SATELLITE-BASED REMOTE SENSING FOR ASSESSING FASHION INDUSTRY ENVIRONMENTAL FOOTPRINT AND URBAN DEGRADATION

A FEASIBILITY STUDY FOR DIGITAL PRODUCT PASSPORT

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Abstract

This study investigates the pivotal role of geospatial technologies, including Geographic Information Systems, remote sensing, and satellite imagery within the fashion industry. Motivated by regulatory advancements like the EU's Digital Product Passport, the study addresses the existing gap in integrating spatial environmental data into product-level transparency frameworks.
The core methodology of this research employs secondary data; this study aims to foresee the integration of remotely tracking both the direct and indirect (latent) environmental impacts of intensive fashion and textile production. Direct impacts assessed for their detectability include water pollution (e.g., color and thermal anomalies), air pollution (e.g., particulate matter and trace gas concentrations), and solid waste accumulation (e.g., landfill expansion and spectral signatures of textile waste). Latent urban degradation elements, such as signs of overcrowding, infrastructural deficiencies, and resource depletion, are also explored for their spatial detectability within surrounding urban environments. The compilation of existing research, impacts, and detection methodologies into a structured matrix is intended to serve as a foundation for subsequent applied investigations within the domain of fashion production. Ultimately, this study assesses the suitability and potential of these technologies to enhance environmental monitoring and systemic accountability within the fashion sector. It seeks to lay the groundwork for integrating verifiable geospatial intelligence into sustainability frameworks, including Digital Product Passports, thereby fostering more accountable and data-informed practices at the intersection of industry, environment, and urban systems.

Keywords: *Textile; Supply chains; Remote sensing; Geospatial; Environment*

INTRODUCTION

In recent years, the fashion industry has undergone increasing scrutiny for its environmental and social impacts across global supply chains. In response to this, the European Union has introduced the Digital Product Passport (DPP) as part of its broader strategy toward a circular and sustainable economy. The DPP aims to collect and dissemina-te structured data about products - including their composition, production origins, and environmen-tal footprint - with the goal of enhancing transpa-rency, traceability, and consumer awareness. As this policy framework takes shape, the fashion sector is being pushed toward more data-intensive practices that require new forms of documentation and accountability. The expected increase of data driven decisions and evaluations in this context calls for a robust method for measuring anthropo-genic impacts.

Concurrently, geospatial technologies - including Geographic Information Systems (GIS) and remote sensing - have become increasing-ly sophisticated and accessible, enabling new methods for tracking environmental change, industrial activity, and urban development (Yang & Liu, 2025). These technologies are already widely used in agriculture, mining, forestry, and infrastructure monitoring, yet remain underuti-lized in the fashion industry. Their potential to offer continuous, large-scale, and spatially precise data represents a significant opportunity to extend the reach and granularity of DPP systems, particular ly when it comes to tracing environmental impacts and mapping production networks.

Anthropogenic impacts, including land degradation, water pollution, and urban expansion, are currently measured through a variety of environmental indicators (Singh et al., 2024). However, these assessments are often fragmented, industry-agnostic, and lack of integration with product-level data systems such as DPPs. Furthermore, there is limited understanding of how the fashion industry contributes to or correlates with urban degradation in the vicinity of production hubs, especially in developing countries where regulatory oversight may be weak.

Despite these developments, significant knowledge gaps remain. Specifically, there is a lack of research on how GIS and remote sensing technologies can be applied to the fashion industry to support environmental monitoring and compliance. The spatial dimension of Scope 1, 2, and 3 emissions — as well as indicators of industrial misconduct or urban distress — remains poorly mapped. Similarly, the ways in which fashion-intensive industrial zones contribute to the degradation of surrounding urban environments are rarely examined through spatial data.

his study proposes to address these gaps by assessing the feasibility of applying GIS and satellite-based remote sensing to the fashion sector. By the creation of a matrix of impacts and their indicators for possible detection, the study explores how remote sensing can enhance the environmental granularity of DPPs data, monitor urban stress, and serve as a future basis for empirical research. Ultimately, this study aims to test whether these tools can detect spatial markers of intensive textile production and associated urban degradation. It seeks to lay the groundwork for the integration of geospatial intelligence into fashion sustainability frameworks, fostering more accountable and data-informed practices at the intersection of industry, environment, and urban systems.

GEOSPATIAL TECHNOLOGIES FOR ENVIRONMENTAL MONITORING IN THE FASHION SECTOR

As previously stated, the fashion industry, a significant global economic force, is increasingly under scrutiny for its substantial environmental and social impacts across its complex supply chains (Battisti & Spennato, 2024). This pressing concern necessitates a shift towards greater transparency, traceability, and accountability within the sector. Policy initiatives, such as the European Union's Digital Product Passport regulation, are driving this demand for enhanced data visibility. Concurrently, advancements in geospatial technologies offer promising avenues for monitoring and mitigating these impacts, yet their full potential within the fashion industry remains largely untapped.

The Digital Product Passport is emerging as a critical innovation designed to foster traceability, sustainability, and regulatory compliance across various industries, including textiles. As a central element of the EU's Circular Economy Action Plan, DPPs aim to collect and disseminate structured data about products, encompassing aspects like material composition, production origins, and environmental footprint. This digital record serves as a repository of information throughout a product's lifecycle, from its creation to disposal, with the goal of enhancing transparency, promoting sustainability, and facilitating a circular economy (Psarommatis & May, 2024). The mandatory implementation of DPPs aspires to improve resource circularity, reduce emissions, and strengthen supply chain governance by enhancing product traceability and supply chain transparency (Zhang & Seuring, 2024). Beyond just material data, DPPs are envisioned to include information on carbon footprint, repairability, and recycling pathways.

The concept of digital product passports is part of a broader trend towards using digital technologies to improve supply chain systems and ensure sustainability. Blockchain technology, for instance, offers robust solutions for monitoring details such as time and place of elaboration, raw material origins, and material quality throughout the manufacturing process, thereby improving transparency and traceability in the fashion and textile supply chain (Badhwar et al., 2023; Pérez et al., 2020). These technologies enable control and monitoring of textile articles from production to consumer acquisition, addressing concerns about environmental impact and labor rights by enhancing accountability (Amin et al., 2025).

Geospatial technologies, including Geographic Information Systems, remote sensing, and satellite imagery, provide powerful tools for analyzing and monitoring environmental concerns on a large scale. Most importantly, this technology can track latent effects that are not accounted for intensive industrial production in standard reporting. Also, it provides a great tool for overseeing agencies and certificating bodies. While widely used in sectors like agriculture, mining, and forestry, their application within the fashion industry for environmental monitoring is still developing (Moran et al., 2020). However, these technologies offer significant potential to identify and map the environmental footprint of fashion production and waste.

Remote sensing and GIS can be leveraged to:

- **Identify and analyze textile waste** accumulation: Studies have demonstrated the effectiveness of remote sensing and GIS in mapping fast fashion landfills, identifying their spatial extent, and tracking their growth over time. Spectral analysis techniques can differentiate textile waste from natural land cover based on their distinct spectral signatures (Stoyanova & Vitov, 2025).

- **Monitor environmental degradation:** Satellite data can be used for "before-and-after" temporal analysis to detect changes related to land degradation, water pollution, and urban expansion caused by industrial activities (Ruppen et al., 2023; Yuan et al., 2020). This can be particularly valuable in assessing the environmental impacts of production hubs where regulatory oversight might be weak (Velástegui-Montoya et al., 2023).

- **Assess pollution and emissions: Earth** observation systems can monitor various environmental parameters, including water pollution (Karakuş, 2022) and waste detection (Magyar et al., 2023). These tools can provide continuous, large-scale, and spatially precise data, which is crucial for understanding the fashion industry's contribution to environmental issues, including Scope 1, 2, and 3 emissions.

- **Latent urban degradation: GIS markers** of textile industrial activity, when considered alongside environmental stressors, can reveal unforeseen degradation in urban environments. The adverse effects of large-scale production sites may extend beyond immediate cause-and-effect relationships; these applications can track subtle spatial trends like overpopulation, infrastructural deficiencies, and resource depletion. These factors serve as key indicators of potential unsustainability, environmental strain, and under-examined forms of violence against resident populations.

The integration of remote sensing and GIS allows for spatiotemporal analysis, enabling the tracking of changes in textile waste accumulation and the progression of illegal dumping activities. This provides critical insights into landfill expansion trends and supports data-driven decision-making in environmental management. The use of open-source tools and freely accessible data for such analyses further promotes transparency and reproducibility in environmental monitoring efforts (Stoyanova & Vitov, 2025).

Despite the advancements in both DPPs and geospatial technologies, a critical gap exists in integrating spatial data and environmental indicators within the frameworks of product-level data systems like DPPs. Assessments of anthropogenic impacts such as land degradation and water pollution are often fragmented and lack integration with product-specific data. This limits the ability to trace the environmental footprint of products with spatial precision and granularity.

The feasibility of applying GIS and satellite-based remote sensing to the fashion sector lies in its potential to enhance the environmental granularity of DPPs. By detecting spatial markers of intensive textile production and associated urban degradation, these technologies can provide real-world, verifiable data that complements the information contained within a DPP. This integration can lead to more accountable and data-informed practices at the intersection of industry, environment, and urban systems, moving beyond current limitations where the spatial dimension of emissions and indicators of industrial misconduct are poorly mapped. Such an approach would enable a more comprehensive understanding of the entire supply chain's environmental impact, from raw material sourcing to production facilities and waste disposal sites. This application has the potential of bridging the gap of intersectional realities.

THE MATRIX OF INDICATORS OF DIRECT AND LATENT IMPACTS

To achieve its goal, the study systematically identifies and details a “matrix” of impacts, where each type of impact is linked to unique geospatial indicators and the specific remote sensing or GIS techniques capable of tracking them. This isn't a simple list; it's a conceptual framework that maps out how distinct environmental changes translate previously conducted studies, both in the satellite detection field and fashion industry pollution analysis. Widely researched and more straightforward is how to detect direct effects as visible in Table 01, a deeper focus has been done on latent effects visible in Table 02.

For instance, when considering water pollution, the study looks for changes in the water's spectral properties (how it reflects light, which can indicate the presence of dyes or suspended solids) or thermal anomalies (warm spots from discharged heated water), both of which are detectable using multispectral or thermal infrared satellite sensors. For air pollution, the presence of particulate matter can be inferred from changes in Aerosol Optical Depth values, while specialized sensors can map concentrations of trace gases. Solid waste accumulation is assessed by monitoring the spatial expansion of waste sites over time using high-resolution optical imagery and by identifying the unique spectral signatures of textile materials.

Moving to the more subtle latent urban degradation elements, the study proposes that overcrowding could be tracked by analyzing urban sprawl, changes in building density, or the growth of informal settlements through multi-temporal optical imagery and advanced GIS techniques. Infrastructural deficiencies might manifest as land subsidence, detectable with millimeter precision using Interferometric Synthetic Aperture Radar, or the presence of unmanaged waste sites. Lastly, resource depletion can be inferred from changes in surface water body extent (monitored by multispectral imagery or altimetry) or vegetation stress, as revealed by declining vegetation indices like NDVI (Normalized Difference Vegetation Index).

By meticulously detailing these connections between specific impacts and their geospatial indicators, this feasibility study constructs a robust framework. This framework is crucial for laying the groundwork for future integration of this verifiable geospatial intelligence into fashion sustainability frameworks, such as the Digital Product Passport, ultimately fostering more accountable and data-informed practices that bridge the complex realities of industry, environment, and urban systems. (Tab. 01)

TRACKING LATENT URBAN DEGRADATION ELEMENTS

Beyond direct polluting effects, textile production may also contribute to broader urban degradation. Remote sensing and GIS techniques can be harnessed to discern the physical manifestations of these intricate socio-environmental challenges. The far-reaching consequences of extensive production facilities may extend beyond readily apparent cause-and-effect dynamics; consequently, these approaches can be employed to monitor subtle spatial trends, including overpopulation, infrastructural shortcomings, and resource depletion.

OVERCROWDING AND POPULATION DENSITY

Intensive industrial activity, such as large textile production hubs, can act as a magnet for labor, leading to rapid and often unplanned urban growth in surrounding areas. This rapid influx can quickly outpace the development of adequate housing, infrastructure, and services, resulting in overcrowding.

- **How Remote Sensing and GIS Detect It:**
  - Urban Sprawl and Density Changes: Remote sensing excels at mapping land use and land cover changes over time. By analyzing multi-temporal satellite imagery, we can observe the physical expansion of built-up areas (urban sprawl). GIS then allows for the quantification of this expansion and the assessment of changes in building density within these areas (Singh et al., 2024). For instance, an increase in the number of residential structures or the vertical growth of buildings within a defined area, coupled with a lack of new infrastructure, can indicate rising population density (Láng-Ritter et al., 2025; Szarka & Biljecki, 2022). Studies show that remote sensing can identify urban areas based on population density, land cover, and night-time lights, and can assess urban environmental sustainability indicators (Uchiyama & Mori, 2017). Various geospatial and statistical methods are used to estimate population distribution at fine spatial scales, which is essential for urban studies and planning (Láng-Ritter et al., 2025; Szarka & Biljecki, 2022; Zhou et al., 2020). Deep learning approaches coupled with remote sensing images also provide capabilities for estimating

Matrix of Direct Textile Production Pollutants and Remote Sensing Indicators/GIS Detectable Indicators

Pollutant Category	Pollutants/Alterations	Remote Sensing/GIS Detectable Indicators & Mechanisms
Water Pollution	Dyes and Colorants, High Suspended/ Dissolved Solids, Chemical Residues, pH Imbalance, Thermal Discharge.	- **Spectral Analysis of Water Bodies**: Changes in water color and spectral reflectance (e.g., increased reflectance in certain bands for turbidity or specific absorption/reflection patterns for dyes). Multispectral and hyperspectral sensors detect these altered optical properties (Halepoto et al., 2022). - **Thermal Anomaly Detection**: Localized increases in water temperature and the presence of thermal plumes, detectable by thermal infrared sensors (Ferrara et al., 2017; Naimaee et al., 2024). - **Effluent Plume Mapping**: Visible plumes on the water surface due to color, turbidity, or thermal differences, identifiable through optical, thermal, and sometimes radar imagery (Gancheva et al., 2021; Trinh et al., 2017).
Air Pollution	Particulate Matter (PM2.5, PM10), Volatile Organic Compounds, Sulfur Dioxide, Nitrogen Dioxide, Smoke Plumes	- **Aerosol Optical Depth Measurement**: Elevated AOD values over industrial areas and downwind regions, indicating increased concentrations of airborne particulates (Rowley & Karakuş, 2023; Scheibenreif et al., 2021). - **Trace Gas Concentration Mapping**: Spatially resolved maps showing elevated concentrations of specific pollutant gases (e.g., SO2, NO2), detected by specialized atmospheric chemistry sensors (Potts et al., 2021; Wang et al., 2021). - **Smoke Plume Detection**: Visible smoke plumes in high-resolution optical satellite imagery, and thermal anomalies associated with industrial facilities (Xia et al., 2018).
Solid Waste	Textile Waste (clothing dumps), Textile Dyeing Wasted Sludge	- **Spatial Extent and Growth Monitoring**: Mapping and temporal analysis of landfill expansion and textile waste accumulation using high-resolution optical satellite imagery (Magyar et al., 2023; Papale et al., 2023). - **Spectral Signature Analysis and Indexing**: Distinct spectral reflectance patterns from textile materials (both synthetic and organic) that differentiate them from natural land covers. Specialized spectral indices (e.g., Normalized Difference Enhanced Sand Index) enhance detection and classification (Stoyanova & Vitov, 2025).

Tab. 01

population distribution (Huang et al., 2021).

- Informal Settlement Expansion: High-resolution satellite imagery can visually detect the emergence and growth of informal settlements, characterized by irregular patterns, dense construction, and often a lack of formal planning or infrastructure (Cutini et al., 2019). The rapid expansion of such settlements is a strong indicator of unmanaged population growth and potential overcrowding, particularly in areas attracting migrant labor for industrial work (Abebe et al., 2019). Remote sensing data, particularly very high spatial resolution satellite imagery, has proven useful for identifying these informal settlements and monitoring their evolution (Bhangale et al., 2016; Mudau & Mhangara, 2021; Samper & Liao, 2023).

- Population Estimation Proxies: Advanced techniques combine remote sensing data with statistical models or deep learning to estimate population distribution at a finer scale (Huang et al., 2021). By analyzing features like building footprints, road networks, and even night-time lights, these models can infer population density, highlighting areas experiencing significant increases (Bektemyssova et al., 2025; Kii et al., 2023; Zhou et al., 2020).

INFRASTRUCTURAL DEFICIENCIES

Rapid and unplanned urbanization driven by industrial growth often strains existing infrastructure, leading to deficiencies in critical services like water, sanitation, roads, and waste management

- **How Remote Sensing and GIS Detect It:**
  - Land Subsidence: Over-extraction of groundwater to support growing industrial and urban populations can lead to ground subsidence (Medici et al., 2024). This subtle sinking of the land surface can damage buildings and infrastructure (Ciampalini et al., 2021; Miano et al., 2022). Interferometric Synthetic Aperture Radar technology uses radar signals from satellites to precisely measure ground deformation over large areas with millimeter-level accuracy (Bischoff et al., 2020; Deng et al., 2019; Fan et al., 2021; Lee et al., 2025; J. Zhang et al., 2023; Z. Zhang et al., 2023). By tracking subsidence patterns, particularly around industrial zones or densely populated areas, InSAR can indicate stress on groundwater resources and potential damage to underlying infrastructure (Hu et al., 2019; Miano et al., 2022

  - Unmanaged Waste Sites: The presence of informal or unmanaged general waste sites within or near urban areas is a clear sign of inadequate municipal waste management infrastructure (Papale et al., 2023). Remote sensing can identify these sites through their distinct spectral properties, irregular shapes, and often lack of vegetation. Time-series analysis can also track their expansion, reflecting increasing pressure on waste disposal systems (Stoyanova & Vitov, 2025). The integration of GIS helps to spatially assess waste accumulation and identify areas prone to illegal dumping, pointing to systemic infrastructural weaknesses (Ragazzo et al., 2025)

  - Road/Pavement Degradation: While detailed road condition assessment often requires very high-resolution imagery or ground surveys, satellite imagery and remote sensing techniques can identify major disruptions or significant deterioration in road networks (Yu et al., 2024). Changes in road patterns or the development of informal access routes in response to inadequate formal infrastructure can also be observed through multi-temporal analysis of satellite images, as these changes manifest as detectable alterations in the urban fabric.

RESOURCE DEPLETION

The intense demands of both industrial processes and an expanding urban population can lead to the depletion of natural resources, most notably water.

- **How Remote Sensing and GIS Detect It:**
  - Water Scarcity Indicators: Changes in Surface Water Bodies: Satellite imagery is crucial for monitoring the spatial extent and volume of surface water bodies such as rivers, lakes, and reservoirs (Albizua et al., 2012). Decreases in water body size or changes in water levels, quantifiable through multi-temporal analysis, can indicate high water withdrawal rates for industrial processes (e.g., textile dyeing) or urban consumption (Kalhor & Emaminejad, 2019; Palazzoli et al., 2022). Satellite altimetry provides precise measure-

ments of water levels in inland water bodies for effective water resource management (Thakur et al., 2020). Urban areas are a main driver of surface water loss (Palazzoli et al., 2022).
◦ Vegetation Stress: Water scarcity impacts vegetation health. Satellite-derived vegetation indices like NDVI can monitor the greenness and vigor of vegetation (Bondarenko et al., 2021). A decline in NDVI values in areas surrounding industrial or urban centers, particularly during dry seasons, can signal water stress, soil degradation, or changes in local ecosystems due to water diversion or pollution (Kabiraj et al., 2022; Peng et al., 2024). Remote sensing can also monitor plant and soil conditions and provide decision-making support related to drought stress in agriculture (Jindo et al., 2021).
◦ Groundwater Depletion Proxies: While groundwater is not directly visible from space, its depletion can lead to observable surface changes. As mentioned with land subsidence, excessive groundwater extraction can cause the ground to sink. Moreover, the impact of decreased groundwater on vegetation health or the drying up of shallow surface water bodies can be detected, providing indirect evidence of groundwater stress (Vasco et al., 2019; Zhou & Hao, 2025). Remote sensing technologies, including gravimetric measurements and changes in Earth surface height, are increasingly used for monitoring and assessing groundwater at various scales (Chawla et al., 2020; Ibrahim et al., 2024).

- **Land Degradation:**
  Industrial activities and associated urbanization can lead to land degradation, impacting soil quality and ecosystem health (Prokop, 2020; Yuan et al., 2020). Remote sensing can track indicators such as:
  ◦ Changes in Land Surface Temperature: Urbanization and industrialization often lead to an increase in Land Surface Temperature (LST) and Urban Heat Island (UHI) effect, which can be monitored by thermal infrared sensors (Singh et al., 2024).
  ◦ Soil Moisture Index: Some satellite products can infer soil moisture, and a decline can indicate degradation (Kabiraj et al., 2022). Albedo and Vegetation Indices: Changes in surface albedo (reflectivity) and vegetation cover can signify soil exposure and a decline in land productivity (Prokop, 2020). Monitoring these changes provides insights into the extent and severity of land degradation in and around industrial areas (Bondarenko et al., 2021; Sun et al., 2019).

By integrating these geospatial observations, we can build a comprehensive picture of the complex and interconnected environmental and social challenges arising from concentrated industrial development. This spatially explicit understanding is vital for creating effective policies and interventions aimed at sustainable urban and industrial development (Tab. 02).

TESTING: THE CASE EXAMPLE OF VIETNAM SHOES PRODUCTION

Vietnam's transformation into a global footwear and fashion manufacturing hub began in the early 1990s, when market- oriented reforms initiated under Đổi Mới opened the country to foreign investment and spurred the relocation of production from economies facing rising labor costs, particularly Taiwan and China. These reforms enabled Vietnam to develop a competitive industrial base powered by an abundant workforce, improving infrastructure, and increasingly sophisticated manufacturing capabilities, attracting a wave of foreign- invested enterprises that established the foundations of its export- oriented footwear sector. As production capacity expanded through the 1990s and 2000s, the European Union rapidly emerged as a central economic partner, becoming one of Vietnam's largest importers of footwear and accounting for more than 30% of the country's footwear export value by the mid- 2010s. The EU's importance grew further as Vietnam evolved into the EU's largest trading partner in goods within ASEAN, with footwear consistently ranked among the EU's primary imports from Vietnam. This long- term economic integration reached a pivotal milestone with the entry into force of the EU–Vietnam Free Trade Agreement (EVFTA) in August 2020, which eliminated tariffs on a wide range of Vietnamese footwear exports and reinforced Vietnam's role as a strategic production base for the European fashion industry. Together, Vietnam's openness to foreign investment, the inflow of global manufacturers seeking competitive production conditions, and the consolidation of preferential trade relations with the EU have shaped a production landscape whose environmental and urban impacts now demand rigorous geospatial scrutiny.

Matrix of Latent Urban Degradation Elements and Remote Sensing/GIS Detectable Indicators

Latent Element	Geospatial Indicator(s)	Remote Sensing/GIS Techniques & Argumentation
Overcrowding & Population Density	Urban expansion and changes in building density.	**- Urban Sprawl and Density Changes**: Multi-temporal satellite imagery allows for mapping the physical expansion of built-up areas (urban sprawl) and quantifying the rate and pattern of urban growth. GIS facilitates the assessment of changes in building density within these areas, where rapid, unplanned expansion or increased vertical construction can indicate growing population pressure. Remote sensing can identify urban areas based on population density, land cover, and night-time lights, while advanced techniques like deep learning can infer population distribution at fine spatial scales. **- Informal Settlement Expansion**: High-resolution satellite imagery directly reveals the emergence and growth of informal settlements, characterized by irregular patterns and dense construction without formal planning. Their rapid expansion indicates unmanaged population influx and potential overcrowding, particularly around industrial zones attracting labor.
Infrastructural Deficiencies	Land subsidence, unmanaged waste sites, road/pavement degradation.	**- Land Subsidence**: Interferometric Synthetic Aperture Radar precisely measures ground deformation (sinking of land). Subsidence patterns around industrial areas can indicate over-extraction of groundwater, straining water supply infrastructure, or structural stress on other underground utilities and buildings due to overburden. **- Unmanaged Waste Sites**: High-resolution satellite imagery, combined with spectral and textural analysis, identifies and maps unofficial or poorly managed waste accumulation areas. Their presence and growth signify inadequate municipal waste management infrastructure, reflecting a deficiency in public services. **- Road/Pavement Degradation**: While detailed assessment often requires very high-resolution imagery, significant deterioration in road networks or the development of informal access routes in response to inadequate formal infrastructure can be inferred from satellite images through changes in urban texture and connectivity.
Resource Depletion	Changes in surface water bodies, vegetation stress, and proxies for groundwater depletion.	**- Surface Water Body Monitoring**: Multispectral satellite imagery monitors the spatial extent and volume of rivers, lakes, and reservoirs. Decreases in water body size or levels indicate high water withdrawal for industrial processes or urban consumption. Satellite altimetry provides precise measurements of water levels, signifying overall water resource availability. **- Vegetation Stress**: Satellite-derived vegetation indices (e.g., NDVI) assess vegetation health. A decline in these indices in areas near industrial or urban centers can signal water stress, soil degradation, or ecosystem changes due to water diversion or pollution. This reflects the strain on natural resources from industrial and urban demands. - Groundwater Depletion Proxies: While not directly observable, sustained land subsidence detected by InSAR can be a strong proxy for excessive groundwater extraction. Similarly, observable impacts on surface vegetation or water bodies can indirectly point to a depleted groundwater table, as these resources are often interconnected.

Tab. 02

as access to Sentinel- 5 products was not granted within the temporal window considered.

The initial phase of the analysis involved identifying the main footwear production sites in Vietnam, as reported in (Tijdens & Van Klaveren, 2018). It is important to note that these sites correspond to officially declared manufacturing facilities and are therefore presumed to be subject to heightened public and institutional scrutiny. For each site, a surface reference point—defined as a Geographical Reference Point (GRP)—was selected to monitor, over time, the variation of spectral signals and environmental parameters in the immediate surroundings. GRPs were identified exclusively in areas classified as paved surface in 2023, a condition verified through targeted spectroscopic analysis to ensure homogeneous sampling of surface materials.

Once the GRP was established, an Area of Interest (AOI) of identical dimensions was delineated for each site to ensure comparability of results. Satellite image analysis for all AOIs was set to 23 June 2023, a date on which cloud cover over the area was below 30%, the threshold necessary to guarantee radiometric reading quality. Discrepancies in the acquisition dates of certain scenes are attributable to orbital constraints and meteorological conditions, which occasionally hinder the availability of usable imagery.

The first analytical operation concerned the interpretation of natural colour images, aimed at identifying the principal anthropogenic and natural modifications within each AOI. Subsequently, using Landsat data, surface temperature values for the years 2002 and 2023 were examined, as no more recent acquisitions with comparable characteristics were available. The same Landsat datasets were also used to conduct a spectroscopic analysis of each GRP (Fig. 01; Fig. 02), alongside the reconstruction of temporal profiles for temperature, vegetation cover, and soil moisture.

Finally, the AOIs were analysed for land- use change using the global LULC (Land Use/ Land Cover) map derived from ESA Sentinel- 2 imagery at 10- m resolution and compared with regional- scale change data. The combined analyses are visible in Table 03. Variations in moisture, vegetation, temperature, land use, and

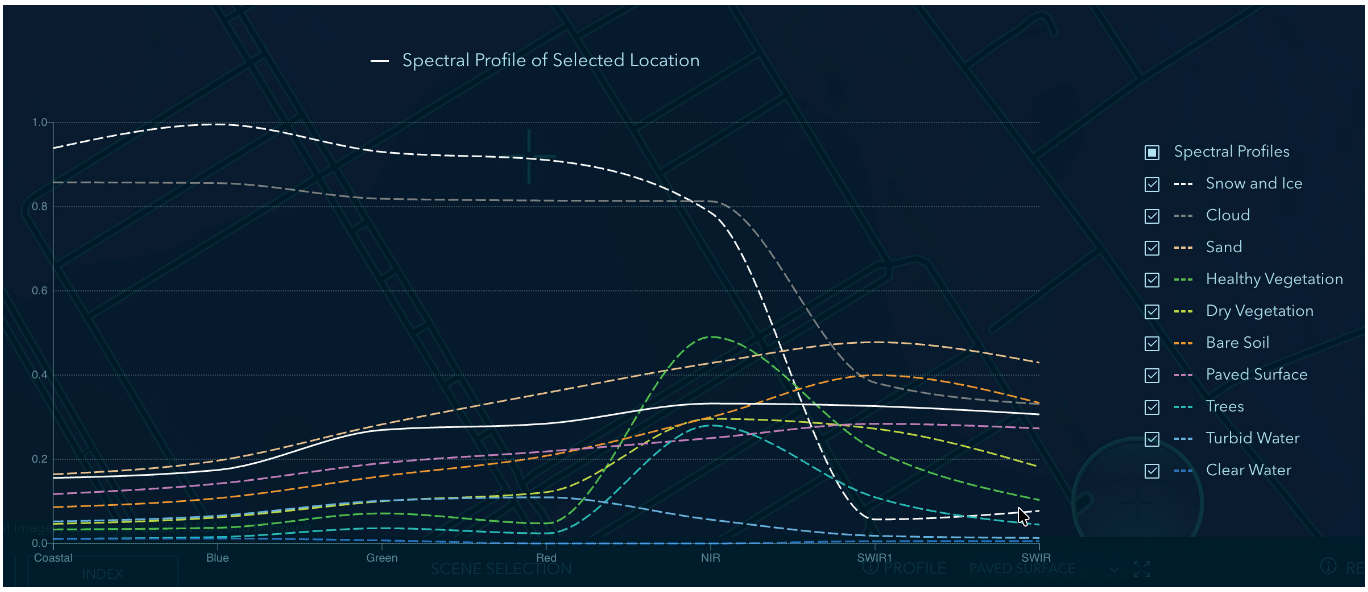


Fig. 01

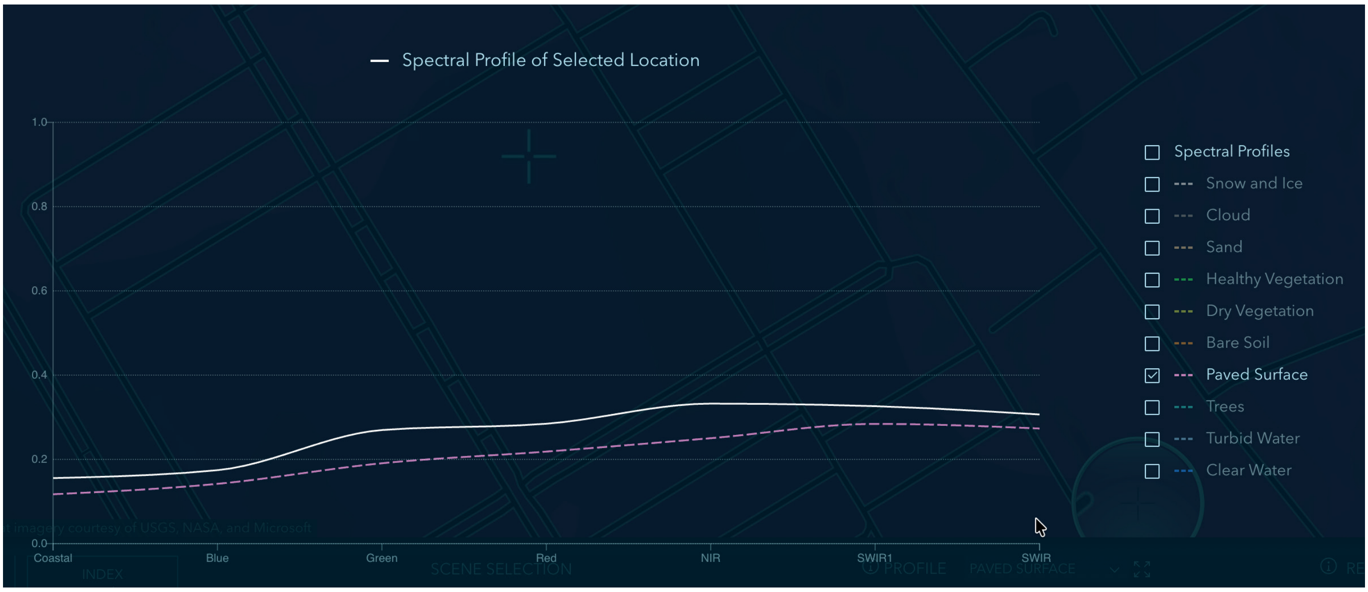


Fig. 02

METHODOLOGY USED, LANDSAT AND COPERNICUS DATA ANALYSIS

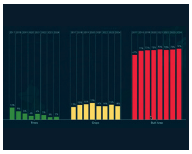
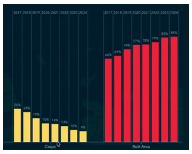
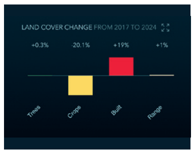
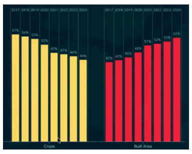
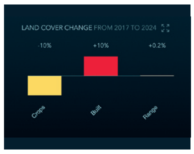
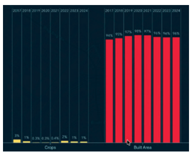
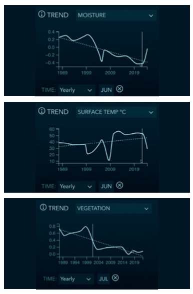
For the purposes of this study, data provided by the Landsat and Copernicus programmes were employed, supplemented and by access to the high- frequency satellite imagery databases.
The methodological approach adopted relies exclusively on the datasets currently accessible and analyzable, with the aim of offering a preliminary technical demonstration of the potential of geospatial indicators. It does not therefore aspire to exhaustiveness; rather, it intends to outline a descriptive and operational framework that may be further expanded in future research. Conversely, it was not possible to include data on air quality and atmospheric greenhouse gas concentrations, the ratio between built- up and green or agricultural surfaces constitute sensitive indicators of potential environmental stress and degenerative phenomena, such as the emergence of urban or industrial heat- island effects. These effects can be linked to environmental changes in the area and, thanks to the availability of historical satellite data, to the establishment of the intensive production facility under analysis.

ANALYSIS OF A SAMPLED SITE

To deepen the analysis, one of the facilities listed in Tab. 03—specifically, the Vietnam Chingluh Shoes Ltd site—was selected as a representative case study. Historical satellite observations reveal that in the earliest usable acquisition from 2006, the manufacturing complex appeared recently established, with primary urbanization works still underway. Although the 2000 image could not be included due to insufficient radiometric quality, it nevertheless indicates that the area consisted predominantly of uncultivated green land, confirming the absence of significant industrialization prior to the installation of the plant.

A comparison with the 2025 satellite imagery illustrates a marked and extensive transformation of the surrounding environment (Fig. 03; Fig.04). The expansion of anthropogenic land use is both pronounced and spatially intrusive, with multiple industrial facilities of differing types emerging around the original manufacturing site. This pattern suggests a progressive and largely uncoordinated densification of industrial activities. Concomitantly, no adequate transporta-

Summary of workflow testing across three development phases

Factory*	**no. empl.**	**Location**	**Geografical Reference Point Selection** (GRP)	**Surface temerature** (Landsat Explorer)	**Land Cover Change 2017-2024** (Copernicus Sentinel-2 Land Cover/Land Use LCLU)	**Overall land cover change 2017-2024** (Copernicus Sentinel-2 Land Cover/Land Use LCLU)	**Index change 1989-2025** (Landsat)
Chang Shin Vietnam Co Ltd	24300	Ấp 1, Tổ 14, Thanh Phú, Vĩnh Cửu, Đồng Nai, Vietnam	Spectral Analysis: 2002: Dry vegetation 2023: Paved surface x: 106.84814 y: 11.00764 NDVI: 0.454 MNDWI: -0.379	2002 (August 01*): Surface Temp: 85°F / 29°C 2023 (June 23): Surface Temp: 138°F / 59°C			
Vietnam Chingluh Shoes Ltd	22400	JFCR+59X Thuan Dao Industri-al Park, TT. Bến Lức, Bến Lức, Long An, Vietnam	Spectral Analysis: 2002: Trees 2023: Paved surface x 106.494 y 10.623 NDVI: 0.077 MNDWI: -0.095	2002 (June 23): Surface Temp: 98°F / 37°C 2023 (June 23): Surface Temp: 119°F / 48°C			
Vinh Long Footwear Co Ltd	22300	5W9M+ XCW, Hoà Phú, Long Hồ, Vĩnh Long, Vietnam	Spectral Analysis: 2002: Trees 2023: Paved surface x: 105.93484 y: 10.16968 NDVI: 0.177 MNDWI: -0.330	2002 (July 23*): Surface Temp: 96°F / 36°C 2023 (June 23): Surface Temp: 117°F / 47°C			
Freetrend VN Industrial Co Ltd	21600	VPRC+G64, Đường số 3, KCX, Thủ Đức, Thành phố Hồ Chí Minh, Vietnam	Spectral Analysis: 2002: Dry vegetation 2023: Paved surface x: 106.72034 y: 10.88884 NDVI: 0.081 MNDWI: -0.488	2002 (August 24*): Surface Temp: 104°F / 40°C 2023 (June 23): Surface Temp: 128°F / 54°C			

***Tijdens & Van Klaveren, 2018**

Tab. 03

Fig. 03

Fig. 04

tion network appears to have developed to support the substantial workforce commuting daily to the area, indicating that industrial expansion occurred without proportional infrastructural planning. The immediate vicinity also shows a high residential density, often characterized by fragile or informal settlement structures, further demonstrating the urban pressures generated by the intensification of production activities.

Spectroscopic analyses reinforce these findings. Beginning in the early 2000s—coinciding with Vietnam's broader opening to foreign investment and the establishment of this manufacturing facility—a sharp decline in vegetation cover and surface moisture is detected at the GRP, paired with a notable rise in average surface temperatures (Fig. 07; Fig. 08). These changes align with multi-temporal patterns observed across the broader Area of Interest (AOI): starting in 2017, the AOI experienced a substantial reduction in cultivated green areas (−20.1%) and a corresponding increase in built-up land cover (+19%). This reconfiguration of the landscape is associated with a generalized increase in surface temperatures (+9 °C), a trend indicative of vegetation stress and symptomatic of localized microclimatic alteration,

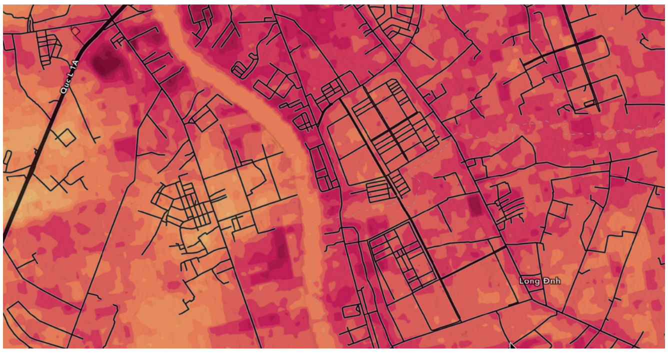


Fig. 05

Fig. 06

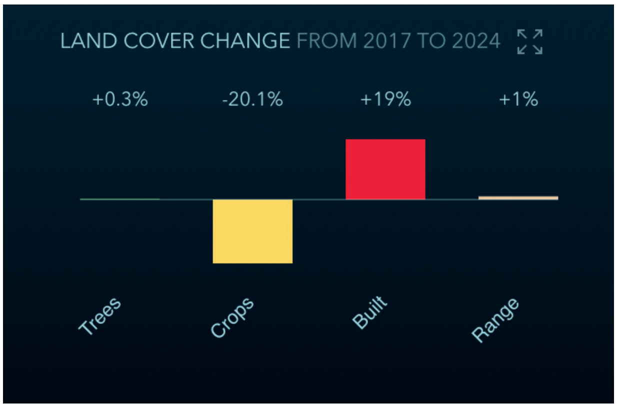


Fig. 07

ISSN: 2975-0466 [Online]

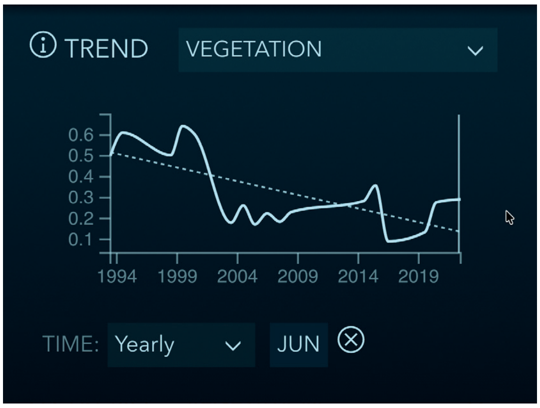


Fig. 08

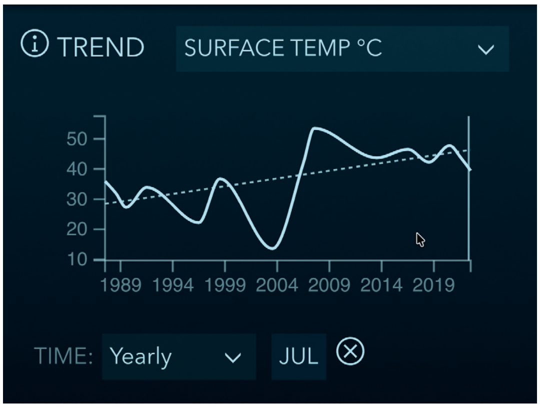


Fig. 09

CONCLUSION

This study illustrates the capacity of satellite based remote sensing and geographic information systems to document and interpret both direct and latent environmental impacts generated by fashion and textile production. Through the analysis of spectral, thermal and land surface indicators, the research demonstrates how industrial expansion can produce rapid and spatially uneven transformations that conventional reporting systems often fail to capture. The Vietnam case study highlights the extent to which concentrated manufacturing activity can alter local ecological conditions in ways that diverge from regional environmental baselines, revealing localized pressures on land use, vegetation cover, surface temperatures and urban systems.

The results also clarify how geospatial indicators can be incorporated within a Digital Product Passport data architecture. Each indicator obtained from remote sensing sources can be expressed as a structured environmental attribute associated with the production site of a given product. These attributes can include spatial coordinates, reference to the area of interest, the date of image acquisition, the sensor or data source employed, the type of environmental indicator observed and the quantitative value derived from satellite analysis. Such information can be stored within the Digital Product Passport as verifiable and machine readable records, ensuring that environmental assessments are informed by externally generated evidence rather than solely by producer declarations.

Operational integration can be achieved through a sequence of data flows that link Earth observation platforms with Digital Product Passport registries. In the first stage, satellite derived indicators are processed at the facility level and organized into a standardized environmental dataset. In the second stage, these datasets are incorporated into the existing data model of the Digital Product Passport, allowing alignment with established environmental reporting categories and facilitating automated updates. In the third stage, an interoperability layer enables continuous exchange of information between remote sensing data services and Digital Product Passport systems, allowing ongoing verification of environmental conditions associated with each production site throughout the life cycle of a product.

The integration of geospatial intelligence with the Digital Product Passport framework suggests a pathway toward more transparent and reliable environmental accountability in global fashion supply chains. The ability to monitor land transformation, stress on natural resources and changes in urban conditions through satellite data provides an independent and scalable method for assessing the environmental footprint of production sites. Future work should focus on developing standardized taxonomies for geospatial indicators, defining protocols for the validation of satellite derived measurements and designing operational models that support the systematic incorporation of Earth observation data into regulatory and market based sustainability instruments. Such advances would help strengthen the evidentiary foundation of the Digital Product Passport and contribute to more robust environmental governance in the fashion industry.

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Landsat Level-2 Imagery:

Landsat Explorer App – Esri, map image is the intellectual property of Esri and is used herein under license.

Landsat Level-2 Image Service - Esri, map image is the intellectual property of Esri and is used herein under license.

Source Landsat Level-2 Imagery – USGS courtesy of the U.S. Geological Survey, Visit the USGS at https://usgs.gov. USGS-authored or produced data and information are considered to be in the U.S. Public Domain and may be used without restriction.

CAPTIONS

[Fig. 01] Spectral profiles of multiple materials, data courtesy of the U.S. Geological Survey via ESRI

[Fig. 02] spectral profiles of paved surface (purple) and sampled point (white), data courtesy of the U.S. Geological Survey via ESRI

[Fig. 03] Satellite image 19/04/2006 Google Earth.

[Fig. 04] Satellite image 21/03/2025 Google Earth.

[Fig. 05] Landsat surface temperature 23/07/2002, data courtesy of the U.S. Geological Survey via ESR (via ESRI).

[Fig. 06] Landsat surface temperature 23/06/2023, data courtesy of the U.S. Geological Survey (via ESRI).

[Fig. 07-08-09] Differences in land cover change between 2017 and 2024 (Data via ESRI).

REFERENCES

Abebe, M. S., Derebew, K. T., & Gemeda, D. O. (2019). Exploiting temporal-spatial patterns of informal settlements using GIS and remote sensing technique: a case study of Jimma city, Southwestern Ethiopia. *ENVIRONMENTAL SYSTEMS RESEARCH*, *8*(1). https://doi.org/10.1186/s40068-019-0133-5

Albizua, L., Donezar, U., & Ibáñez, J. C. (2012). Monitoring urban development consolidation for regional management on water supply using remote sensing techniques. *European Journal of Remote Sensing*, *45*(1), 283. https://doi.org/10.5721/eujrs20124525

Amin, M. A., Baldacci, R., & Kerbache, L. (2025). Blockchain-based green supply chain management framework for sustainable practices in Bangladeshi RMG industries. *Discover Sustainability*, *6*(1). https://doi.org/10.1007/s43621-025-01196-8

Badhwar, A., Islam, S., & Tan, C. S. L. (2023). Exploring the potential of blockchain technology within the fashion and textile supply chain with a focus on traceability, transparency, and product authenticity: A systematic review [Review of Exploring the potential of blockchain technology within the fashion and textile supply chain with a focus on traceability, transparency, and product authenticity: A systematic review]. *Frontiers in Blockchain*, *6*. Frontiers Media. https://doi.org/10.3389/fbloc.2023.1044723

Battisti, J., & Spennato, A. (2024). *FASHIONING INEQUALITY THE SOCIOECONOMIC IMPLICATIONS OF FAST FASHION'S GLOBAL REACH*.

Bektemyssova, G., Bykov, A., Moldagulova, A., Omarov, S., Shaikemelev, G., Nuralykyzy, S., & Umutkulov, D. (2025). Analysis of Spatial Aggregation and Activity of the Urban Population of Almaty Based on Cluster Analysis. *Sustainability*, *17*(7), 3243. https://doi.org/10.3390/su17073243

Bhangale, U., Rathod, V., Rajgor, N., Rami, J., & Kurte, K. (2016). *Identification of informal settlement using Remote Sensing Images*. https://doi.org/10.1145/2979779.2979876

Bischoff, C. A., Ferretti, A., Novali, F., Uttini, A., Giannico, C., & Meloni, F. (2020). Nationwide deformation monitoring with SqueeSAR® using Sentinel-1 data. *Proceedings of the International Association of Hydrological Sciences*, *382*, 31. https://doi.org/10.5194/piahs-382-31-2020

Bondarenko, N., Lyubimova, T., & Reshetnikova, Y. M. (2021). Using the NDVI vegetation index to assess land degradation in industrial agglomeration. *IOP Conference Series Earth and Environmental Science*, *723*(3), 32062. https://doi.org/10.1088/1755-1315/723/3/032062

Chawla, I., Karthikeyan, L., & Mishra, A. K. (2020). A review of remote sensing applications for water security: Quantity, quality, and extremes [Review of A review of remote sensing applications for water security: Quantity, quality, and extremes]. *Journal of Hydrology*, *585*, 124826. Elsevier BV. https://doi.org/10.1016/j.jhydrol.2020.124826

Ciampalini, A., Farina, P., Lombardi, L., Nocentini, M., Taurino, V., Guidi, R., Pina, F. della, & Tavarini, D. (2021). Integration of Satellite InSAR with a Wireless Network of Geotechnical Sensors for Slope Monitoring in Urban Areas: The Pariana Landslide Case (Massa, Italy). *Remote Sensing*, *13*(13), 2534. https://doi.org/10.3390/rs13132534

Cutini, V., Pinto, V. D., Rinaldi, A. M., & Rossini, F. (2019). Informal Settlements Spatial Analysis Using Space Syntax and Geographic Information Systems. In *Lecture notes in computer science* (p. 343). Springer Science+Business Media. https://doi.org/10.1007/978-3-030-24302-9_25

Deng, J., Li, T., & Da-fu, F. (2019). Urban Ground Surface Subsidence Monitoring Based on Time Series InSAR Technology. *IOP Conference Series Earth and Environmental Science*, *283*(1), 12058. https://doi.org/10.1088/1755-1315/283/1/012058

Fan, J., Xiong, X., & Peng, X. (2021). Research on methods of investigation and analysis of highway slope stability after flood based on Insar and field investigation. *IOP Conference Series Earth and Environmental Science*, *783*(1), 12057. https://doi.org/10.1088/1755-1315/783/1/012057

Gancheva, I., Peneva, E., & Slabakova, V. (2021). Detecting the Surface Signature of Riverine and Effluent Plumes along the Bulgarian Black Sea Coast Using Satellite Data. *Remote Sensing*, *13*(20), 4094. https://doi.org/10.3390/rs13204094

Halepoto, H., Gong, T., & Memon, H. (2022). Current status and research trends of textile wastewater treatments—A bibliometric-based study. *Frontiers in Environmental Science*, *10*. https://doi.org/10.3389/fenvs.2022.1042256

Hu, B., Chen, J., & Zhang, X. (2019). Monitoring the Land Subsidence Area in a Coastal Urban Area with InSAR and GNSS. *Sensors*, *19*(14), 3181. https://doi.org/10.3390/s19143181

Huang, X., Zhu, D., Zhang, F., Liu, T., Li, X., & Zou, L. (2021a). Sensing population distribution from satellite imagery via deep learning: model selection, neighboring effect, and systematic biases. *arXiv* (Cornell University).

https://doi.org/10.48550/arXiv.2103.02155
Huang, X., Zhu, D., Zhang, F., Liu, T., Li, X., & Zou, L. (2021b). Sensing population distribution from satellite imagery via deep learning: model selection, neighboring effect, and systematic biases. *arXiv* (Cornell University). https://doi.org/10.48550/arxiv.2103.02155
Ibrahim, A., Wayayok, A., Shafri, H. Z. M., & Toridi, N. M. (2024). Remote Sensing Technologies for Unlocking New Groundwater Insights: A Comprehensive Review [Review of Remote Sensing Technologies for Unlocking New Groundwater Insights: A Comprehensive Review]. *Journal of Hydrology X*, *23*, 100175. Elsevier BV. https://doi.org/10.1016/j.hydroa.2024.100175
Jindo, K., Kozan, O., Iseki, K., Maestrini, B., Evert, F. K. van, Wubengeda, Y., Arai, E., Shimabukuro, Y. E., Sawada, Y., & Kempenaar, C. (2021). Potential utilization of satellite remote sensing for field-based agricultural studies. *Chemical and Biological Technologies in Agriculture*, *8*(1). https://doi.org/10.1186/s40538-021-00253-4
Kabiraj, S., Duraisekaran, E., & Ramaswamy, M. (2022). Combination of remote-sensing spectral indices to classify the areas of land degradation in West Burdwan district, India. *Environmental Earth Sciences*, *81*(7). https://doi.org/10.1007/s12665-022-10338-4
Kalhor, K., & Emaminejad, N. (2019). Sustainable development in cities: Studying the relationship between groundwater level and urbanization using remote sensing data. *Groundwater for Sustainable Development*, *9*, 100243. https://doi.org/10.1016/j.gsd.2019.100243
Karakuş, O. (2022). On Advances, Challenges and Potentials of Remote Sensing Image Analysis in Marine Debris and Suspected Plastics Monitoring. *arXiv* (Cornell University). https://doi.org/10.48550/arXiv.2210.06090
Kii, M., Tamaki, T., Suzuki, T., & Nonomura, A. (2023). Estimating urban spatial structure based on remote sensing data. *Scientific Reports*, *13*(1). https://doi.org/10.1038/s41598-023-36082-8
Láng-Ritter, J., Keskinen, M., & Tenkanen, H. (2025). Global gridded population datasets systematically underrepresent rural population. *Nature Communications*, *16*(1). https://doi.org/10.1038/s41467-025-56906-7
Lee, S.-J., Yun, H., & Kim, T. (2025). Monitoring of High-Speed Railway Ground Deformation Using Interferometric Synthetic Aperture Radar Image Analysis. *Applied Sciences*, *15*(8), 4318. https://doi.org/10.3390/app15084318
Magyar, D., Cserép, M., Vincellér, Z., & Molnár, A. D. (2023). Waste Detection and Change Analysis based on Multispectral Satellite Imagery. *arXiv* (Cornell University). https://doi.org/10.48550/arXiv.2303.14521
Medici, C., Soldato, M. D., Fibbi, G., Bini, L., Confuorto, P., Mannori, G., Mucci, A., Pellegrineschi, V., Bianchini, S., Raspini, F., & Casagli, N. (2024). InSAR data for detection and modelling of overexploitation-induced subsidence: application in the industrial area of Prato (Italy). *Scientific Reports*, *14*(1). https://doi.org/10.1038/s41598-024-67725-z
Miano, A., Carlo, F. D., Mele, A., Giannetti, I., Nappo, N., Rompato, M., Striano, P., Bonano, M., Bozzano, F., Lanari, R., Mazzanti, P., Meda, A., Prota, A., & Mugnozza, G. S. (2022). GIS Integration of DInSAR Measurements, Geological Investigation and Historical Surveys for the Structural Monitoring of Buildings and Infrastructures: An Application to the Valco San Paolo Urban Area of Rome. *Infrastructures*, *7*(7), 89. https://doi.org/10.3390/infrastructures7070089
Moran, D., Giljum, S., Kanemoto, K., & Godar, J. (2020). From Satellite to Supply Chain: New Approaches Connect Earth Observation to Economic Decisions. *One Earth*, *3*(1), 5. https://doi.org/10.1016/j.oneear.2020.06.007
Mudau, N., & Mhangara, P. (2021). Investigation of Informal Settlement Indicators in a Densely Populated Area Using Very High Spatial Resolution Satellite Imagery. *Sustainability*, *13*(9), 4735. https://doi.org/10.3390/su13094735
Naimaee, R., Kiani, A., Jarahizadeh, S., Asadollah, S. B. H. S., Melgarejo, P., & Jódar-Abellán, A. (2024). Long-Term Water Quality Monitoring: Using Satellite Images for Temporal and Spatial Monitoring of Thermal Pollution in Water Resources. *Sustainability*, *16*(2), 646. https://doi.org/10.3390/su16020646
Palazzoli, I., Montanari, A., & Ceola, S. (2022). Influence of Urban Areas on Surface Water Loss in the Contiguous United States. *AGU Advances*, *3*(1). https://doi.org/10.1029/2021av000519
Papale, L. G., Guerrisi, G., Santis, D. D., Schiavon, G., & Frate, F. D. (2023). Satellite Data Potentialities in Solid Waste Landfill Monitoring: Review and Case Studies [Review of Satellite Data Potentialities in Solid Waste Landfill Monitoring: Review and Case Studies]. *Sensors*, *23*(8), 3917. Multidisciplinary Digital Publishing Institute. https://doi.org/10.3390/s23083917
Paramitha, N. A. (2020). The increasing of Interleukin 6 and Superoxide Dismutase 3 nasal wash in textile industry workers exposed by occupational air pollutant. *Indian Journal of Science and Technology*, *13*(29), 2102. https://doi.org/10.17485/ijst/v13i29.369
Peng, M., Liu, Y., Khan, A., Ahmed, B., Sarker, S., Ghadi, Y. Y., Bhatti, U. A., Al-Razgan, M., & Ali, Y. A. (2024). Crop monitoring using remote sensing land use and land change data: Comparative analysis of deep learning methods using pre-trained CNN models. *Big Data Research*, *36*, 100448. https://doi.org/10.1016/j.bdr.2024.100448
Pérez, J. J. B., Queiruga-Dios, A., Martínez, V. G., & Rey, A. M. del. (2020). Traceability of Ready-to-Wear Clothing through Blockchain Technology. *Sustainability*, *12*(18), 7491. https://doi.org/10.3390/su12187491
Potts, D., Ferranti, E., Timmis, R., Brown, A. S., & Hey, J. V. (2021). Satellite Data Applications for Site-Specific Air Quality Regulation in the UK: Pilot Study and Prospects. *Atmosphere*, *12*(12), 1659. https://doi.org/10.3390/atmos12121659
Prokop, P. (2020). Remote sensing of severely degraded land: Detection of long-term land-use changes using high-resolution satellite images on the Meghalaya Plateau, northeast India. *Remote Sensing Applications Society and Environment*, *20*, 100432. https://doi.org/10.1016/j.rsase.2020.100432
Psarommatis, F., & May, G. (2024). Digital Product Passport: A Pathway to Circularity and Sustainability in Modern Manufacturing. *Sustainability*, *16*(1), 396. https://doi.org/10.3390/su16010396
Ragazzo, A. V., Mei, A., Mattei, S., Fontinovo, G., & Grosso, M. (2025). Illegal Abandoned Waste Sites (IAWSs): A Multi-Parametric GIS-Based Workflow for Waste Management Planning and Cost Analysis Assessment. *Earth*, *6*(2), 33. https://doi.org/10.3390/earth6020033
Rowley, A., & Karakuş, O. (2023). Predicting air quality

via multimodal AI and satellite imagery. *Remote Sensing of Environment*, *293*, 113609. https://doi.org/10.1016/j.rse.2023.113609

Roy, M., Sen, P. K., & Pal, P. (2020). An integrated green management model to improve environmental performance of textile industry towards sustainability. *Journal of Cleaner Production*, *271*, 122656. https://doi.org/10.1016/j.jclepro.2020.122656

Ruppen, D., Runnalls, J., Tshimanga, R. M., Wehrli, B., & Odermatt, D. (2023). Optical remote sensing of large-scale water pollution in Angola and DR Congo caused by the Catoca mine tailings spill. *International Journal of Applied Earth Observation and Geoinformation*, *118*, 103237. https://doi.org/10.1016/j.jag.2023.103237

Samper, J. M. C., & Liao, W. (2023). Testing the Informal Development Stages Framework Globally: Exploring Self-Build Densification and Growth in Informal Settlements. *Urban Science*, *7*(2), 50. https://doi.org/10.3390/urbansci7020050

Scheibenreif, L., Mommert, M., & Borth, D. (2021). Estimation of Air Pollution with Remote Sensing Data: Revealing Greenhouse Gas Emissions from Space. *arXiv* (Cornell University). https://doi.org/10.48550/arXiv.2108.13902

Singh, S., Shukla, A., & Jain, K. (2024). Assessing the urbanization-induced impact on environmental parameters of a city from a remote-sensing perspective. *Remote Sensing Applications Society and Environment*, *34*, 101169. https://doi.org/10.1016/j.rsase.2024.101169

Song, H., Mehdi, S. R., Li, Z., Wang, M., Wu, C., Venediktov, V. Y., & Huang, H. (2023). Investigating the rate of turbidity impact on underwater spectral reflectance detection. *Frontiers in Marine Science*, *10*. https://doi.org/10.3389/fmars.2023.1031869

Stoyanova, E., & Vitov, V. (2025). Mapping fast fashion landfills: remote sensing and GIS approach to analyze textile waste. *˜The œinternational Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences/ International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *1389*. https://doi.org/10.5194/isprs-archives-xlviii-g-2025-1389-2025

Sun, B., Li, Z., WenTao, G., Zhang, Y., Gao, Z., Song, Z., Qin, P., & Tian, X. (2019). Identification and assessment of the factors driving vegetation degradation/regeneration in drylands using synthetic high spatiotemporal remote sensing Data—A case study in Zhenglanqi, Inner Mongolia, China. *Ecological Indicators*, *107*, 105614. https://doi.org/10.1016/j.ecolind.2019.105614

Szarka, N., & Biljecki, F. (2022). Population estimation beyond counts—Inferring demographic characteristics. *PLoS ONE*, *17*(4). https://doi.org/10.1371/journal.pone.0266484

Tijdens, K.G. & Van Klaveren, M. (2018). *Mapping the Global Garment Supply Chain. Presentation of a WageIndicator Garment Industry report*. AIAS Lunch Seminar, 1 november 2018. [EN]

Thakur, P. K., Garg, V., Kalura, P., Agrawal, B., Sharma, V., Mohapatra, M., Kalia, M., Aggarwal, S. P., Calmant, S., Ghosh, S., Dhote, P. R., Sharma, R., & Chauhan, P. (2020). Water level status of Indian reservoirs: A synoptic view from altimeter observations. *Advances in Space Research*, *68*(2), 619. https://doi.org/10.1016/j.asr.2020.06.015

Trinh, R., Fichot, C. G., Gierach, M. M., Holt, B., Malakar, N. K., Hulley, G., & Smith, J. L. (2017). Application of Landsat 8 for Monitoring Impacts of Wastewater Discharge on Coastal Water Quality. *Frontiers in Marine Science*, *4*. https://doi.org/10.3389/fmars.2017.00329

Uchiyama, Y., & Mori, K. (2017). Methods for specifying spatial boundaries of cities in the world: The impacts of delineation methods on city sustainability indices. *The Science of The Total Environment*, *592*, 345. https://doi.org/10.1016/j.scitotenv.2017.03.014

Vasco, D. W., Farr, T. G., Jeanne, P., Doughty, C., & Nico, P. (2019). Satellite-based monitoring of groundwater depletion in California's Central Valley. *Scientific Reports*, *9*(1). https://doi.org/10.1038/s41598-019-52371-7

Velástegui-Montoya, A., Escandón-Panchana, P., Peña-Villacreses, G., & Herrera-Franco, G. (2023). Land use/land cover of petroleum activities in the framework of sustainable development. *Cleaner Engineering and Technology*, *15*, 100659. https://doi.org/10.1016/j.clet.2023.100659

Wang, Q., Li, Q., Wang, Z., Chen, H., Ma, P., Fan, P., & Liu, C. (2021). An operational monitoring method for full coverage pollution enterprises based on satellite remote sensing. *Atmospheric Pollution Research*, *12*(4), 141. https://doi.org/10.1016/j.apr.2021.02.008

Xia, H., Chen, Y., & Quan, J. (2018). A simple method based on the thermal anomaly index to detect industrial heat sources. *International Journal of Applied Earth Observation and Geoinformation*, *73*, 627. https://doi.org/10.1016/j.jag.2018.08.003

Yang, D., & Liu, X. (2025). A Framework for Mapping Urban Spatial Evolution: Quantitative Insights from Historical GIS and Space Syntax in Xi'an. *Sustainability*, *17*(7), 3113. https://doi.org/10.3390/su17073113

Yu, J., Jiang, J., Fichera, S., Paoletti, P., Layzell, L., Mehta, D., & Luo, S. (2024). Road Surface Defect Detection -- From Image-based to Non-image-based: A Survey. *arXiv* (Cornell University). https://doi.org/10.48550/arXiv.2402.04297

Yuan, J., Bian, Z., Yan, Q., Gu, Z., & Yu, H. (2020). An Approach to the Temporal and Spatial Characteristics of Vegetation in the Growing Season in Western China. *Remote Sensing*, *12*(6), 945. https://doi.org/10.3390/rs12060945

Zhang, A., & Seuring, S. (2024). Digital product passport for sustainable and circular supply chain management: a structured review of use cases [Review of Digital product passport for sustainable and circular supply chain management: a structured review of use cases]. *Internation al Journal of Logistics Research and Applications*, *1*. Taylor & Francis. https://doi.org/10.1080/13675567.2024.2374256

Zhang, J., Ke, C., Shen, X., Lin, J., & Wang, R. (2023). Monitoring Land Subsidence along the Subways in Shanghai on the Basis of Time-Series InSAR. *Remote Sensing*, *15*(4), 908. https://doi.org/10.3390/rs15040908

Zhang, Z., Hu, C., Wu, Z., Zhang, Z., Yang, S., & Wang, Y. (2023). Monitoring and analysis of ground subsidence in Shanghai based on PS-InSAR and SBAS-InSAR technologies. *Scientific Reports*, *13*(1). https://doi.org/10.1038/s41598-023-35152-1

Zhao, Y., Shen, Q., Wang, Q., Yang, F., Wang, S., Li, J., Zhang, F., & Yao, Y. (2020). Recognition of Water Colour Anomaly by Using Hue Angle and Sentinel 2 Image. *Remote Sensing*, *12*(4), 716. https://doi.org/10.3390/rs12040716

Zhou, Q., Zheng, Y., Shao, J., Lin, Y., & Wang, H. (2020). An Improved Method of Determining Human Population Distribution Based on Luojia 1-01 Nighttime Light Imagery and Road Network Data—A Case Study of the City of

Shenzhen. *Sensors*, *20*(18), 5032. https://doi.org/10.3390/s20185032

Zhou, W., & Hao, L. (2025). How Urban Expansion and Climatic Regimes Affect Groundwater Storage in China's Major River Basins: A Comparative Analysis of the Humid Yangtze and Semi-Arid Yellow River Basins. *Remote Sensing*, *17*(7), 1292. https://doi.org/10.3390/rs17071292