Open-Source Remote Sensing Analysis for E-Governance using Python for NDVI and Vegetation Index Analysis

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ABSTRACT
Urban planning in India increasingly depends on accurate and timely geospatial data for sustainable development. This paper presents the design and implementation of a Tkinter-based Python GUI application that computes vegetation indices from satellite raster data and integrates statistical and graphical analytics. The system is developed to aid E-Governance activities in Chhatrapati Sambhajinagar (Aurangabad) by simplifying raster data handling and automating NDVI, EVI, SAVI, and other vegetation index calculations. Users can interactively select raster bands, compute indices, visualize spatial patterns, analyze statistical metrics, and generate graphical representations using open-source libraries. A case study using Landsat data from 2013 demonstrates the tool's application in urban vegetation monitoring. Results show that the system provides effective spatial and statistical insights, helping planners detect vegetation stress, water bodies, and urban expansion zones with minimal technical overhead.

Keywords
Remote Sensing, Vegetation Indices, E-Governance, Python GUI, Tkinter, Rasterio, NDVI, Urban Monitoring, NDVI, EVI, SAVI .

1. INTRODUCTION
Urbanization has dramatically transformed the socio-environmental fabric of Indian cities, demanding advanced tools and strategies for effective urban planning and governance. As cities expand, the need for sustainable infrastructure management, environmental monitoring, and public resource optimization becomes increasingly critical. E-Governance, a technology-driven governance model, has emerged as a pivotal approach to address these challenges by integrating Geographic Information Systems (GIS) and remote sensing tools for data-driven decision-making (Caragliu et al., 2011; Aljoufie et al., 2013).

Remote sensing data, particularly raster imagery obtained from satellites such as Landsat, Sentinel, and MODIS, offers valuable insights into land cover, vegetation health, urban sprawl, and hydrological patterns (Roy et al., 2020). Among the tools used for analyzing such data, vegetation indices like NDVI (Normalized Difference Vegetation Index), EVI (Enhanced Vegetation Index), and SAVI (Soil-Adjusted Vegetation Index) are widely recognized for their ability to detect vegetation density, soil moisture, and drought conditions (Huete, 1988; Tucker, 1979). These indices support municipal bodies in making evidence-based decisions regarding urban greenery, land degradation, and sustainable development planning.

Despite the availability of advanced GIS software platforms such as ArcGIS, ERDAS Imagine, and ENVI, their cost and complexity often hinder widespread adoption among smaller government departments and educational institutions. On the other hand, Python—a widely used open-source programming language—offers libraries like Rasterio, NumPy, Matplotlib, and Tkinter that can be used to build powerful and affordable alternatives (Gillies et al., 2022). However, most Python-based geospatial tools require scripting expertise, limiting accessibility to non-programmers.

To address this gap, we present a Tkinter-based desktop application for computing, analyzing, and visualizing multiple vegetation indices from raster datasets. The application simplifies raster data handling by allowing users to load bands, calculate indices (NDVI, SAVI, EVI, NDWI, MNDWI, NDSI, NDBI, UI, PRI, CIgreen), view plots (histogram, boxplot, scatter), and inspect detailed statistical summaries (mean, median, standard deviation, range, coefficient of variation) through an intuitive graphical interface. By leveraging open-source libraries such as Rasterio (https://rasterio.readthedocs.io/), NumPy (https://numpy.org/), Matplotlib (https://matplotlib.org/), and Seaborn (https://seaborn.pydata.org/), the tool offers high performance and flexibility without cost barriers.

This system is particularly tailored for E-Governance applications, demonstrated through a case study in the city of Aurangabad. The city, which is experiencing rapid urbanization, can benefit from automated monitoring of green infrastructure, assessment of vegetation health, and detection of water bodies using satellite data. By offering a plug-and-play interface for environmental analysis, the application empowers municipal authorities, researchers, and planners to integrate remote sensing into day-to-day governance processes with minimal training.

The following sections of this paper describe the technical methodology, GUI design, raster processing workflow, vegetation index algorithms, case study results, and recommendations for enhancing smart city initiatives through open-source geospatial tools.

2. RESEARCH METHODOLOGY
The methodology adopted in this study involves the

development of a raster processing and visualization system using Python and open-source libraries to calculate vegetation indices for E-Governance applications in Chhatrapati Sambhajinagar. The process includes five main stages: GUI system design, raster input processing, vegetation index computation, visualization/statistical analysis, and performance validation.

3. GUI SYSTEM DESIGN

The application interface was developed using Python's Tkinter library. The GUI comprises a list of raster bands on the left panel and buttons to compute different indices such as NDVI, SAVI, EVI, NDWI, etc. The right side contains tabs for Visualization, Statistics, and Graphs, enabling complete interaction with the dataset without the need for programming knowledge Figure 1 shows the implemented GUI of the system.

3.1 Vegetation Index Computation with Equations

3.1.1 Normalized Difference Vegetation Index (NDVI)

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

3.1.2 Enhanced Vegetation Index (EVI)

$$EVI\ 2.5 = \frac{NIR - RED}{NIR + 6 * RED - 7.5 * BLUE + 1}$$

3.1.3 Soil-Adjusted Vegetation Index (SAVI)

$$SAVI = \left(\frac{NIR - RED}{NIR + RED + L}\right) * (1 + L)$$

3.1.4 Normalized Difference Water Index (NDWI)

$$NDWI = \frac{GREEN - SWIR}{GREEN + SWIR}$$

3.1.5 Modified NDWI (MNDWI)

$$MNDWI = \frac{GREEN - SWIR}{GREEN + SWIR}$$

3.1.6 Normalized Difference Soil Index (NDSI)

$$NDSI = \frac{GREEN - SWIR}{GREEN + SWIR}$$

3.1.7 Normalized Difference Built-up Index (NDBI)

$$NDBI = \frac{SWIR - NIR}{SWIR + NIR}$$

3.1.8 Urban Index (UI)

$$UI = \frac{SWIR - NIR}{SWIR + NIR}$$

3.1.9 Chlorophyll Index Green (CIgreen)

$$CI_{green} = \left(\frac{NIR}{GREEN}\right) - 1$$

3.1.10 Photochemical Reflectance Index (PRI)

$$PRI = \frac{GREEN - RED}{GREEN + RED}$$

The Normalized Difference Vegetation Index (NDVI) is one of the most widely used indicators for assessing the presence and condition of green vegetation. It helps distinguish between healthy vegetation and barren land or built-up surfaces. To improve vegetation monitoring, especially in dense forest or agricultural areas, the Enhanced Vegetation Index (EVI) was developed. It corrects for atmospheric influences and soil background noise, offering more sensitivity in high biomass regions. Another related metric, the Soil-Adjusted Vegetation Index (SAVI), includes a soil brightness correction factor, making it suitable for areas where vegetation is sparse and soil exposure is significant.

For water body detection, the Normalized Difference Water Index (NDWI) is highly effective. It enhances the identification of open water features by reducing confusion with vegetation. A refined version known as the Modified NDWI (MNDWI) further improves accuracy in distinguishing water bodies, especially in urban environments where built-up features may interfere with basic indices.

In terms of soil identification, the Normalized Difference Soil Index (NDSI) is used to map and analyze bare soil areas. This can be useful in agriculture, drought assessment, and land degradation studies. To detect urban expansion and built-up infrastructure, the Normalized Difference Built-up Index (NDBI) is applied. It is particularly valuable in urban planning and land-use classification. A similar metric, the Urban Index (UI), also serves to identify impervious surfaces like roads and buildings in satellite imagery.

On the biochemical side, the Chlorophyll Index Green (CIgreen) is employed to estimate chlorophyll concentration in plants, providing insights into crop health and productivity. Lastly, the Photochemical Reflectance Index (PRI) is used to monitor photosynthetic activity and light use efficiency, offering valuable information for ecological and agricultural studies focused on plant stress and productivity.

3.2 Raster File Handling

Raster images in formats like .tif, .img, and .hdf are loaded using the Rasterio library. Each image band is read as a NumPy array for mathematical manipulation. Raster files are typically multi-band satellite images (e.g., Red, NIR, Blue, Green), used in vegetation index formulas. The application ensures that NaN values are excluded from all computations to avoid distortion in results.

3.3 Visualization and Statistical Analysis

After calculating any vegetation or land surface index, the system provides both graphical and statistical insights to support data interpretation. The computed index is first visualized through a false-color plot using Matplotlib, which includes a colorbar to clearly indicate value ranges. To further analyze data distribution and trends, the system generates multiple plots such as a histogram, boxplot, and scatter plot using the Seaborn library.

Computes statistical metrics:

$$mean: \mu = \frac{1}{2}\sum x_i$$

$$Standard\ Deviation: \sigma = \sqrt{\frac{1}{n}\sum (x_i - \mu)^2}$$

$$Coefficient\ of\ Variation: CV = \left(\frac{\sigma}{u}\right) * 100$$

In addition to visual representations, the system calculates key statistical metrics. These include the mean value, which represents the average intensity of the index across the image;

the standard deviation, which indicates how much the data values deviate from the average; and the coefficient of variation, which expresses the extent of variability in relation to the mean. These statistical values offer deeper insights into the variability and spread of the index data.

All computed statistics are displayed in the dedicated Statistics Tab, providing a summary for quick analysis, while all visual plots are organized under the Graphs Tab, ensuring a clean and user-friendly interface for exploring spatial data patterns. .

4. GUI FOR E-GOVERNANCE SYSTEM

This interface is designed to allow non-technical users—such as urban planners, environmental officers, and municipal staff—to perform advanced vegetation index analysis from satellite-based raster datasets with ease. Built using Python's Tkinter library, the GUI offers an accessible and interactive platform that simplifies the process of remote sensing analysis by eliminating the need for complex GIS software. Users can effortlessly load multi-band raster images, select specific bands, and compute a variety of vegetation indices including NDVI, EVI, SAVI, NDWI, MNDWI, and others. The left panel provides a scrollable band list and a set of clearly labeled buttons for initiating index calculations, while the main workspace features three organized tabs: Visualization, Statistics, and Graphs. The Visualization tab displays georeferenced index maps with intuitive color scales (e.g., green for healthy vegetation and red for degraded areas), allowing users to interpret spatial patterns instantly. The Statistics tab summarizes computed results with key metrics such as mean, median, standard deviation, and coefficient of variation, supporting quantitative assessment of vegetation health. The Graphs tab provides deeper insights through interactive scatter plots, histograms, and boxplots. Together, these components form a comprehensive yet user-friendly analytical tool that empowers local governance bodies in Chhatrapati Sambhajinagar to make data-driven decisions for urban environmental management.

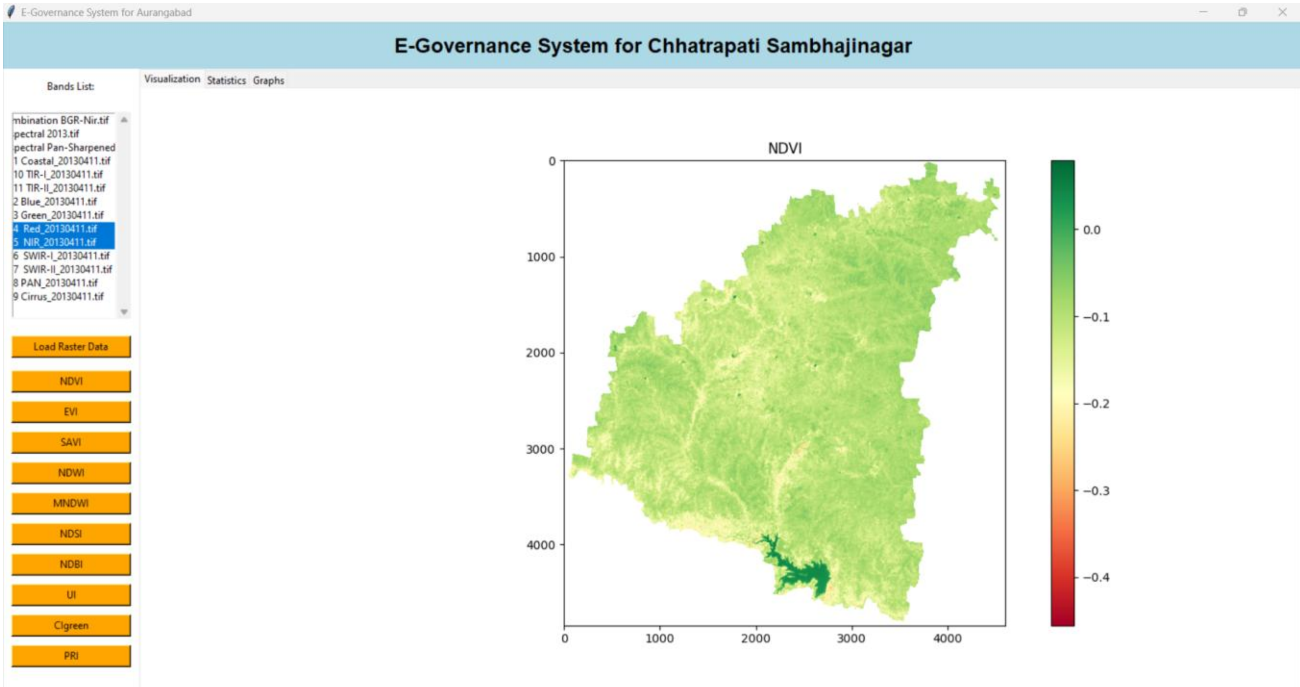

Figure 1: NDVI Visualization Output of Chhatrapati Sambhajinagar in the E-Governance GUI

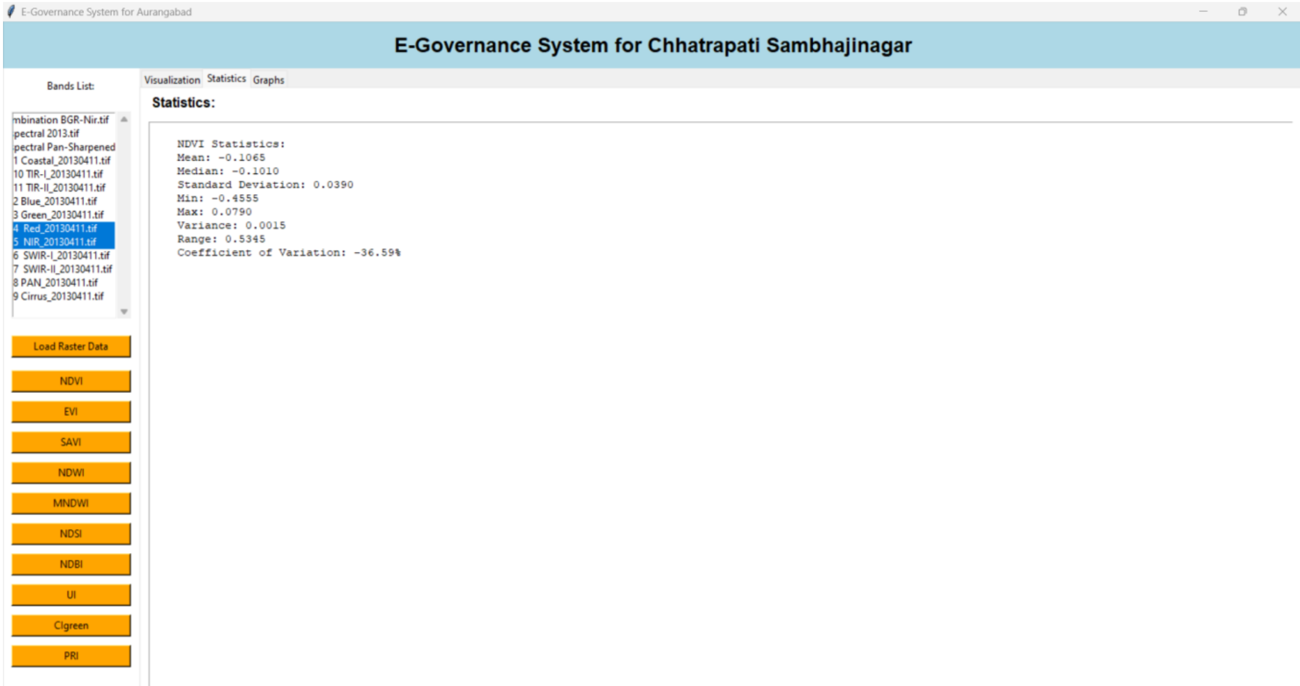

Figure 2: NDVI Statistical Summary Panel in the E-Governance GUI for Chhatrapati Sambhajinagar

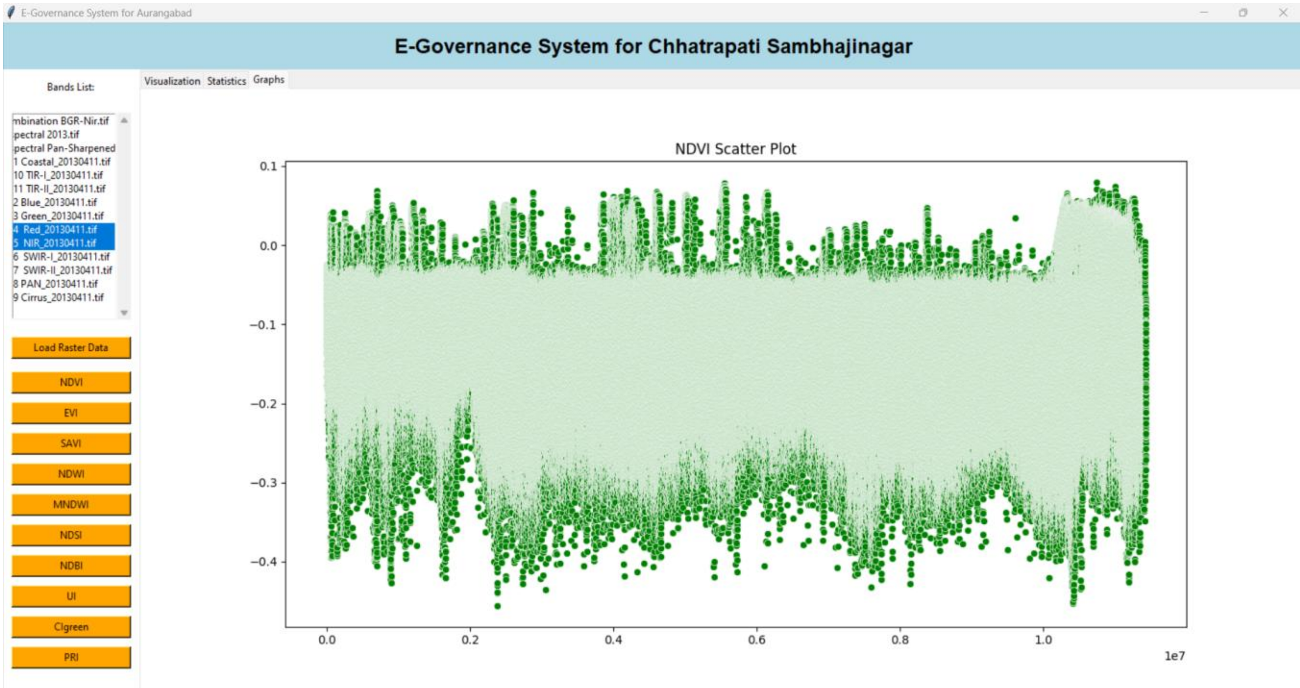

Figure 3: NDVI Scatter Plot Visualization in the E-Governance GUI for Chhatrapati Sambhajinagar

Fig 1: If necessary, the images can be extended both columns

5. CONCLUSION

The proposed Tkinter-based GUI application bridges the gap between advanced geospatial analysis and accessible E-Governance tools by offering a complete solution for vegetation index computation, visualization, and statistical analysis. By leveraging open-source libraries and a user-friendly design, the system empowers non-technical users—particularly those in municipal and environmental sectors—to extract meaningful insights from satellite data without the need for specialized GIS software. Its application in Chhatrapati Sambhajinagar highlights its effectiveness in visualizing urban vegetation health, identifying environmental stress zones, and supporting data-driven decision-making. The inclusion of real-time graphical outputs and comprehensive statistical summaries enhances interpretability and fosters a more proactive governance model. Future work may focus on expanding the system's capabilities through cloud data integration, time-series analysis, and web-based deployment to support broader applications in climate monitoring, disaster management, and precision urban planning.

5.1 Future Work

While the current version of the E-Governance GUI system provides robust functionality for raster-based vegetation index analysis, there are several directions in which this work can be extended to enhance its capabilities and scalability for broader real-world applications. One of the primary areas for future enhancement is the integration of cloud-based data access, allowing users to directly connect to remote repositories such as Google Earth Engine, USGS Earth Explorer, or Copernicus Open Access Hub. This would eliminate the need for manual downloading of satellite imagery and streamline data acquisition.

Another promising extension is the incorporation of temporal analysis functionality, enabling users to analyze changes in vegetation indices over time. By supporting time-series NDVI and EVI trend analysis, the system could offer more advanced insights into seasonal vegetation patterns, drought detection, and long-term urban green cover monitoring.

Moreover, transforming the current desktop application into a web-based platform or mobile app would increase its accessibility across devices and geographies. With frameworks like Django, Flask, or React, the system could be redeployed as a responsive web application, ideal for field usage and multi-user collaboration.

Additionally, future versions of the system could integrate machine learning modules for automated classification of land cover types, anomaly detection in vegetation trends, or prediction of environmental risks. This could be paired with a report generation feature, allowing the export of computed indices, statistical summaries, and maps in PDF or Excel formats for documentation or policy reporting.

To support multilingual users across diverse administrative regions, multi-language support can be added to the GUI, particularly in regional languages such as Marathi or Hindi, further enhancing usability for local governance personnel.

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