Developing and applying an Agro-environmental Quality Index (AQI) for Caconde-SP, Brazil: a first approximation using remote sensing and Google Earth Engine

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Abstract

Continuous environmental quality monitoring is crucial for sustainability, particularly given the increased food production demanded by population growth. Smallholder farmers, responsible for a significant portion of global and Brazilian agricultural output, require practical tools to assess and enhance the agro-environmental sustainability of their activities. In this context, orbital remote sensing and platforms such as the Google Earth Engine (GEE) offer efficient solutions for deriving biophysical (NDVI, NDWI, BSI, LST) and topographic (slope) indicators, which are essential for constructing Agro-environmental Quality Indices (AQI). This study developed and applied a methodology for the monthly monitoring of AQI in the municipality of Caconde-SP, Brazil, utilizing Sentinel-2, Landsat 8, and SRTM data processed within GEE for the period between 2021 and 2023. NDVI, NDWI, BSI, LST, and slope were calculated, normalized, and combined through a weighted sum to generate the AQI, subsequently classified into five levels. The results demonstrate the feasibility of this approach, with GEE efficiently processing multi-sensor data and enabling continuous monitoring. The proposed AQI, although preliminary and requiring further validation and refinement, presents itself as a promising tool for environmental diagnostics at the municipal scale. This methodology contributes to agro-environmental monitoring by introducing a replicable and cost-effective approach with potential for adaptation to other regions.

Keywords: Agro-environmental Quality Index, Remote Sensing, Google Earth Engine.

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1. Introduction

Environmental quality is a multidimensional approach reflecting the conservation status and health of ecosystems, crucial for human well-being and sustainability (Sturbois et al., 2023). Continuous environmental quality monitoring is fundamental for identifying degraded areas, assessing the impact of anthropogenic activities, and supporting public policies aimed at environmental conservation and recovery (Jia et al., 2021). However, traditional field monitoring methods can be costly, time-consuming, and present logistical and temporal limitations.

Concurrently, the projected global population growth to approximately 10 billion people by 2050 underscores the urgent need for an alarming 98% increase in food production (United Nations Development Programme, 2021). Considering that roughly 90% of the world's farmers are smallholders cultivating less than two hectares of land, with regions like Asia and Sub-Saharan Africa producing 80% of their food on small farms, the role of this sector is increasingly significant. In Brazil, smallholder farmers occupy 23% of productive areas, account for 23% of the gross value of agricultural production, and provide 67% of rural employment. Beyond food production, family farming contributes to the economic dynamism of 90% of municipalities with up to 20,000 inhabitants, representing 68% of the national total and 40% of the income of the country's economically active population. (Confederação Nacional dos Trabalhadores na Agricultura, 2023). The development of methods and technologies for agro-environmental sustainability indicators has the potential to be a practical tool to assist small and medium-sized producers in the technical and environmental development of their production systems.

In this context, orbital remote sensing emerges as a powerful tool, enabling the systematic acquisition of data on the Earth's surface with broad spatial coverage and at various temporal and spectral resolutions (Ponzoni et al., 2018). From satellite imagery, it is possible to derive a series of biophysical indices that correlate with aspects of environmental quality, such as vegetation status (e.g., NDVI), moisture (e.g., NDWI), bare soil exposure (e.g., BSI), and land surface temperature (LST) (Gao, 1996; Rikimaru et al., 2002; Sobrino et al., 2004; Huete, 2012). The combination of these indicators, along with topographic variables such as slope, can result in robust and spatially explicit Agro-environmental Quality Indices (AQI).

The increasing availability of free satellite data, such as those from the Sentinel (ESA) and Landsat (USGS/NASA) missions, coupled with the development of cloud-based geoprocessing platforms like Google Earth Engine (GEE), has revolutionized environmental monitoring practices (Gorelick et al., 2017). GEE provides access to a vast catalog of geospatial data and computational power to process them on a planetary scale, eliminating the need for local download and storage of large data volumes and significantly reducing processing time (Kumar; Mutanga, 2018).

Given the above, the objective of this work is to develop and apply a methodology for the monthly monitoring of agro-environmental quality in the municipality of Caconde-SP, utilizing an Agro-environmental Quality Index (AQI) derived from remote sensing data processed on the Google Earth Engine platform, covering the period from 2021 to 2023. This study aims to provide a diagnosis of the area's environmental dynamics and demonstrate the feasibility of the approach to support territorial management and future research.

2. Methods

The study was carried out in the Caconde Agrotechnological District (DAT), São Paulo, Brazil (Figure 1). The municipality of Caconde, located in the northeast of São Paulo state, Brazil, features a diverse landscape with remnants of Atlantic Forest, agricultural activities, pastures, and water bodies, including part of the Caconde Hydroelectric Power Plant (HPP) reservoir. This heterogeneity, combined with land-use pressures, makes the region a relevant case study for developing and applying agro-environmental quality monitoring methodologies.

The entire process was conducted within the Google Earth Engine (GEE) environment using the Python programming language, accessing data from both GEE's native catalog and external APIs of governmental and environmental institutions.

Data base: a) Sentinel-2 MSI (MultiSpectral Instrument), b) Landsat 8 OLI/TIRS; and c) SRTM (Shuttle Radar Topography Mission).

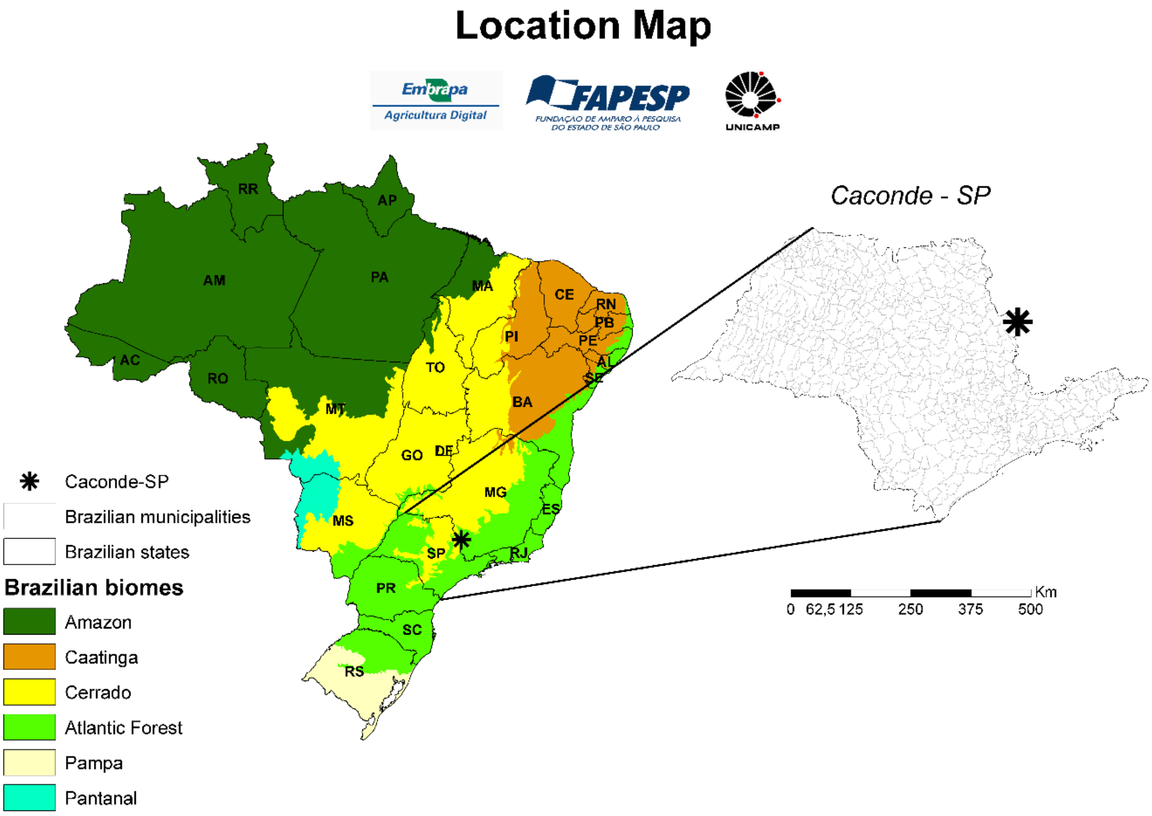

Figure 1. Location map of Agrotechnological District at Caconde, SP.

The analysis period was from December 1, 2024, to December 31, 2024. Data Processing and AQI Calculation: a) Calculation of Biophysical Indices; b) Normalized Difference Vegetation Index (NDVI); c) Normalized Difference Water Index (NDWI); d) Bare Soil Index (BSI); e) Land Surface Temperature (LST); f) Slope; and g) Normalization of Indices.

The AQI was calculated as a weighted sum of the normalized indicators, multiplied by 100 to present a scale from 0 to 100:

$$AQI = (NDVI\_norm * 0.3) + (NDWI\_norm * 0.2) + (BSI\_norm\_inv * 0.2)$$
$$+ (LST\_norm\_inv * 0.2) + (Slope\_norm\_inv * 0.1)) * 100$$

The weights were assigned based on the theoretical relevance of each indicator to overall agro-environmental quality, with NDVI receiving the highest weight due to its strong correlation with ecosystem health. This represents an initial approximation, and the weights may be adjusted in future studies based on field validation or multi-criteria analysis methods (Malczewski, 2006).

3. Results and Discussion

This layer in Figure 2, represents the final result of the weighted integration of the various environmental indicators previously discussed (Relief, Slope, LST, NDWI, NDVI, BSI, and potentially EVI, among others). The AQI is classified into a defined number of classes (in this case, five, ranging from "Very Poor" to "Excellent") to facilitate the interpretation and communication of results (Malczewski, 2006). Each class reflects an aggregated level of agro-environmental quality, enabling the identification of priority areas for intervention, monitoring, or conservation. The definition of the ranges for each class and the weights assigned to each indicator in the AQI composition are critical steps that depend on specialized knowledge, literature, and the specific characteristics of the study area.

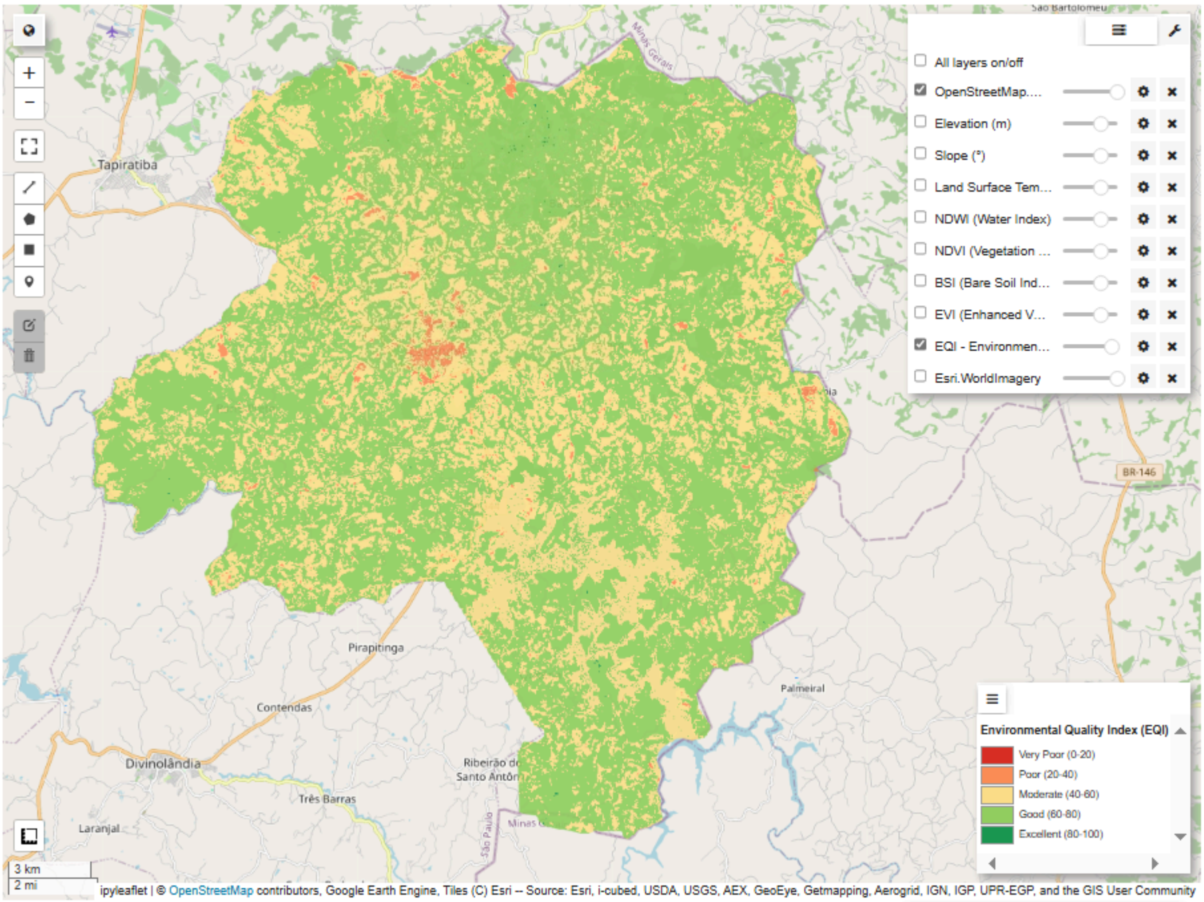

Figure 2. Agro-environmental Quality Index (AQI) for December 2024.

The combined analysis of these layers, through an AQI model, offers a synoptic and quantifiable view of the agro-environmental state, which is essential for sustainable planning and adaptive management of natural resources in agricultural landscapes.

It is important to emphasize that the AQI presented herein is a model and, as such, a simplification of the complex environmental reality. The choice of indicators, their respective weights, and the normalization thresholds are crucial and can be refined. The use of a monthly median for Sentinel-2 and Landsat 8 imagery is an effective strategy to mitigate cloud contamination, a common challenge in tropical regions (Gorelick et al., 2017). However, during months with persistent cloud cover, the quality of the median may be compromised, or, in the case of Landsat, high-quality scenes may be unavailable, necessitating the use of a default value for LST.

The methodology demonstrated GEE's capability to efficiently process a time series of multi-sensor data for a considerable study area, generating results rapidly and automatically. This enables continuous monitoring and periodic updating of the AQI, which is essential for adaptive environmental management.

4. Conclusion

This study demonstrated the feasibility of constructing an Agro-environmental Quality Index (AQI) using remote sensing data and the GEE. This platform proved to be an effective tool for the agile processing of large data volumes, facilitating continuous monitoring.

The proposed AQI, although requiring field validation and potential enhancement through the inclusion of other indicators or weight adjustments, already stands as a promising tool for environmental diagnostics and decision-making support for public managers and researchers.

This work contributes to the field of agro-environmental monitoring by presenting a replicable and cost-effective approach for assessing agro-environmental quality at the municipal scale, with the potential for adaptation to other regions and contexts.

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