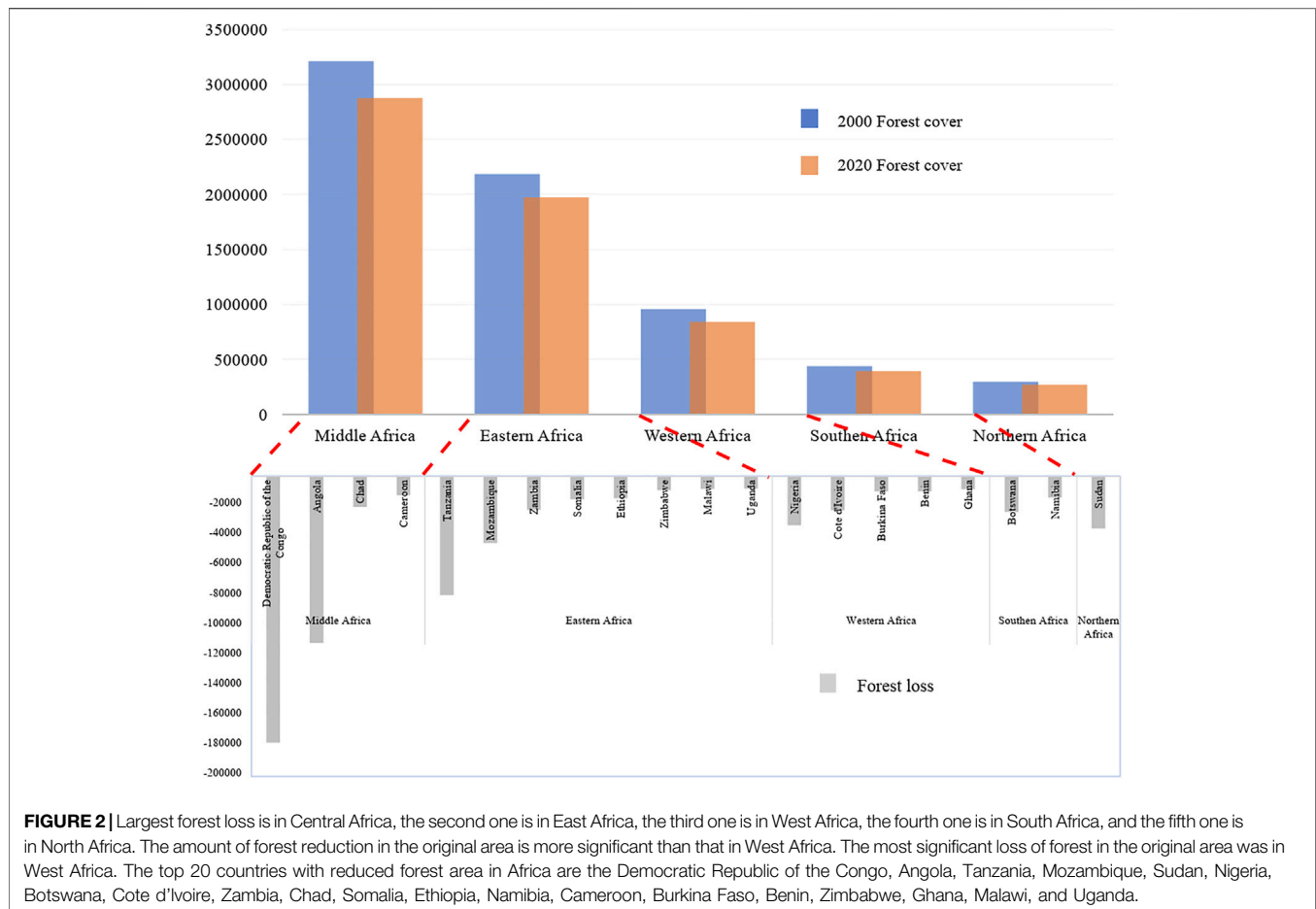$$x_j = \frac{1}{T_n} \sum_{t=1}^{T} \sum_{i=1}^{n} x_{ij}^t; \qquad (6)$$

$$S_j^2 = \frac{1}{T_n} \sum_{t=1}^{T} \sum_{i=1}^{n} \left(x_{ij}^t - x_j \right)^2; \qquad (7)$$

$$X = \left(X_{ij} \right)_{T_n \times p} \in R^{T_n \times p}. \qquad (8)$$

Step 3. Calculate the covariance matrix $V \in R^{p \times p}$ of the X matrix.

Step 4. Find the first m eigenvalues $\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_m$ of the matrix V and the corresponding eigenvectors $\mu_1, \mu_2 \ldots \mu_m$; they are orthonormal, and $\mu_1, \mu_2 \ldots \mu_m$ is called the global principal axis.

Step 5. Calculate the global principal fraction and calculate the representation accuracy of the original data: $Q = \frac{\sum_{i=1}^{m} \lambda_i}{p}$, generally Q ≥ 85%.

FIGURE 2 | Largest forest loss is in Central Africa, the second one is in East Africa, the third one is in West Africa, the fourth one is in South Africa, and the fifth one is in North Africa. The amount of forest reduction in the original area is more significant than that in West Africa. The most significant loss of forest in the original area was in West Africa. The top 20 countries with reduced forest area in Africa are the Democratic Republic of the Congo, Angola, Tanzania, Mozambique, Sudan, Nigeria, Botswana, Cote d'Ivoire, Zambia, Chad, Somalia, Ethiopia, Namibia, Cameroon, Burkina Faso, Benin, Zimbabwe, Ghana, Malawi, and Uganda.

4 RESULTS

4.1 Forest Cover and Its Change in 21 Years

The distribution of forests in Africa is extremely uneven in terms of the differences in precipitation, sunshine, soil properties, geographical location, natural conditions, and other factors. More than 45% of forests are distributed in Central Africa, 30% in East Africa, 13% in West Africa, 6.2% in South Africa, and 4.2% in North Africa. The forest area has decreased in recent 20 years. The largest loss is in Central Africa, the second one is in East Africa, the third one is in West Africa, the fourth one is in South Africa, and the fifth one is in North Africa. However, the most significant loss of the forest area was in West Africa, which has a loss percentage more than 12%. The percentage of forest area loss has decreased more than 10% in Central Africa and South Africa and 9.6% in East Africa and North Africa. More than 80 percent of the forest loss occurred in these 14 countries: the Democratic Republic of the Congo, Angola, Tanzania, Mozambique, Sudan, Nigeria, Botswana, Cote d'Ivoire, Zambia, Chad, Somalia, Ethiopia, Namibia, and Cameroon (**Figure 2**).

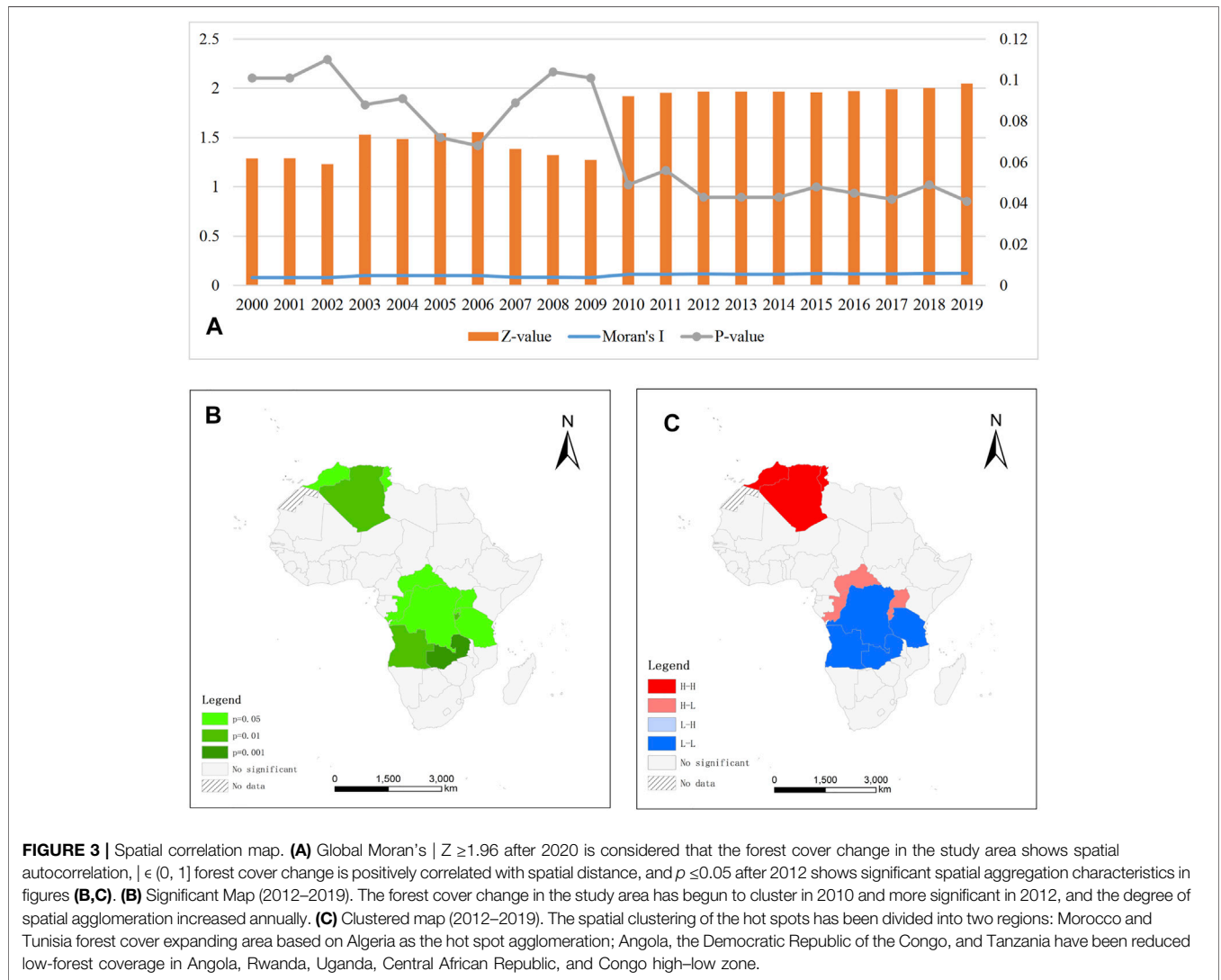The Democratic Republic of the Central African Republic has experienced the largest loss of forest, accounting for about a quarter of the total in Africa, more than half of the loss in Central Africa, and equal to the sum of the loss in West, South, and North Africa. Middle Africa had the second largest loss of Chad forests, losing nearly a third of its total forest area in 20 years. Eastern Africa's Tanzania has the third largest forest in Africa and never changed for 20 years. Cote d'Ivoire and Benin forests in West Africa have lost 44 and 24% more of their original forest area. Gambia in Western Africa, which was not originally rich in forest resources, has lost nearly a third of its original forest area. Eastern Africa's Malawi and Uganda have both lost more than a quarter of their forests in 20 years.

Just seven countries have shown a net increase in the forest area over the past 20 years. Only five countries showed significant growth (more than 200 square kilometers). Algeria, Morocco, and Tunisia in North Africa, East Africa, and Swaziland in South Africa have shown forest improvement, but the forest growth area just accounts for only 1% of the loss area.

It is worth mentioning that more countries have realized the importance of forest protection and put into actions gradually. They have slowed down the rate of deforestation and actively regulated in Rwanda, Kenya, and Ghana. It experienced a low point toward growing year by year

TABLE 3 | Moran's I estimate of national and regional forest cover change from 2000 to 2019.

Indicator	Index	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
Net change in forest cover	Moran's I	0.08	0.08	0.08	0.101	0.101	0.101	0.101	0.084	0.084	0.080
	Z-value	1.2884	1.2888	1.2305	1.529	1.4855	1.5446	1.5534	1.3853	1.3210	1.2726
	p-value	0.101	0.101	0.11	0.088	0.091	0.072	0.068	0.089	0.104	0.101
	Indexes	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
	Moran's I	0.112	0.112	0.117	0.112	0.112	0.121	0.119	0.119	0.123	0.124
	Z-value	1.9178	1.954	1.9664	1.9664	1.9664	1.9579	1.970	1.990	2.003	2.0481
	p-value	0.049	0.056	0.043	0.043	0.043	0.048	0.045	0.042	0.049	0.041

FIGURE 3 | Spatial correlation map. **(A)** Global Moran's | Z ≥1.96 after 2020 is considered that the forest cover change in the study area shows spatial autocorrelation, | ∈ (0, 1] forest cover change is positively correlated with spatial distance, and *p* ≤0.05 after 2012 shows significant spatial aggregation characteristics in figures **(B,C)**. **(B)** Significant Map (2012–2019). The forest cover change in the study area has begun to cluster in 2010 and more significant in 2012, and the degree of spatial agglomeration increased annually. **(C)** Clustered map (2012–2019). The spatial clustering of the hot spots has been divided into two regions: Morocco and Tunisia forest cover expanding area based on Algeria as the hot spot agglomeration; Angola, the Democratic Republic of the Congo, and Tanzania have been reduced low-forest coverage in Angola, Rwanda, Uganda, Central African Republic, and Congo high–low zone.

although the forest area in Rwanda has been still decreasing in the past 20 years.

4.2 Spatial Correlation Features of Forest Cover Change

Global spatial autocorrelation analysis of net forest cover change values from 2000 to 2019 has been conducted in order to analyze the spatial correlation characteristics of forest cover change in different countries and regions in Africa. The results have illustrated (**Table 3**) that Moran's I indexes of forest cover change in the past 20 years were all positive, indicating that forest cover change presented a positive correlation of spatial aggregation. However, 0≤Z≤1.65 and *p* ≥0.05 in the first decade of the 21st century did not adapt the significance test. Forest cover reduction in the study area was judged to be random in that period

(of course, subjected to technical means, early statistical data may not be accurate enough to affect the calculation results). Until 2010 and 2012, when $p \leq 0.05$, only less than 5% of the data distribution in the study area is likely to be random, and the probability of data aggregation is greater than that of random distribution. $Z \geq 1.65$ and 1.96 can significantly reject the null hypothesis. The results have demonstrated that the forest cover change in the study area has begun to cluster in 2010 and more significant in 2012, and the degree of spatial agglomeration increased annually. The spatial correlation of forest cover change amongst neighboring countries or regions has been increasingly strengthened.

Moran's I estimate of national and regional forest cover change in the study area from 2000 to 2019 was analyzed (**Figure 3A**). A Global Moran's I $Z \geq 1.96$ after 2020 indicates that the forest cover change in the study area shows spatial autocorrelation, $I \in (0, 1]$ forest cover change is positively correlated with spatial distance, and $p \leq 0.05$ after 2012 shows significant spatial aggregation characteristics in **Figures 3B,C**. The LISA index has been used to study the local agglomeration characteristics of forest cover change in the region further. The LISA significance map and agglomeration map have passed the 95% significance test via ArcGIS software analysis. The spatial clustering of the hot spots has been divided into two regions: Morocco and Tunisia forest cover expanding area based on Algeria as the hot spot agglomeration; Angola, the Democratic Republic of the Congo, and Tanzania have been reduced low-forest coverage in Angola, Rwanda, Uganda, Central African Republic and Congo high–low zone.

4.3 GPCA Calculation Results and Analysis

A 54×21×21 dimensional sequential stereo data table was constructed, including sample points from 54 countries and regions, 21 driving index variables, and 21 data tables from 2000 to 2020. According to the analysis steps of GPCA, the global principal component factors were extracted by SPSS 26. In the analysis, the maximum variance transaction rotation method is adopted. After 11 iterations, the results tend to converge. According to the principle that the eigenvalue is greater than 1, a total of 6 principal components are extracted. The cumulative contribution rate of the first principal component is 33.189%; the cumulative contribution rate of the second principal component is 17.490%; the third to sixth principal components play a similar role, with accumulative contribution rates of 6.966%, 6.052%, 5.355% and 5.023%, respectively. In the process of reducing the dimension of the data table from 21 to 6, 74.075% of the information in the original data table is retained, and the original features are basically completely preserved (See **Table 4**). The six main components are population, rural population, urban population, labor force, GDP, unemployment, death rate, foreign direct investment (net inflows), consumer price index, and terrestrial protected areas (% of the total land area).

In order to investigate whether there is a certain linear relationship among economic, social, demographic, and geographical evaluation indexes affecting forest cover and whether GPCA analysis method is suitable, the KMO test and

TABLE 4 | Generalized eigenvalues of principal components and accumulative percentage.

Principal component	Eigenvalues	Variance percentage (%)	Variance contribution rate (%)
C1	6.970	33.189	33.189
C2	3.673	17.490	50.679
C3	1.463	6.966	57.645
C4	1.271	6.052	63.697
C5	1.125	5.355	69.052
C6	1.055	5.023	74.075

TABLE 5 | KMO and Bartlett's test.

KMO and Bartlett's test		
Kaiser–Meyer–Olkin measure of sampling adequacy		0.783
Bartlett's test of sphericity	Approx. Chi-square	30845.267
	df	210
	sig	0.000

Bartlett sphericity test are selected for analysis, and the results are shown in **Table 5**. The KMO statistic is 0.783 and Sig. < 0.005, indicating that there is correlation for each variable, and the factor analysis is effective and got better results.

4.4 Forest Cover Change and Driving Factors on the Geographical Detector

The geographical detector is an emerging statistical method for driving force and factor analysis of spatial data (Wang, 2010), which is mainly composed of four detectors: factor detector, interactive detector, ecological detector, and risk detector. The first three detection functions are mainly adopted and conducted. Factor detection: The influence of economic, social, demographic, and natural factors (**Table 2**) on the spatial distribution of forest cover change can be calculated via factor detection analysis (q value). The larger the q value is, the greater the influence of this factor on forest cover change is. Ecological detection: Ecological detection is demonstrated to compare the significant differentiation in the spatial distribution of forest cover amongst economic, social, demographic, and natural factors. Interaction detection: The interactions are implemented amongst different influence factors. Based on the single factor q value comparative analysis and the q value sum of the two factors and the q value following the two interactive factors, we can identify whether the two post-interactive factors increase or decline their influence on the spatial distribution of forest cover or whether play an independent role themselves.

Factor detectors are first used to obtain the q values for five targeted years of 2000, 2005, 2010, 2015, and 2019 in the timescale (shown in **Table 6**). The explanatory power of the bold numerical factors all passed the 95% significance level. Overall, some significant factors have a great impact on the spatial differentiation analysis of forest cover change, such as

TABLE 6 | Factor detection results of spatial differentiation of forest cover change.

Factor		Year 2000			Year 2005			Year 2010			Year 2015			Year 2019		
Driver	Symbolic representation	q	p	Rank	q	p	Rank	q	p	Rank	q	p	Rank	q	p	Rank
GDP	X1	0.06	0.74	18	0.10	0.39	15	0.04	0.81	18	0.03	0.82	19	0.03	0.84	18
Foreign direct investment (BoP, current US$)	X2	0.15	0.27	10	0.46	0.07	1	0.26	0.33	3	0.36	0.08	1	0.26	0.28	5
Goods exports	X3	0.02	0.94	20	0.16	0.47	10	0.10	0.42	13	0.10	0.56	12	0.09	0.51	12
Goods imports	X4	0.07	0.59	16	**0.29**	**0.02**	4	0.19	0.11	7	0.20	0.08	8	0.15	0.20	9
Foreign direct investment, net inflows (% of GDP)	X5	0.16	0.45	9	0.05	0.82	19	0.06	0.57	17	0.06	0.78	16	0.01	0.99	21
Net ODA received	X6	0.02	0.87	19	0.01	0.97	21	0.09	0.42	15	0.02	0.90	21	0.01	0.95	20
Consumer price index	X7	**0.48**	**0.00**	1	0.12	0.27	11	0.14	0.17	10	0.09	0.41	14	0.03	0.87	17
Unemployment	X8	0.10	0.30	15	0.10	0.31	16	0.01	0.95	20	0.06	0.60	17	0.06	0.59	15
Forest rents	X9	0.02	0.93	91	0.12	0.43	12	0.15	0.27	9	0.18	0.25	9	0.14	0.22	10
Access to clean fuels and technologies for cooking	X10	0.11	0.38	14	0.06	0.55	18	0.04	0.77	19	0.05	0.67	18	0.06	0.59	14
GDP growth	X11	0.20	0.32	7	0.03	0.81	20	0.01	0.99	21	0.03	0.83	20	0.04	0.79	16
Population, total	X12	**0.36**	**0.04**	2	**0.31**	**0.04**	3	**0.31**	**0.04**	2	**0.29**	**0.05**	6	0.26	0.11	6
Rural population	X13	0.29	0.06	4	0.27	0.16	6	0.23	0.10	6	0.33	0.09	3	0.35	0.08	2
Urban population	X14	**0.29**	**0.04**	3	0.26	0.08	7	0.25	0.11	4	0.21	0.13	7	0.29	0.07	4
Labor force	X15	0.25	0.08	6	0.27	0.16	5	0.23	0.09	5	0.33	0.09	4	0.24	0.08	8
Death rate	X16	0.12	0.21	11	0.11	0.28	14	0.09	0.34	14	0.10	0.32	13	0.03	0.87	19
Birth rate	X17	0.11	0.27	12	0.18	0.10	9	0.16	0.14	8	0.17	0.11	10	**0.25**	**0.04**	7
Compulsory education	X18	0.11	0.28	13	0.11	0.25	13	0.10	0.28	12	0.12	0.23	11	0.11	0.24	11
Land area	X19	0.28	0.06	5	0.24	0.09	8	**0.31**	**0.04**	1	**0.30**	**0.05**	5	**0.30**	**0.05**	3
Terrestrial protected areas	X20	0.06	0.58	17	0.08	0.41	17	0.08	0.41	16	0.08	0.42	15	0.08	0.47	13
Arable land	X21	0.17	0.22	8	**0.33**	**0.04**	2	0.11	0.35	11	**0.34**	**0.02**	2	**0.45**	**0.01**	1

The q statistics of significant drivers (P ≤ 0.05) are displayed in bold.

consumer price index, agricultural land area, goods import, urbanization population, goods export, and human birth rate. These six factors can be regarded as the leading factors affecting forest cover change this year in terms of their Q values which are all greater than 0.25. However, each driving factor showed a trend of fluctuation in the temporal scale. Consumer price index and urban population had significant effects in 2000 only, with q values of 0.48 and 0.29, respectively. The effect of the human birth rate on forest cover increased annually until it reached a significant level in 2019, with a value of 9 of 0.25. Total population, land area, and agricultural land area played important roles in the disturbance of forest cover all in this time span. The weight of the total population decreased annually, while the proportion of agricultural land increased. The former decreased from 0.36 down to 0.26 between 2019 and 2020, and the latter increased from 0.17 to 0.45 from 2019 to 2000.

To further explore the changes of interpreting power of forest disturbance based on the interaction of different driving factors, the sample analysis is implemented based on the demonstrated illustration of 2000, 2005, 2010, 2015, and 2019. The interactive factor detection mechanism of the leading factors picked on forest cover change was analyzed (shown in **Table 7**): The demonstration illustrated that each factor was significantly correlated and independent in rare cases. About 76.67% of the interaction categories among several leading factors were non-linear enhancement, more than 18.33% were dual factors enhancement, and only 5% were single factor independence. The explanatory power of factor interaction illustrates differentiation and shows the

characteristics of fluctuation in timescale excluded that the interaction of X4 (goods import) and X14 (urban population) is increasing from 0.71 to 0.88 between 2019 and 2020.

5 DISCUSSION

Many scholars have been sorting out, improving, and verifying the development and evolution results of various direct driving factors under the UN SDGs constantly (Griggs et al., 2013; Weitz et al., 2019a; Weitz et al., 2019b; Guo, 2020; Guo et al., 2020; Guo et al., 2021). The IPBES global assessment provides a global review of the scientific evidence on major environmental and secondary social impacts of drivers of change, including the drivers, pressures, and responses sections of the DPSIR framework (Merino et al., 2019). The impact of geographical and climatic factors on forest cover change is likely to occur over a longer time series, but human activities are likely to be more rapid and straightforward, excluding accidental natural disasters, pest, and disease disasters or forest fires. The potential synergistic effect research method between the forest cover index in UN SDGs and human social and economic development has been illustrated further in terms of current research contributions.

Multiple driven factors play a role of different structure of the 6 principal components via global principal component analysis. The significant factors are influencing the forest cover change via the geographical detector monitoring all drivers annually. The two results of each analysis have been demonstrated slightly different subject to the inconsistency of research

TABLE 7 | Interactive detection results of spatial differentiation of forest cover change.

Factor interaction	Year 2000 q (Xi∩Xj)	q (Xi+Xj)	Type	Year 2005 q (Xi∩Xj)	q (Xi+Xj)	Type	Year 2010 q (Xi∩Xj)	q (Xi+Xj)	Type	Year 2015 q (Xi∩Xj)	q (Xi+Xj)	Type	Year 2019 q (Xi∩Xj)	q (Xi+Xj)	Type
X4∩X7	0.55	0.55	I	0.43	0.41	NE	0.78	0.32	NE	0.31	0.30	NE	0.30	0.18	NE
X4∩X12	0.68	0.43	NE	0.57	0.60	DE	0.48	0.49	DE	0.45	0.50	DE	0.50	0.40	NE
X4∩X14	0.71	0.36	NE	0.75	0.55	NE	0.77	0.44	NE	0.79	0.42	NE	0.88	0.43	NE
X4∩X19	0.73	0.35	NE	0.78	0.53	NE	0.63	0.50	NE	0.85	0.50	NE	0.79	0.45	NE
X4∩X21	0.43	0.24	NE	0.54	0.62	DE	0.42	0.30	NE	0.49	0.55	DE	0.83	0.60	NE
X7∩X12	0.87	0.84	NE	0.47	0.43	NE	0.70	0.45	NE	0.42	0.39	NE	0.80	0.30	NE
X7∩X14	0.93	0.77	NE	0.55	0.38	NE	0.82	0.39	NE	0.46	0.31	NE	0.54	0.32	NE
X7∩X19	0.83	0.76	NE	0.73	0.36	NE	0.83	0.45	NE	0.81	0.39	NE	0.46	0.34	NE
X7∩X21	0.75	0.65	NE	0.63	0.45	NE	0.81	0.25	NE	0.68	0.44	NE	0.54	0.48	NE
X12∩X14	0.72	0.66	NE	0.49	0.57	DE	0.79	0.56	NE	0.47	0.51	DE	0.43	0.54	DE
X14∩X19	0.54	0.57	DE	0.53	0.50	NE	0.50	0.57	DE	0.51	0.51	I	0.88	0.59	NE
X19∩X21	0.38	0.45	DE	0.66	0.56	NE	0.43	0.43	I	0.77	0.64	NE	0.80	0.75	NE

DE: Double enhancement q (Xi+Xj)>q (Xi∩Xj)>Max (q (Xi), q (Xj)); NE: Non-linear enhancement q (Xi∩Xj)>q (Xi+Xj); I: Independence q (Xi∩Xj) = q (Xi+Xj)
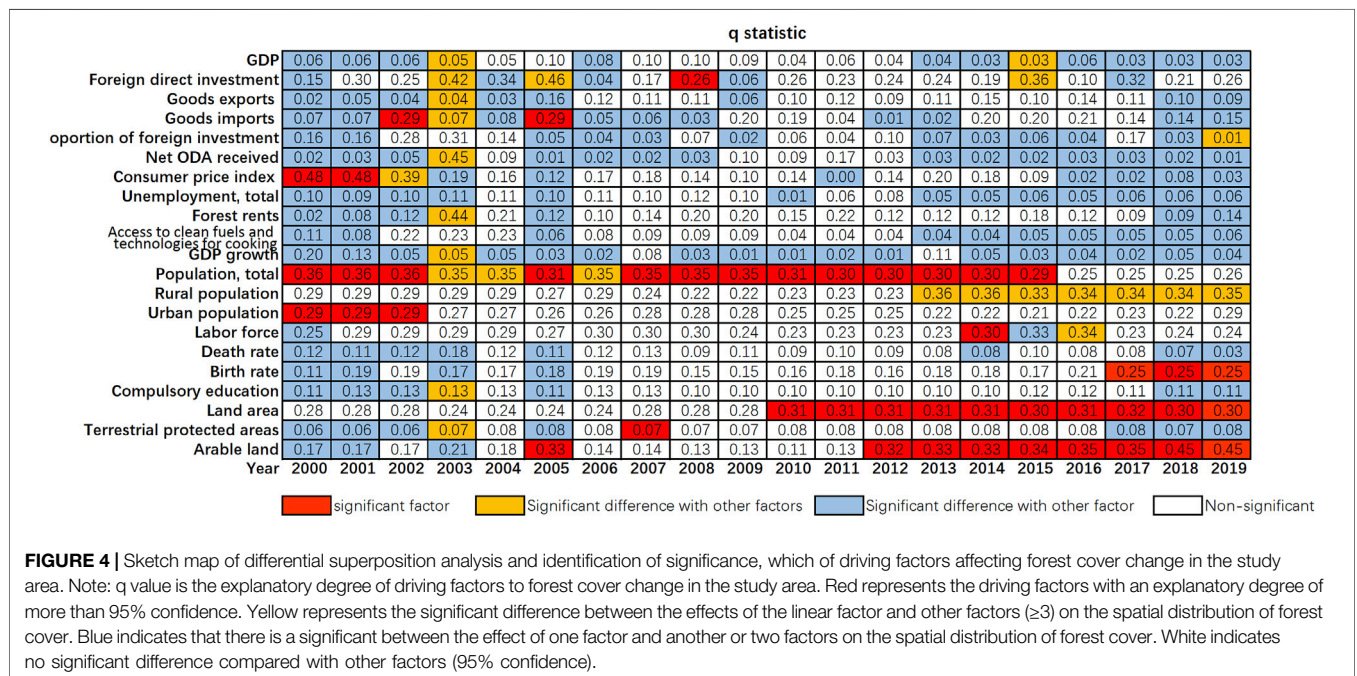

FIGURE 4 | Sketch map of differential superposition analysis and identification of significance, which of driving factors affecting forest cover change in the study area. Note: q value is the explanatory degree of driving factors to forest cover change in the study area. Red represents the driving factors with an explanatory degree of more than 95% confidence. Yellow represents the significant difference between the effects of the linear factor and other factors (≥3) on the spatial distribution of forest cover. Blue indicates that there is a significant between the effect of one factor and another or two factors on the spatial distribution of forest cover. White indicates no significant difference compared with other factors (95% confidence).

purpose, timescale, and precision. Global principal component analysis has placed all the data in the last 20 years on the same 3D observation model to abstract dimension reduction. The results of driving factors influencing the last 20 years have been extracted. The geographical detector has detected the significant drivers of forest cover change each year to verify and summarize the significant common factors over the past 20 years. The both extracted analyses of driving factors of forest cover change can be in support of making decision further.

A comprehensive analysis of 21 driving factors in 54 countries and regions in the target area for 20 consecutive years was completed by using geographical detectors (see **Figure 4**), and forest cover change and driving factors can be summarized into four stages: in the first stage, the factors causing the reduction of

forest cover are complicated in the first 4 years of the 21st century (2000–2003). The consumer price index (CPI) has the significant and highest explanatory power, which can reflect the degree of inflation or deflation. The second is the total population. The pressure caused by the total and urban population also shows a significant impact. In addition, almost all other factors showed significantly different trends in the effects of two factors at the same time. In the second stage, the rapid growth of the total population in the study area was the most important and significant explanatory factor driving the rapid decrease of forest cover from 2004 to 2009. Meanwhile, the factors promoting regional economic development were different from population pressure and played a moderating role in influencing the change of forest cover gradually. In the third stage, the

expansion of cultivated land in the study area has a significant impact year by year from 2010 to 2015, especially in the area with a larger land area, the amount of deforestation and land conversion is greater. The growth of total population still has a relatively significant explanation for forest change, but the impact value decreases year by year. In Stage 4, the growth of the cultivated land for forest cover to reduce the influence of the significant increase from 2016 to 2019 (Williams et al., 2021), the chance of vast country in deforestation is greater, and with the development of economy, the total population bearing pressure on forest change is no longer significant; the neo-birth rate can significantly represent more of a certain explanation on forest cover change; in addition, changes in the number of rural population have significant differences with other factors (≥3) on the spatial distribution of forest cover, which becomes extremely complicated.

6 CONCLUSION

Forest cover change assessment has become one of the key indicators of Sustainable Development Goals (SDGs). Africa is experiencing unprecedented deforestation of forest resources. The study area is composed of data from 54 countries and regions from 2000 to 2020. Spatial autocorrelation analysis, global principal component analysis, and geographic detector model are used to illustrate the spatio-temporal patterns of forest cover change in Africa. The driving effects of population growth, economic and trade, social development, and cultivated land expansion on forest cover change in different timescale were analyzed in geographical spatial heterogeneity. Relevant conclusions are as follows:

1) The distribution of forests in Africa is extremely uneven. Based on the distributed quantities, Africa has the largest forest area in Central Africa, the second in East Africa, the third in West Africa, the fourth in South Africa, and the fifth in North Africa. In the past 20 years, the forest area decreased significantly, and the forest area decreased more significantly than that in West Africa including the Democratic Republic of the Congo, Angola, Tanzania, Mozambique, Sudan, Nigeria, Botswana and Cote d 'Ivoire, Zambia, Chad, Somalia, Ethiopia, Namibia, and Cameroon. Only 7 countries showed a net increase in the forest area during the 20 years, and only 5 countries showed a significant increase (over 200 square kilometers). Algeria, Morocco, and Tunisia in North Africa, East Africa, and Swaziland in South Africa have presented an increase status, but forest growth accounts for only 1% of the loss.

2) The forest cover change in the study area began to show the clustering from 2010 to 2012 and became more significant. The degree of spatial agglomeration increased year by year, and the spatial correlation of forest cover change between neighboring countries or regions became increasingly stronger. The LISA index was used to study the local agglomeration characteristics of forest cover change. The spatial clustering of hot spots was divided into two regions:

first, Algeria as a hot spot clustering in Morocco and Tunisia increased forest cover area; in the other place, Zambia was the coldest spot with a significant clustering in Angola, the Democratic Republic of the Congo, and Tanzania have reduced their low-forest coverage to Angola, Rwanda, Uganda, Central African Republic, and Congo high–low zone.

3) Total population, land area, cultivated land, urban population, consumer price index, and birth rate are the main factors influencing the temporal evolution of forest cover change in Africa. It can be divided into four stages to interpret the different explanations and significance of each factor for forest cover change in the study area. In the first stage, the factors causing the reduction of forest cover are complicated in the first 4 years of the 21st century (2000–2003). The consumer price index (CPI) has the significant and highest explanatory power, which can reflect the degree of inflation or deflation. The second is the total population. The pressure caused by the total and urban population also shows a significant impact. In addition, almost all other factors showed significantly different trends in the effects of two factors at the same time. In the second stage, the rapid growth of the total population in the study area was the most important and significant explanatory factor driving the rapid decrease of forest cover from 2004 to 2009. Meanwhile, the factors promoting regional economic development were different from population pressure and played a moderating role in influencing the change of forest cover gradually. In the third stage, the expansion of cultivated land in the study area has a significant impact year by year from 2010 to 2015, especially in the area with a larger land area, the amount of deforestation and land conversion is greater. The growth of total population still has a relatively significant explanation for forest change, but the impact value decreases year by year. In Stage 4, the growth of the cultivated land for forest cover to reduce the influence of the significant increase from 2016 to 2019, the chance of vast country in deforestation is greater, and with the development of economy, the total population bearing pressure on forest change is no longer significant; the neo-birth rate can significantly represent more of a certain explanation on forest cover change; in addition, changes in the number of rural population have significant differences with other factors (≥3) on the spatial distribution of forest cover, which becomes extremely complicated.

DATA AVAILABILITY STATEMENT

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

AUTHOR CONTRIBUTIONS

HX, JL, NF, and GH conceived the research project. HX and HW performed simulations and wrote the manuscript. XZ, TL, ZZ, WW, RY, YG, BC, and QC contributed to model development. All other authors contributed to data and commented on or approved the manuscript.

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