Evaluating the Sensitivity of Spectral Indices for Detecting Waste Dumping Sites Using Satellite Imagery

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Abstract *Open dumping sites are areas that have various negative impacts on their surroundings. Waste stack piled up haphazardly not only emit disgusting smell into the environment but also threaten the health of vegetation and wetlands. Therefore, the identification and temporal monitoring of such areas are valuable for decision-makers. In this study, Sentinel imageries covering four-year period were used for the open dumping site currently being used in Bartin province of Türkiye. Dumping Detection Index (DDI), designed to identify such sites, was calculated for each year. Additionally, the Global Environment Monitoring Index (GEMI), which was reported to be under-evaluated for dumping sites in the literature, was calculated. The expansion of the site over the years was evaluated comparatively for both indexes and the areas where subsequent deposition was carried out were determined. The identified regions were supported by change graphs as well as average index values. The relationship between GEMI and DDI was shown to be directly proportional to the amount of waste deposited, regardless of the magnitude of the spread on the ground. It was also been demonstrated that GEMI provides more evident visual results than DDI for stored waste and surrounding vegetation.*

Keywords: DDI, GEMI, Open Dumping Site, Remote Sensing, Solid Waste, Spectral Index

Introduction

Solid waste accumulated in open areas through wild storage techniques is one of the important environmental problems for underdeveloped and developing countries. In these areas, called Open Dumping Sites (ODSs), solid waste is accumulated irregularly. The solid waste that has become a pile is then pressed amateurishly. Because there's no soil cover like in landfills operated by local authorities such as municipalities, the bad smell spreads around and the resulting leachate threatens surrounding wetlands. Furthermore, this outdated storage technique which is typically located in hilly and wooded areas, traps rainwater, negatively impacting the growth of surrounding vegetation (Osra et al., 2024). Establishing facilities for the regular storage of solid waste requires significant financial resources. Because not every local government in every country has these resources, they are often forced to use ODSs. In addition to the increasing negative environmental impacts as the amount of stored waste increases, the emergence of events such as fires (Chavan et al., 2022) that cause loss of life and property created the need to detect, monitor and map these areas for decision-makers (Fraternali et al., 2024). For these operations, remotely sensed (RS) images are considered as an efficient data source (Vambol et al., 2019).

For the detection and temporal monitoring of ODSs, aerial photographs (Silisuar et al., 2022) and satellite images (Papale et al., 2023) were frequently processed in the scope of RS images. Aerial photographs used for ODSs are generally obtained by unmanned aerial vehicles (Incekara et al., 2019; de Sousa Mello et al., 2022). Landsat and Sentinel imagery, obtained through passive remote sensing, and SAR imagery, obtained through active remote sensing, were used as satellite images (Gill et al., 2019; Silva et al., 2023) Because of their much higher spatial resolution compared to satellite imagery, aerial photographs are often preferred for applications such as separating the waste pile according to types in the field or identifying their recyclability (Bansal and Tripathi, 2024). Landsat images were mainly preferred due to thermal bands, which show temperature differences relative to the surrounding ODSs (Yan et al., 2014). Sentinel imagery, with its spatial resolution three times better than Landsat, was often preferred for generating spectral indexes for ODSs (Vanguri et al., 2023). Researchers have utilized SAR imagery for detection, volumetric changes based on digital elevation models, and deformation analysis (Ali et al., 2009; Du et al., 2021). Despite numerous studies in the literature, analyses of ODSs have been predominantly conducted using spectral indexes (Karimi and Ng, 2022; Mahmood et al., 2023). These indexes were generally the Normalized Difference Vegetation Index (NDVI) (Rouse et al., 1974), the Normalized Difference Water Index (NDWI) (McFeeters, 1996), and the Land Surface Temperature (LST) (Yalcinkaya et al., 2025). However, there are indexes that minimize the constraints of the basic ones and have much more complex equations, but were not adequately addressed for ODSs. (Fraternali et al., 2024). One of them is Global Environment Monitoring Index (GEMI) (Pinty and Verstraete, 1992) and in this study, it was evaluated in conjunction with the Dumping Detection Index (DDI) (Cadau et al., 2013) which was developed for the detection of ODSs.

Study Area

The study area handled in this study is an ODS located in Bartin Province, Türkiye. Bartin is one of Türkiye's most important cities in terms of tourism. Bartin is well known, with its natural beauty and coastal zone, and has been subject to ODS for many years. The storage site was shown in Figure 1. Its proximity to holiday destinations and its location make this site even more important for research. Since the site cannot meet the city's solid waste storage demand, it has recently become a concern, with waste being deposited on the roads providing access to the site (Url-1, Url-2).

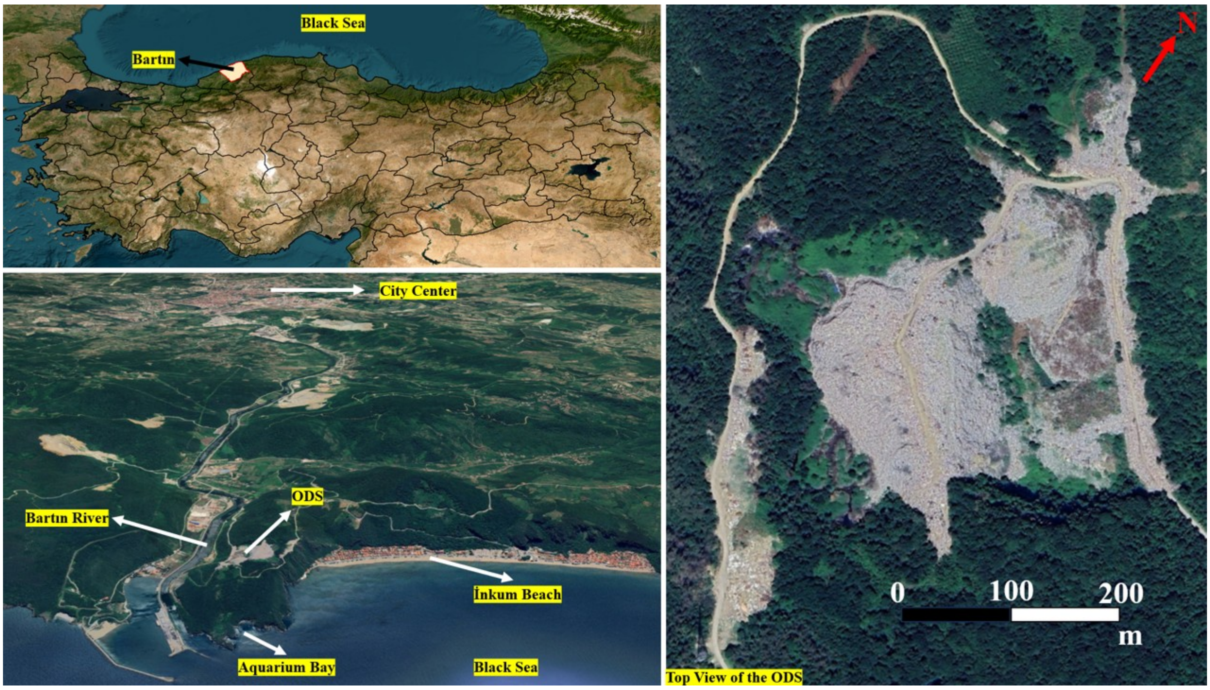

Figure 1: Study area.

Data and Methodology

Sentinel 2 satellite images were used in the study. The acquired images were at the L2A level. The workflow implemented for these images was presented in Figure 2. The images cover a four-year period from 2022 to 2025. All images were from September of the respective year. To work with surface reflectance values, each pixel in the spectral bands used to create the spectral indexes was divided by 10,000. After these spectral bands were stacked, an identically sized image segment was clipped from each image, including the ODS, and the evaluation was conducted on these image parts.

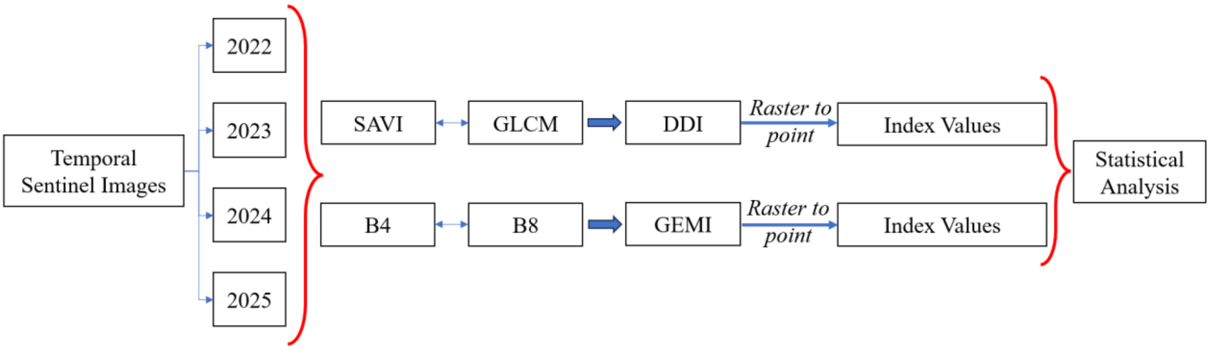

Figure 2: Applied methodology.

The DDI and GEMI indexes were used in the study. The DDI is an index developed for the identification of dumping sites. It is defined by the multiplication of entropy and the Soil

Adjusted Vegetation Index (SAVI) (Cadau et al., 2013). Entropy is a familiar concept in image processing, serving as a measure of image complexity. The entropy value in an image is typically calculated from the gray-level histogram of that image. While there are various methods to calculate entropy values, in this study, the entropy value for each image is calculated using the Gray Level Co-Occurrence Matrix (GLCM) technique. SAVI is an advanced version of NDVI. It provides clearer discrimination by better eliminating the effects of ground reflectance of soil (Xue and Su, 2017). In this context, unlike NDVI, it uses the L parameter, also known as the soil correction factor. The most commonly used L value in the literature is 0.5, which was also chosen in this study. The GLCM, SAVI, and DDI formulas are presented below.

$$Entropy = \sum_{j=0}^{N_g} \sum_{i=0}^{N_g} p(i,j) \times \log[p(i,j)] \quad (1)$$

where:

$p(i,j)$ is the GLCM value

N_g is the gray levels

$$SAVI = \frac{(NIR - Red) \times (1 + L)}{(NIR + Red + L)} \quad (2)$$

$$DDI = -SAVI \times Entropy^2 \quad (3)$$

The GEMI (Pinty and Verstraete, 1992), like SAVI, is an advanced version of NDVI, but its calculation is more complex. Unlike NDVI, it is less affected by atmospheric factors. Considering the same region, it offers a broader range of representation than NDVI. In the GEMI formula presented below, firstly the η factor is calculated using the RED and NIR bands. The index value is then determined using the calculated η factor and the RED band (Verstraete and Pinty, 2002). The multispectral images for each year and the corresponding index images were presented in Figure 3.

$$\eta = \frac{2(NIR^2 - RED^2) + 1.5 \cdot NIR + 0.5 \cdot RED}{NIR + RED + 0.5} \quad (4)$$

$$GEMI = \eta \cdot (1 - 0.25 \cdot \eta) - \frac{RED - 0.125}{1 - RED} \quad (5)$$

Where:

Ƞ is intermediate factor

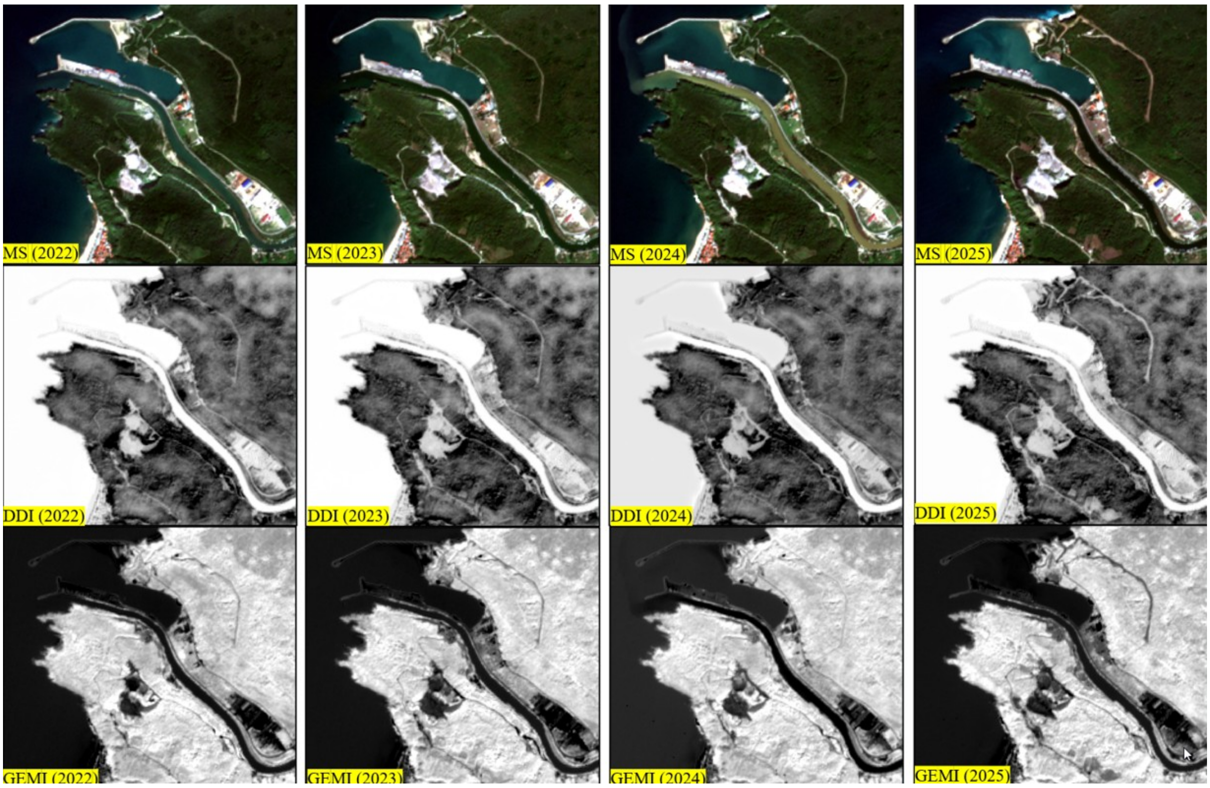

Figure 3: Multispectral, DDI, and GEMI images for four-year period.

Results and Discussion

To demonstrate the relationship between GEMI and DDI, image segments were obtained from each image in Figure 3, covering only the storage area and surrounding roads. DDI and GEMI images for ODS and its surroundings for different years are presented in Figure 4.

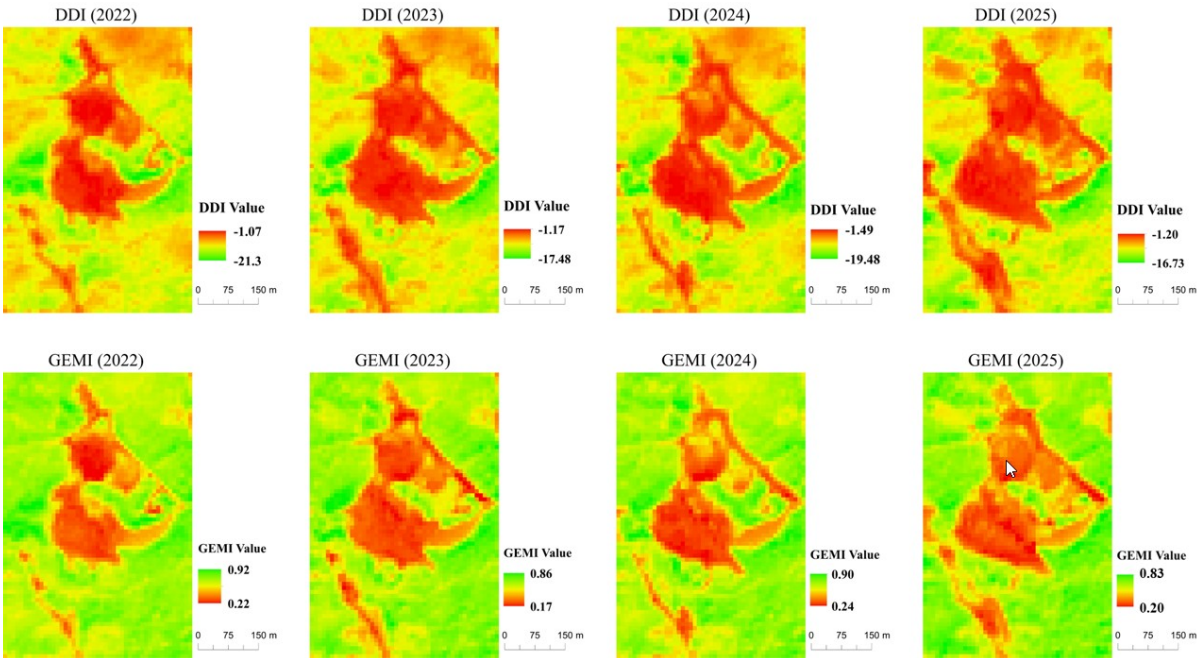

Figure 4: DDI and GEMI images only for ODS and its surroundings.

When the images in Figure 4 are examined, the irregular characteristics of ODS can be easily identified. It is expected that the amount of waste stored in a landfill will increase in a trend. For an ODS like in this study, because there is no controlled accumulation, the areas where waste is concentrated change over the years. It was observed that the storage area expanded from 2022 to 2023. Furthermore, waste accumulation can be observed on the access road in the lower left part of the ODS. The area represented in green in the middle of the ODS in 2023 (the area without waste) appeared to have grown in 2024. Considering that there is no actively operated landfill in Bartin, and waste accumulated in ODS during this period, the accumulation may have occurred to form a hill. However, in 2025, the green area in the middle of the site largely turns red, indicating an increase in waste accumulation in the ODS. The news reports in September 2024 for the province and field covered in the study were actually about the road extending from the bottom right of the field shown in Figure 3 towards the Bartin River. Due to maximum storage capacity of the ODS, approximately 1 km of waste had accumulated along this road, and the road was closed to traffic. Because the width of the road was lower than the spatial resolution of the image used, it could not be captured by the indexes. This situation highlights the need to provide higher-resolution images or enhance existing ones with super-resolution techniques for more effective monitoring. However, when the 2025 images are examined in Figure 4, it was clear that the amount of waste on the access road in the bottom left of the ODS increased significantly compared to previous years. All these evaluations demonstrated the importance of index images as a dataset for ODS monitoring. A comparison of DDI and GEMI revealed that, although DDI was designed to identify waste storage areas, GEMI alone provided more meaningful images. This was because the distinction between waste storage and vegetation was more pronounced in GEMI images.

For the statistical relationship between DDI and GEMI, points were generated from the images in Figure 4. Each pixel was represented by a point, as illustrated in Figure 5. This allowed the relationship between two datasets from the same year to be revealed because the values of pixels belonging to the same location in two images were obtained. It also enabled the creation of a graph of changes within each index over the years. The change graphs of the field values for both indices were presented comparatively in Figure 6. The average values calculated for each year based on the values in this graph are presented in Table 1. Scatter plots representing the relationship between DDI and GEMI were presented in Figure 7.

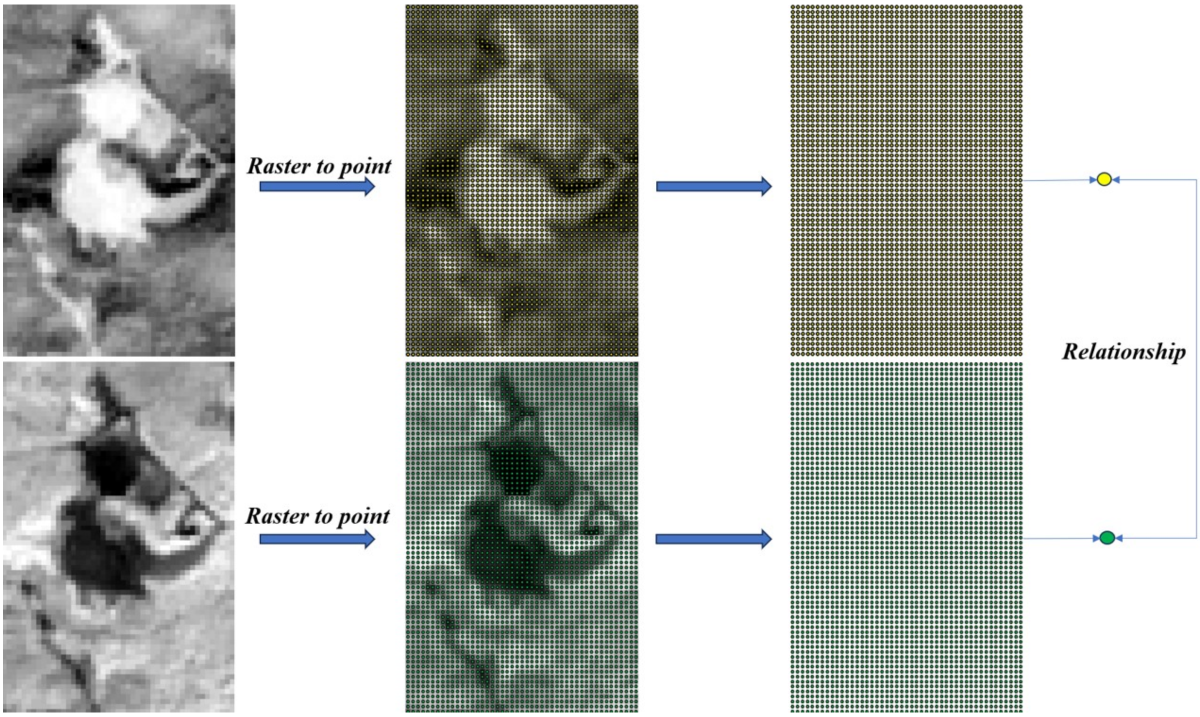

Figure 5: Generating points for each pixel of raster images.

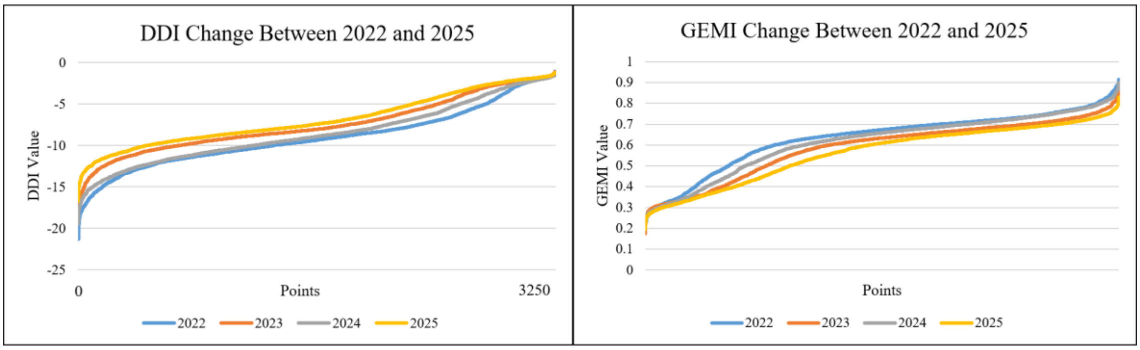

Figure 6: DDI and GEMI change graphs between 2022 and 2025.

Table 1: Average index values

Year	Average DDI	Average GEMI
2022	-9.0858	0.6339
2023	-7.5124	0.5873
2024	-8.5679	0.6149
2025	-6.9009	0.5631

The increasing trend of pixel index values for ODS and its surroundings was similar in both graphs. Because SAVI uses a negative sign when squaring entropy in the DDI formulation, regions closer to 0 represent areas where waste is deposited. The expansion of the site as waste is deposited means a decrease in surrounding vegetation. For this reason, the difference between the curves in the DDI graph was greater in the lower left corner of the graph. Similarly, for this reason, the difference between the curves was greater toward the end of the graph than in the middle. For GEMI, higher values represent vegetation, while lower values represent areas where waste is deposited. The reason the difference between the 2022 and 2025 curves in the GEMI graph was greater on the left, where the lower values are, is due to the expansion of the site as waste is deposited. The values in Table 1 support the assessments made for Figure 4. They were also consistent with the trend of the curves in the graphs in Figure 6. However, it is not always possible to clearly establish a relationship between the average value and the increase in waste volume in ODS. The main reason for this was that the spatial growth resulting from storage was not solely horizontal. The accumulation of waste, which formed a peak, prevented the average DDI value from being closer to 0 compared to the previous year, despite an increase in stored waste. The same situation also applied to GEMI.

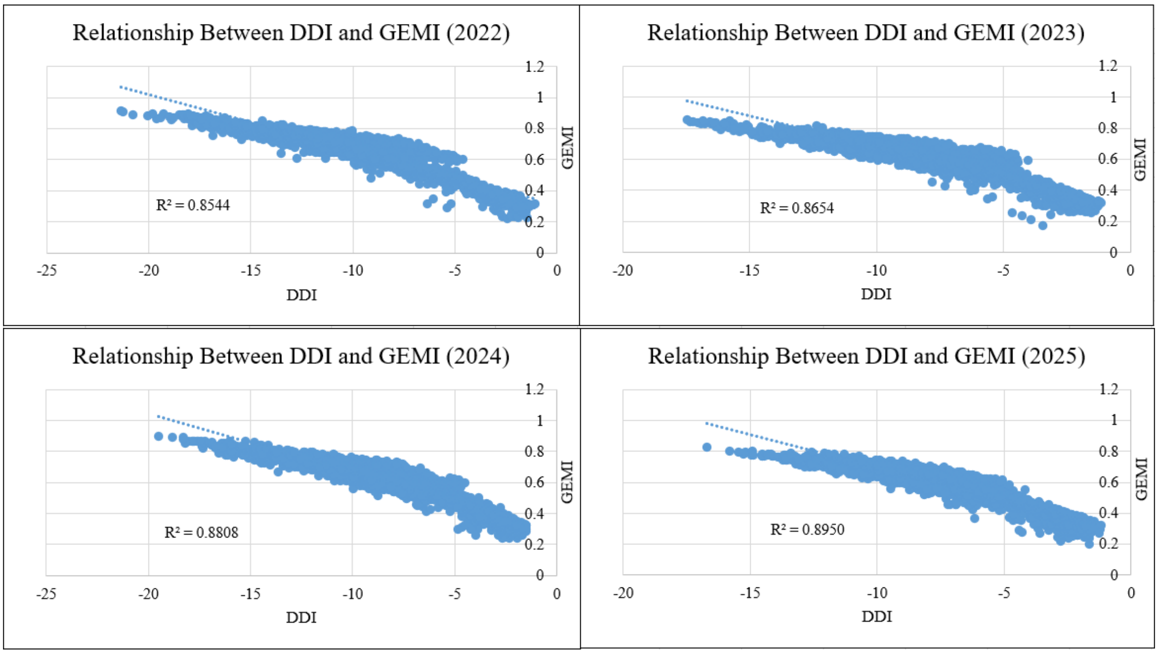

Figure 7: Scatter plots for DDI and GEMI.

It is known that no other storage area was used in Bartin during the period covered in this study, other than the ODS. Therefore, while ground expansion varied positively and negatively in different parts of the ODS over the years, the total amount of waste is known to have increased continuously from 2022 to 2025. In this context, the calculated R^2 values indicate that the correlation between DDI and GEMI is directly proportional to the amount of stored waste. This result suggests that DDI and GEMI will have a higher correlation for other ODSs with greater storage capacity.

Conclusion and Recommendation

Within the scope of the study, the DDI formulated for the detection of ODSs in the literature and the GEMI index, which was not sufficiently mentioned for the detection, monitoring, or mapping of ODSs, were discussed comparatively. The results obtained were evaluated by visual comparisons as well as statistical analysis. In addition to being free of charge like Landsat, Sentinel imagery's higher spatial resolution makes it more suitable for monitoring ODSs. The availability of Sentinel S2C, in particular, facilitates more rigorous monitoring at narrower temporal resolution intervals. However, it is also important that the indexes used for ODSs are correlated with LST. Sentinel is not as effective as Landsat in this aspect. Although the most significant environmental impact of the region studied in this study is solid waste dumped on the road providing access to the site, the spatial resolution limitation prevented a definitive determination. Solid waste storage in ODSs is a common occurrence in underdeveloped and developing countries. Increasing the resolution of existing imagery with deep learning techniques or directly acquiring high-resolution imagery will yield more reliable results.

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