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HISTORICAL DETECTION OF VEGETATION COVER CHANGES IN THE COASTAL AREA OF BATANG REGENCY (2010 - 2024) USING THE LANDTRENDR ALGORITHM

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ABSTRACT

Urbanization and large-scale infrastructure development are major drivers of vegetation cover changes in coastal areas, with significant implications for land-use planning and vegetation management. This study aims to detect and analyze historical vegetation cover changes in the coastal area of Batang Regency, Central Java, Indonesia, over the period 2010–2024 using the LandTrendr algorithm. The study area covers approximately 110 km² and is characterized by intensive development pressure from two major national strategic projects: the Batang Coal-Fired Power Plant (PLTU) and the Batang Integrated Industrial Zone (KITB). Vegetation changes were assessed using the Normalized Burn Ratio (NBR) as the spectral index, with the Greatest Change scenario applied to identify the segment of largest magnitude per pixel. Accuracy assessment was conducted using a 3×3 confusion matrix with 225 validation points through stratified random sampling. The results indicate an overall accuracy of 71.56% with a Kappa coefficient of 0.57. Over the study period, total vegetation gain reached 555.57 ha while total loss amounted to 338.13 ha, yielding a net positive change of +217.44 ha. Temporally, gain was dominant in the early observation period, peaking in 2010, while loss increased significantly after 2020 coinciding with active construction phases of PLTU and KITB. Spatially, 80.2% of total loss was concentrated in the PLTU and KITB zone, whereas gain was more dispersed across urban and riparian areas. These findings provide a spatial-temporal baseline for vegetation management and land-use planning in coastal areas facing intensive infrastructure development pressure.

Keywords *: Normalized Burn Rasio; Remote Sensing; Time-series analysis; LandTrendr; Land Cover Dynamics.*

1. INTRODUCTION

Urbanisation and industrialisation are the main drivers of land cover change in various regions. This situation is caused by increasing human needs, which result in land or vegetation being replaced by concrete (OECD, 2018; Ramadhan *et al.*, 2022; Sun, Linghu and Zhang, 2024). Changes in land cover can lead to the release of carbon stored in the soil. This will inevitably result in the soil being unable to sequester carbon and cause a decline in carbon stocks (Zhu *et al.*, 2022; W. Jiang *et al.*, 2024). Land cover changes that tend to remove vegetation will disrupt the carbon cycle and cause carbon emissions into the atmosphere to rise, which in turn triggers climate change (Lal, 2004). Detected changes in vegetation cover can subsequently be used as a basis for estimating carbon stock dynamics (Zhu *et al.*, 2022; W. Jiang *et al.*, 2024) and for developing emission mitigation strategies in coastal areas under pressure from intensive development (Hong *et al.*, 2024).

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Coastal areas are characterised by rapid urbanisation. Coastal regions are often densely populated (Smiraglia *et al.*, 2023) and possess abundant supporting resources (Zhai *et al.*, 2023). Consequently, coastal areas are frequently designated as growth centres, as is the case with the northern coast of Central Java. The northern coast of Central Java is one of the regions in Indonesia experiencing intense pressure for land conversion (Sanjoto, Ramadhan and Aji, 2025), in line with the rapid growth of industry and infrastructure along the northern coastal corridor of Java Island (*Pantura*), which directly threatens the sustainability of vegetation cover and carbon stocks in the region (Gandharum *et al.*, 2024).

Batang Regency has many new growth centres and is home to several large-scale development projects. These projects are the Coal-Fired Power Plant (PLTU) and the Batang Integrated Industrial Zone (KITB), both located on the northern side of Batang Regency, or the coastal area of Batang Regency (Pemerintah Kabupaten Batang, 2019). These two infrastructure projects are supported by arterial roads and the Pantura motorway, which improve accessibility to the area whilst accelerating land-use conversion pressures in the surrounding areas. The co-location of the PLTU and KITB in the northern coastal region of Batang creates intense and spatially concentrated land-use conversion pressures, which have the potential to cause significant impacts on vegetation cover and conditions in the area.

Monitoring changes in vegetation and land cover is a crucial step in understanding the dynamics of carbon stock changes and the impacts of ongoing development. Remote sensing-based approaches using satellite time-series analysis have proven effective for detecting historical land cover changes across extensive spatial areas, whilst addressing the limitations of bi-temporal classification methods that are prone to errors (Mugiraneza, Nascetti and Ban, 2020). One method that can be used is LandTrendr (*Landsat-based Detection of Trends in Disturbance and Recovery*), which can map vegetation change conditions across large, well-defined spatial areas (Kennedy *et al.*, 2018; Murakami and Tsutsumida, 2025). In this study, vegetation cover is not classified into discrete land cover types but is operationalized as spectral disturbance and recovery segments detected through changes in the Normalized Burn Ratio (NBR) over time. Using the LandTrendr algorithm, a decline in NBR is treated as vegetation loss and an increase as vegetation gain, consistent with established LandTrendr-based studies (Kennedy *et al.*, 2018; Umarhadi *et al.*, 2023). Among available time-series algorithms for vegetation detection such as CCDC and BFAST (Zhu, 2017), LandTrendr was selected for its use of annual composites, which enables disturbance and recovery events to be resolved and attributed to a specific year across a long-term record (Pasquarella *et al.*, 2022), making it well suited to detecting year-to-year vegetation change over the 15-year observation period of this study.

LandTrendr has been widely used to map changes in vegetation cover, proving effective in mapping vegetation dynamics in forest areas (Umarhadi *et al.*, 2023; P. Li *et al.*, 2024; Parracciani *et al.*, 2024), Mining areas (Xiao *et al.*, 2020; Xie *et al.*, 2024), and Urban areas (Yan and Wang, 2021; Murakami and Tsutsumida, 2025). Applications to coastal ecosystems have also emerged, though these have focused primarily on natural landscapes such as mangroves and wetlands (de Jong *et al.*, 2021), where vegetation change is largely driven by natural and climatic processes rather than anthropogenic land conversion. Research conducted to monitor vegetation changes in coastal regions, particularly in Indonesia, remains limited. In particular, no study has quantitatively documented the spatio-temporal dynamics of vegetation cover in a coastal area simultaneously subjected to two large-scale national strategic projects (a coal-fired power plant and an integrated industrial zone) over a 15-year observation period. Therefore, this study aims to detect and analyse historical vegetation changes in the coastal areas of Batang Regency during the period 2010–2024 using the LandTrendr algorithm. The novel contribution of this study lies not in the algorithm itself, but in its application to quantitatively document vegetation cover dynamics in a coastal landscape simultaneously experiencing co-located pressure from two major national strategic infrastructure projects over a 15-year period. The results of this study are expected to provide comprehensive spatio-temporal information as a basis for spatial planning and the management of coastal vegetation in areas experiencing the pressures of intensive infrastructure development.

2. STUDY AREA

The research was conducted in the coastal area of Batang Regency, Central Java Province (**Fig. 1**). The study area was defined based on the land system approach developed by the National Geospatial Information Agency (BIG), taking into account coastal geomorphological aspects, covering an area of 110 km² (Badan Informasi Geospasial, 2021). Geomorphologically, this area is characterised by low-lying terrain with relatively gentle coastal slopes and is composed of alluvial materials consisting of sandy loam and fine sand. The coastal area of Batang Regency faces significant development pressures from several sources, including the expansion of Batang City, the construction of the 2×1,000 MW Batang Coal-Fired Power Plant, and the 450-hectare Batang Integrated Industrial Zone (KITB). These conditions make the coastal area of Batang Regency a relevant location for studying the dynamics of land cover change resulting from large-scale development activities.

3. DATA AND METHODS

The study utilised Landsat imagery data within the Google Earth Engine (GEE) platform. Landsat imagery was used in this study because it is available as multitemporal data from 1972 to the present day, and is also available in multispectral format with consistent spatial resolution (30 metres) (Wulder *et al.*, 2022). The data used are Tier 1 surface reflectance products that have been atmospherically corrected by the USGS using the LEDAPS algorithm for Landsat 5–7 (Schmidt *et al.*, 2013) and LaSRC for Landsat 8–9 (Vermote *et al.*, 2018). Images were acquired between 1 May and 30 September each year to minimise the effects of cloud cover (Zhou *et al.*, 2025) and seasonal vegetation variations (Umarhadi *et al.*, 2023). Annual composites were created using median values, with masking applied to pixels identified as clouds, cloud shadows, and water bodies.

The spectral index used is the *Normalized Burn Ratio* (NBR). NBR was selected due to its high capability in detecting temporal changes in vegetation conditions, including reductions (loss) and increases (gain) in vegetation cover (Yu *et al.*, 2024). NBR values are derived from the Near-Infrared (NIR) band, which is sensitive to the canopy, and the shortwave infrared (SWIR2) band, which responds to water content in vegetation and soil (Alcaras *et al.*, 2022). When vegetation is disturbed, the NIR value decreases whilst the SWIR2 value increases, making changes in the NBR a sensitive indicator of both forest degradation and regeneration. The NBR is calculated using the following formula:

$$NBR = \frac{NIR - SWIR2}{NIR + SWIR2} \tag{1}$$

where NIR and SWIR2 denote the near-infrared and second shortwave-infrared bands, respectively (Key and Benson, 2006).

Band designations vary by Landsat sensor: for Landsat 4–5 (Thematic Mapper, TM) and Landsat 7 (Enhanced Thematic Mapper Plus, ETM+), NIR corresponds to Band 4 and SWIR2 to Band 7; for Landsat 8–9 (Operational Land Imager, OLI), NIR corresponds to Band 5 and SWIR2 to Band 7. All Landsat sensors used in this study were harmonised to a common surface reflectance scale prior to NBR calculation.

NBR was selected as the spectral index for this study following its established use as the default index in LandTrendr-based vegetation change detection since the algorithm's original development (Kennedy, Yang and Cohen, 2010). The sensitivity of NBR to canopy water content and structural vegetation dynamics allows for the detection of vegetation changes driven by various disturbance agents, extending its utility beyond burn severity assessment to processes such as land clearing for infrastructure development (Xiao *et al.*, 2020; de Jong *et al.*, 2021; Umarhadi *et al.*, 2023; H. Li *et al.*, 2024; Murakami and Tsutsumida, 2025). Although the LandTrendr algorithm can in principle be applied to any single spectral band or index (Kennedy, Yang and Cohen, 2010).

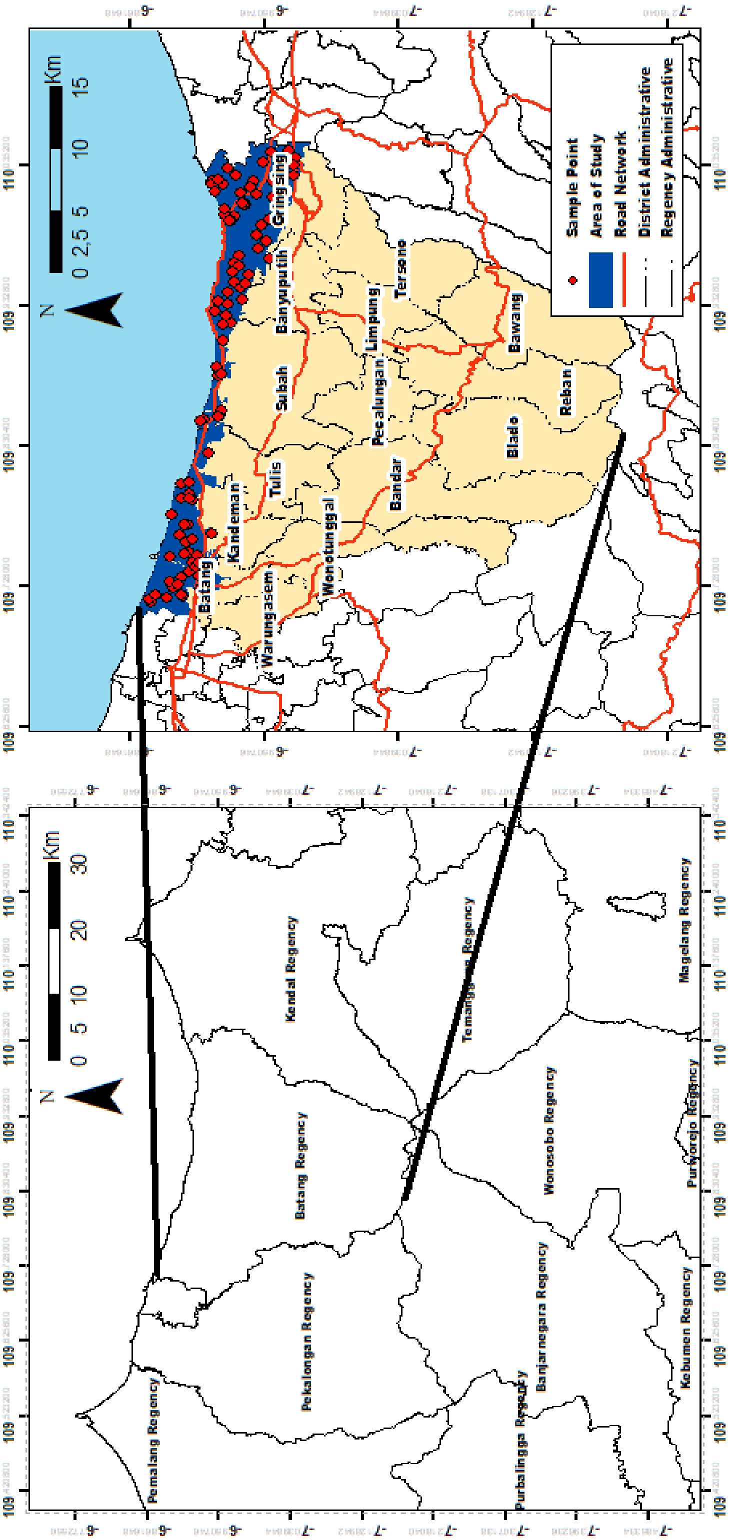

Fig. 1. Location of Batang Coastal Area.

A review of LandTrendr applications shows that NBR and NDVI are by far the most commonly used, whereas greenness-based indices such as the Enhanced Vegetation Index (EVI) and the Soil-Adjusted Vegetation Index (SAVI) rarely appear in the LandTrendr literature (Pasquarella *et al.*, 2022). Between NBR and NDVI, NBR has consistently been shown to be more sensitive to vegetation moisture and structural change, offering lower noise interference and higher detection accuracy than NDVI, which instead correlates more closely with vegetation greenness alone; this has been demonstrated both in forest disturbance mapping (Hislop *et al.*, 2019) and, more recently, in urban riparian vegetation subject to land clearing from urban development (Hislop *et al.*, 2025). As EVI and SAVI remain largely untested within the LandTrendr framework, their comparative performance for coastal and agricultural vegetation monitoring represents a direction for future research. As EVI and SAVI remain largely untested within the LandTrendr framework, their comparative performance for coastal and agricultural vegetation monitoring represents a direction for future research. While previous LandTrendr applications, such as Umarhadi *et al.*, (2023), were conducted in forested landscapes, NBR responds to the loss of green biomass and canopy structure regardless of vegetation type, supporting its use in the mixed coastal landscape of this study. However, NBR is comparatively less sensitive to gradual phenological changes, such as those associated with paddy field cultivation cycles, than indices such as NDVI. This limitation is discussed further in relation to the accuracy assessment results

Changes in vegetation cover were detected using the LandTrendr algorithm. LandTrendr was selected for its ability to detect long-term spectral changes in Landsat time-series data, including both abrupt and gradual changes (Kennedy *et al.*, 2018). This algorithm works by simplifying annual spectral trajectories into linear segments, so that significant changes can be identified temporally at each pixel. Specifically, for each pixel, LandTrendr fits a series of straight-line segments to the annual NBR trajectory by iteratively identifying candidate breakpoints, referred to as vertices, that mark the start and end of periods of stability, recovery, or disturbance. Among the candidate vertex sets, the algorithm selects the best-fitting segmentation using an F-statistic-based model selection procedure, which balances model fit against model complexity to avoid overfitting spurious short-term noise. The resulting output for each pixel is an array recording, for every year in the time series, the observed spectral value, the fitted (segmented) value, and an indicator of whether that year corresponds to a vertex. This structure allows the magnitude, duration, and timing of each detected disturbance or recovery segment to be extracted, which forms the basis for the parameter choices summarised in **Table 1**. Implementation was carried out using the LT-GEE module within the Google Earth Engine platform with the following parameters.

Table 1.

Used Parameters.

Parameter	Value	Description
Maximum Segments	6	Maximum number of spectral trajectory segments
Spike Threshold	0.9	Threshold for spike removal in the trajectory
Vertex Count Overshoot	3	Number of extra vertices to consider during fitting
Prevent One-Year Recovery	True	Prevent segments from recovering in a single year
Recovery Threshold	0.25	Maximum rate of spectral recovery allowed
P-value Threshold	0.05	Significance threshold for best-fit model selection
Best Model Proportion	0.75	Proportion of vertices for best-fit model
Min Observations Needed	6	Minimum observations required for fitting

The output from LandTrendr consists of values representing gain and loss in vegetation cover. The 'Greatest Change' scenario is used to identify segments with the greatest magnitude of change at each pixel. Each pixel is counted only once based on the year in which the change was detected, so that the annual area values are exclusive and do not overlap between periods. A new change is detected when there are 5 pixels of change (0.45 hectares). A loss is detected when there is a temporal decrease in the NBR value, indicating vegetation cover degradation, whilst a gain is detected when the NBR value rises.

Accuracy testing was carried out through visual inspection using Google Earth to evaluate the detection results of the LandTrendr algorithm. The visual assessment was conducted taking into account the availability of historical high-resolution imagery on the Google Earth platform for the relevant year. The accuracy of the detection results was evaluated using a 3×3 confusion matrix covering three classes: loss, gain, and no-change, with the metrics Overall Accuracy (OA), User Accuracy (UA), Producer Accuracy (PA), and the Kappa coefficient. A total of 225 test points were determined through stratified random sampling with an even allocation of 75 points per class.

The 75-points-per-class allocation exceeds the widely applied rule-of-thumb minimum of 50 samples per class for thematic accuracy assessment (Congalton, 1991), and the overall sample size and allocation scheme is further consistent with the approach used by Umarhadi *et al.*, (2023), who applied the same NBR-based LandTrendr approach to validate forest loss and gain in an Indonesian social-forestry landscape using 75 stratified random points per class (150 points total), achieving overall accuracies of 78.67% for loss and 85.33% for gain; the present study extends this per-class allocation to a third class (no-change), yielding 225 points in total. While proportional allocation is generally recommended for unbiased area estimation (Olofsson *et al.*, 2014), equal allocation was adopted here to ensure adequate representation of the minority change classes (gain and loss), which are of primary interest in this study; the corresponding trade-off for area-weighted precision is acknowledged in the Limitations paragraph.

4. RESULT

4.1. Validation of LandTrendr Algorithm

Validation was carried out using a 3×3 confusion matrix on 225 test points within a study area of 110 km². The test results showed an Overall Accuracy (OA) of 71.56% with a Kappa coefficient of 0.57 (**Table 2**). These values represent the accuracy of the cumulative 2010–2024 change classification, in which each pixel is assigned to its class of greatest change magnitude over the full observation period, rather than to a specific year.

Table 2.

Results of the LandTrendr Algorithm Validation Testing.

Prediction\ Reference	Loss	Gain	No-Change	Total	UA (%)
Loss	55	10	10	75	73.33
Gain	5	59	11	75	78.67
No-Change	8	20	47	75	62.67
Total	68	89	68	225	
PA (%)	80.88	66.29	69.12		
Overall Accuracy (Oa): 71.56% Kappa: 0.57					

The highest User Accuracy (UA) was obtained for the gain class (78.67%), followed by the loss class (73.33%) and the no-change class (62.67%). The highest Producer Accuracy (PA) was obtained for the loss class (80.88%), followed by the no-change class (69.12%) and the gain class (66.29%). This pattern indicates that the reduction class is detected most effectively, as land clearing is sudden in nature and results in a sharp decline in NBR values. The primary source of error lies between the gain and no-change classes: as many as 20 actual gain points were classified as no change, leading to the low PA for the gain class. This is likely due to the gradual nature of vegetation growth, making it difficult to distinguish from stable land cover conditions. The relatively low PA for the gain class (66.29%) suggests that vegetation gain estimates in this study should be interpreted as a lower bound, as gradual vegetation recovery may be partially misclassified as no-change.

4.2. Temporal Change in Vegetation Cover

LandTrendr modelling provides information on land cover changes in the coastal areas of Batang Regency for the period 2010–2024. Land cover changes were assessed by evaluating changes in the Normalized Burn Ratio (NBR) within the study area. NBR values are sensitive to vegetation conditions and density. Three parameters such as : duration, magnitude, and timing of change were used to assess land cover changes. The temporal modelling results indicate that gains tended to occur at the start of the observation period, whilst loss tended to occur after 2020. This temporal pattern forms the basis for further analysis to identify the relationship between land cover change dynamics and development activities in the study area.

Temporal modelling results reveal differing patterns between gain areas and loss. Gain areas tended to dominate at the start of the observation period, peaking in 2010 at 168.7 ha, whilst loss areas began to rise significantly from the mid-period, reaching their peak in 2020 (73.6 ha) and 2023 (71.6 ha). These differences in temporal patterns indicate the presence of distinct driving factors between vegetation gain and loss in Batang Regency (**Fig. 2**).

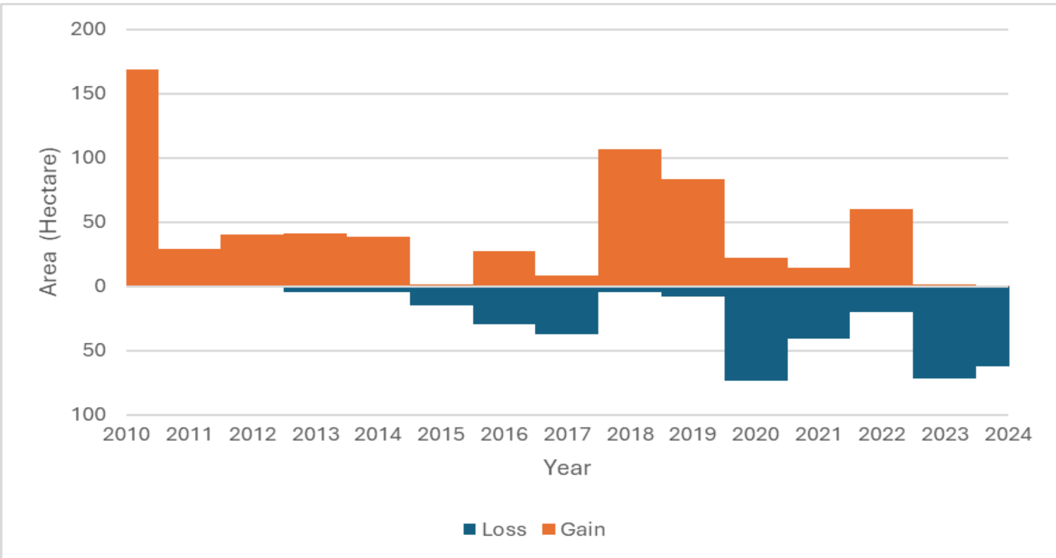

Fig. 2. Loss and Gain Trends.

The gain observed in Batang Regency fluctuated throughout the observation period. The largest gain occurred in 2010 (168.7 ha), after which the figure declined. In the last two years of the observation period (2023: only 1.4 ha, and 2024: only 0.6 ha), there was no significant gain. The dominant gain in vegetation at the start of the observation period (2010) is thought to be linked to revegetation and greening activities in urban areas and along riverbanks. In subsequent periods, the gain in vegetation in Batang City has been in line with the Batang Regency Government's greening programmes, including the Green Batang Movement and the Rajawali Urban Forest. (Antara Jawa Tengah, 2017; Dinas Komunikasi dan Informatika Kabupaten Batang, 2017).

The area of vegetation loss in Batang Regency has shown a significant increase since the mid-point of the observation period. vegetation loss rates began to rise between 2015 and 2017, coinciding with the active construction phase of the Batang Coal-Fired Power Plant (Wiangga, 2017), before surging sharply in 2020 (73.6 ha) and 2023 (71.6 ha) following the commencement of construction of the KITB (Bisnis.com Semarang, 2020). This pattern is consistent with land clearing activities during the construction phases of these two large-scale projects, though confounding factors such as agricultural land conversion and informal settlement expansion cannot be fully excluded without ground-truth verification. This situation is exacerbated by the fact that the rate of loss since 2020 has consistently exceeded the rate of gain, indicating that the changes occurring are permanent and have not yet been offset by vegetation recovery.

4.3. Spatial Pattern in Vegetation Change

Spatially, there are distinct patterns between gain and losses (**Fig. 3**). Gain tend to be scattered across the coastal areas of Batang Regency, whilst loss tend to be concentrated around the coal-fired power plant (PLTU) and the Batang Integrated Industrial Zone (KITB), as well as in the city of Batang. These differing patterns are due to variations in the driving factors associated with the gains and losses. Loss is more heavily influenced by anthropogenic activities, whilst gain tends to be associated with revegetation and revegetation processes. Overall, the study area recorded a positive net change, with a total gain of 555.57 ha and a loss of 338.13 ha during the observation period (**Table 3**).

The greatest reduction was observed at the sites of the coal-fired power plant and the Integrated Industrial Zone. The presence of these facilities reflects anthropogenic pressure as centres of economic activity in the coastal area. This reduction is also linked to the construction of the coal-fired power plant and the Integrated Industrial Zone, which took place in 2020. The total loss detected reached 271.08 ha, equivalent to 80.2% of the total loss along the coast of Batang Regency. The loss began to increase significantly from 2015 and peaked in 2020 (52.29 ha), 2023 (61.38 ha), and 2024 (51.39 ha). There was also a gain in vegetation within the PLTU and KITB areas of 261.09 ha, peaking in 2019 (59.13 ha) and 2022 (55.62 ha), attributed to vegetation planting in open areas within the site.

Table 3.

Accumulative Change in Coastal Batang.

Zone	***Gain (ha)***	***Loss (ha)***	***Net (ha)***
PLTU & KITB	261.09	271.08	-9.99
Batang City	100.71	27.81	+72.90
Outside both Zone	193.77	39.24	+154.53
Total	**555.57**	**338.13**	**+217.44**

The pattern of gain is randomly distributed. The trend of gain is observed in areas around river courses and in the city of Batang. The city of Batang tends to show a gain in vegetation cover. The gain in vegetation in the city of Batang was particularly significant in 2010 (68.85 ha), accounting for 68.3% of the total gain in the city. The gain observed in Batang City may be attributed to revegetation programmes. Loss was relatively low throughout the observation period, peaking in 2020 (14.13 ha), which is likely linked to the expansion of built-up areas in the urban region.

Vegetation recovery in the areas surrounding the river is also supported by the rice fields located in the coastal region of Batang Regency. Gains are observed in several rice field areas, which is likely due to variations in planting times from year to year. The algorithm used in the study captures agricultural activity as a gain in vegetation cover; this is because dynamic agricultural activity can be identified by LandTrendr (J. Jiang *et al.*, 2024). The loss observed is also quite low, suggesting that anthropogenic pressure remains concentrated in the areas of the coal-fired power plant (PLTU) and the Batang Integrated Industrial Zone (KITB). Urban activity has not yet occurred on a large scale; consequently, in other areas outside Batang City, the PLTU, and the KITB, the final values tend to be positive, with a gain of 193.77 ha and a reduction of only 39.24 ha.

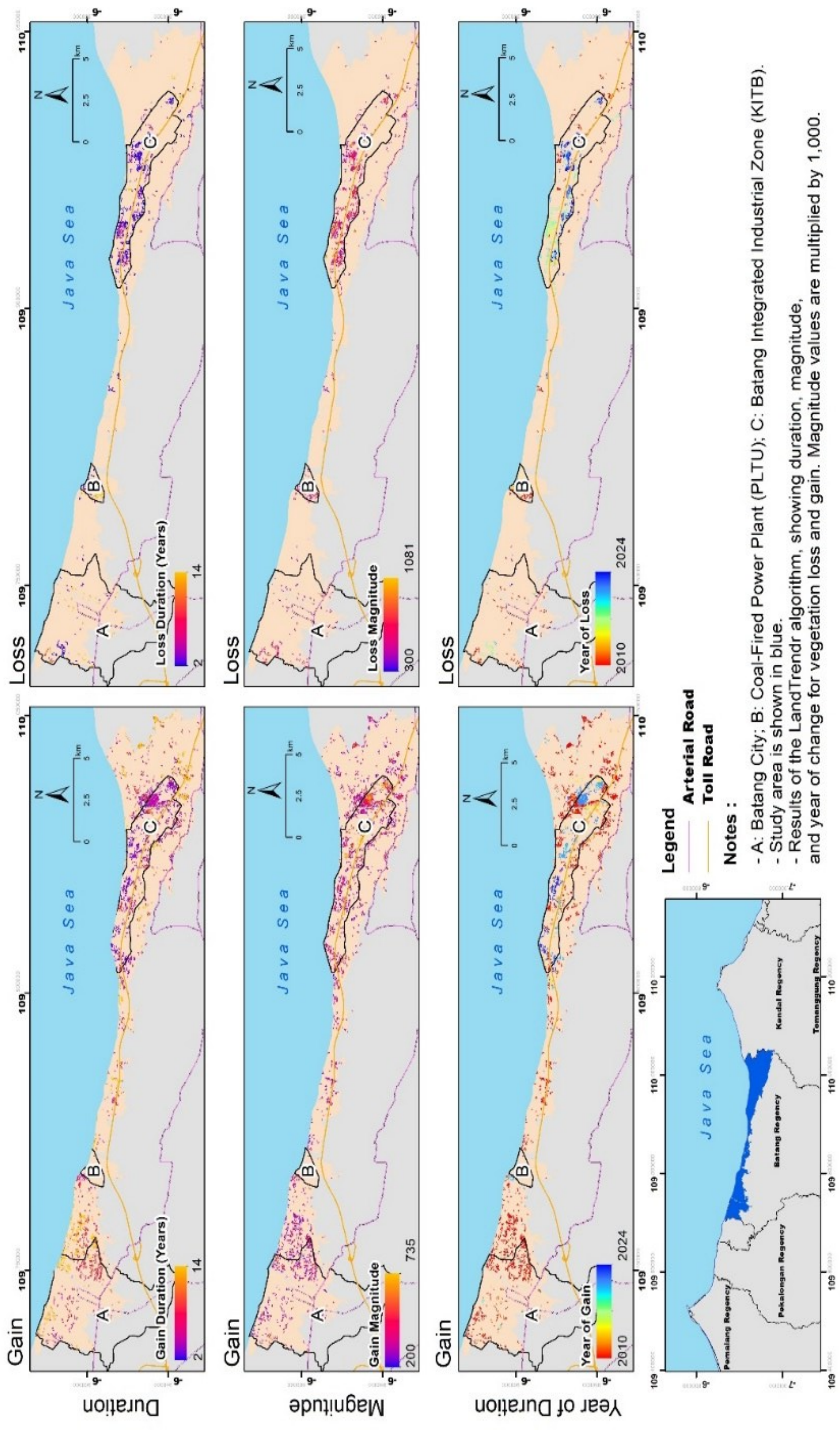

Fig.3. Map of Changes along the Coast of Batang Regency.

5. DISCUSSION

This study demonstrates that the LandTrendr algorithm can be used to detect the development of urban activity and changes in land cover. One observable pattern is the impact of new economic hubs, such as coal-fired power plants and Integrated Industrial Zones. The development of economic hubs tends to lead to a reduction in vegetation, which is subsequently followed by an increase in vegetation. Infrastructure development, as an indicator of urban activity, can be effectively identified using the LandTrendr algorithm due to the clearing of vegetated land, which causes changes in the NBR value. This phenomenon was also investigated by Hu et al., (2024) who used the LandTrendr algorithm to identify developments in Beijing. The increase resulting from planting processes indicates that the LandTrendr algorithm needs to be applied annually over a long period. A long time series can be used to better identify patterns of change (Kennedy *et al.*, 2018; Xu *et al.*, 2024).

This study utilised Landsat 5, 7, 8 and 9 imagery from 2010 to 2024. Landsat was chosen due to its long-term data record, despite its spatial resolution of only 30 metres. Consequently, vegetation detection is only feasible over large areas (Cao *et al.*, 2025). Landsat was chosen because the study area covers nearly 110 km², necessitating medium spatial resolution to ensure effective and efficient data processing (Gong *et al.*, 2013; Wulder *et al.*, 2022). The year 2010 was selected to observe developments over the preceding 15-year period and as it marked the initial year of the coal-fired power plant's implementation (Ismail, 2014).

Reported accuracy for LandTrendr-based change detection varies considerably across the literature and depends strongly on land-cover context. In relatively homogeneous forest settings, overall accuracies of 89–96% (Kappa 0.77–0.91) have been reported for disturbance and recovery detection (Cao *et al.*, 2025), and accuracies of 84% (disturbance) and 81% (reclamation) have been reported for a coal-mining disturbance study using LandTrendr on Google Earth Engine (Xiao *et al.*, 2020).

A methodologically closer precedent is Umarhadi *et al.*, (2023), who applied the same NBR-based LandTrendr approach and the same 75-points-per-class sampling design used in this study to a social-forestry landscape in Indonesia, reporting overall accuracies of 78.67% for loss and 85.33% for gain. In more heterogeneous, mixed land-cover settings closer to the present study, reported accuracies are lower still: Xie et al. (2024) obtained 71.25% (Kappa 0.67) for disturbance-year detection and 76.92% (Kappa 0.72) for restoration-year detection in abandoned open-pit mining landscapes, and a global comparative assessment of change-detection algorithms found that LandTrendr's best-performing configuration achieved an F1 score of only 71.29% for urban change detection (Murakami and Tsutsumida, 2025). The Overall Accuracy obtained in this study (71.56%) therefore falls within the range reported for LandTrendr applications in heterogeneous, non-forest-dominated landscapes, and is closely comparable to the 71.25–71.29% accuracy reported by Xie *et al.*, (2024) and Murakami and Tsutsumida, (2025), rather than being anomalously low. The comparatively lower accuracy relative to forest-dominated studies is consistent with the mixed coastal, urban, and agricultural land cover of Batang Regency, where the NBR signal is more heterogeneous across land-cover types.

The loss and gain observed in Batang Regency are influenced by various policy and development factors. These findings are consistent with those of Yang et al., (2021) who found that in urban areas of China, vegetation tends to gain in city centres due to greening program, but undergoes significant degradation in areas of expansion and new development. A similar pattern has been identified in Batang Regency, showing a gain in vegetation cover associated with greening programmes in urban areas and along riverbanks, whilst loss is concentrated in coastal infrastructure expansion zones driven by the construction of coal-fired power plants and the Batang Integrated Industrial Zone. This indicates that the dynamics of land cover change in Batang result from the interaction between development pressures and concurrent vegetation restoration efforts. The spatial distribution of these changes across the study area is shown in **Fig. 3**.

6. LIMITATION AND FUTURE WORKS

The areas surrounding the coal-fired power plant and the KITB are subject to dynamic changes in land cover. Further monitoring can utilise data from Sentinel-2 (10-metre spatial resolution) and focus on the areas of the coal-fired power plant and the KITB. Construction work at the coal-fired power plant and the KITB has been ongoing since 2015; consequently, the process of vegetation recovery requires careful attention in light of the ongoing development.

Land-use planning must take into account the resulting impacts. The LandTrendr algorithm has proven to be a useful tool for monitoring these impacts. The provision of vegetation buffer zones around coal-fired power plants and industrial complexes is a key mitigation measure required to counteract the significant reduction in vegetation cover. Furthermore, urban greening programmes are beneficial in maintaining vegetation cover, and can therefore serve as a mitigation measure against rising carbon emissions (Bherwani, Banerji and Menon, 2024). Collaboration between local government, Integrated Industrial Zone managers, and local stakeholders is considered vital in developing strategies for the sustainable management of coastal vegetation.

Several limitations of this study warrant acknowledgement. A primary constraint is the 30 m spatial resolution of the Landsat imagery employed, which limits the detection of fine-scale vegetation change, particularly along narrow riparian corridors and small urban green patches. A further source of uncertainty arises from the validation approach: accuracy assessment relied on visual interpretation of historical high-resolution imagery in Google Earth rather than field-based ground-truthing, which was not feasible across a 15-year historical record; this approach may introduce interpretation uncertainty, particularly for subtle vegetation changes. Additionally, the relatively low Producer's Accuracy obtained for the gain class (66.29%) indicates a risk of confusion between gradual vegetation recovery and stable land cover, attributable in part to the phenological cycles of paddy fields being registered as apparent vegetation gain by the LandTrendr algorithm. Gain estimates reported here should therefore be interpreted as a lower bound. The selection of 2010 as the baseline year, intended to capture approximately 15 years of change encompassing the period of major infrastructure development, may also introduce an edge effect, as vegetation dynamics immediately preceding the observation window could not be captured. Finally, although the equal-allocation sampling design (75 points per class) is consistent with Umarhadi *et al.*, (2023) and appropriate for characterising minority change classes, it may affect the precision of area-weighted accuracy estimates relative to the proportional allocation approach recommended by Olofsson *et al.*, (2014). Future studies aiming to produce area estimates with quantified uncertainty should therefore consider adopting proportional allocation. The comparative performance of alternative spectral indices, such as EVI and SAVI, within the LandTrendr framework likewise remains unexplored and constitutes a direction for future research.

7. CONCLUSIONS

The LandTrendr algorithm can be used to monitor changes in land cover occurring along the coast of Batang Regency. Land cover monitoring is carried out using changes in NBR values as a proxy for changes in vegetation cover; thus, the primary indicator used is existing vegetation cover.

Results for the coastal areas of Batang Regency show patterns of vegetation gain and loss that vary both spatially and temporally. Vegetation gain tended to occur at the start of the observation period, whilst loss occurred during the implementation of the PLTU and KITB development programmes in 2020. Spatially, it is evident that the loss was concentrated in the PLTU and KITB areas, whilst the gain tended to be spread more evenly. Vegetation gain was influenced by the greening programme in Batang City and changes to existing rice fields. Quantitatively, total gain reached 555.57 ha with a reduction of 338.13 ha, with the PLTU and KITB areas accounting for 80.2% of the total loss. It is hoped that these findings will serve as a basis for spatial planning and coastal vegetation management, particularly in responding to the pressures of intensive infrastructure development in the coastal areas of Batang Regency. Future monitoring of the PLTU and KITB areas is essential as development programmes are still ongoing. While the findings are specific to Batang Regency, the analytical framework applied here may be transferable to other coastal areas experiencing comparable large-scale infrastructure pressures.

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REFERENCES

Alcaras, E. *et al.* (2022) "Normalized Burn Ratio Plus (NBR+): A New Index for Sentinel-2 Imagery," *Remote Sensing*, 14(7), pp. 1–19. Available at: https://doi.org/10.3390/rs14071727.

Antara Jawa Tengah (2017) "Batang Siap Memperluas Wilayah Terbuka Hijau." Available at: https://jateng.antaranews.com/berita/174680/batang-siap-memperluas-wilayah-terbuka-hijau.

Badan Informasi Geospasial (2021) "Ina-LandSystem: Informasi Geospasial Tematik Sistem Lahan Skala 1:50.000." Cibinong, Indonesia.

Bherwani, H., Banerji, T. and Menon, R. (2024) "Role and value of urban forests in carbon sequestration: review and assessment in Indian context," *Environment, Development and Sustainability*, 26(1), pp. 603–626. Available at: https://doi.org/10.1007/s10668-022-02725-5.

Bisnis.com Semarang (2020) "Pembangunan Kawasan Industri Terpadu Batang Dipacu." Available at: https://semarang.bisnis.com/read/20201223/536/1334916/pembangunan-kawasan-industri-terpadu-batang-dipacu.

Cao, P. *et al.* (2025) "Using LandTrendr to analyze forest disturbance, recovery, and attribution in Hunan province from 2001 to 2024," *Ecological Indicators*, 176(May), p. 113712. Available at: https://doi.org/10.1016/j.ecolind.2025.113712.

Congalton, R.G. (1991) "A review of assessing the accuracy of classifications of remotely sensed data," *Remote Sensing of Environment*, 37(1), pp. 35–46. Available at: https://doi.org/10.1016/0034-4257(91)90048-B.

Dinas Komunikasi dan Informatika Kabupaten Batang (2017) "Hutan Rajawali Destinasi Baru Masyarakat Kota Batang." Available at: https://berita.batangkab.go.id/detail/108/hutan-rajawali-destinasi-baru-masyarakat-kota-batang.

Gandharum, L. *et al.* (2024) "Past and future land use change dynamics: assessing the impact of urban development on agricultural land in the Pantura Jabar region, Indonesia," *Environmental Monitoring and Assessment*, 196(7). Available at: https://doi.org/10.1007/s10661-024-12819-4.

Gong, P. *et al.* (2013) "Finer resolution observation and monitoring of global land cover: First mapping results with Landsat TM and ETM+ data," *International Journal of Remote Sensing*, 34(7), pp. 2607–2654. Available at: https://doi.org/10.1080/01431161.2012.748992.

Hislop, S. *et al.* (2019) "A fusion approach to forest disturbance mapping using time series ensemble techniques," *Remote Sensing of Environment*, 221(November 2018), pp. 188–197. Available at: https://doi.org/10.1016/j.rse.2018.11.025.

Hislop, S. *et al.* (2025) "Monitoring Riparian Vegetation in Urban Areas With Sentinel-2 Satellite Imagery," *Ecological Management & Restoration*, 26(1). Available at: https://doi.org/10.1111/emr.12624.

Hong, W. *et al.* (2024) "Spatiotemporal changes in urban forest carbon sequestration capacity and its potential drivers in an urban agglomeration: Implications for urban CO2 emission mitigation under China's rapid urbanization," *Ecological Indicators*, 159(January), p. 111601. Available at: https://doi.org/10.1016/j.ecolind.2024.111601.

Hu, T. *et al.* (2024) "Extraction of Building Construction Time Using the LandTrendr Model With Monthly Landsat Time Series Data," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 17, pp. 18335–18350. Available at: https://doi.org/10.1109/JSTARS.2024.3409157.

Ismail, I. (2014) "KENDALA INVESTASI DI ERA OTONOMI DAERAH (Studi Kasus Pembangunan Proyek PLTU di Kabupaten Batang) Isa Ismail," 5(1).

Jiang, J. *et al.* (2024) "A Cropland Disturbance Monitoring Method Based on Probabilistic Trajectories," *Remote Sensing*, 16(21). Available at: https://doi.org/10.3390/rs16214048.

Jiang, W. *et al.* (2024) "Land use changes in the Min River basin and their impact on carbon storage," *Journal of King Saud University - Science*, 36(9), p. 103404. Available at: https://doi.org/10.1016/j.jksus.2024.103404.

de Jong, S.M. *et al.* (2021) "Mapping mangrove dynamics and colonization patterns at the Suriname coast using historic satellite data and the LandTrendr algorithm," *International Journal of Applied Earth Observation and Geoinformation*, 97(November 2020), p. 102293. Available at: https://doi.org/10.1016/j.jag.2020.102293.

Kennedy, R.E. *et al.* (2018) "Implementation of the LandTrendr algorithm on Google Earth Engine," *Remote Sensing*, 10(5), pp. 1–10. Available at: https://doi.org/10.3390/rs10050691.

Kennedy, R.E., Yang, Z. and Cohen, W.B. (2010) "Detecting trends in forest disturbance and recovery using yearly Landsat time series: 1. LandTrendr - Temporal segmentation algorithms," *Remote Sensing of Environment*, 114(12), pp. 2897–2910. Available at: https://doi.org/10.1016/j.rse.2010.07.008.

Key, C. and Benson, N. (2006) "Landscape Assessment: Ground measure of severity, the Composite Burn Index; and Remote sensing of severity, the Normalized Burn Ratio.," in *FIREMON: Fire Effects Monitoring and Inventory System*, p. LA 1-51.

Lal, R. (2004) "Soil carbon sequestration to mitigate climate change," *Geoderma*, 123(1–2), pp. 1–22. Available at: https://doi.org/10.1016/j.geoderma.2004.01.032.

Li, H. *et al.* (2024) "Identification of urban waterlogging indicators and risk assessment based on MaxEnt Model: A case study of Tianjin Downtown," *Ecological Indicators*, 158(December 2023), p. 111354. Available at: https://doi.org/10.1016/j.ecolind.2023.111354.

Li, P. *et al.* (2024) "Mapping planted forest age using LandTrendr algorithm and Landsat 5–8 on the Loess Plateau, China," *Agricultural and Forest Meteorology*, 344(June 2023), p. 109795. Available at: https://doi.org/10.1016/j.agrformet.2023.109795.

Mugiraneza, T., Nascetti, A. and Ban, Y. (2020) "Continuous monitoring of urban land cover change trajectories with landsat time series and landtrendr-google earth engine cloud computing," *Remote Sensing*, 12(18). Available at: https://doi.org/10.3390/RS12182883.

Murakami, T. and Tsutsumida, N. (2025) "Comparative Global Assessment and Optimization of LandTrendr, CCDC, and BFAST Algorithms for Enhanced Urban Land Cover Change Detection Using Landsat Time Series," *Remote Sensing*, 17(14), pp. 4–6. Available at: https://doi.org/10.3390/rs17142402.

OECD (2018) "Monitoring Land Cover Change." OECD Paris, France.

Olofsson, P. *et al.* (2014) "Good practices for estimating area and assessing accuracy of land change," *Remote Sensing of Environment*, 148, pp. 42–57. Available at: https://doi.org/10.1016/j.rse.2014.02.015.

Parracciani, C. *et al.* (2024) "Land cover changes in grassland landscapes: combining enhanced Landsat data composition, LandTrendr, and machine learning classification in google earth engine with MLP-ANN scenario forecasting," *GIScience and Remote Sensing*, 61(1). Available at: https://doi.org/10.1080/15481603.2024.2302221.

Pasquarella, V.J. *et al.* (2022) "Demystifying LandTrendr and CCDC temporal segmentation," *International Journal of Applied Earth Observation and Geoinformation*, 110(April). Available at: https://doi.org/10.1016/j.jag.2022.102806.

Pemerintah Kabupaten Batang (2019) "Rencana Tata Ruang Wilayah Kabupaten Batang Tahun 2019 - 2039." Indonesia: Peraturan Daerah Kabupaten Batang.

Ramadhan, M.F. *et al.* (2022) "Study of Methane Gas Emissions from Agricultural Activities and its Coping Strategies in Bedog Sub-watershed," *IOP Conference Series: Earth and Environmental Science*, 1039(1). Available at: https://doi.org/10.1088/1755-1315/1039/1/012014.

Sanjoto, T.B., Ramadhan, M.F. and Aji, A. (2025) "Modeling land cover dynamics using Markov chain and cellular automata in Batang Regency," *Ecological Engineering and Environmental Technology*, 26(2), pp. 342–350. Available at: https://doi.org/10.12912/27197050/199460.

Schmidt, G. *et al.* (2013) *Landsat ecosystem disturbance adaptive processing system (LEDAPS) algorithm description*.

Smiraglia, D. *et al.* (2023) "The Increasing Coastal Urbanization in the Mediterranean Environment: The State of the Art in Italy," *Land*, 12(5). Available at: https://doi.org/10.3390/land12051017.

Sun, P., Linghu, L. and Zhang, M. (2024) "Relationship between regional economic development and its associated land use changes: A case study of Shaanxi province in China," *World Development Sustainability*, 4(December 2023), p. 100122. Available at: https://doi.org/10.1016/j.wds.2023.100122.

Umarhadi, D.A. *et al.* (2023) “Monitoring forest gain and loss based on LandTrendr algorithm and Landsat images in KTH Pati social forestry area, Indonesia,” *Journal of Applied and Natural Science*, 15(3), pp. 1051–1060. Available at: https://doi.org/10.31018/jans.v15i3.4781.

Vermote, E. *et al.* (2018) “LASRC (Land Surface Reflectance Code): Overview, application and validation using MODIS, VIIRS, LANDSAT and Sentinel 2 data’s.,” *International Geoscience and Remote Sensing Symposium (IGARSS)*, pp. 8173–8176.

Wiangga, L.S. (2017) “Pembangunan Konstruksi PLTU Batang Diprediksi Capai 40% Tahun Ini.” Available at: https://ekonomi.bisnis.com/read/20170302/44/633180/pembangunan-konstruksi-pltu-batang-diprediksi-capai-40-tahun-ini.

Wulder, M.A. *et al.* (2022) “Fifty years of Landsat science and impacts,” *Remote Sensing of Environment*, 280(April), p. 113195. Available at: https://doi.org/10.1016/j.rse.2022.113195.

Xiao, W. *et al.* (2020) “Mapping annual land disturbance and reclamation in a surface coal mining region using google earth engine and the landtrendr algorithm: A case study of the shengli coalfield in Inner Mongolia, China,” *Remote Sensing*. Available at: https://doi.org/10.3390/rs12101612.

Xie, J. *et al.* (2024) “Exploring the restoration stability of abandoned open-pit mines by vegetation resilience indicator based on the LandTrendr algorithm,” *Ecological Indicators*, 166(April). Available at: https://doi.org/10.1016/j.ecolind.2024.112392.

Xu, H. *et al.* (2024) “Mapping annual dynamics of surface mining disturbances in the northeastern Tibetan Plateau using Landsat imagery and LandTrendr algorithm,” *Environmental Monitoring and Assessment*, 196(10), pp. 1–20. Available at: https://doi.org/10.1007/s10661-024-13095-y.

Yan, X. and Wang, J. (2021) “Dynamic monitoring of urban built-up object expansion trajectories in Karachi, Pakistan with time series images and the LandTrendr algorithm,” *Scientific Reports*, 11(1), pp. 1–15. Available at: https://doi.org/10.1038/s41598-021-02565-9.

Yang, K. *et al.* (2021) “Impact of urban expansion on vegetation: The case of China (2000–2018),” *Journal of Environmental Management*, 291(April), p. 112598. Available at: https://doi.org/10.1016/j.jenvman.2021.112598.

Yu, Y. *et al.* (2024) “Disturbance types play a key role in post-disturbance vegetation recovery in boreal forests of Northeast China,” *Ecological Indicators*, 168(January), p. 112745. Available at: https://doi.org/10.1016/j.ecolind.2024.112745.

Zhai, X. *et al.* (2023) “Coupled patterns of natural and anthropogenic resources in typical ecosystems in coastal areas of China,” *Environmental Research*, 239(P2), p. 117411. Available at: https://doi.org/10.1016/j.envres.2023.117411.

Zhou, Q. *et al.* (2025) “Toward Seamless Global 30-m Terrestrial Monitoring: Evaluating 2022 Cloud Free Coverage of Harmonized Landsat and Sentinel-2 (HLS) V2.0,” *IEEE Geoscience and Remote Sensing Letters*, 22, pp. 1–5. Available at: https://doi.org/10.1109/LGRS.2025.3533923.

Zhu, L. *et al.* (2022) “Land use/land cover change and its impact on ecosystem carbon storage in coastal areas of China from 1980 to 2050,” *Ecological Indicators*, 142(June). Available at: https://doi.org/10.1016/j.ecolind.2022.109178.

Zhu, Z. (2017) “Change detection using landsat time series: A review of frequencies, preprocessing, algorithms, and applications,” *ISPRS Journal of Photogrammetry and Remote Sensing*, 130, pp. 370–384. Available at: https://doi.org/10.1016/j.isprsjprs.2017.06.013.