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Dataset Development on Vegetation Resilience of Urban Green Spaces in Shanghai (2001–2022)

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Abstract: Vegetation resilience is a key factor in determining the ability of vegetation to adapt to climate change. Although some studies have comprehensively assessed global vegetation, research on the local scale remains limited. Furthermore, the assessment results from different methods exhibit significant uncertainty. In this study, we developed a vegetation resilience dataset for urban green spaces in Shanghai based on the theory of critical slowing down. Using MODIS NDVI data—with a 250-m resolution—from 2001 to 2022, we processed time series data through seasonal and trend decomposition methods based on a locally weighted regression, along with a moving average and harmonic analysis. Vegetation resilience was assessed using variance or first-order autocorrelation coefficients. The dataset included 3 resilience assessment outcomes, which demonstrated a high level of consistency, indicating the dataset's reliability and stability. This dataset provides the spatial distribution of green spaces in Shanghai and 3 distinct vegetation resilience assessment metrics spanning the period from 2001 to 2022. The green space distribution and vegetation resilience assessment data are archived in .tif format with a spatial resolution of 250 m, while the study area boundary is provided as vector data in .shp format. The dataset consists of 28 data files with data size of 812 KB (Compressed into one file with 726 KB).

Keywords: resilience; critical slowing down theory; green space; climate adaptability; vegetation resilience

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Dataset Availability Statement:

The dataset supporting this paper was published and is accessible through the *Digital Journal of Global Change Data Repository* at: https://doi.org/10.3974/geodb.2024.12.04.V1.

1 Introduction

The increase in extreme climate changes and anthropogenic disturbances have caused global

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vegetation degradation and loss. Despite the enhancement and implementation of numerous projects aimed at vegetation restoration and rehabilitation, fundamentally reversing the ongoing trend of vegetation degradation remains difficult[1]. This issue is especially prominent in urban ecosystems, where landscape plants require significant manpower and resources to maintain them. Disturbances, such as extreme climate events, have already had a noticeable impact on green spaces in urban landscapes[2]. Vegetation resilience is a critical indicator that quantifies the capacity of vegetation to recover to equilibrium states following disturbances. Assessing the resilience of urban green spaces provides a fundamental basis for understanding how these areas respond to external perturbations. In recent years, the theory of critical slowing down has captured increasing attention among assessors of vegetation resilience. This theory evaluates vegetation resilience by examining fluctuations in functional indicators and the slowed recovery rate following a disturbance[3]. Vegetation resilience estimated using the critical slowing down theory is typically derived from a long series of continuous spatial data. This approach is widely applicable. It effectively addresses the cumulative effects of disturbances and provides quantitative assessment results[4]. For example, methods based on this theory often use the variance or first-order autocorrelation coefficient (Auto-Regressive (model) of order 1, AR(1)) to measure system resilience[3]. However, vegetation resilience data derived from this theory are considerably uncertain, primarily due to variations in the methods used to eliminate linear and seasonal trends in time series data across different studies. Given that both variance and AR(1) yield consistent results in resilience assessments based on the theory of critical slowing down, the aim of this study was to quantify the uncertainty in the assessment results by examining the deviation between these two indicators[5]. In addition, due to the complexity of detrending time series data, we selected a simplified detrending algorithm with higher computational efficiency[6]. The reliability of this algorithm was assessed by comparing its results with those obtained from conventional algorithms. In summary, to comprehensively assess and compare the performance of different methods, we estimated the vegetation resilience dataset for urban green spaces in Shanghai using MODIS NDVI data at 250-m resolution from 2001 to 2022, employing multiple methods based on the theory of critical slowing down.

2 Metadata of the Dataset

The metadata of the Vegetation resilience dataset for urban green spaces in Shanghai (2001–2022, V1.0)[7] is summarized in Table 1. It includes the dataset full name, short name, authors, year of the dataset, spatial resolution, data format, data size, data files, data publisher, and data sharing policy, etc.

3 Methods

3.1 Data Sources

This study utilized the Normalized Difference Vegetation Index (NDVI) data from 2001 to 2022 to assess vegetation resilience. The NDVI data were obtained from the MOD13Q1 Version 6 product[1] from NASA's Terra satellite, captured by the MODIS sensor. The dataset consists of 16-day composites with a spatial resolution of 250 m. Reliable data were filtered through the "pixel reliability" and "NDVI quality" bands of the MOD13Q1 data product,

[1] NASA. https://www.earthdata.nasa.gov/search.

Table 1 Metadata summary of the Vegetation resilience dataset for urban green spaces in Shanghai (2001–2022, V1.0)

Items	Description
Dataset full name	Vegetation resilience dataset for urban green spaces in Shanghai (2001–2022, V1.0)
Dataset short name	SH_Green_Resilience_1.0
Authors	Sun, D. Q., National Forestry and Grassland Administration, 15501298321@163.com Sun, W. R., National Forestry and Grassland Administration, 15501023599@163.com Cheng, X. Y., Shanghai Gardening-Landscaping Construction Co., Ltd., 1160421734@qq.com Wang, J., Shanghai Gardening-Landscaping Construction Co., Ltd., wjbear@126.com Cheng, F. Y., Zhejiang A&F University, chengfangyan@zafu.edu.cn
Geographical region	Shanghai, China
Year	2001–2022
Spatial resolution	250 m
Data format	.shp and.tif
Data size	726 KB (after compression)
Data files	Boundary of the study area; Spatial distribution of green space coverage; Vegetation resilience based on STL_AR1, V2_AR1, V2_VAR
Foundations	Science and Technology Commission of Shanghai Municipality (22dz1209403); Shanghai Construction Group Co., Ltd. (24JCSF-24); Zhejiang A&F University (2024LFR069)
Data publisher	Global Change Research Data Publishing & Repository, http://www.geodoi.ac.cn
Address	No. 11A, Datun Road, Chaoyang District, Beijing 100101, China
Data sharing policy	(1) *Data* are openly available and can be free downloaded via the Internet; (2) End users are encouraged to use *Data* subject to citation; (3) Users, who are by definition also value-added service providers, are welcome to redistribute *Data* subject to written permission from the GCdataPR Editorial Office and the issuance of a *Data* redistribution license; and (4) If *Data* are used to compile new datasets, the “ten percent principal” should be followed such that *Data* records utilized should not surpass 10% of the new dataset contents, while sources should be clearly noted in suitable places in the new dataset[8]
Communication and searchable system	DOI, CSTR, Crossref, DCI, CSCD, CNKI, SciEngine, WDS, GEOSS, PubScholar, CKRSC

excluding areas with poor vegetation growth conditions (i.e., regions with NDVI values consistently below 0.1). Land use data were sourced from the Dynamic World global land environment dataset[2] at a 10-m resolution. The study area encompasses Shanghai municipality, with administrative boundaries derived from the 2024 national administrative boundary map of China provided by Amap.

3.2 Algorithmic Principles

3.2.1 Extraction of Urban Green Spaces

To extract urban green spaces, a reclassification analysis of the Dynamic World dataset was performed. First, data from the past 10 years (2015–2024) were filtered, and the most frequently occurring land cover class for each image element was identified as its primary land cover type. Next, land cover types dominated by green space were extracted and included trees (label=1), shrub and scrub (label=5), and grass (label=2), while all other land cover types were reclassified as “other”. Finally, the map of land cover types was reclassified to a resolution of 250 m.

3.2.2 Estimation of Vegetation Resilience

Three algorithms were employed to estimate vegetation resilience, including two methods for calculating the AR(1) index and one for calculating the VAR index. The first method utilized a simplified STL (seasonal-trend decomposition using Loess) approach to process time series data[6]. The detailed steps follow: (1) calculate the monthly mean and multi-year

[2] Google, WRI. https://www.dynamicworld.app/explore/.

monthly mean for the NDVI time series for each pixel; (2) subtract the multi-year monthly mean from the monthly mean to remove the seasonal trend; (3) perform a moving average on the seasonally detrended data and subtract this moving average to remove the long-term trend; (4) compute the AR(1) index using a sliding window (referred to as STL_AR1).

The second method combined the moving average and harmonic analysis to process the NDVI time series[5]. (1) compute the mean NDVI using a rolling window to capture the long-term trend; (2) subtract the rolling average from the original NDVI data to obtain a detrended data series; (3) apply a third-order harmonic analysis to the detrended data to model the seasonal pattern; (4) subtract the fitted seasonal pattern from the detrended data to obtain the residual series; (5) calculate AR(1) and variance (referred to as V2_AR1 and V2_VAR) using a five-year sliding window (with a one-year step).

To ensure the reliability of the results, only data with a V2_AR1 to V2_VAR ratio between 0.5 and 2.0 were selected[5]. The consistency of trends between STL_AR1 and V2_AR1 was also assessed to validate the reliability of the simplified resilience algorithm. Furthermore, since STL_AR1 employs an autoregressive model, negative values in this dataset represent areas where this assessment method is unsuitable, and these negative-value regions (accounting for 14% of the total statistical area) were excluded from our analysis. The V2_AR1 data, which utilizes an autocorrelation approach, indicates stronger ecosystem resilience when negative values are larger in magnitude, reflecting faster recovery rates of vegetation to equilibrium states. Similarly, the V2_VAR method based on variance analysis yields comparable results to V2_AR1, with larger negative values signifying greater vegetation resilience.

3.3 Technical Workflow

Based on the above methodology, NDVI data, land use data, and administrative boundary data from the Amap were first collected for preliminary data processing. Next, green space types from the land use data were extracted, reclassified, and resampled to a resolution of 250 m. These were combined with administrative boundary data to define the extent of green spaces in Shanghai. Vegetation resilience was estimated using two methods: simplified STL and a combination of the moving average and harmonic analysis, each processing and analyzing NDVI time series data independently. Finally, the results from the different methods were integrated and clipped to generate the final vegetation resilience dataset for green spaces in Shanghai (Figure 1).

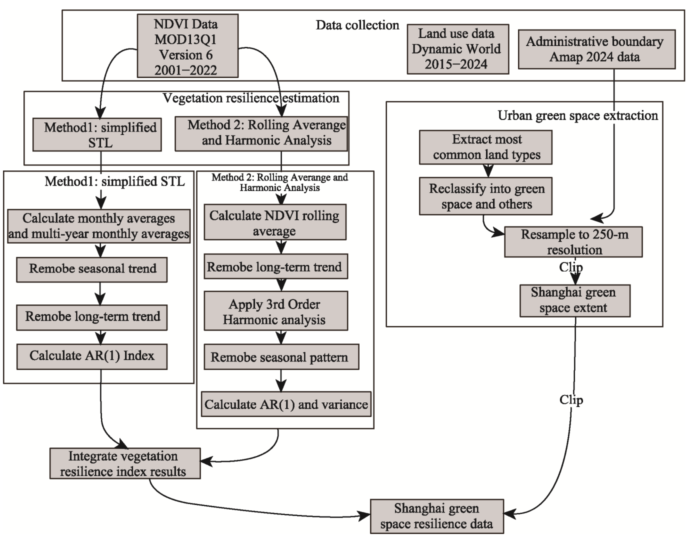

Figure 1 Flowchart of the dataset processing

4 Data Results and Validation

4.1 Dataset Composition

This dataset comprises 5 data layers: one vector data layer delineating the study area boundary (.shp) and 4 raster data layers with a spatial resolution of 250 m (GREEN_R, STL_AR1, V2_AR1, and V2_VAR). The raster data layers are defined as follows: GREEN_R represents the proportion of green space within each 250-m grid cell, derived from Dynamic World data spanning 2015–2024; STL_AR1 represents vegetation resilience data quantified using the AR(1) index, derived from a simplified Seasonal and Trend decomposition using Loess (STL) method; V2_AR1 represents vegetation resilience data quantified using the AR(1) index, obtained through rolling average and harmonic analysis processing; V2_VAR represents vegetation resilience data quantified using the variance index, also obtained through rolling average and harmonic analysis processing.

4.2 Data Results

Green spaces in Shanghai are mainly distributed in the suburbs and peripheral areas, the proportion of green space in the city center is relatively low. This distribution pattern reflects the typical green space structure of a large city like Shanghai. The overall trends in vegetation resilience, estimated using different methods, are consistent (Figures 2). Spatially, green spaces in the suburbs and urban periphery generally show higher vegetation resilience (e.g., such areas as the outskirts of Qingpu District and Hengsha Island), while vegetation resilience in the city center is relatively low. However, green spaces in coastal areas, such as Pudong New Area, Jinshan District, and Fengxian District, also show relatively low resilience, which may be linked to environmental stressors (e.g., strong winds and salinity changes in coastal regions)[9]. The study results for STL_AR1 were significantly higher than those for V2_AR1 and V2_VAR, possibly because of the simplified algorithm used in STL_AR1 for data processing and analysis, which could overlook minor differences in values across regions. In addition, no clear relationship was observed between the magnitude of vegetation resilience per unit area and the proportion of green space (Figure 3), with no discernible pattern in vegetation resilience distribution across varying proportions of green space. Different vegetation types may have varying levels of adaptability and recovery capacity, which could affect their overall resilience performance[5].

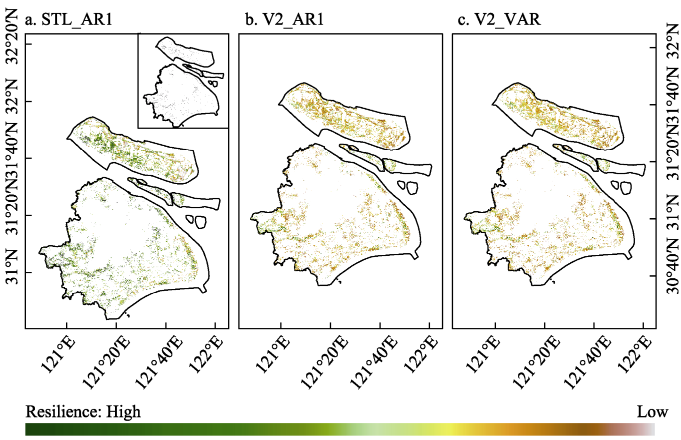

Figure 2 Vegetation resilience distribution maps of Shanghai urban green space based on different methods

(Note: The black area in the inset of Figure 2a displays areas with negative values, indicating regions where this modelling approach is not applicable)

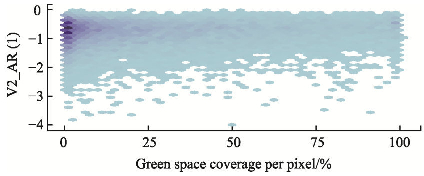

Figure 3 Relationship between vegetation resilience and proportional green space coverage

4.3 Data Validation

The reliability of the model results was evaluated by comparing vegetation resilience estimates derived from different methods. Comparing the AR(1) index results calculated by 2 methods revealed that the overall estimates were consistent (Figure 4a). The linear relationship between them (p<0.000,1) was significant, though the correlation was weak (R^2=0.09). This finding suggests that the simplified algorithm (STL_AR1) can be a useful tool for assessing vegetation resilience, providing a viable method for rapid evaluations. However, the simplification of time series data processing in this method, while enhancing computational efficiency, may lead to the oversight of subtle variations in the time series. As a result, its outcomes could tend to be more concentrated and may not fully capture the nuanced differences in vegetation resilience across different regions. In contrast, more complex methods (e.g., V2_AR1) are capable of processing time series data with greater precision, capturing more detailed changes, and offering a more comprehensive and potentially more accurate assessment of vegetation resilience. In addition, the results of the 2 resilience indices (AR(1) and variance indices) estimated using the same moving average and harmonic analysis were highly consistent (Figure 4b). Many sample points were concentrated near the 1:1 reference baseline, indicating that this method is stable and consistent.

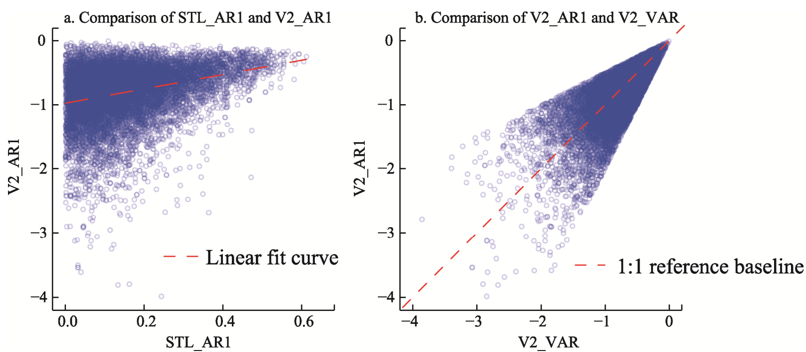

Figure 4 Uncertainty analysis of vegetation resilience estimates based on different algorithms

5 Discussion and Conclusion

In this study, we developed a vegetation resilience dataset for urban green spaces in Shanghai using MODIS NDVI data from 2001 to 2022; the basis was the theory of critical slowing down and the use of multiple methods. The assessment results across various indicators in this dataset had a high degree of consistency and aligned with theoretical expectations, demonstrating both stability and reliability.

Throughout our analysis, we identified 2 notable phenomena in specific regions: negative STL_AR1 coefficients and inconsistencies between AR(1) and variance trends. These anomalies were predominantly observed in tropical rainforests and high-latitude northern regions, potentially attributable to multiple factors. First, data quality limitations, including remote sensing signal saturation, noise interference, and resolution constraints, particularly in high-biomass areas and regions with frequent cloud cover. Second, the inherent complexity of ecosystems, characterized by non-linear dynamics or unstable system states. Third, external anthropogenic disturbances and extreme climate events that modify ecosystem responses. Additionally, the fundamental assumptions of AR(1) models—

predicated on linear stationarity—may not hold in ecosystems undergoing rapid transformation or ecological transition phases. These observations further highlight the sensitivity of current methodologies to short time-series data and spatial resolution limitations. Given that negative values lack clear ecological interpretation, and inconsistent AR(1)-variance trends suggest potentially unreliable estimates, we designated these regions as model-inapplicable and excluded them from subsequent analyses. Future research directions should focus on developing non-linear or non-stationary time-series approaches better suited to complex ecological systems, while integrating multi-source data to enhance assessment reliability.

Based on the constructed dataset, we found that green spaces in Shanghai are primarily located in the suburbs and peripheral areas, with lower proportion of green space in the city center. This pattern reflects the typical spatial distribution of green spaces in large cities. Suburban and peripheral green spaces generally have high vegetation resilience, while the resilience of green spaces in the city center and certain coastal areas is relatively low. No significant correlation between the proportion of green space and resilience was observed, indicating that vegetation resilience may be influenced more by vegetation type and environmental conditions than simply the extent of coverage. This study provides an important scientific basis for the management and ecological planning of urban green spaces in Shanghai. It offers a new perspective for the quantitative assessment of vegetation resilience in urban green spaces, which is significant for enhancing the sustainability and climate adaptability of urban ecosystems.

Author Contributions

Sun, D. Q. and Wang, J. designed the overall development of the dataset. Sun, W. R. and Cheng, X. Y. collected and processed the data. Sun, D. Q., Sun, W. R. and Cheng, F. Y. designed the models and algorithms. Sun, D. Q. and Cheng, F. Y. validated the data. All authors contributed to write the data paper.

Conflicts of Interest

The authors declare no conflicts of interest.

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