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Uncovering true significant trends in global greening

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ABSTRACT

The global greening trend, marked by significant increases in vegetation cover across ecoregions, has attracted widespread attention. However, even robust traditional methods, like the non-parametric Mann-Kendall test, often overlook crucial factors such as serial correlation, spatial autocorrelation, and multiple testing, particularly in spatially gridded data. This oversight can lead to inflated significance of detected spatiotemporal trends. To address these limitations, this research introduces the True Significant Trends (TST) workflow, which enhances the conventional approach by incorporating pre-whitening to control for serial correlation, Theil-Sen (TS) slope for robust trend estimation, the Contextual Mann-Kendall (CMK) test to account for spatial and cross-correlation, and the adaptive False Discovery Rate (FDR) correction. Using AVHRR NDVI data over 42 years (1982–2023), we found that conventional workflow identified up to 50.96% of the Earth's terrestrial land surface as experiencing statistically significant vegetation trends. In contrast, the TST workflow reduced this to 38.16%, effectively filtering out spurious trends and providing a more accurate assessment. Among these significant trends identified using the TST workflow, 76.07% indicated greening, while 23.93% indicated browning. Notably, considering areas (pixels) with NDVI values above 0.15, greening accounted for 85.43% of the significant trends, with browning making up the remaining 14.57%. These findings strongly validate the ongoing global greening of vegetation. They also suggest that incorporating more robust analytical methods, such as the True Significant Trends (TST) approach, could significantly improve the accuracy and reliability of spatiotemporal trend analyses.

1. Introduction

A growing body of remote sensing research reports notable global greening, with widespread increases in vegetation cover across ecoregions (Chen et al., 2019b; Chi Chen et al., 2019a; Chen et al., 2024; Guo et al., 2018; Los, 2013; Schut et al., 2015; Xiao and Moody, 2005; Zhao et al., 2018; Zhu et al., 2016). However, conclusions about greening often rely on monotonic trend analyses of NDVI, LAI, and similar parameters, which may lack statistical rigour, particularly in the context of spatiotemporal trend analysis (Cortés et al., 2020). In this research, we address these analyses' limitations and propose a new workflow for monotonic trend analysis of spatiotemporal gridded data.

The gold standard for measuring trend slope typically relies on the Theil-Sen estimator, while trend significance is commonly assessed using non-parametric tests like the Mann-Kendall test (Eastman and ClarkLabs, 2021). However, monotonic trend analyses in

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spatial gridded data often overlook the effects of serial correlation (Anderson, 2014), spatial autocorrelation (Getis, 1995), and multiple testing (James et al., 2021).

Although serial correlation, spatial autocorrelation, and multiple testing are each well-recognised issues in geography and environmental sciences (García, 2003; Rogerson, 2024), they have not been considered together in spatiotemporal trend analysis, with the most significant omissions occurring in remote sensing-based trend analysis research (Gutiérrez Hernández and García, 2024). Neglecting to account for these factors simultaneously can lead to misleading conclusions, as they may artificially inflate the statistical significance of detected trends or mask genuine patterns. This issue is often associated with Type I errors, also known as false positives, which occur when a test incorrectly rejects a true null hypothesis.

We aim to address this significant gap by analysing global vegetation trends' magnitude, direction, and significance using an innovative methodological approach that integrates serial, spatial, and cross-correlations controls and multiple testing corrections. These techniques have not previously been applied in a unified workflow, which we term True Significant Trends (TST). This research involves a comprehensive global analysis of spatiotemporal trends in NDVI data over 42 years, from 1982 to 2023.

2. Materials & methods

2.1. Remote sensing data

This research used the Advanced Very High-Resolution Radiometer (AVHRR) NDVI data from the Vegetation Health Products provided by NOAA's STAR (NOAA, 2024). These data are derived from the Advanced Very High-Resolution Radiometer (AVHRR) onboard NOAA's polar-orbiting satellites. NDVI values are derived from atmospherically corrected surface reflectance data acquired by the AVHRR sensor. The AVHRR NDVI dataset, originally at 4 km resolution, was resampled to a 10-min resolution using bilinear interpolation, covering 570,652 pixels globally.

Initially, 2184 images were processed, corresponding to 52 weekly raster images per year, covering 42 years from 1982 to 2023. To address missing or incorrect pixel values (cloud contamination, sensor noise, etc.), and to fill gaps in our dataset, two interpolation methods were applied to achieve a complete and curated series: linear temporal interpolation was used to fill in missing images, while harmonic interpolation was employed to correct erroneous pixel values by fitting a harmonic regression (Roerink et al., 2000).

Finally, an annual spatiotemporal time series was generated, representing the median NDVI value per year from 1982 to 2023. The median was used because it is less sensitive to outliers and extreme values (Forthofer et al., 2007), providing a more robust measure of central tendency for capturing consistent annual vegetation trends.

2.2. Research workflow for true significant trends (TST)

Fig. 1 illustrates the True Significant Trends (TST) workflow, detailed in the following sections. In the supplementary information (attached document), we offer a more comprehensive explanation of the statistical foundations, including detailed descriptions and mathematical equations related to the statistical methods used, which support the overall framework of this workflow.

2.2.1. Serial correlation control

We applied a pre-whitening process to the 42-year median NDVI values time series using the *Prewhiten* module included in the *Earth Trends Modeler* (ETM) of the *TerrSet 2020 Geospatial Monitoring and Modeling Software* (Eastman and ClarkLabs, 2021).

Pre-whitening refers to the removal of serial correlation in the error (noise) component of a series (Kulkarni and von Storch, 1995; von Storch, 1999). Yue and Wang (2002) criticised the original pre-whitening procedure for increasing the likelihood of accepting the null hypothesis of no trend. To overcome this, we used the iterative method proposed by Wang and Swail (2001), which effectively addresses this issue. This procedure eliminates first-order serial correlation in the time series data using a multi-stage pre-whitening technique. Typically, the pre-whitening process reduces the sample size by one, as there is no prior value for the first observation. In ETM (Eastman and ClarkLabs, 2020), however, the Prais-Winsten transformation is used to estimate the value for the first date, allowing the entire dataset to be maintained (Kmenta, 2004; Prais and Winsten, 1954).

2.2.2. Robust trend analysis considering spatial cross-correlation

Building on the pre-whitened 42-year median NDVI time series, we applied the Theil-Sen (TS) estimator to this pre-whitened series to determine the slope magnitude and direction, followed by the Contextual Mann-Kendall (CMK) test, a modification of the traditional Mann-Kendall (MK) test, to assess statistical significance at an alpha level of 0.05. These analyses were conducted using the *Kendall* module in *TerrSet (2020) Geospatial Monitoring and Modeling Software* (Eastman and ClarkLabs, 2023).

The Theil-Sen (TS) slope estimator calculates the median slope from all possible pairwise comparisons of observation values. This non-parametric technique for estimating the magnitude of trends in time series data was introduced by Theil (1950) and later refined by Sen (1968). A widely used method is the MK test to assess the significance of the TS slope. Like the TS approach, the MK test evaluates the slopes between all possible pairs of data points (Mann, 1945). In the MK test, the data are ordered chronologically, with each data point serving as a reference for the subsequent data points in time (Kendall, 1975). We used the CMK test, an enhanced version of the traditional MK test, to assess the statistical significance of interannual trends (Neeti and Eastman, 2011). Unlike the original MK test, the CMK test sequentially incorporates contextual information from first-order eight neighbours to correct for spatial correlation while addressing the cross-correlation.

According to Neeti and Eastman (2011), the CMK method reduces the detection of spurious trends while increasing confidence in the presence of consistent ones. Furthermore, applying the TS slope offers the distinct advantage of filtering out inter-annual variability shorter than 0.29 times the length of the series. Together, these techniques are non-parametric and robust against the influence of outliers.

2.2.3. Adaptive False Discovery Rate control

We applied the adaptive False Discovery Rate (FDR) control using the Benjamini et al. (2006) procedure to the significance gridded data generated by the CMK test for interannual median NDVI trends. The analysis was conducted on pixel-level data across our study area, covering 570,652 within the masked region. For implementation, we used the *multtest* package in R (Pollard et al., 2023), leveraging a custom wrapper for raster data provided by the *terra* package (Hijmans, 2024; R Core Team, 2021).

The original FDR approach introduced by Benjamini and Hochberg (BH) provided a robust framework for controlling the false discovery rate. The FDR is defined as the expected proportion of falsely rejected null hypotheses among all the hypotheses that have been rejected as significant (Benjamini and Hochberg, 1995). However, it assumes a constant threshold across all hypotheses, which may not be optimal in every context, particularly in situations of positive spatial dependency or when there is heterogeneity among the hypotheses. Benjamini et al. (2006) proposed an adaptive linear step-up procedure that refines earlier approaches, including the adaptive method from Benjamini and Hochberg (2000). It introduces a more precise two-stage process that improves the estimation of the number of true null hypotheses and adjusts the significance threshold accordingly. This approach enhances the control of the FDR, particularly in contexts with positively dependent test statistics or a low proportion of true nulls.

3. Results & discussion

Fig. 2 highlights the significant interannual NDVI trends detected across the global terrestrial land surface where AVHRR NDVI data is available, identified over 42 years, from 1982 to 2023, using the True Significant Trends (TST) workflow. This AVHRR NDVI analysis reveals that approximately 38.16% of the global terrestrial land surface experienced statistically significant vegetation trends. Moreover, of the significant trends observed, 76.07% were increases in vegetation (greening) and 23.93% decreased (browning). When analysing areas with an NDVI value above 0.15, the greening trends account for 85.43%, with browning trends comprising 14.57%.

Fig. 3 illustrates the impact of increasingly sophisticated trend analysis methods, each designed to control variance and Type I errors, on detecting significant NDVI trends. The MK test applied to the raw, non-pre-whitened time series identified the highest percentage of significant trends (50.96%), reflecting its sensitivity to noise and temporal correlations. The CMK test applied to the raw data slightly reduced this percentage to 47.54%, indicating a modest improvement in trend detection by including spatial context. Pre-whitening further decreased the detected trends, with the MK and CMK tests showing 44.59% and 43.08%, respectively. The True Significant Trends (TST) method, which integrates pre-whitening, the CMK test, and the adaptive FDR correction, identified the lowest percentage of significant trends (38.16%). This reduction highlights the TST method's greater robustness, as it filters out less reliable trends and thus provides a more stringent and accurate assessment of significant vegetation trends.

Applying the MK test alone, without pre-whitening, can lead to overestimating significant trends (Hamed and Ramachandra Rao, 1998). This initial approach, which is commonly used, may result in a higher incidence of false positives because it fails to account for both temporal and spatial dependencies within the data. The modest reduction in detected trends when using the CMK test without pre-whitening suggests that incorporating spatial context helps to filter out some spurious trends by considering the influence of neighbouring data points (Neeti and Ronald Eastman, 2014). However, it does not fully address the issues related to serial correlation.

Integrating pre-whitening, spatial adjustments, and the adaptive FDR correction, the TST workflow identifies the most reliable trends. Pre-whitening ensures that trends are not artefacts of serial correlation, accounts for spatial correlation while addressing cross-correlation, and the adaptive FDR correction reduces the probability of false discoveries across multiple tests. In comparison, in the most closely related study to our research, Cortés et al. (2021) made a valuable contribution by addressing serial correlation and multiple testing using permutation methods for trend analysis. Still, their approach did not account for spatial and cross-correlation in trend testing.

Findings from the TST workflow (Fig. 2) provide robust quantitative evidence of widespread global greening, with a significant portion of Earth's terrestrial land surface showing measurable increases in vegetation cover over the past four decades. The predominance of greening trends, especially in regions with NDVI values above 0.15, suggests a general increase in vegetation productivity in many areas. This could be attributed to CO_2 fertilisation, climate change, and land use changes, as indicated by other investigations (Chen et al., 2024; Piao et al., 2019; Zhu et al., 2016). Although vegetation greening has been reported on all continents, it is particularly pronounced in Eurasia, including regions of Europe and China (Chen et al., 2019a). In contrast, although less frequent, browning trends indicate that certain areas, especially arid ecoregions, are experiencing vegetation degradation (Pan et al., 2018).

4. Conclusions

Applying a new proposed workflow methodology (True Significant Trends, TST) we reveal a striking global greening trend, with a significant portion of the Earth's terrestrial land surface showing increases in vegetation cover over the past four decades, particularly in Eurasia. Each stage of the TST workflow—incorporating pre-whitening, spatial and cross-correlation, and the adaptive FDR correction—progressively enhances the accuracy of detecting significant trends. The new TST methodology suggests that conventional methods used so far may overestimate areas with significant NDVI trends due to their limited ability to control for spurious findings. By effectively filtering out spurious results at each stage, the TST workflow provides a more reliable understanding of spatiotemporal trends. We recommend applying this approach across different scales and in any trend analysis involving spatiotemporal data to improve the precision and robustness of findings.

CRediT authorship contribution statement

Oliver Gutiérrez-Hernández: Writing – review & editing, Visualization, Validation, Supervision, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Luis V. García:** Writing – review & editing, Methodology, Investigation.

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Declaration of ethical statement

The authors declare that all ethical practices have been followed in relation to the development, writing, and publication of the article.

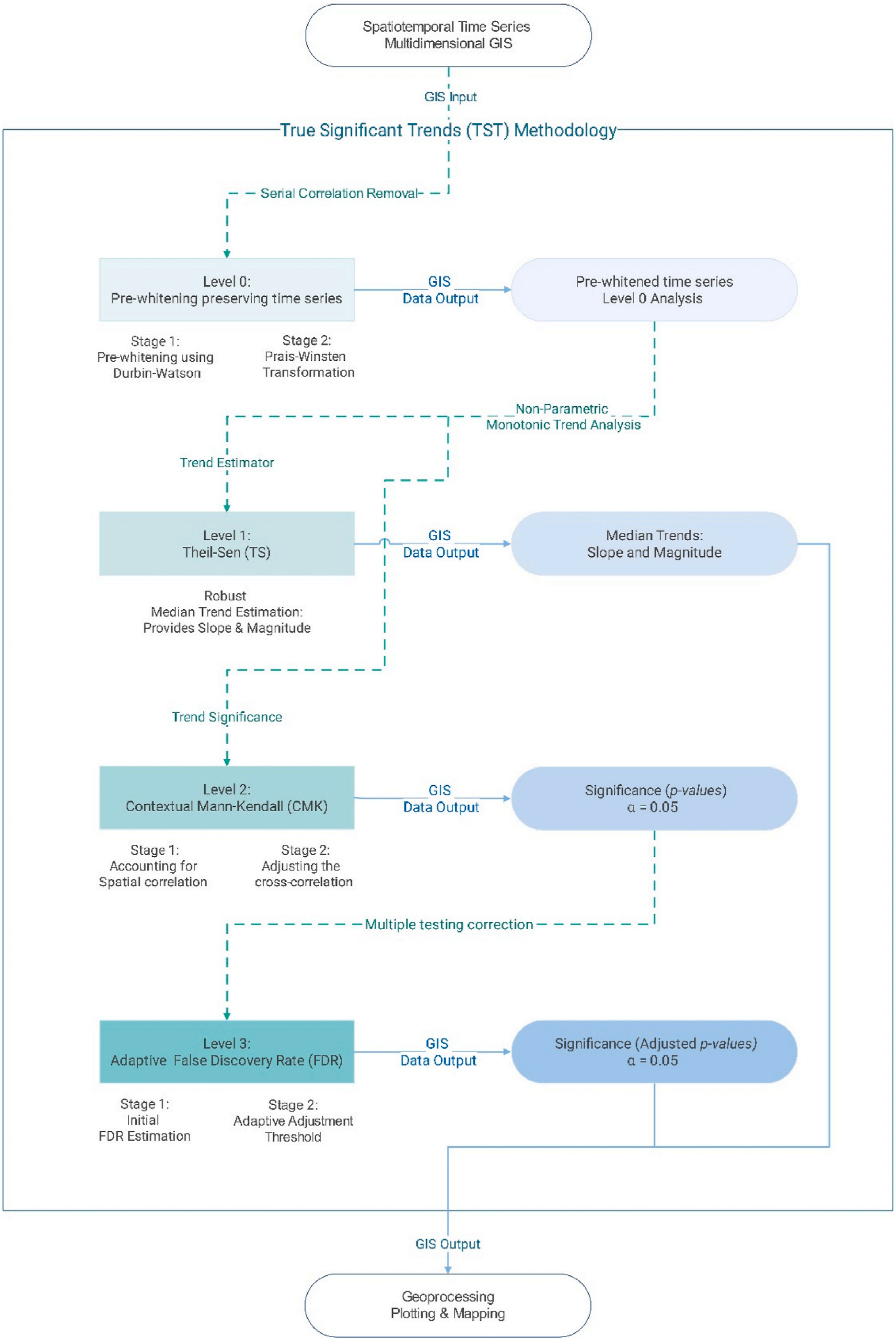

Fig. 1. The True Significant Trends (TST) Workflow.

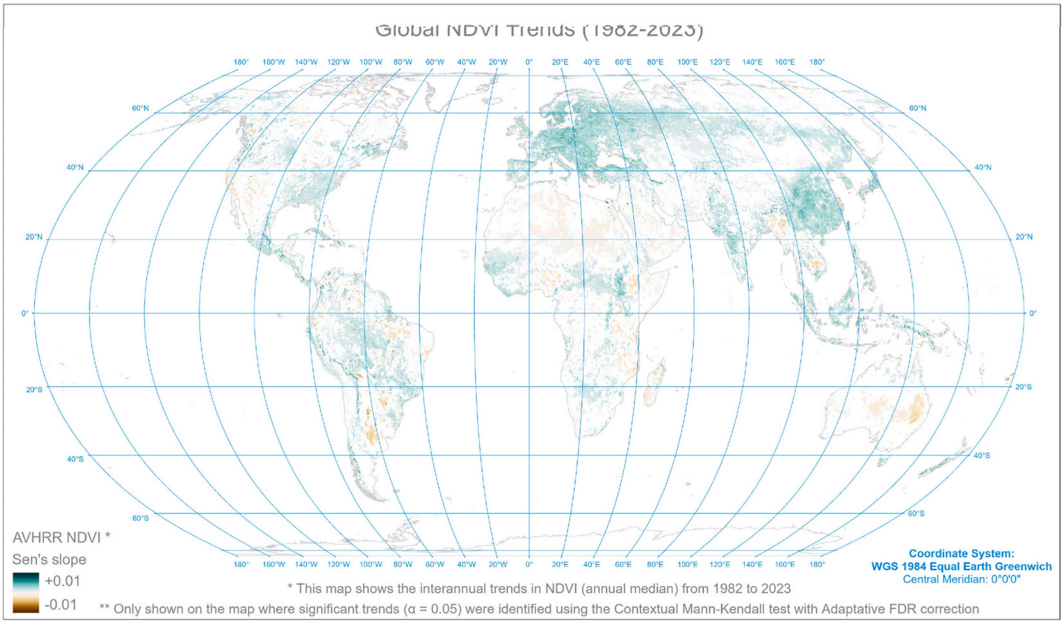

Fig. 2. Significant Global AVHRR NDVI Trends (1982–2023) After Applying True Significant Trends Analysis.
Note: This map exclusively highlights significant interannual NDVI trends derived from the median annual values of weekly AVHRR NDVI data spanning 1982 to 2023. Before trend detection using the CMK test, a pre-whitening process was applied to mitigate the effects of serial autocorrelation. Trends were identified at an alpha level of 0.05, with *p*-values adjusted using the 2006 adaptive False Discovery Rate (FDR) method to account for multiple testing. The magnitude and direction of these trends were quantified using the Theil-Sen (TS) estimator.

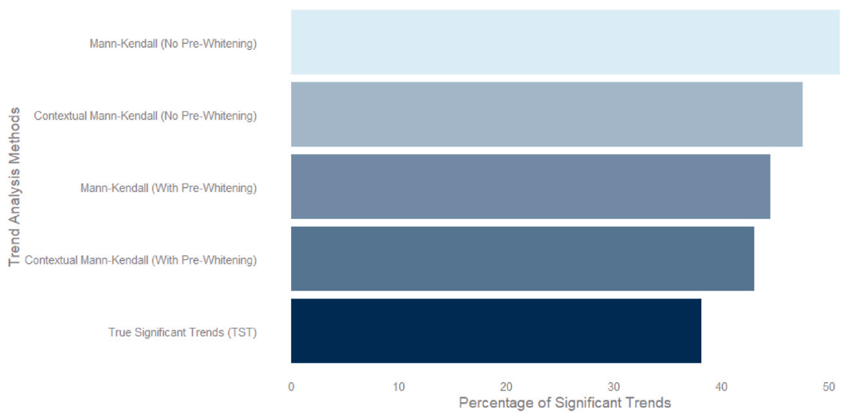

Fig. 3. Progressive Filtering of Identified Significant Global AVHRR NDVI Trends (1982–2023) by Analysis Methods.
Note: This graph depicts the percentage of significant NDVI trends identified through various trend analysis methods. The x-axis shows the percentage of significant trends, while the y-axis lists the methods used. "MK (No Pre-whitening)" refers to the Mann-Kendall test applied to the raw, non-pre-whitened time series. "CMK (No Pre-whitening)" denotes the CMK test applied to the raw data. "MK (With Pre-whitening)" indicates the Mann-Kendall test applied after pre-whitening. "CMK (With Pre-whitening)" involves the CMK test applied to the pre-whitened time series. Finally, "TST" stands for True Significant Trends, which integrates Pre-whitening, the CMK test, and the adaptive FDR correction to improve the robustness of trend detection. The gradient of blue shades reflects the robustness of each method, with darker shades indicating higher robustness.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.rsase.2024.101377.

Data availability

Data will be made available on request.

References

Anderson, O.D., 2014. Serial Correlation. Wiley StatsRef: Statistics Reference Online. Wiley. https://doi.org/10.1002/9781118445112.stat03529.
Benjamini, Y., Hochberg, Y., 1995. Controlling the false discovery rate: a practical and powerful approach to multiple testing. J. R. Stat. Soc. Ser. B Methodol. 57, 89–300. https://doi.org/10.1111/j.2517-6161.1995.tb02031.x.
Benjamini, Y., Hochberg, Y., 2000. On the adaptive control of the false discovery rate in multiple testing with independent statistics. J. Educ. Behav. Stat.
Benjamini, Y., Krieger, A.M., Yekutieli, D., 2006. Adaptive linear step-up procedures that control the false discovery rate. Biometrika 93, 491–507. https://doi.org/10.1093/biomet/93.3.491.
Chen, Chen, He, B., Yuan, W., Guo, L., Zhang, Y., 2019b. Increasing interannual variability of global vegetation greenness. Environ. Res. Lett. 14, 124005. https://doi.org/10.1088/1748-9326/ab4ffc.
Chen, Chi, Park, T., Wang, X., Piao, S., Xu, B., Chaturvedi, R.K., Fuchs, R., Brovkin, V., Ciais, P., Fensholt, R., Tømmervik, H., Bala, G., Zhu, Z., Nemani, R.R., Myneni, R.B., 2019. China and India lead in greening of the world through land-use management. Nat. Sustain. 2, 122–129. https://doi.org/10.1038/s41893-019-0220-7.
Chen, X., Chen, T., He, B., Liu, S., Zhou, S., Shi, T., 2024. The global greening continues despite increased drought stress since 2000. Glob Ecol Conserv 49, e02791. https://doi.org/10.1016/j.gecco.2023.e02791.
Cortés, J., Mahecha, M., Reichstein, M., Brenning, A., 2020. Accounting for multiple testing in the analysis of spatio-temporal environmental data. Environ. Ecol. Stat. 27, 293–318. https://doi.org/10.1007/s10651-020-00446-4.
Cortés, J., Mahecha, M.D., Reichstein, M., Myneni, R.B., Chen, C., Brenning, A., 2021. Where are global vegetation greening and browning trends significant? Geophys. Res. Lett. 48. https://doi.org/10.1029/2020GL091496.
Eastman, J., ClarkLabs, 2023. TerrSet: geospatial monitoring and modeling software, Version 19.08.
Eastman, J., ClarkLabs, 2021. Earth trends modeler in TerrSet 2020.
Eastman, J., ClarkLabs, 2020. TerrSet 2020: Geospatial Monitoring and Modeling Software. Manual. Clark University, Worcester MA (USA).
Forthofer, R.N., Lee, E.S., Hernandez, M., 2007. Descriptive methods. In: Biostatistics. Elsevier, pp. 21–69. https://doi.org/10.1016/B978-0-12-369492-8.50008-X.
García, L.V., 2003. Controlling the false discovery rate in ecological research. Trends Ecol. Evol. 18, 553–554. https://doi.org/10.1016/j.tree.2003.08.011.
Getis, A., 1995. Cliff, A.D. And ord, J.K. 1973: spatial autocorrelation. London: pion. Prog. Hum. Geogr. 19, 245–249. https://doi.org/10.1177/030913259501900205.
Guo, M., Li, J., He, H., Xu, J., Jin, Y., 2018. Detecting global vegetation changes using mann-kendal (MK) trend test for 1982–2015 time period. Chin. Geogr. Sci. 28, 907–919. https://doi.org/10.1007/s11769-018-1002-2.
Gutiérrez Hernández, O., García, L.V., 2024. Multiple testing in remote sensing: addressing the elephant in the room. SSRN. http://dx.doi.org/10.2139/ssrn.4891512.
Hamed, K.H., Ramachandra Rao, A., 1998. A modified Mann-Kendall trend test for autocorrelated data. J. Hydrol. (Amst.) 204, 182–196. https://doi.org/10.1016/S0022-1694(97)00125-X.
Hijmans, R., 2024. Terra: Spatial Data Analysis.
James, G., Witten, D., Hastie, T., Tibshirani, R., 2021. Multiple Testing, pp. 553–595. https://doi.org/10.1007/978-1-0716-1418-1_13.
Kendall, M., 1975. Rank Correlation Methods. Charles Griffin, London.
Kmenta, J., 2004. Elements of Econometrics. The University of Michigan Press.
Kulkarni, A., von Storch, H., 1995. Monte Carlo experiments on the effect of serial correlation on the mann-kendall test of trend. Meteorol. Z. 4, 82–85. https://doi.org/10.1127/metz/4/1992/82.
Los, S.O., 2013. Analysis of trends in fused AVHRR and MODIS NDVI data for 1982–2006: indication for a CO_2 fertilization effect in global vegetation. Global Biogeochem. Cycles 27, 318–330. https://doi.org/10.1002/gbc.20027.
Mann, H., 1945. Nonparametric tests against trend. Econometrica 13, 245–259. https://doi.org/10.2307/1907187.
Neeti, N., Eastman, J.R., 2011. A contextual mann-kendall approach for the assessment of trend significance in image time series. Trans. GIS 15, 599–611. https://doi.org/10.1111/j.1467-9671.2011.01280.x.
Neeti, N., Ronald Eastman, J., 2014. Novel approaches in Extended Principal Component Analysis to compare spatio-temporal patterns among multiple image time series. Remote Sens. Environ. 148, 84–96. https://doi.org/10.1016/j.rse.2014.03.015.
NOAA, 2024. AVHRR NDVI Data from the Vegetation Health Products.
Pan, N., Feng, X., Fu, B., Wang, S., Ji, F., Pan, S., 2018. Increasing global vegetation browning hidden in overall vegetation greening: insights from time-varying trends. Remote Sens. Environ. 214, 59–72. https://doi.org/10.1016/j.rse.2018.05.018.
Piao, S., Wang, X., Park, T., Chen, C., Lian, X., He, Y., Bjerke, J.W., Chen, A., Ciais, P., Tømmervik, H., Nemani, R.R., Myneni, R.B., 2019. Characteristics, drivers and feedbacks of global greening. Nat. Rev. Earth Environ. 1, 14–27. https://doi.org/10.1038/s43017-019-0001-x.
Pollard, K., Gilberrt, H., Ge, Y., Taylor, S., Dudoit, S., 2023. Multtest. Resampling-Based Multiple Hypothesis Testing, Version 2.58.
Prais, S., Winsten, C., 1954. Trend estimators and serial correlation. Cowles Commission Discussion Paper 383.
R Core Team, 2021. R: a language and environment for statistical computing. https://doi.org/10.1007/978-3-540-74686-7.

Roerink, G.J., Menenti, M., Verhoef, W., 2000. Reconstructing cloudfree NDVI composites using Fourier analysis of time series. Int. J. Rem. Sens. 21, 1911–1917. https://doi.org/10.1080/014311600209814.

Rogerson, P.A., 2024. Testing hypotheses when you have more than a few. Geogr. Anal. https://doi.org/10.1111/gean.12412.

Schut, A.G.T., Ivits, E., Conijn, J.G., Ten Brink, B., Fensholt, R., 2015. Trends in global vegetation activity and climatic drivers indicate a decoupled response to climate change. PLoS One 10, 1–21. https://doi.org/10.1371/journal.pone.0138013.

Sen, P., 1968. Estimates of the regression coefficient based on Kendall's tau. Journal ofthe American Statistical Association 63, 1379–1389. https://doi.org/10.1080/01621459.1968.10480934.

Theil, H., 1950. A rank-invariant method of linear and polynomial regression analysis I, II and III. In: Proceedings of the Section of Sciences, Koninklijke Academie Van Wetenschappen Te, pp. 386–392. Amsterdam.

von Storch, H., 1999. Misuses of statistical analysis in climate research. In: Analysis of Climate Variability. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 11–26. https://doi.org/10.1007/978-3-662-03744-7_2.

Wang, X.L., Swail, V.R., 2001. Changes of extreme wave heights in northern hemisphere oceans and related atmospheric circulation regimes. J. Clim. 14, 2204–2221. https://doi.org/10.1175/1520-0442(2001)014<2204:COEWHI>2.0.CO;2.

Xiao, J., Moody, A., 2005. Geographical distribution of global greening trends and their climatic correlates: 1982–1998. Int. J. Rem. Sens. 26, 2371–2390. https://doi.org/10.1080/01431160500033682.

Yue, S., Wang, C.Y., 2002. Applicability of prewhitening to eliminate the influence of serial correlation on the Mann-Kendall test. Water Resour. Res. 38. https://doi.org/10.1029/2001WR000861.

Zhao, L., Dai, A., Dong, B., 2018. Changes in global vegetation activity and its driving factors during 1982–2013. Agric. For. Meteorol. 249, 198–209. https://doi.org/10.1016/j.agrformet.2017.11.013.

Zhu, Z., Piao, S., Myneni, R.B., Huang, M., Zeng, Z., Canadell, J.G., Ciais, P., Sitch, S., Friedlingstein, P., Arneth, A., Cao, C., Cheng, L., Kato, E., Koven, C., Li, Y., Lian, X., Liu, Y., Liu, R., Mao, J., Pan, Y., Peng, S., Peñuelas, J., Poulter, B., Pugh, T.A.M., Stocker, B.D., Viovy, N., Wang, X., Wang, Y., Xiao, Z., Yang, H., Zaehle, S., Zeng, N., 2016. Greening of the Earth and its drivers. Nat. Clim. Change 6, 791–795. https://doi.org/10.1038/nclimate3004.