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Monitoring Forest Disturbance Using Sentinel Data: A Case Study of Non-seasonal Time Series Approach

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ABSTRACT Monitoring deforestation and reforestation dynamics is critical for forest conservation, particularly in biodiversity-rich regions, such as Khyber Pakhtunkhwa (KPK), Pakistan. The current study aimed to introduce a novel application of the PVts-β method for non-seasonal time series analysis using Sentinel-1 radar imagery. Moreover, the study also addressed limitations of traditional approaches, such as reliance on optical data and sensitivity to cloud cover. By quantifying deforestation (7,985 hectares) and reforestation (4,098 hectares) between 2018 and 2022, the study highlighted significant land cover changes. As compared to the existing methods, such as Breaks for Additive Season and Trend (BFAST) and Continuous Change Detection and Classification (CCDC), PVts-β offers advantages in computational efficiency and disturbance detection accuracy, as validated through performance metrics and sensitivity analysis. The results provide actionable insights for conservation strategies and policy-making, emphasizing the adaptability of the methodology to various regions and forest types. The current study advances remote sensing applications in forest monitoring, offering a robust framework to address global environmental challenges.

INDEX TERMS Breaks for Additive Season and Trend (BFAST), forest disturbance, non-seasonal approach, radar imagery, Sentinel-1

I. INTRODUCTION

Deforestation has become a highly relevant issue, especially with increasing utilization of remote sensing to observe vegetation dynamics [1]. Remote sensing technology provides significant benefits over traditional site-based methods, for instance, it provides not only local as well as global information [2]. Such flexibility is quite helpful in thorough tracking of vegetation change including forest fragmentation. Furthermore, it is also helpful for sound management of environment. Additionally, the cost-effectiveness of remote sensing technology in conjunction with vast archives of satellite images makes this technology even more applicable in other branches of ecology and management contexts.

Remote sensing focuses on repeatability, objectivity, and consistency, which are the three principles very important for monitoring and sustainable management of natural resources [3]–[5]. Such principles make data more reliable and reproducible, giving confidence to the derived insights

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and assisting in the informed decision-making [6]. Researchers utilized remote sensing data to test multiple methods in order to track vegetation changes, applying approaches ranging from AI-driven algorithms to time series analyses that use vegetation indices and fractional cover measures [7]. Human activities, especially those that convert forests for other land uses and cause sustained canopy, cover reduction below the 10% threshold [8], have had profound impacts on global biodiversity and land productivity. Forest change is a major driver of comprehensive acreage cover dynamics [9]. Forestry is decisive to life system service area, such as graphite seizure, microclimate regulation, evaporation-consideration cycle control, and variety of life forms conservation [10], [11]. This is evident in tropical regions, where rapid deforestation due to land-use shifts is a growing concern. Tropical deforestation alone contributes 10-15% of human caused hot house fume secretions [12]. Meanwhile, during 1980s tropical forest loss posed a serious threat to variety of life, natural community services, and the sustainable availability of adequate proceeding a global scale [13]–[15]. The process of acquiring data about earth's surface has been pivotal in environmental research. Particularly the unveiling of Landsat-1 in 1972 [16]. Unrestricted access to Landsat archives greatly enhances effective tenders, systematic research, and breakthroughs by analyzing hefty volumes of illustrations [17]. For instance, Landsat data from 2000-2012 enabled global monitoring of forest changes, revealing a net deforestation of 1.5 million km² [18]. A range of effective methods have been developed to harness the chronological resolution of Landsat archives, allowing for precise mapping of tropical deforestation on both local and comprehensive scales [19] –[22]. However, according to [23] many time-series-based detection algorithms, such as Breaks for Additive Season and Trend (BFAST) [23] and Continuous Change Detection and Classification (CCDC) [24], face significant challenges (i) it involves an overly complex set of calibration parameters, hindering efficient deforestation monitoring, in addition (ii) these rely on cyclic variations in the recorded successive data points. [25] Proposed an alternative recognition method called PVts-β, which features a single tuning limit and does not rely on the periodic components of the sequentially collected data points..

Nonetheless, optical-based monitoring systems face difficulties due to cloud cover in tropical areas [26] . For forest monitoring, Synthetic Aperture Radar (SAR) data provides an alternative by piercing clouds in addition to optical data [27]. Multisensory data fusion technologies that incorporate both optical sensors and SAR have demonstrated the ability to enhance the precision of forest mapping, although speckle noise can be an issue with the SAR data. Additionally, the intensity-hue saturation (IHS) method, wavelet merging, Principal Component Analysis (PCA), and other techniques have advanced to combine SAR with visual data [28]. However, agreement on the most effective way to combine optical and SAR data in order to map deforestation, particularly in tropical forests, is still difficult [29]. Vegetation modification exposure methods in time series analysis may be broadly classified as seasonal or non-seasonal. Seasonal approaches use the cyclical constituent of time series data to simulate and detect variations in vegetation patterns wished-for (e.g., those proposed by [30]. Altogether, these patterns are exceedingly dependent upon the periodic constituent of the successive collected data points. Non-seasonal techniques, on the other hand, do not rely on seasonal trends, allowing for greater flexibility in implementation. These methods are typically implemented in programming languages, such as Python and R. Furthermore, these methods offer promising potential to detect vegetation changes. Although, their integration with platforms, such as Google Earth Engine (GEE) is still limited.

Recent advancements in remote sensing, such as AI-driven methods and multisensory data fusion, have demonstrated potential to enhance forest monitoring capabilities. However, their integration into operational workflows is still limited due to high computational demands and reliance on complex models. By contrast, the PVts-β method provides a simplified yet effective approach, balancing accuracy and efficiency, which is particularly suitable for regions with limited resources.

A. OBJECTIVES

The current study presented threefold objectives:

(1) to evaluate the effectiveness of the PVts-β method in order to detect deforestation and reforestation dynamics in KPK

(2) to assess the adaptability of the methodology to diverse forest types and regions.

By addressing these goals, the study aimed to contribute to the growing body of research on forest conservation while providing actionable insights for policymakers and stakeholders.

The remaining study is structured as follows: Section 2 discusses the study area, section 3 provides details on methodology including the PVts-β framework and data processing pipeline, section 4 presents the results including performance comparisons and sensitivity analyses, and section 5 concludes the research with a summary of contributions and directions for future research.

II. STUDY AREA

The geographic coordinates of the region where research is used is between about 69.056°E and 74.576°E longitude and 32.034°N and 35.859°N latitude within the Khyber Pakhtunkhwa (KPK, province of Pakistan. KPK is significant in its diversity, showing a mixture of green valley landscapes to steep mountain terrain. The region prides itself to have valuable biodiversity as well as enormous carbon sequestration. However, this province is now increasingly exposed to widespread deforestation. It is driven mainly by the activities in the logging, agricultural industries, and mining sectors. This kind of rapid forest cover loss raises serious threats to vital ecosystem services, which intensifies environmental challenges both for the local populations and the greater Pakistani state. The rate of deforestation has been increasing during the past few years. Therefore, monitoring and intervention are urgently required to maintain ecological balance and sustainability in this very sensitive region on earth.

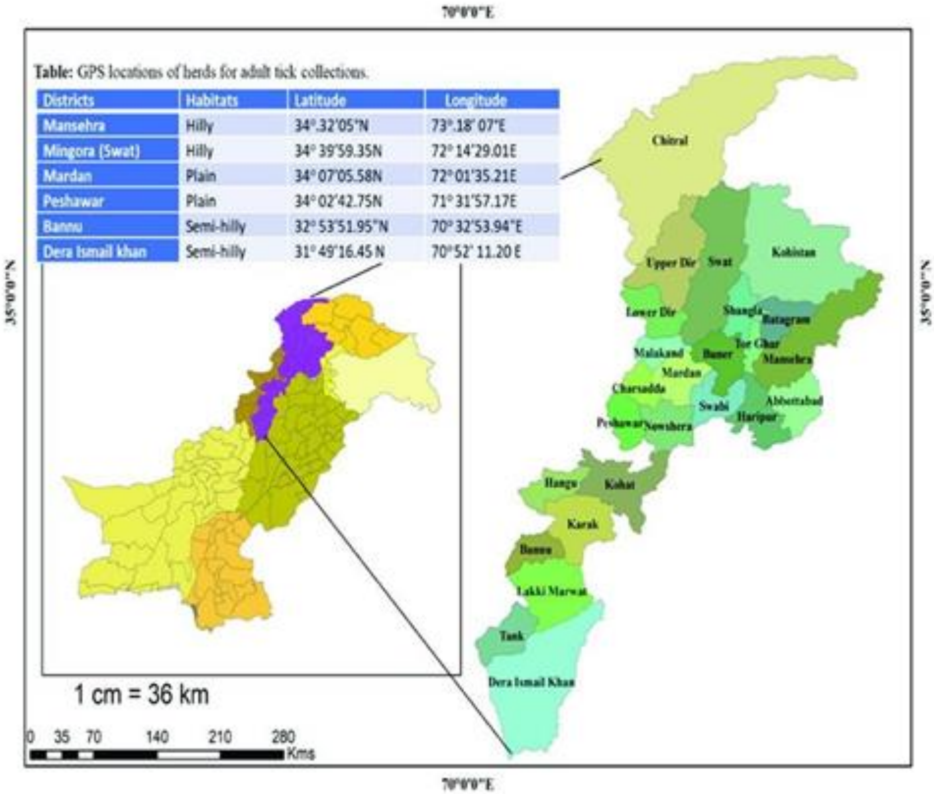

FIGURE 1. This map illustrates the geographical extent of the Khyber Pakhtunkhwa (KPK) region, Pakistan.

A. DATA DESCRIPTION

The current study utilized data concerning the dynamics of vegetation and disturbances in forests, focusing more on deforestation viewed using remote sensing methods. This is because it can monitor wide areas at different sizes and is less expensive since satellite image databases are freely accessible. Sentinel-1 is a C-band synthetic aperture radar with an extensive range of uses, as well as deforestation assessment. This study utilized VH polarization obtained in Interferometric Wide Sweep mode using Ground Range Detected (GRD) format. GEE preprocessed calibration and terrain correction. The VH radar's backscattering coefficient (σ0) is measured in decibels. To convert digital number (DN) values to dB, the following formula is used:

$$dB_{i,j} = 10 * \log_{10}(\mathrm{DN}_{i,j}{}^{2} + A^{2})$$

In this formula, either i and j denote the location (row and column), while AAA signifies the tuning factor obtained from the sigma naught standards in the LUT. To detect deforestation using the PVts-β procedure, it is essential to employ a combination of Earth Engine and Python libraries. Specifically, the following libraries would be used:

- **Geemap**: This library offers an interactive interface. This makes

Google Earth Engine's data and functions available within the Python environment, thus making it easier to carry out geospatial analysis tasks.

- **Forestools**: It is a powerful collection of tools and functionalities created to enhance the effectiveness of forest change detection and analysis.

Python libraries would also be added for data visualization to present the results.

B. COLLECTION AND PREPARATION OF SENTINEL-1 DATA

The data needs to be divided into reference and target years during the successive data collection points analysis for the detection of changes. The arithmetic mean and dispersion are computed from the reference period for the years 2016-2017. Whereas, in the target year, specific attention is given to areas with instances of deforestation. The current study specifically focused on the identification of deforestation events for the time period (2018-2021).

C. INTRODUCTION TO THE PVTS-B APPROACH

In time series, logging activity detection methods may be broadly categorized as either cyclic or non-cyclic. Therefore, the PVts-β method falls into the category of non-seasonal detection. This is because it is independent of the seasonal aspect of time series data that its effectiveness depends on seasonal approaches. This makes the quality better and also improves the mapping ability of forest disturbances by deforestation through the PVts-β methodology. To use the PVts-β technique, definite parameters need to be assembled. For any particular pixel, an arithmetic mean and dispersion were calculated after determining how and when an event would happen in deforestation in relation to the time series acquired. A detection of environmental disturbances is given based on some thresholds, predetermined for that effect as calculated earlier. The advantages of this approach have been well-illustrated by various authors, especially when it comes to its utility in remote sensing and monitoring of the environment. Further insights into detection methods may be found in works of [14], [15].

- The specific time period when a deforestation event is going to be identified is the temporal position n of the pixel under consideration, $P_{i,j}$:

$$P_{i,j} = s_1 + s_2 + s_3 + \cdots + s_{n-1} + s_n$$

- The mean ($\mu_{i,j}$) and its standard deviation ($\sigma_{i,j}$) for the same pixel $s_{i,j}$ (from s_1 to s_{n-1}). If the value for position (n) is less than the established limit ($L_{i,j\ n-1}$)

$$L_{i,j\ n-1} = \mu_{i,j} - \beta * \sigma_{i,j}$$

Then, a commotion is perceived in the forests (for instance, deforestation), where, $L_{i,j\ n-1}$ is the lower limit, β is the verge scale, and i, j is the row and column spot of a given pixel.

This parameter was calibrated with NDVI and EVI in the work of [16] for NDFI indices in the work as shown in Figure 2. Therefore, the optimal β values can be visualized for different indices. The PVts-β technique relies heavily on calibrating the threshold magnitude (β). β values were calibrated based on vegetation indices to provide reference values for optimal performance. It is important to note that β values can be modified based on study requirements or regional variables for accurate cartography.

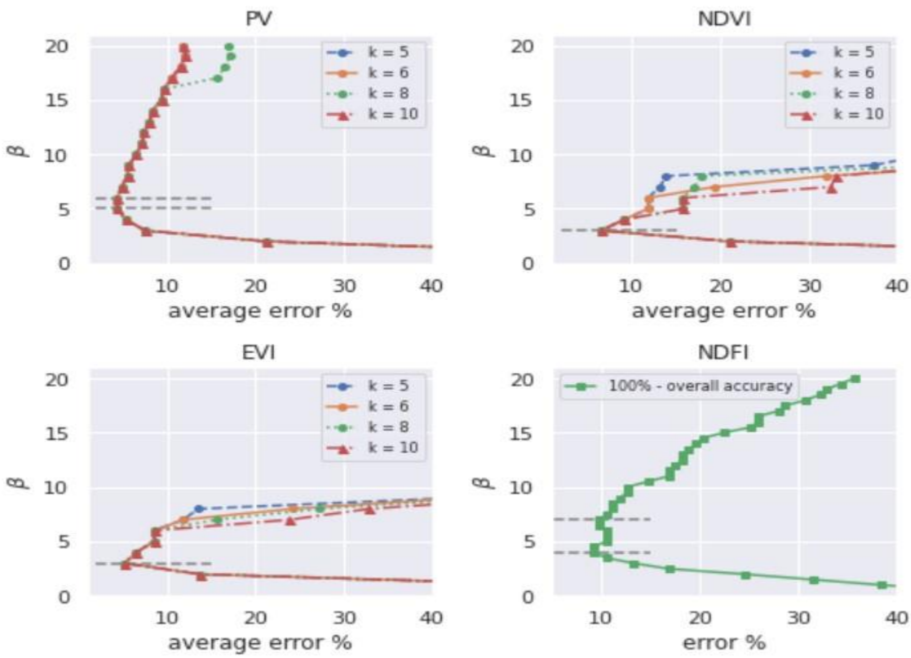

FIGURE 2. Referenced beta values for forest disturbance detection

D. DETECTING CHANGES TO MAP DEFORESTATION

In the current research, radar images from Sentinel-1 were used to detect deforestation. Sentinel-1, a C-band synthetic aperture radar, provides useful data for the assessment of deforestation. This is achieved by using Ground Range Detected (GRD) formats and VH polarization acquired via the Interferometric Wide Swath method. Preprocessing stages, such as calibration and terrain correction, are carried out within the Google Earth Engine environment. The radar backscattering coefficients (σ_0) from Sentinel-1 imagery are measured in decibels (dB). A calibration factor is used to convert digital number (DN) values to dB. Furthermore, no filter is first employed to reduce speckle noise, keeping spatial resolution. Figure 2 shows the forest commotion map and the range comparison of that disturbance is shown in Table I.

TABLE I

FOREST DISTURBANCE IN KPK, PAKISTAN

Forest Disturbance	Area (ha)
Deforestation	7,985
Reforestation	4,098

E. DETECTING DISTURBANCE USING TIME SERIES

The time series analysis indicated substantial trends in vegetation dynamics within the studied area throughout the observation period. Temporal changes in vegetation cover were examined using satellite data from numerous years, revealing patterns of forest loss and gain.

Distinct temporal patterns arose, with noticeable oscillations, reflecting seasonal differences in vegetation growth and phenology.

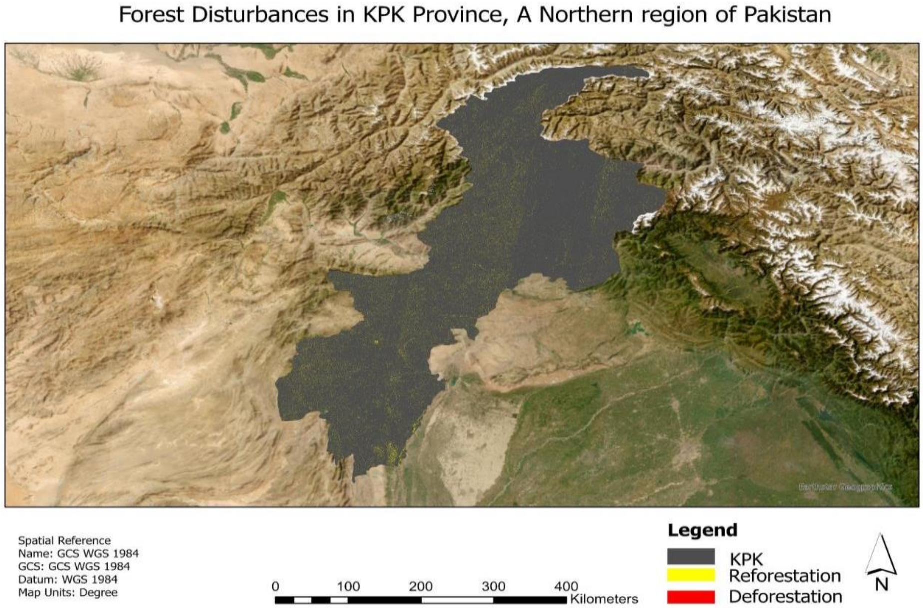

FIGURE 3. Map of forest disturbance in KPK

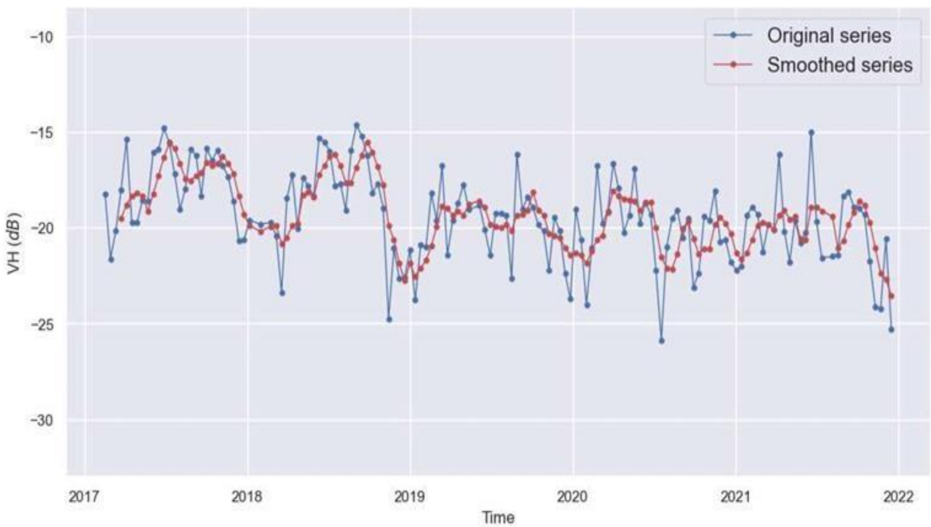

FIGURE 4. This figure depicts the temporal pattern of forest disturbances detected using the PVts-β method. Each data point represents a significant change in forest cover, highlighting trends in deforestation and reforestation over the study period.

These deforestation events were primarily focused in areas with heavy human activity, such as agricultural development and logging operations. In contrast, instances of vegetation recovery and regrowth were detected, indicating natural regeneration processes or reforestation efforts. The time series revealed that 2020-2021 was the most disturbed year in KPK and most of the reforestation was from 2021-2022. Overall, the time series analysis revealed important insights into the dynamics of land-living cover alteration and forest commotion in the study area, providing a foundation for informed decision-making and targeted conservation interventions.

F. IMPACT OF DETECTING DEFORESTATION IN TIME SERIES DOMAIN

It is critical to analyze detection approaches based on time series. Time series analysis provides significant advantages. Detecting subtle changes in photosynthetic activity over time is more effective than using machine or deep learning classifications ("probably"). One disadvantage of time series is the possible presence of outliers. It might be harder to carry out a deeper analysis if atmospheric noise and seasonality are not removed or accounted for. Time series analysis is now much more accessible. This is mainly because platforms, such as Earth Engine have been built with detection algorithms directly suited for time series. On the other hand, the PVts-β method simply presents a very simple yet user-friendly approach that has no account for seasonality. It relies on a single calibration parameter for the detection of deforestation, so it is easy to apply for any user with whatever level of expertise. Its simplicity and effectiveness place PVts-β as an asset for forest monitoring. The results emphasize practicality and applicability to different environmental conditions (for more details see [15]). It underscores a method that is convenient, efficient, and valuable both in addressing the difficulties being faced in deforestation while promoting sustainable forest management techniques. Furthermore, affordability would make PVts-β an invaluable strategic tool for effective forest monitoring.

III. CONCLUSION AND FUTURE DIRECTIONS

The findings underscore the effectiveness of the PVts-β method to detect forest disturbances using Sentinel-1 radar imagery. However, it is important to acknowledge the limitations of the proposed methodology.

The outcomes of the current study are quite valuable, especially with regard to deforestation and reforestation in KPK, Pakistan. As revealed by the results, a substantial degree of deforestation occurred mainly in areas with high sensitivity to human-induced perturbations, such as logging and agricultural land encroachment. There has been a notable rate of reforestation following the disturbance. It also shows that the years 2020-2022 were critical to have an increase in terms of deforestation activities and later years indicated recovery and regeneration in the ecosystem. Therefore, there is an urgent need to take preventive actions against the processes of deforestation and activities which encourage sustainable management of forests. Such approaches are essential to maintain ecological balance and ensure the health of forest ecosystems.

For future sustainability, joint efforts involving governmental agencies, local communities, and conservation organizations would be essential to preserve the ecological integrity and biodiversity of KPK.

A. LIMITATIONS

One significant limitation of the current study is its reliance on Sentinel-1 data. This may restrict its applicability in regions where such data is unavailable or insufficient. Additionally, while radar data addresses cloud cover issues inherent in optical imagery, seasonal noise and variations in radar backscatter due to environmental factors may pose challenges in accurately identifying disturbances.

B. FUTURE RESEARCH IMPLICATIONS

Future studies could explore integrating multisensory data, including optical and radar sources, to mitigate these limitations and enhance detection robustness.

C. POLICY IMPLICATIONS

The policy implications of these findings are substantial. By quantifying deforestation and reforestation dynamics, this study provided actionable insights for conservation strategies in KPK region. Policymakers may leverage these insights to design targeted interventions for forest management, reforestation programs, and monitoring systems. Furthermore, the adaptability of the PVts-β method to various regions highlights its potential as a scalable tool for global forest monitoring initiatives, particularly in areas with limited resources or persistent cloud cover.

Potential applications of the methodology extend beyond forest disturbance monitoring. It could be applied to detect land use changes, track agricultural dynamics, and monitor ecosystem restoration efforts. These applications can support broader environmental management goals, addressing challenges, such as habitat loss, climate change mitigation, and biodiversity conservation.

Overall, this study contributed to the growing body of research on remote sensing and forest monitoring by presenting a novel, efficient, and scalable approach. By addressing its limitations and exploring its broader applications, the PVts-β method can serve as a foundation for advancing sustainable environmental management practices.

CONFLICT OF INTEREST

The author of the manuscript has no financial or non-financial conflict of interest in the subject matter or materials discussed in this manuscript.

DATA AVALIABILITY STATEMENT

The data associated with this study will be provided by the corresponding author upon request.

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