Advanced Backscatter Modeling for Enhanced Detection of Forest Disturbances in the Indian Subcontinent

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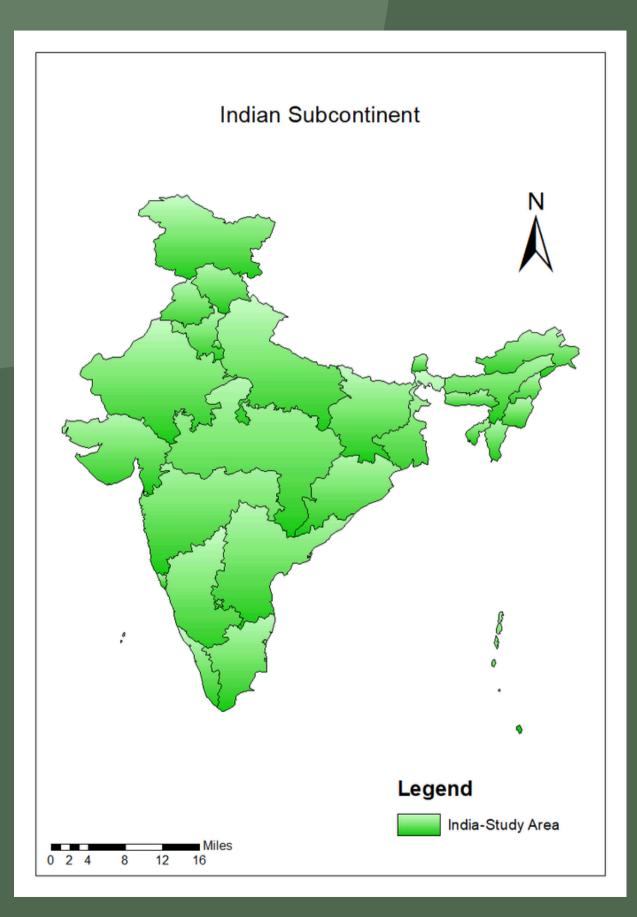
presentation participates in



Outstanding Student

Introduction

- Forests in the Indian subcontinent are vital ecosystems, supporting biodiversity and essential ecological services.
- Synthetic Aperture Radar (SAR) data, especially backscatter, is effective for monitoring changes due to its cloud-penetrating and vegetation-sensitive properties.
- Traditional backscatter analysis struggles to detect subtle forest changes in complex terrain and mixed vegetation types.
- This study investigates advanced backscatter modeling techniques to better detect and characterize forest disturbances.
- Techniques used include:
- Temporal filtering
- Polarization decomposition
- Machine learning-based classification



Objectives

- 1. To develop and apply an advanced backscatter modeling framework using multi-temporal Sentinel-1 SAR data for detecting and mapping forest disturbances across diverse ecological zones of the Indian subcontinent, incorporating the Coherence Stability Index (CSI) to assess structural forest changes over time.
- 2. To evaluate forest degradation intensity through the integration of the Forest Degradation Index (RFDI) with polarization-based Radar backscatter metrics, aiming to improve the sensitivity and reliability of disturbance detection in heterogeneous forest landscapes.

Methodology

- Source: Use Sentinel-1 SAR multi-temporal data (VV and VH polarizations) over the Western Ghats.
- Preprocessing: Apply radiometric calibration, terrain correction, and speckle filtering.
- Time-Series Stack: Create time-series backscatter stacks to capture forest dynamics.
- Index Computation:

Compute Coherence Stability Index (CSI) for temporal coherence changes.

Derive Radar Forest Degradation Index (RFDI) from VH and VV backscatter.

Additional Features: Extract SAR metrics like backscatter ratio and texture features.

• Classification:

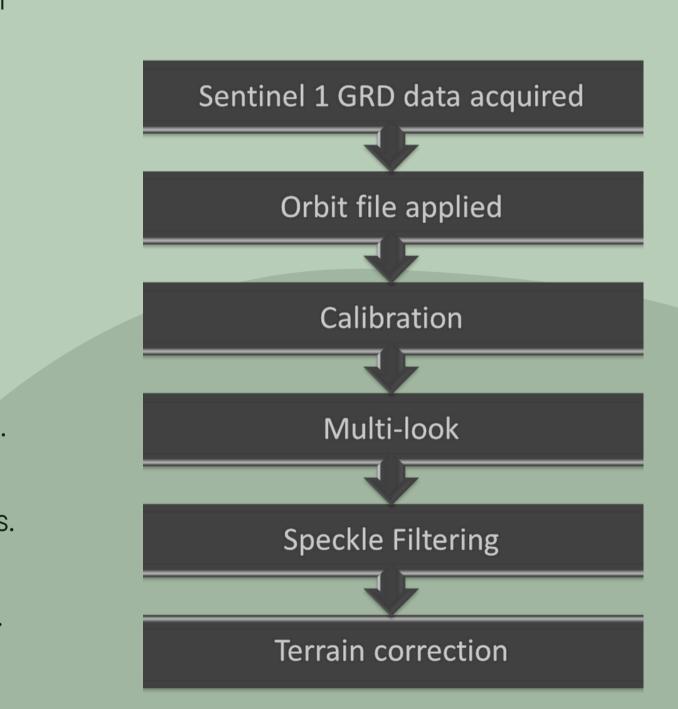
Use a supervised machine learning model (Random Forest) to classify disturbed vs. undisturbed forests.

Train and validate using ground truth data and high-resolution Sentinel-2 imagery.

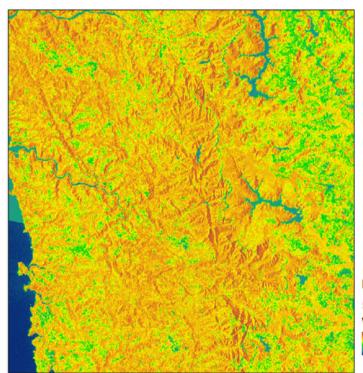
• Evaluation:

Assess model accuracy with standard metrics.

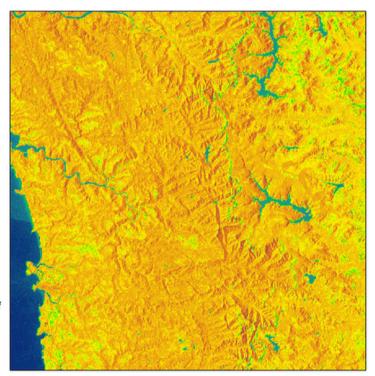
Validate spatially with known disturbance events.



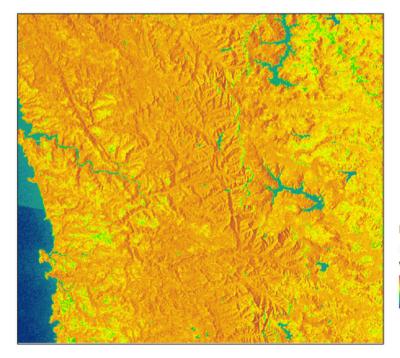
Analysis



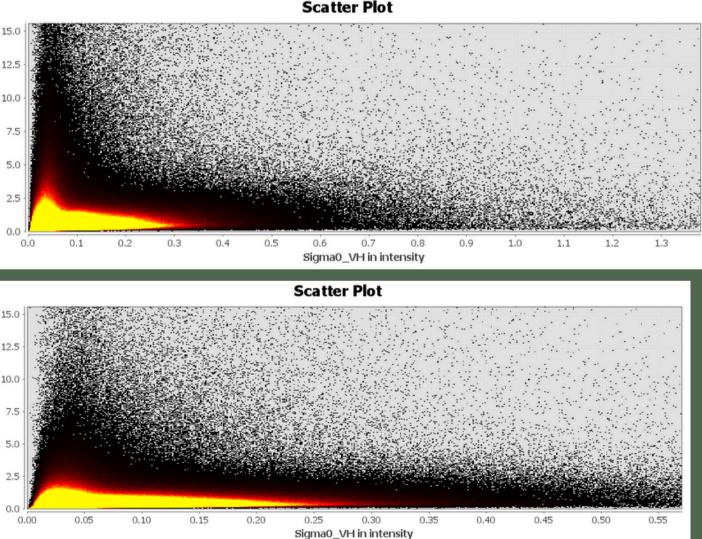
Legend S1_VH_PreMonsoon_2023.tif Value - High : 583 Low: -3930



Legend S1_VH_Monsoon_2023.tif Value High : 583 Low : -3930

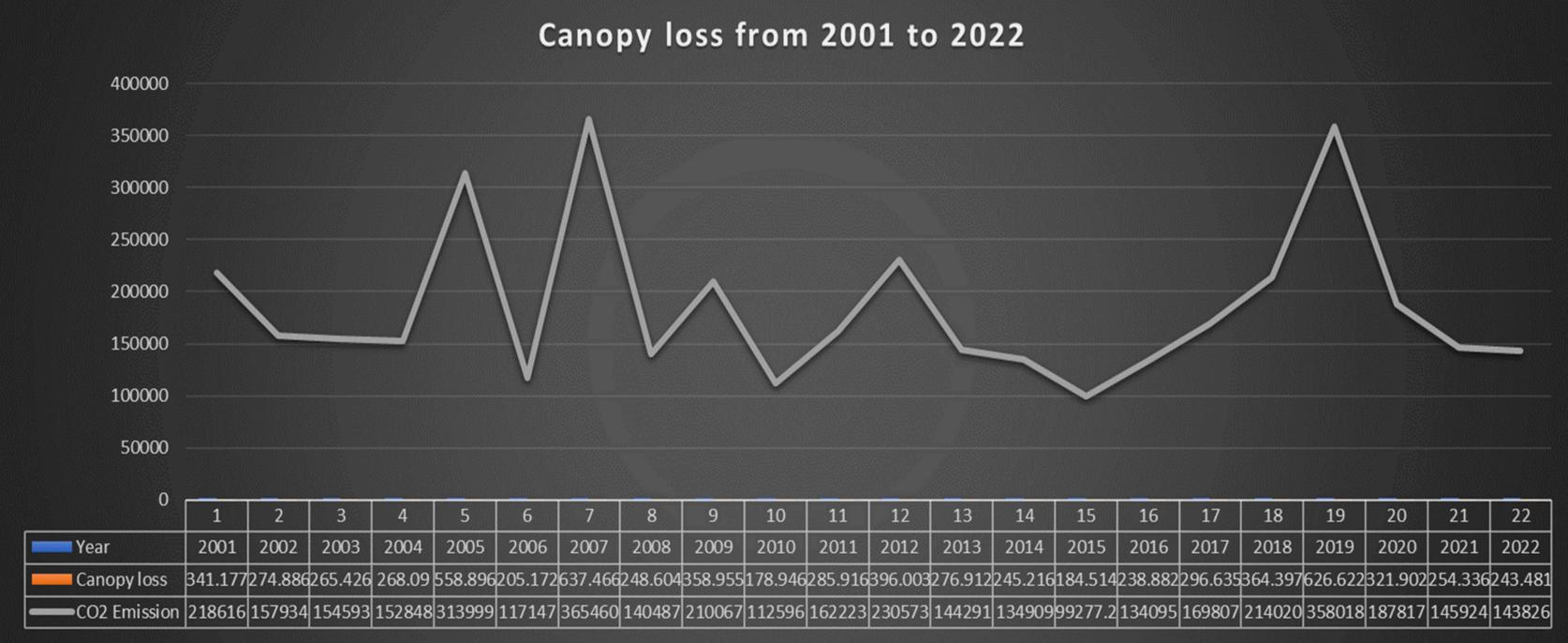


Legend S1_VH_PostMonsoon_2023.tif Value High : 583 Low : -3930



Scatter Plot

Analysis



Year

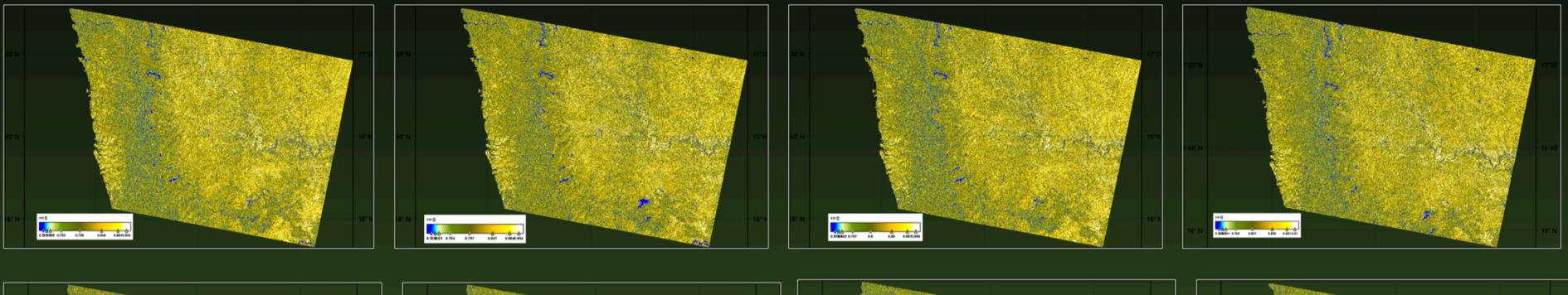
14	15	16	17	18	19	20	21	22
2014	2015	2016	2017	2018	2019	2020	2021	2022
45.216	184.514	238.882	296.635	364.397	626.622	321.902	254.336	243.481
34909	99277.2	134095	169807	214020	358018	187817	145924	143826

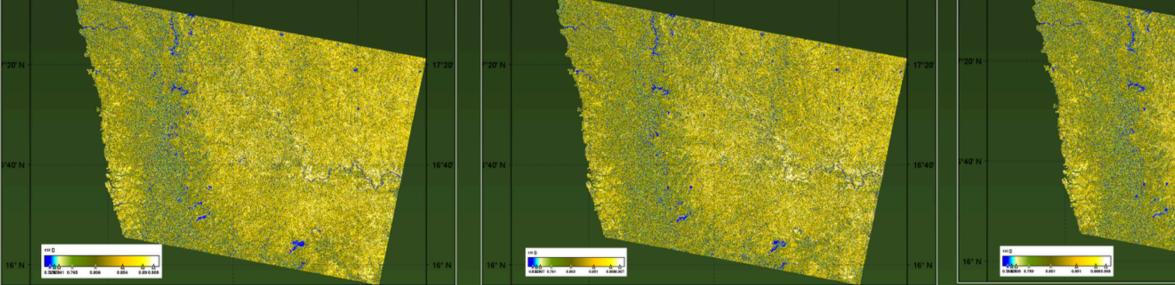
Canopy Structure Index (CSI)

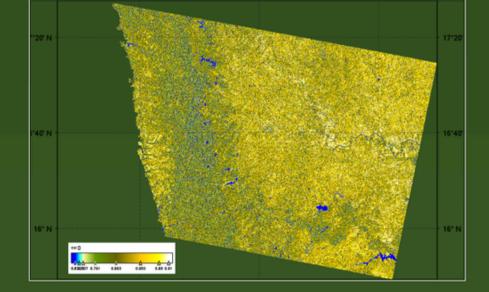
- Optical remote sensing-derived metric integrated in radar.
- High CSI: Dense, undisturbed forests.
- Low CSI: Sparse, degraded canopies.

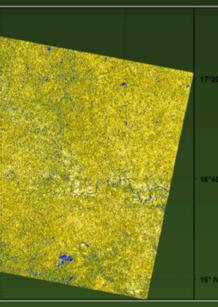
 $CSI = \frac{(VH+VV)}{(VH-VV)}$

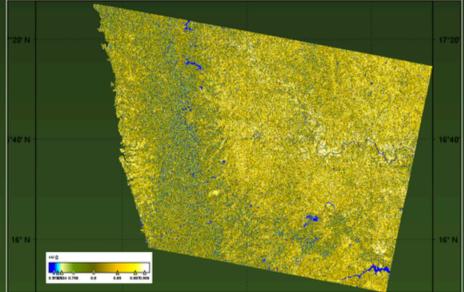
CSI (PRE-DISTURBANCE, 2017-2023)



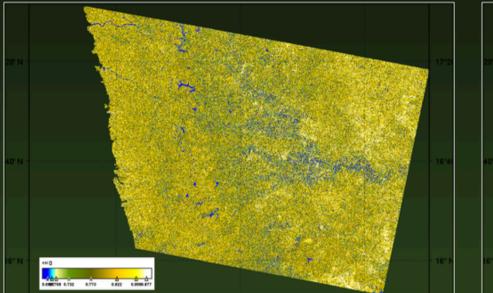


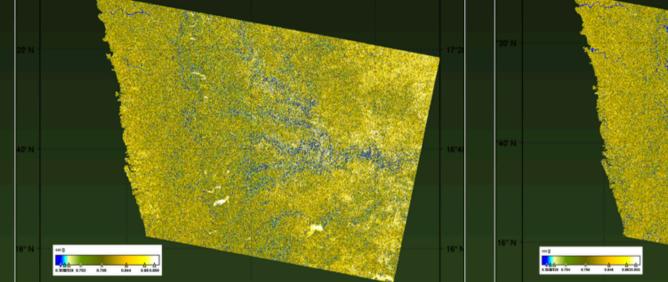


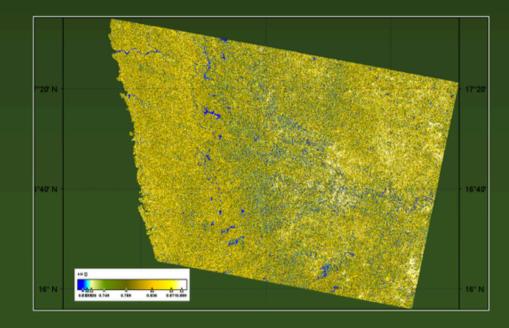


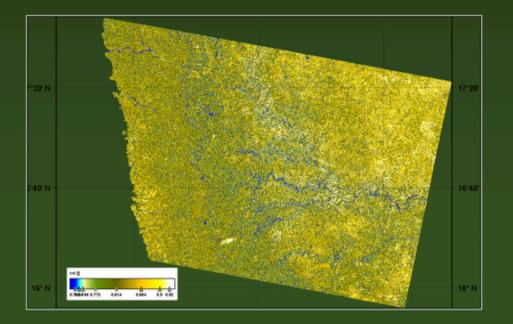


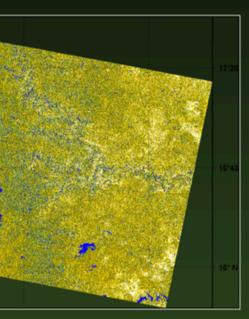
CSI (POST-DISTURBANCE, 2017-2023)

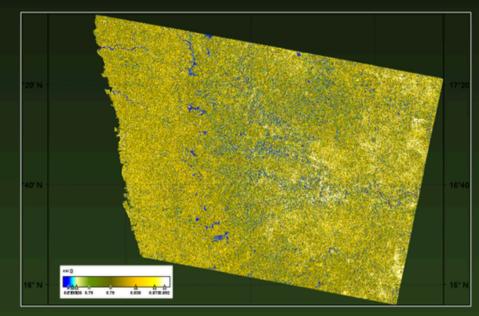


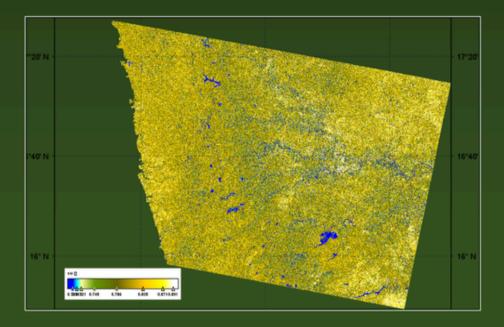












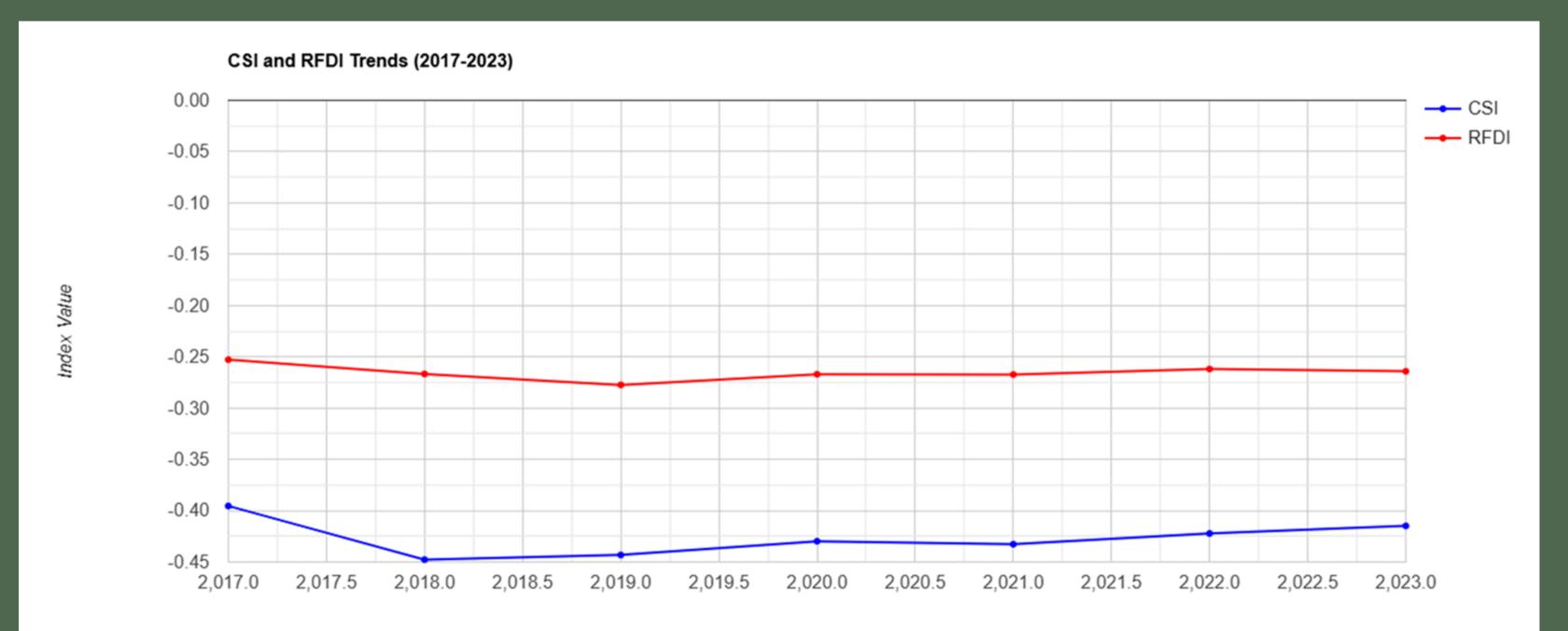
Radar Forest Degradation Index (RFDI)

- Derived from Synthetic Aperture Radar (SAR) data.
- High RFDI: Significant degradation.
- Low RFDI: Stable forest structures.

$$RFDI = \frac{VH + VV}{(VH - VV)} \times \left(\frac{1}{Backscatter}\right)$$

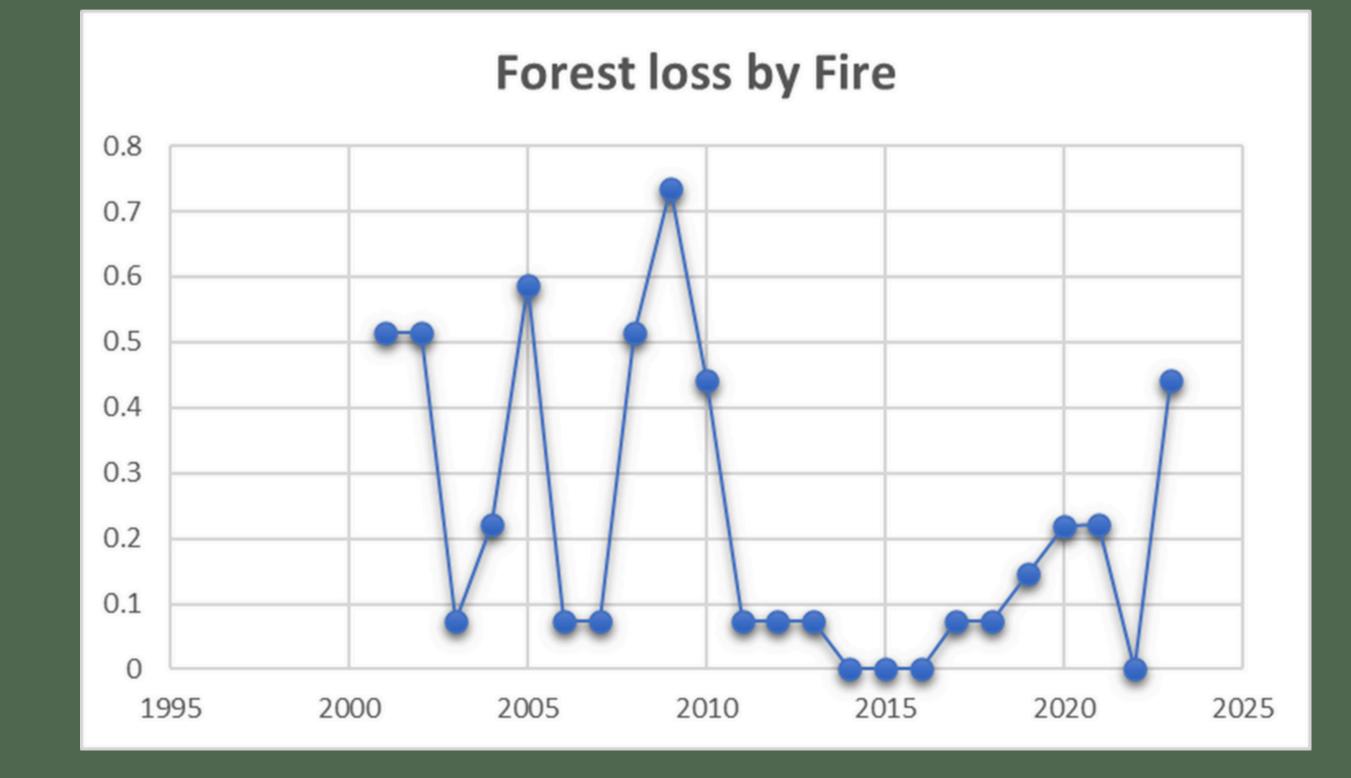


Results



Year

Results



High risk zones

