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Spatiotemporal Analysis of Global Forest Cover Change Based on Remote Sensing Data

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Abstract: *Forest cover is an important indicator of the spatial distribution of forest resources, ecosystem status, and carbon-cycle processes. Against the background of intensifying global climate change and continued expansion of human activities, long-term monitoring of forest-cover change is of great significance. Based on the European Space Agency Climate Change Initiative (ESA CCI) Plant Functional Types (PFT) product, this study extracts four forest-cover classes from 1992 to 2020, namely evergreen broadleaf forest, deciduous broadleaf forest, evergreen needleleaf forest, and deciduous needleleaf forest. Annual global forest-cover time series are constructed through reclassification, overlay, resampling, and threshold masking. Methodologically, this paper applies the Theil-Sen median slope estimator and the Mann-Kendall significance test to identify forest-cover trends, and introduces ordinary least squares (OLS) linear regression as a comparative method. The results show that high-cover forests are mainly concentrated in the Amazon Basin, the Congo Basin, northern Eurasia, temperate forests of North America, and Southeast Asia. From 1992 to 2020, global forest cover showed a slight overall decreasing trend, and the area with significant decrease was markedly larger than the area with significant increase. The significant-change area identified by the OLS method was about 1.9 times that identified by the Sen-MK method, indicating a stronger trend-amplification effect. The Sen-MK method is less sensitive to outliers and short-term fluctuations and therefore provides more robust trend judgments. The results can provide data support and methodological references for dynamic monitoring of global forest resources, ecological environment assessment, carbon-cycle research, and sustainable forest management.*

Keywords: *Forest cover; Remote sensing; ESA CCI PFT; Theil-Sen; Mann-Kendall; Linear regression; Spatiotemporal change*

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I. Introduction

Against the background of intensifying global climate change and the continuous expansion of human activities, forest ecosystems are undergoing significant spatiotemporal changes. As an important component of terrestrial ecosystems, forests play essential roles in maintaining ecological balance, regulating climate, protecting biodiversity, and supporting the carbon cycle. Forest cover reflects the coverage status of the forest canopy on the land surface. It is not only a key indicator for evaluating the distribution and change of forest resources, but also a critical parameter in ecosystem function assessment, carbon-stock estimation, water-cycle simulation, and ecological environment monitoring**Error! Reference source not found.Error! Reference source not found.** .

Changes in forest cover are jointly affected by climate change, natural disturbances, and human activities **Error! Reference source not found.**23**Error! Reference source not found.**. Natural processes such as rising temperature, precipitation variation, droughts, floods, forest fires, and pests and diseases can alter forest growth environments and affect their spatial distribution. Human activities such as agricultural expansion, urban construction, infrastructure development, and commercial logging can lead to forest loss, whereas afforestation, conversion of cropland to forest, and ecological restoration projects may promote forest recovery**Error! Reference source not found.**3]5]. Therefore, forest-cover change often exhibits clear regional differences and complex dynamic characteristics.

The development of remote sensing technology has provided important support for monitoring forest cover at the global scale[35]. Compared with traditional ground surveys, remote sensing data have the advantages of broad spatial coverage, strong temporal continuity, and high update efficiency, and can support quantitative analysis of forest-change processes over long time series. However, due to factors such as spatial resolution, classification accuracy, forest-type definition, mixed pixels, and resampling errors, uncertainty remains in forest-cover extraction and trend determination**Error! Reference source not found.**9]. It is therefore necessary to combine long-term remote sensing data with robust statistical analysis methods to systematically study changes in global forest cover.

Based on this background, this paper uses ESA CCI PFT data to extract four major forest functional types from 1992 to 2020 and to construct annual global forest-cover time series. On this basis, the nonparametric Sen-MK trend analysis method is adopted to identify areas with significant forest-cover change, while OLS linear regression is used as a comparative approach. The study reveals the spatial distribution, interannual dynamics, and trend characteristics of forest cover at the global scale, and quantitatively compares differences between the two methods in identifying significant changes. The findings provide a scientific basis for dynamic monitoring of global forest resources and for the formulation of ecological conservation policies.

II. Data and Methods

2.1 Data source

The remote sensing data used in this study were obtained from the global land-cover dataset developed under the European Space Agency Climate Change Initiative (ESA CCI), specifically the global Plant Functional Types (PFT) product v2.0.82**Error! Reference source not found.**6]. This product is generated by integrating multi-source remote sensing observations and provides annual global vegetation functional-type information from 1992 to 2020. With a spatial resolution of 300 m, good spatiotemporal consistency, and global coverage, the product is suitable for long-term studies of forest-cover change.

According to the PFT classification system, this study selected four forest functional types for analysis: evergreen broadleaf forest, deciduous broadleaf forest, evergreen needleleaf forest, and deciduous needleleaf forest. These four forest types differ markedly in thermal conditions, precipitation conditions, phenological characteristics, and spatial distribution, and therefore can comprehensively represent the coverage patterns and change processes of the major global forest types.

2.2 Data preprocessing and forest-cover extraction

The original PFT data were first preprocessed. Because the original data were in NetCDF format, annual files were read and checked for projection, spatial extent, raster alignment, resolution, and missing values to ensure consistency and comparability among multi-temporal datasets. The four forest-cover proportions were then extracted according to vegetation-type codes and summed at the pixel scale to obtain annual total forest cover**Error! Reference source not found.**6**Error! Reference source not found.**. The total forest cover was calculated as follows:

$$F_{total,t} = F_{EBF,t} + F_{DBF,t} + F_{ENF,t} + F_{DNF,t} \tag{1}$$

where $F_{EBF,t}$, $F_{DBF,t}$, $F_{ENF,t}$, and $F_{DNF,t}$ represent the cover of evergreen broadleaf forest, deciduous broadleaf forest, evergreen needleleaf forest, and deciduous needleleaf forest in year t, respectively. To eliminate possible differences in spatial alignment and resolution among years and to facilitate global-scale statistical analysis, the forest-cover data were resampled to a uniform 0.25° latitude-longitude grid using bilinear interpolation. Because forest cover is a continuous proportional variable, bilinear interpolation can effectively preserve gradual spatial variation.

2.3 Extraction of stable forest areas

After annual forest-cover data were obtained, the multi-year mean forest cover for 1992-2020 was calculated to reduce the influence of short-term interannual fluctuations on forest-area determination. In this paper, a threshold method was used to extract stable forest areas: grid cells with multi-year mean forest cover greater than 50% were defined as forest areas and used as the spatial mask for subsequent trend analysis**Error! Reference source not found.**8**Error! Reference source not found.**. The multi-year mean forest cover was calculated as follows:

$$\bar{F} = \frac{1}{n}\sum_{i=1}^{n} F_i \tag{2}$$

The forest-area definition rule is as follows:

$$Forest = \begin{cases} 1, & \bar{F} > 0.5 \\ 0, & \bar{F} \le 0.5 \end{cases} \tag{3}$$

where $\bar{F}$ represents the multi-year mean forest cover from 1992 to 2020,F_i denotes the forest cover in year i, and $n$denotes the number of study years; in this study, $n = 29$. This threshold rule highlights areas where forest cover was relatively stable and dominant during the study period, thereby reducing interference from transitional vegetation, sparse woodland, and mixed pixels in the trend-analysis results.

2.4 Trend analysis methods

Based on the extracted forest-cover data, annual time series from 1992 to 2020 were constructed at the pixel scale, and two types of methods were used for trend analysis. The primary method was the Theil-Sen median slope estimator combined with the Mann-Kendall nonparametric significance test[1214]. This method is insensitive to outliers and does not require the data to follow a normal distribution, making it suitable for trend detection in large-area, long time-series remote sensing data. The Sen slope was calculated as follows:

$$\beta_{Sen} = median\left(\frac{x_j - x_i}{j - i}\right), \forall i < j \tag{4}$$

where x_i and x_j denote forest cover in years i and j, respectively. When $\beta_{Sen} > 0$ forest cover shows an increasing trend; when $\beta_{Sen} < 0$, forest cover shows a decreasing trend.

The Mann-Kendall significance test (MK test) is a nonparametric statistical method used to determine whether a time series has a significant trend, without requiring the data to follow a specific distribution. Its sign function is defined as follows:

$$sgn(x_j - x_i) = \begin{cases} 1, & x_j - x_i > 0 \\ 0, & x_j - x_i = 0 \\ -1, & x_j - x_i < 0 \end{cases} \tag{5}$$

The Mann-Kendall statistic S was calculated as:

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

The statistic S reflects the overall trend direction of the time series. Its variance $Var(S)$ was calculated as:

$$Var(S) = \frac{n(n-1)(2n+5)}{18} \tag{7}$$

The standardized test statistic Z was further calculated as:

$$Z = \begin{cases} \frac{S-1}{\sqrt{V_{ar}(S)}}, S > 0 \\ 0, S = 0 \\ \frac{S+1}{\sqrt{V_{ar}(S)}}, S < 0 \end{cases} \tag{8}$$

The Z value was used to assess trend significance: $Z > 0$ indicates an increasing trend, $Z < 0$ indicates a decreasing trend, and a larger $|Z|$ indicates a more significant trend.

Ordinary least squares (OLS) linear regression was used as a reference method. For each pixel-level forest-cover time series, a linear regression model $y = ax + b$ was established, where y denotes forest cover, x denotes year, a denotes the change slope, b denotes the intercept, and the slope and its significance p value were recorded.

The slope a was calculated as:

$$a = \frac{\sum_{t=1}^{n}(t - \bar{t})(y_t - \bar{y})}{\sum_{t=1}^{n}(t - \bar{t})^2} \tag{9}$$

The standard error S_a of the slope and the t statistic were then calculated as:

$$S_a = \sqrt{\frac{\sum_{t=1}^{n}(y_t - \hat{y_t})^2}{(n-2)\sum_{t=1}^{n}(t - \bar{t})^2}} \tag{10}$$

$$t = \frac{a}{S_a} \tag{11}$$

The p value of the two-sided test (based on the t distribution) was calculated as follows:

$$p = 2 \cdot [1 - F_{t,n-2}(|t|)] \tag{12}$$

where $F_{t,n-2}$ is the cumulative distribution function of the t distribution with $n - 2$ degrees of freedom.

Unified trend classification rules were defined for the two trend-analysis methods. For Sen-MK trend analysis, the Slope reflects the rate of increase or decrease in forest cover, and the Z value was used for trend significance testing: when $Slope > 0$ and $|Z| \geq 1.96$, the area was classified as a significant increase in forest cover; when $Slope < 0$ and $|Z| \geq 1.96$, it was classified as a significant decrease in forest cover; areas that did not satisfy these significance criteria were classified as having no significant change. For the OLS linear regression method, $p < 0.05$ was used as the significance criterion. Significant change areas were first screened, and significant increase and significant decrease were then distinguished according to the sign of the regression slope.

III. Results and Analysis

3.1 Spatial distribution characteristics of global forests

Based on the threshold rule that multi-year mean forest cover should be greater than 50%, this study extracted the global stable forest distribution during 1992-2020. The results show that high-cover forests are mainly concentrated in the Amazon Basin of South America, the Congo Basin of Africa, the Siberian coniferous forest region in northern Eurasia, the temperate forest region of North America, and localized contiguous areas in Southeast Asia and eastern Oceania. Overall, the distribution of high-cover forests is highly consistent with global climatic zones that have favorable hydrothermal conditions. The three major tropical rainforest regions and the Northern Hemisphere coniferous forest belt constitute the main body of global forest cover.

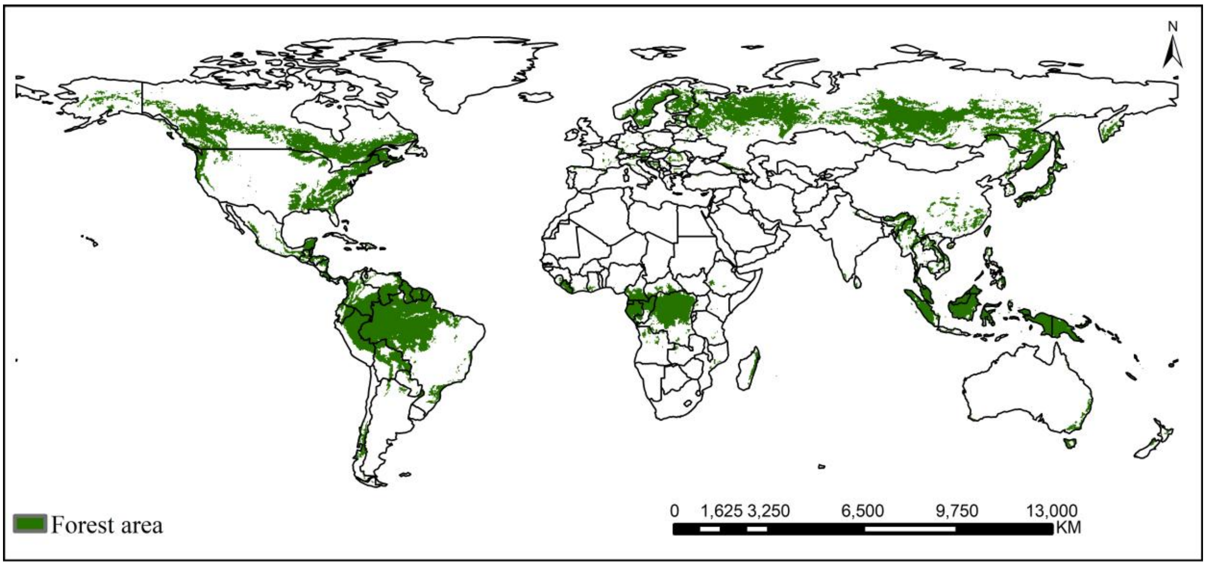

Fig. 1 Spatial distribution of stable global forests from 1992 to 2020

From the latitudinal perspective, forests in low-latitude regions have high cover and strong spatial continuity, mainly supported by year-round warm and humid climatic conditions. In middle- and high-latitude regions, forests occur more commonly in zonal patterns, especially in northern Eurasia and northern North America, where large coniferous forest belts are formed. Forest distribution in temperate regions is relatively fragmented and is mainly concentrated in eastern North America, western Europe, and the East Asian monsoon region. Its spatial pattern is influenced by both natural conditions and human activities.

3.2 Overall characteristics of global forest-cover change

From 1992 to 2020, global forest cover showed a slight overall decreasing trend, but the magnitude of change differed clearly among regions and forest types. Forest-cover decline was more pronounced in tropical regions and may be related to human activities such as agricultural expansion, commercial logging, plantation development, and infrastructure construction. In some middle- and high-latitude regions, local increases in forest cover occurred under the influence of vegetation recovery, ecological projects, and sustainable management. Overall, global forest-cover change shows a spatial differentiation pattern characterized by obvious tropical degradation and localized recovery in middle- and high-latitude regions.

3.3 Change trends based on OLS linear regression

To identify long-term trends in global forest cover from a parametric statistical perspective, this study first applied OLS linear regression to analyze the significant-change pattern within stable forest areas. The results show that areas with significant decrease are widely distributed in the Amazon rainforest, the Congo Basin, tropical Southeast Asia, and some middle- and high-latitude forestry activity zones in North America and Eurasia. Areas with significant increase occur in patchy patterns in central North America, northern Europe, northern and southwestern China, the northern Indian subcontinent, and parts of Siberia. Overall, areas with significant decrease are much more continuous and occupy a larger proportion than areas with significant increase.

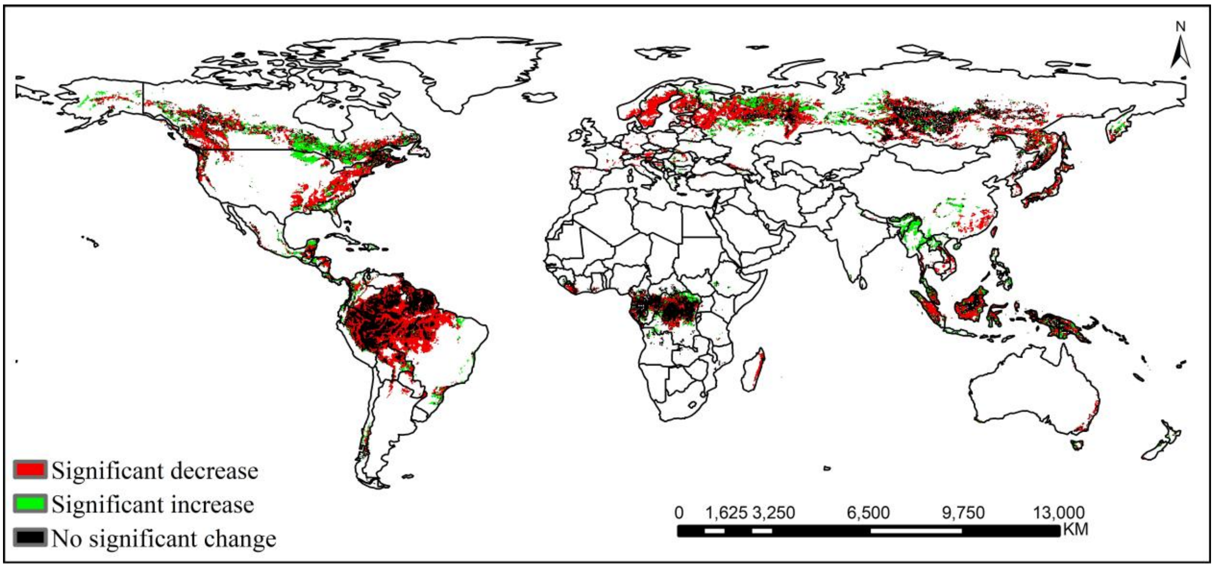

Fig. 2 Distribution of significant forest-cover changes based on OLS linear regression

The OLS method can sensitively capture linear trends in forest cover over time, but its results are also susceptible to anomalous years, short-term fluctuations, and classification noise. Therefore, in long-term remote sensing time-series analysis, linear regression results should be compared with nonparametric trend methods to improve the reliability of trend determination.

3.4 Change trends based on Sen-MK

On the basis of the OLS analysis, the Sen-MK method was further used to identify trends in global forest cover. The results show that the spatial pattern of significant changes identified by Sen-MK is generally consistent with the OLS results, but the significant-change area is markedly smaller. Areas with significant decrease remain concentrated in the southeastern agricultural-pastoral ecotone of the Amazon rainforest, commercial forestry harvesting zones in middle- and high-latitude North America and Eurasia, plantation expansion areas on Sumatra and Kalimantan in Southeast Asia, and some primary forest logging areas in the southern Congo Basin. Areas with significant increase are mostly scattered patches and are mainly located in ecological restoration or sustainable management regions such as central North America, northern Europe, northern China, and northwestern India.

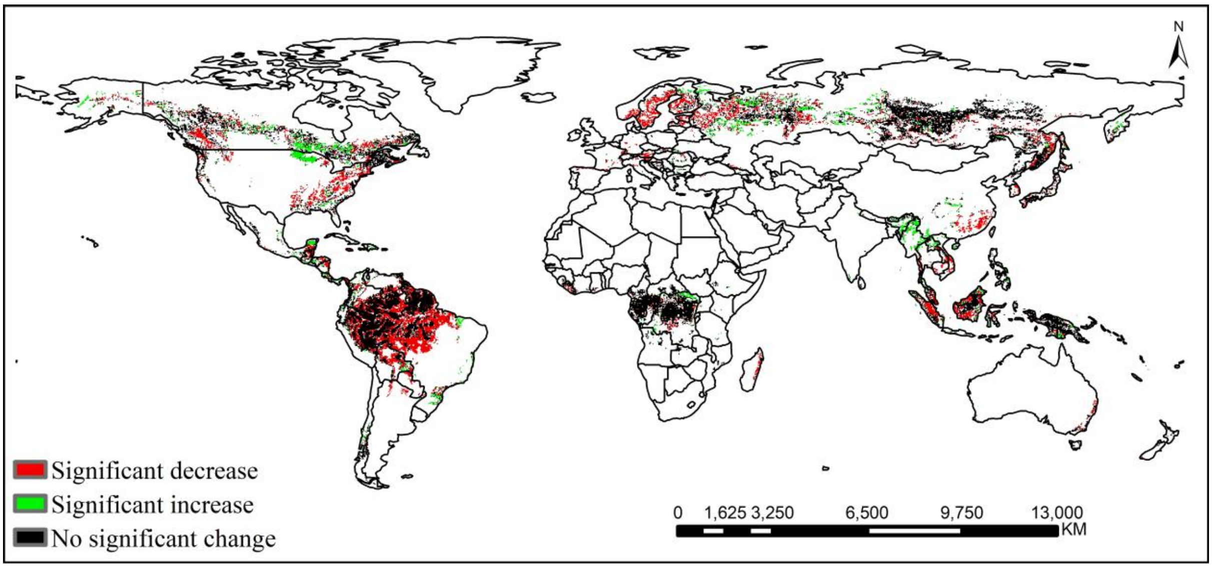

Fig. 3 Distribution of significant forest-cover changes based on Sen-MK trend analysis

The Sen-MK method is insensitive to outliers and short-term oscillations and emphasizes sustained and stable monotonic changes in the time series. Therefore, its identification of significant-change areas is relatively conservative, but it has better robustness in large-area, long time-series forest-cover monitoring.

3.5 Comparison of the two trend-analysis methods

To further quantify the differences between the two methods in identifying significant-change areas, this study used the total area of stable forest grid cells as the baseline and calculated the proportions of significant increase, significant decrease, and total significant change. The results show that the total significant-change area identified by OLS linear regression accounted for 58.80%, including 15.42% significant increase and 43.37% significant decrease. The total significant-change area identified by the Sen-MK method accounted for 30.55%, including7.95%significant increase and 22.60% significant decrease. The significant-change area identified by OLS was about 1.9 times that identified by Sen-MK.

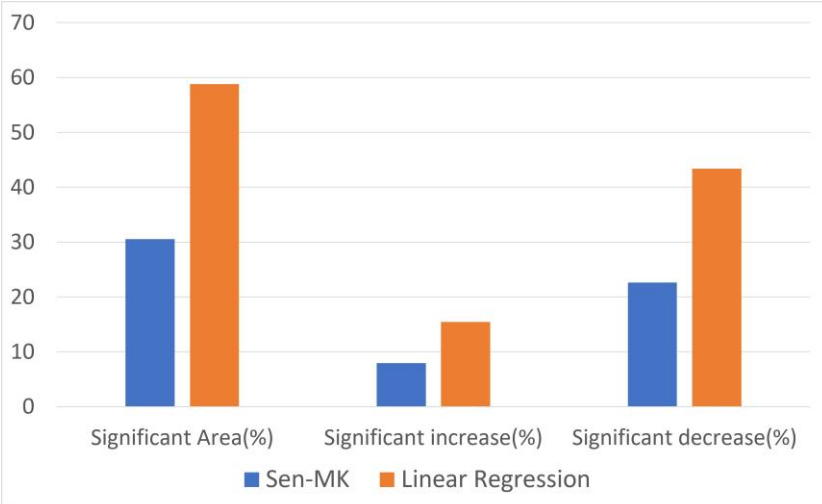

Fig. 4 Comparison of significant-change area proportions identified by Sen-MK and OLS

Both methods consistently show that the proportion of area with significant decrease is higher than that with significant increase, indicating that global forest cover was dominated by a decreasing trend during the study period. However, the OLS method is more sensitive to change signals and can more easily classify areas with weak changes or areas affected by noise as significant, showing an obvious trend-amplification effect. By contrast, the Sen-MK method is more conservative and can more stably reflect sustained long-term changes.

3.6 Result interpretation and methodological uncertainty

The spatial pattern of global forest-cover change reflects the combined influence of climate background, topographic conditions, land-use intensity, and ecological conservation policies. Tropical forest regions, especially the Amazon Basin, the Congo Basin, and tropical Southeast Asia, are the main concentration areas of significant decrease in forest cover. These regions are generally affected by human activities such as agricultural expansion, commercial logging, infrastructure construction, and plantation development. In contrast, areas with significant increase are mainly distributed in some middle- and high-latitude regions or in regions where ecological restoration projects have been implemented, possibly related to natural vegetation recovery, conversion of cropland to forest, afforestation, and sustainable forest management.

This study still involves certain uncertainties. First, although ESA CCI PFT data have good spatiotemporal continuity, classification errors may occur in areas with strong landscape heterogeneity or in forest-nonforest transition zones. Second, resampling the original 300 m data to a 0.25° grid improves the computational efficiency of global-scale analysis, but it may also smooth local change characteristics. Third, using a 50% threshold to extract stable forest areas helps reduce interference from mixed pixels, but may exclude sparse forests, plantations, and transitional forest areas. Future studies should integrate higher-resolution imagery, field validation data, climate variables, land-use data, and socioeconomic indicators to further reveal the driving mechanisms of forest-cover change.

IV. Conclusion

(1) Based on ESA CCI PFT data from 1992 to 2020, this study constructed annual forest-cover time series for four forest types, namely evergreen broadleaf forest, deciduous broadleaf forest, evergreen needleleaf forest, and deciduous needleleaf forest. The Sen-MK and OLS methods were then used to analyze the spatiotemporal characteristics of global forest-cover change. The results show that stable global forests are

mainly concentrated in the Amazon Basin, the Congo Basin, northern Eurasia, temperate forests of North America, Southeast Asia, and eastern Oceania. The overall distribution pattern is highly consistent with global climatic zones and hydrothermal conditions.

(2) Both trend-analysis methods indicate that global forest cover showed a slight but widespread decreasing trend from 1992 to 2020. Areas with significant decrease are mainly located in tropical forest regions and some middle- and high-latitude forestry activity zones, whereas areas with significant increase are relatively fragmented and are mainly distributed in regions with notable forest recovery, ecological projects, or sustainable management.

(3) The quantitative comparison shows that the significant-change area identified by OLS linear regression is much larger than that identified by the Sen-MK method. The proportions of total significant change, significant increase, and significant decrease identified by OLS are all about 1.9 times those identified by Sen-MK. This indicates that OLS is more sensitive to short-term fluctuations and outliers and has a clear trend-amplification effect. The Sen-MK method is more robust and conservative and can more reliably reflect persistent long-term trends.

(4) For large-area, long time-series forest-cover monitoring, the Sen-MK method is recommended as the primary approach for qualitative trend determination, while the OLS method can be used as a supplementary tool to identify hotspots with strong linear changes or large change magnitudes. The integrated application of the two methods can improve the reliability of forest-change assessment results and provide scientific support for global forest-resource management, ecological restoration, and climate-change response.

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