



Research article

Coupling coordination degree and spatiotemporal dynamics: diagnosing the Nile Delta urban ecosystem and socioeconomic lag

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Abstract: Rapid urbanization has profoundly altered socioeconomic–ecological interactions, particularly within environmentally sensitive deltaic systems. This study evaluates the spatiotemporal evolution of socioeconomic–ecological coordination in the Nile Delta, Egypt, from 2010 to 2023, using the coupling coordination degree model (CCDM) and spatial autocorrelation analysis. Multi-source remote sensing data processed through Google Earth Engine (GEE) were used to construct consistent socioeconomic and environmental indicators, while the entropy weight method (EWM) was applied to determine objective indicator weights. The results reveal a nonlinear temporal coordination trajectory, with the average CCD declining from 0.72 in 2010 to a low of 0.54 in 2015, followed by a limited recovery to 0.55 in 2020 and a stronger recovery to 0.63 in 2023. Furthermore, the dominant constraint shifted from ecological lag in 2010 to socioeconomic lag during the 2020–2023 period, indicating that improvements in environmental conditions were not accompanied by comparable socioeconomic advancement. Spatially, the Delta shifted from a polarized center–periphery pattern toward greater spatial homogeneity at moderate coordination levels, although significant spatial dependence persisted and low–low clusters expanded along the northern coastal fringe. These findings demonstrate how dominant constraints and spatial configurations of socioeconomic–ecological coordination can change over time within a highly dynamic delta system. By extending CCD-based assessment to an underrepresented African deltaic context, this study advances the understanding of the spatial and temporal patterns of socioeconomic–ecological coupling under environmental change.

Keywords: coupling coordination degree (CCD); spatiotemporal dynamics; socioeconomic lag; urban-ecological system; remote sensing; google earth engine (GEE); entropy weight method (EWM); Nile Delta

1. Introduction

Measuring sustainability at the frontier of socioeconomic and ecological systems is a central challenge in global sustainability science, representing a fundamental shift in how sustainable development is monitored and managed [1,2]. This challenge is especially pronounced in deltaic regions, which serve as dynamic, complex interfaces where social, economic, and ecological processes interact in often nonlinear and unpredictable ways [3]. Deltas such as the Nile Delta are not merely geographic landforms but coupled human–natural entities characterized by high population densities, intensive agricultural and industrial activities, and heightened vulnerability to environmental change [4,5]. Consequently, there is a global need to develop integrated measurement systems that capture these interactions, inform adaptive management strategies, and support sustainable development pathways amid climate change, land degradation, and socioeconomic transformation [1,3,6].

Within this global context, the Nile Delta holds exceptional regional importance as Egypt's primary agricultural and economic heartland, supporting more than 40 million inhabitants and producing 60%–65% of the country's food supply [7]. Yet, it is considered a critical frontier of climate vulnerability [8]. Despite its significance, the region faces compounded, interrelated threats: land subsidence, sediment deprivation following the construction of the Aswan High Dam, rapid and often unplanned urban expansion, groundwater salinization, and the growing threat of sea-level rise [9,10]. These pressures jointly threaten ecological integrity and socioeconomic viability, making the Nile Delta a critical case study for advancing sustainability measurement and management [9].

In response to these challenges, a wide range of global and regional sustainability assessment frameworks have been proposed to evaluate the interactions between environmental integrity and socioeconomic development [11,12]. These frameworks generally rely on composite indicator systems supported by spatial analytical tools to assess land and resource sustainability, environmental security, and social well-being. While such approaches provide valuable insights into vulnerability patterns in deltaic regions, their applicability and effectiveness vary considerably across contexts, particularly in rapidly urbanizing and data-constrained environments in developing countries [13–15].

Nevertheless, the use of existing sustainability measurement systems has revealed important limitations. Many frameworks are constrained by high data requirements and methodological complexity, limiting their scalability and contextual adaptability. Key socioeconomic dimensions, such as governance, infrastructure, and development efficiency, remain underrepresented [12,16]. Moreover, these approaches often struggle to capture the dynamic, nonlinear interactions that fundamentally characterize deltaic socio-ecological systems [5].

As a result, recent advances in sustainability assessment have increasingly emphasized the integration of socioeconomic dimensions, governance structures, infrastructure development, and economic diversification [13,17]. These assessments are supported by weighted indicator systems, resilience-based approaches, and spatial decision support systems that explicitly consider social acceptability and economic viability [18,19]. Therefore, these developments have been reflected in applications in the Nile Delta, where the social aspect is as essential as the environmental aspect [20,21].

Alongside these conceptual advances, GIS and remote sensing technologies have transformed sustainability assessment by facilitating the integration of multi-layered spatial datasets and enabling consistent monitoring of environmental change over time [1,22]. However, the effectiveness of these technologies within comprehensive sustainability frameworks remains strongly dependent on their integration with socioeconomic indicators and context-specific analytical models.

Against this background, coupling-based quantitative models have become important tools for assessing interactions between socioeconomic and ecological systems. Coupling coordination degree (CCD) approaches have been extensively applied across Asian regions and, to a lesser extent, other international contexts [23,24]. However, their application to African deltaic socio-ecological systems remains limited. This gap is particularly relevant to the Nile Delta, where rapid urban expansion, conversion of agricultural land, climate vulnerability, coastal erosion, and land subsidence interact within a densely populated and economically important deltaic system [25,26]. Therefore, the contribution of this study lies not in introducing a new methodological framework but in extending CCD-based socio-ecological assessment to a highly vulnerable African delta system. Using multi-source remote sensing datasets and cloud-based geospatial analysis, the study examines the spatiotemporal evolution of socioeconomic–ecological coordination across the Nile Delta and identifies its changing spatial patterns and dominant subsystem constraints. This contributes region-specific evidence to the broader CCD literature and helps address the limited representation of African deltaic systems in existing research.

2. Literature review

2.1. *The theoretical evolution of urban-eco sustainability*

The assessment of sustainability at the intersection of socioeconomic and ecological systems has become a central focus of global research, particularly in environmentally sensitive regions such as deltas. Analytical approaches have increasingly shifted from assessing individual subsystems toward examining their interactions and coordination over space and time. Among these approaches, the coupling coordination degree model (CCDM) has become an established framework for evaluating the degree of coordination between socioeconomic and eco-environmental systems [27,28]. Rather than treating economic development and ecological conditions as independent dimensions, the CCD framework provides a quantitative basis for examining whether these subsystems evolve in a mutually supportive or increasingly imbalanced manner [27,29].

A consistent perspective across socio-ecological research is that these relationships are nonlinear and may involve both trade-offs and synergies. Rapid urbanization, for example, can generate imbalances between socioeconomic development and environmental capacity, with spatial disparities and uneven development influencing the resulting coordination patterns [30]. At broader regional scales, sustainability trajectories have likewise been shown to emerge from interactions among ecosystem structure, resilience, activity, and services rather than from independent changes in individual components [31].

The CCDM has subsequently been applied across a wide range of urban, agricultural, water, energy, and coastal systems [8,17,19,27]. Its applications commonly employ composite indicator systems to represent socioeconomic and ecological conditions, using approaches such as the entropy weighting method (EWM), the analytic hierarchy process (AHP), and principal component analysis (PCA) [17]. The integration of remote sensing has further expanded these applications by providing spatially consistent indicators of vegetation condition, land surface temperature, urban expansion, and other environmental and human-activity characteristics [12,29]. These developments have enabled CCD-based assessments to examine both temporal changes in subsystem coordination and spatial differences in leading and lagging conditions.

2.2. Global applications of the coupling coordination degree model

Empirically, the CCDM has been widely applied across diverse regional contexts, including coastal, deltaic, urban, and river-basin systems. In China, applications to the Bohai Sea Rim and Yangtze River Delta have revealed pronounced spatiotemporal patterns, development gradients, and regional disparities in sustainability outcomes [8,32]. In other deltaic environments, the model has also been extended to account for processes such as land subsidence, sediment compaction, sediment transport, tidal dynamics, and sea-level rise, demonstrating its adaptability to environmentally sensitive coastal systems [33].

Recent applications have examined the interaction between urbanization, economic development, and ecological conditions at different spatial scales. Studies in the Yellow River Basin have identified gradual improvements in coordination between new-type urbanization and ecosystem service values, with NDVI emerging as an important positive driver [6,34]. Similarly, applications of the Production–Living–Ecological Spaces framework have identified persistent spatial conflicts arising from the encroachment of production and living spaces onto ecological land [6]. In the Chengdu–Chongqing urban agglomeration, remote sensing–based ecological indices have shown that rapid economic growth can coincide with elevated environmental pressure and lagging ecological conditions [28]. At broader spatial scales, studies of water–economic coordination have also identified substantial regional heterogeneity associated with water availability, industrial intensity, technological innovation, and investment capacity [34,35].

Evidence from outside China further demonstrates that CCD-based approaches can capture distinct regional trajectories under different environmental and socioeconomic conditions. Research on the Lake Iseo Basin in Italy identified changes in the balance between ecological and socioeconomic constraints over time [36], while studies in Poland have applied convergence-based approaches to examine spatial differentiation in coordination and development across municipalities [37]. These cases demonstrate that the CCD framework is not restricted to rapidly urbanizing Chinese regions and can be adapted to different institutional, environmental, and spatial contexts.

Nevertheless, the literature remains strongly concentrated in China and, more broadly, in Asian contexts, while applications from Africa and the Middle East remain limited. This geographic imbalance raises questions about the transferability of indicators, thresholds, and coordination patterns developed primarily from Chinese cases to socio-ecologically distinct regions. This issue is particularly relevant for the Nile Delta, where intensive agricultural dependence, rapid urban expansion, coastal vulnerability, and environmental pressures interact within a densely populated deltaic system [7,9,25,26]. These differences highlight the importance of interpreting CCD-based coordination patterns in relation to the specific environmental, socioeconomic, and institutional context of each region.

2.3. Synergizing remote sensing Big Data

The increasing availability of satellite-based Earth observation has expanded the capacity to monitor socioeconomic and ecological conditions at fine spatial and temporal scales. Remote-sensing indicators such as the Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), land surface temperature (LST), and built-up indices provide spatially consistent measures of vegetation condition, environmental stress, and human-induced land transformation. When combined with socioeconomic and environmental datasets, these indicators can support the identification of spatial vulnerability patterns and improve the assessment of interactions between human activity and

ecological conditions [28,34].

Cloud-based platforms such as Google Earth Engine (GEE) have further enhanced these capabilities by enabling the processing of large, multi-source geospatial datasets without the computational limitations associated with conventional local workflows [33,38]. GEE facilitates the integration and processing of long-term satellite archives and spatial datasets, allowing environmental indicators to be generated consistently across large and heterogeneous regions. Its application is particularly valuable in data-constrained settings where conventional socioeconomic and environmental data may be spatially fragmented or available only at limited temporal intervals [7].

The integration of remote-sensing indicators with socioeconomic variables can therefore provide a more spatially explicit representation of coupled socio-ecological systems. However, remotely sensed indicators primarily capture observable spatial characteristics of environmental conditions and human activity and cannot fully represent socioeconomic structures, institutional capacity, employment patterns, accessibility, or production systems [39,40]. Their use within integrated assessment frameworks consequently requires careful indicator selection and interpretation.

2.4. Socio-ecological research in the Nile Delta: existing gaps

In the context of the Nile Delta, existing Egyptian studies have predominantly addressed environmental and socioeconomic sustainability from sector-specific perspectives. The literature reveals extensive research on land-use and land-cover change and its driving forces [38], groundwater deterioration assessed using DRASTIC and hydro-geophysical approaches [1], sea-level rise impacts on land sustainability [41], and coastal erosion coupled with sediment deficits. Additionally, studies have explored waterway degradation and pollution [42], remote sensing applications in agriculture and land resources [10], and drainage water reuse within sustainability frameworks [8]. Collectively, this literature demonstrates that the Nile Delta represents a highly socio-ecologically vulnerable system and highlights the urgent need for integrated approaches to land, water, and environmental management strategies [20,43].

Despite the expanding body of research on the Nile Delta, several critical gaps remain. Existing studies have not incorporated cloud-based platforms such as Google Earth Engine (GEE) to generate consistent, high-resolution ecological indicators for delta-scale assessments [38,33]. In addition, most research adopts a sectoral approach, examining environmental or socioeconomic systems separately rather than as interconnected components of a coupled system [1,20]. Furthermore, available analyses remain spatially fragmented and provide a limited comprehensive spatiotemporal assessment of the interactions between these systems [9,33,38].

The Nile Delta is a particularly suitable context for CCD-based analysis because of the fundamental interdependence of its social, economic, and ecological systems [1,33]. Intensive agricultural production, urban expansion, groundwater use, and coastal processes interact across a densely populated and spatially constrained region [1,7,44]. These characteristics emphasize the need for assessment approaches capable of capturing both temporal change and spatial differentiation rather than examining environmental pressures in isolation. Accordingly, this study addresses these gaps by applying a CCD-based framework to the Nile Delta and integrating ecological and socioeconomic systems using GEE-derived indicators, thereby providing a consistent spatiotemporal assessment of socioeconomic–ecological coordination and its spatial differentiation.

2.5. Methodological and spatial limitations of the CCD model

Although the CCDM has proven widely useful, its application is limited by several inherent challenges related to data quality, methodological assumptions, and geographical diversity. The model's reliability depends greatly on the selection of indicators, the completeness of available data, and the approach taken to assign weights. When weighting schemes are subjective or poorly suited to the context, they can introduce significant bias into the resulting coordination measures [45]. Methodologically, traditional CCDM frameworks often assume linear relationships and fixed weights, which restrict their ability to account for the complex, nonlinear interactions and feedback mechanisms characteristic of real-world systems [46]. Moreover, marked disparities between subsystem development levels may artificially inflate the overall CCD value, potentially creating a misleading impression of coordination when deficiencies exist in one or more subsystems [2]. Furthermore, the influence of spatial heterogeneity and localized clustering further complicates the comparison of results across geographically diverse units [2,47]. Finally, because coordination dynamics are shaped by specific local environmental conditions, socioeconomic factors, and evolving policy contexts, conventional models frequently lack the capacity for robust, long-term comparative analysis [48,49]. These limitations highlight the importance of context-sensitive indicator selection, objective weighting, and spatially explicit interpretation. In particular, CCD results should be interpreted as measures of coordination between defined subsystems rather than as direct evidence of causal relationships among them.

3. Materials and methods

3.1. Study area: Nile Delta functional environment

Egypt is situated within a diverse regional environmental framework consisting of functionally distinct environmental domains. This study adopted the Freshwater Ecoregions of the World (FEOW) classification as a reliable global framework for defining ecological regions based on hydrological, environmental, and biodiversity characteristics. This classification was selected because it reflects variations in climate, water resources, and ecosystem characteristics, allowing the study to evaluate environmental sensitivity and human impacts more effectively than relying solely on administrative boundaries.

These ecoregions are presented in Figure 1, highlighting the clear ecological gradient across the country. These ranges include, from east to west, the Sinai Peninsula (435), a transitional area between African and West Asian ecosystems, the Great Deserts region (503), characterized by severe water scarcity and an arid environment, and the Dry Plain Range (504), reflecting an ancient climatic legacy of historical drainage networks.

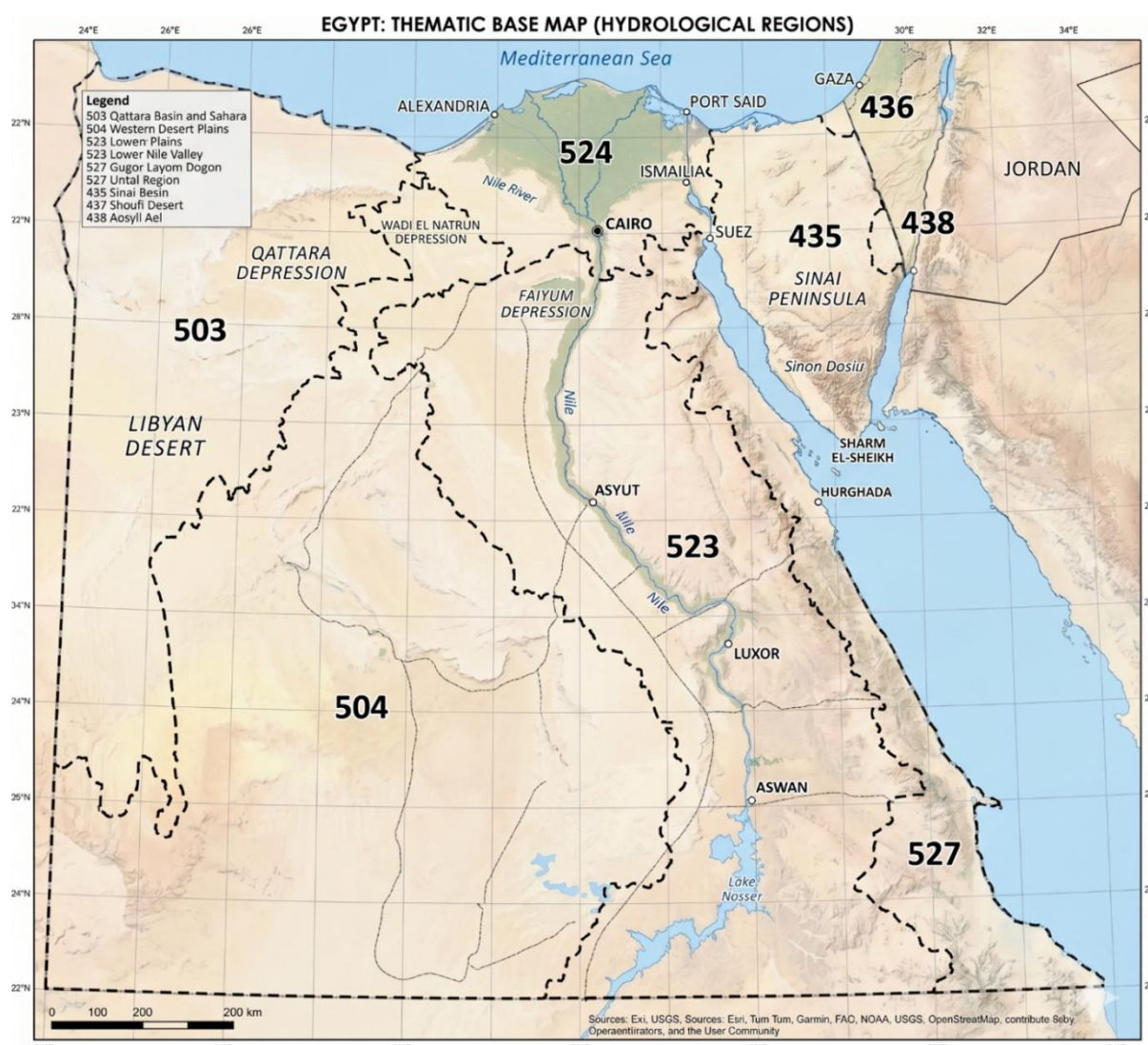


Figure 1. Classification of ecological regions in Egypt. Source: Authors' preparation based on data retrieved from <https://feow.org/ecoregions/details>.

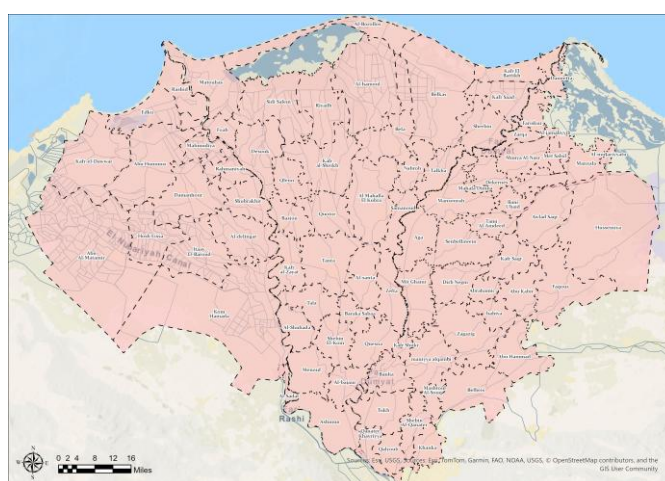


Figure 2. Boundaries of the study area. Source: Authors' preparation based on the Freshwater Ecoregions of the World (FEOW) and administrative boundaries of Egypt.

In contrast with these dry and marginal ranges, the Nile system stands out as a unique ecological unit, extending from the lower Nile region (523) to the Nile River Delta (524), which represents the final stage of the river floodplain and the most stable and functionally interconnected ecological range. The delta is a dynamic sedimentary system encompassing the main river branches (Rashid and Damietta), coastal lakes, and associated wetlands. It borders the Western Red Sea Drainage Basin Range (527) to the north, which is a hyper-arid ecosystem radically different from the humid Nile environment. Based on this ecological gradient, this research relies on functional ecological boundaries rather than administrative divisions to define its spatial scope, as these boundaries better reflect the actual relationships between natural components and human activities. Figure 2 illustrates the boundaries of the study area, excluding desert ranges outside the direct environmental impact of the Nile system. Internally, administrative divisions of governorate centers (districts) were utilized for data organization due to the absence of clear internal spatial ecological borders.

3.2. *Data sources and cloud-based processing*

3.2.1. Socioeconomic indicators

To represent socioeconomic dimensions as driving forces and pressures on the ecosystem, this study relies on remote sensing (RS) proxy indicators, given the limited availability and coarse spatial and temporal resolution of conventional statistical datasets. The Nighttime Lights (NTL) Index serves as the primary proxy for human and economic activity, urbanization, and energy consumption. Since no single continuous nighttime-light dataset spans the full study period, a multi-sensor approach was used: DMSP-OLS (version 4, stable lights band) for 2010 and VIIRS-DNB for 2015, 2020, and 2023, given its higher radiometric sensitivity. Following georeferencing, background-noise correction, and aggregation to the district level, NTL values were normalized separately for each observation year using min–max normalization. This approach supports comparison of relative socioeconomic intensity and spatial patterns across the study period rather than direct comparison of absolute radiance values between DMSP-OLS and VIIRS-DNB. Although formal cross-sensor radiometric calibration and uncertainty propagation were not performed, the year-specific normalization provides a consistent relative scale for the temporal analysis while avoiding interpretation of inter-sensor differences as absolute changes in radiance.

Urban pressure was captured through the Normalized Built-up Index (NDBI), derived from Landsat's NIR and SWIR bands of Landsat imagery. NDBI captures the spatial intensity and extent of built-up development and is therefore used as a proxy for urban expansion and associated anthropogenic pressure. For this reason, NDBI is treated as a socioeconomic/urban pressure indicator rather than an ecological state variable, maintaining the distinction between human pressures and environmental responses.

The selection of NTL and NDBI prioritized spatial and temporal consistency across districts and years over dimensional completeness. The two indicators provide complementary coverage of human activity intensity and urban expansion, respectively, while enabling a consistent longitudinal assessment across the study area. The use of these indicators was guided by the availability of comparable district-level data throughout the study period. A key limitation is that these indicators do not fully capture socioeconomic structure, employment patterns, accessibility, demographic characteristics or production systems, and consequently cannot represent all mechanisms through which socioeconomic development influences ecological conditions. Accordingly, NTL and NDBI are treated as spatial proxies for human activity and urban expansion rather than as comprehensive

measures of socioeconomic development.

3.2.2. Ecosystem indicators

To characterize the state of the ecosystem and the impacts of anthropogenic pressures, a set of environmental indicators was selected to capture vegetation condition, moisture levels, surface water dynamics, urban ecological structure, ecosystem functioning, and air quality. The NDVI, NDWI, and NDMI indices were employed to monitor vegetation health, moisture content, and surface water variability, respectively. NDVI was derived from MODIS (MOD13Q1) data at 250-m spatial resolution using 16-day composites, from which annual mean values were calculated for the defined spatial units to reduce seasonal variability. In contrast, NDWI and NDMI were generated from surface reflectance Level-2 Landsat data, using Landsat 5 for 2010 and Landsat 8/9 for the period 2015–2023, with cloud masking (QA_PIXEL) applied to produce consistent annual averages.

To represent urban ecological structure, impervious surface indices were included as indicators of ecosystem condition, reflecting functional alterations in land surfaces. The NDISSI index was utilized to capture spatial patterns of imperviousness while minimizing spectral confusion between bare soil and built-up areas, particularly in transitional zones along the Nile Delta margins. Sensor-specific data were applied, using Landsat 5 for 2010 and high-resolution Sentinel-2 imagery (10 m) for 2023. Ecosystem functioning was represented by net primary productivity (NPP), derived from the annual MODIS MOD17A3HGF product at 500-m resolution, indicating carbon sequestration capacity. In addition, nitrogen dioxide (NO₂) concentrations were incorporated as an air quality indicator using Sentinel-5P (TROPOMI) Level-3 products processed offline (OFFL) for 2018–2023 to ensure data consistency and reliability.

3.3. Methodology and data

This methodological framework outlines an integrated quantitative approach to analyze interactions between socioeconomic and ecological systems. The framework combines objective weighting methods with dynamic coupling analysis models to assess the development level of individual subsystems and measure their degree of coordination. The framework design consists of two main components: the entropy weighting method (EWM) for determining objective indicator weights, and the CCDM for measuring the strength of interaction and spatial differentiation.

3.3.1. Entropy weighting method (EWM)

The entropy weighting method is an objective approach for determining the relative weights of multidimensional indicators by evaluating data dispersion. Unlike subjective methods, EWM assumes that an indicator with greater variation across spatial or temporal units contains more information and, therefore, warrants a higher relative weight. This reduces systematic bias and enhances reliability when combining socioeconomic and environmental datasets with different units and statistical properties [29,50,51].

The number of indicators was not used as a criterion for assigning greater importance to either subsystem. Within each subsystem, the EWM determines the relative contribution of individual indicators according to their information content and variability. At the subsystem level, the CCDM subsequently assigns equal importance to the socioeconomic and ecological systems through $\alpha=\beta=0.5$. Thus, the unequal number of indicators reflects the composition and data availability of the respective

subsystems rather than unequal weighting between them.

To provide a clear mathematical framework for the evaluation, the following step-by-step procedure was utilized to process the indicator data:

A. Data standardization: Raw data are normalized to a dimensionless range (0 to 1) to eliminate the effect of different units of measurement, through Eqs (1) and (2):

- For positive indicators (where a higher value indicates a better condition):

$$X'_{ij} = \frac{(X_{ij} - X_{jmin})}{(X_{jmax} - X_{jmin})} \quad (1)$$

- For negative (inverse) indicators (where a higher value indicates a worse situation):

$$X'_{ij} = \frac{(X_{jmax} - X_{ij})}{(X_{jmax} - X_{jmin})} \quad (2)$$

B. Indicator weighting: The proportion of the indicator j in year I is given by Eq (3):

$$P_{\{ij\}} = \frac{\{X'_{\{ij\}}\}}{\{\sum_{\{i=1\}}^{\{m\}} X'_{\{ij\}}\}} \quad (3)$$

C. Entropy value: Calculated for each indicator using Eq (4):

$$E_j = -k \sum_{\{i=1\}}^{\{m\}} P_{\{ij\}} \cdot \ln(P_{\{ij\}}) \quad (4)$$

D. Entropy weight, given by Eq (5):

$$W_j = \frac{\{1 - E_j\}}{\sum_{\{j=1\}}^{\{n\}} \{1 - E_j\}} \quad (5)$$

E. Comprehensive subsystem value, given by Eq (6):

$$U_i = \sum_{\{j=1\}}^{\{n\}} W_j \times X'_{\{ij\}} \quad (6)$$

As shown in Table 1, NTL receives the highest weight within the socioeconomic subsystem (61.95%), while NDBI accounts for 38.05%. Within the ecological subsystem, NDWI has the highest weight (31.15%), followed by NPP (20.48%) and NDISSI (14.07%). The remaining indicators receive lower weights, including NDMI (9.56%), NDVI (7.06%), NO₂ (6.06%), LST (6.02%), and agricultural pressure (5.60%). These weights represent the relative information contribution of the indicators within the EWM framework, reflecting their spatial and temporal variability in the study dataset, rather than their direct causal importance.

Table 1. Evaluation indicators of socioeconomic and ecological systems.

System	Indicator	Direction	Entropy (e)	Redundancy (d)	Weight (Wj)	Dataset/platform (GEE ID)	Sensor/satellite
Socioeconomic	Nighttime	(+)	0.922718	0.07728237	0.619507	NOAA/DMSP-OLS & VIIRS/DNB	DMSP & Suomi NPP
	Lights (NTL)	Positive					
	Built-up ratio	(+)	0.952534	0.047465727	0.380493	LANDSAT/L5, L8, L9	Landsat
	(NDBI)	Positive					TM/OLI
	Vegetation	(+)	0.989778	0.010221722	0.070595	MODIS/061/MOD13Q1	MODIS
	(NDVI)	Positive					(Terra)
	Water Index	(+)	0.954894	0.045105682	0.311518	LANDSAT/L5, L8, L9	Landsat
Eco- Environmental	(NDWI)	Positive					TM/OLI
	Moisture	(+)	0.986155	0.013844565	0.095616	LANDSAT/L5, L8, L9	Landsat
	Index	Positive					TM/OLI
	(NDMI)						
	Net primary	(+)	0.970349	0.029650956	0.204781	MODIS/061/MOD17A3HGF	MODIS
	prod. (NPP)	Positive					(Terra)
	Agri.	(-)	0.991897	0.008102849	0.055961	Calculated	Derived
	pressure	Negative					
	Impervious	(-)	0.979626	0.020374128	0.140712	LANDSAT & Sentinel-2	Landsat & Sentinel-2
	(NDISSI)	Negative					
	Land surface	(-)	0.991284	0.008716209	0.060198	LANDSAT/L8/TIRS	Landsat 8
	temp (LST)	Negative					
	Air pollution	(-)	0.991223	0.008777294	0.060619	COPERNICUS/S5P/OFFL	Sentinel-5P
	(NO_2)	Negative					

Note: (+) represents a positive indicator, (-) represents a negative indicator. Source: Prepared by the authors based on data indicators from GEE.

3.3.2. Coupling coordination degree model (CCDM)

The CCDM is used to assess the level of interaction and synergy between the socioeconomic and ecological systems. Unlike simple coupling models that only measure the strength of interaction, the CCDM integrates the individual development levels of each subsystem [6,28,50]. This approach provides a comprehensive understanding of whether systems are evolving in harmony or if development is occurring at the expense of ecological integrity. In this study, the model facilitates the classification of districts within the Nile Delta into specific stages of developmental balance or imbalance.

The calculation of the CCDM follows a three-step mathematical procedure:

A. Degree of coupling (C): This index measures the strength of interaction between the socioeconomic and ecological systems, independent of their development levels:

$$C = \left\{ \frac{\prod_{i=1}^{\{n\}} U_i}{\left[\frac{1}{n} \sum_{i=1}^{\{n\}} U_i \right]^n} \right\}^{\left\{ \frac{1}{n} \right\}} \quad (7)$$

B. Comprehensive Coordination Index (T): This index reflects the overall development level of

the combined systems, assigning relative importance weights (α and β) to each subsystem:

$$T = \sum_{i=1}^{\{n\}} \alpha_i \times U_i \quad (8)$$

$$\{with\} \sum_{i=1}^{\{n\}} \alpha_i = 1 \quad (9)$$

Here, coefficients α and β denote the relative weights assigned to the socioeconomic system and the ecosystem, respectively. In this study, they were set to equal values ($\alpha = \beta = 0.5$), reflecting equal importance for both systems.

C. Coupling coordination grade (D): The final indicator used to classify the level of coordination in the region:

$$D = \sqrt{\{C \times T\}} \quad (10)$$

Here, D represents the degree of coupling coordination, while T represents the overall development index of the socioeconomic and environmental subsystems. To provide a precise scientific diagnosis of the study area, the CCD values are classified into five major coordination categories. Furthermore, the relative development conditions between socioeconomic and ecological systems are utilized to identify lagging subsystems, as detailed in Table 2.

Table 2. Classification of coupling coordination categories, subtypes, and their scientific interpretation.

Primary development stage	Coordination level	Value range	Relative development condition	Corresponding subtypes
Balanced development	Superior coordination	0.9–1.0	Balanced: $ U_1 - U_2 \leq 0.1$ Ecological lagging: $U_1 - U_2 > 0.1$	Sub 1 / 2 / 3 (high-quality)
	Good coordination	0.8–0.9		
	Intermediate coordination	0.7–0.8	Socioeconomic lagging: $U_2 - U_1 > 0.1$	Sub 4 / 5 / 6 (good coordination)
	Primary coordination	0.6–0.7	Economic obstruction: $U_2 \ll U_1$ under low coordination conditions	
Transitional Development	Reluctant coordination	0.5–0.6	Ecological obstruction: $U_1 \ll U_2$ under low coordination conditions	Sub 7 / 8 / 9 (basic coordination)
	Verge of disorder	0.4–0.5		
Unbalanced Development	Slight disorder	0.3–0.4		Sub 10 / 11 / 12 (dissonance)
	Moderate disorder	0.2–0.3	General rupture: Both U_1 and U_2 are weak ($ U_1 - U_2 \leq 0.1$)	
	Serious disorder	0.1–0.2		
	Extreme disorder	0.0–0.1	with very low D General rupture	

Note: The coupling coordination degree (D) reflects the overall coordination status between the socioeconomic subsystem (U_2) and the

ecological subsystem (U_1). The relative development condition is determined based on the magnitude and direction of the difference between U_1 and U_2 . Source: Prepared by the authors based on data indicators [11,27,28,34].

3.3.3. Spatial autocorrelation: Moran's I

Spatial autocorrelation analysis was conducted to determine whether coordination levels exhibit clustered, dispersed, or random spatial patterns. Statistical significance was evaluated using Moran's I statistics together with the corresponding z-scores and p-values [6,45].

Spatial relationships between districts were defined using a K-nearest neighbors (KNN) approach, whereby each district was connected to its eight nearest neighboring districts ($k = 8$). A K-nearest neighbors spatial weights matrix was constructed to represent spatial interactions among districts and was subsequently row-standardized before conducting Global Moran's I and Local Moran's I (LISA) analyses.

Global spatial autocorrelation was measured using the Global Moran's I index, which captures the overall degree of spatial dependence across the study area:

$$\text{Moran's I} = \frac{\sum_{i=1}^m \sum_{j=1}^m (D_i - \bar{D})(D_j - \bar{D}) \phi_{ij}}{S^2 \sum_{i=1}^m \sum_{j=1}^m \phi_{ij}} \quad (11)$$

Here, W_{ij} represents the spatial weights matrix. Moran's I values range from -1 to 1 , indicating spatial dispersion, randomness, or clustering. In this study, the index was used to evaluate the spatial organization of coupling coordination patterns across the Nile Delta.

The statistical significance of Global Moran's I was assessed using a permutation-based randomization procedure implemented in ArcGIS Pro with 499 permutations. The observed Moran's I values were compared against a distribution generated through random spatial rearrangements to calculate the corresponding z-scores and p-values.

Local spatial heterogeneity was further examined using local indicators of spatial association (LISA), which identify local clusters and spatial outliers:

$$\frac{n(x_i - \bar{x}) \sum_{j=1}^n w_{ij}(x_j - \bar{x})}{\sum_{i=1}^n w_{ij}(x_j - \bar{x})^2} \quad (12)$$

Local indicators of spatial association (LISA) were computed using the same row-standardized K-nearest neighbors spatial weights matrix ($k = 8$). Statistical significance was assessed using 499 random permutations implemented in ArcGIS Pro. Local clusters were classified into high-high (H-H), low-low (L-L), high-low (H-L), and low-high (L-H) categories according to their local spatial association patterns.

No false discovery rate (FDR) correction or additional multiple-testing correction procedure was applied, as the LISA analysis was primarily employed as an exploratory tool for identifying local spatial clustering patterns. The resulting LISA maps provide detailed insights into the spatial differentiation of coordination levels and the emergence of local hot spots and cold spots within the Nile Delta.

4. Results

4.1. Temporal characteristics of coupling coordination in the Nile Delta

The temporal evolution of the CCD between the socioeconomic and ecological systems in the

Nile Delta shows a clearly nonlinear pattern between 2010 and 2023. As evidenced in Table 3, the region maintained a relatively high level of coordination in 2010, with an average CCD of 0.72. This indicates that at the start of the study period, development dynamics were largely within the delta's environmental carrying capacity.

However, this initial state was followed by a sharp decline in 2015, with the average CCD falling to its lowest recorded level of 0.54. This decline reflects a period of structural imbalance, where rapid, often unregulated socioeconomic expansion exceeded the limits of sustainable ecosystem functions. Following this decline, the Nile Delta entered a phase of sustained partial recovery from 2015 to 2023. The average CCD rose slightly to 0.55 by 2020 and reached 0.63 in 2023. Therefore, as illustrated in Figure 3, this upward trend supports the observation that although all governorates experienced a decline after 2010, they have steadily moved toward partial recovery in recent years. The nonlinear variation in CCD values reflects a complex interplay of environmental pressures and socioeconomic shifts.

Table 3. Descriptive statistics of coupling coordination degree (CCD) in the Nile Delta districts (2010–2023).

Year	Average (Mean)	Standard deviation	Minimum value	Maximum value
2010	0.72	0.037	0.62	0.82
2015	0.54	0.083	0.24	0.71
2020	0.55	0.050	0.46	0.74
2023	0.63	0.041	0.55	0.78

Source: Prepared by the authors using ArcGIS Pro (Spatial Statistics Tools).

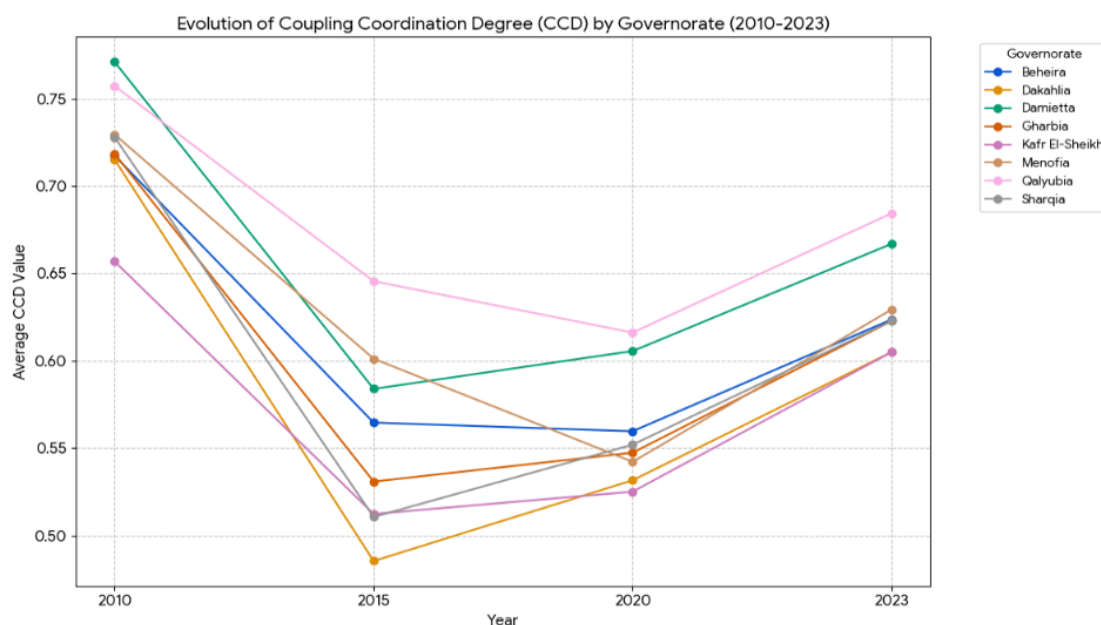


Figure 3. Temporal evolution of the coupling coordination degree (CCD) across governorates in the Nile Delta (2010–2023). Source: Prepared by authors using ArcGIS Pro (Spatial Analysis and Spatial Statistics Tools).

4.2. Spatial characteristics of coupling coordination in the Nile Delta

The spatial distribution of the CCD across the Nile Delta shows a clear center–periphery gradient. The highest coordination levels are consistently concentrated within the central urbanized districts, such as Tanta, Mansoura, and Damanhour. These core regions benefit from a combination of fertile soils, dense populations, and robust infrastructure, which together provide a foundation for socioeconomic momentum to balance development with environmental management. In contrast, the lowest CCD values occur in the marginal zones, specifically the northern coastal belt and the desert fringes. While districts such as Damietta and Kafr El-Battikh emerged with the highest coordination performance by 2023, peripheral districts like Bani Obeid and Awlad Sakr continue to lag, remaining in a transitional or near-imbalanced state.

Critically, the degree of spatial disparity has also changed significantly over time. As indicated by the statistical parameters in Table 3, the spatial gap between districts widened drastically in 2015, with the range reaching 0.47 and the standard deviation increasing to 0.083. This peak in variance signifies a period of extreme regional inequality in coordination, affecting the periphery districts far more severely than the central cores. However, by 2023, a process of spatial convergence and regional homogenization became evident. The range narrowed to 0.23, and the standard deviation dropped to 0.041. This narrowing gap, coupled with the overall recovery in values shown in Figure 4, suggests that the Nile Delta is moving toward a more balanced regional state.

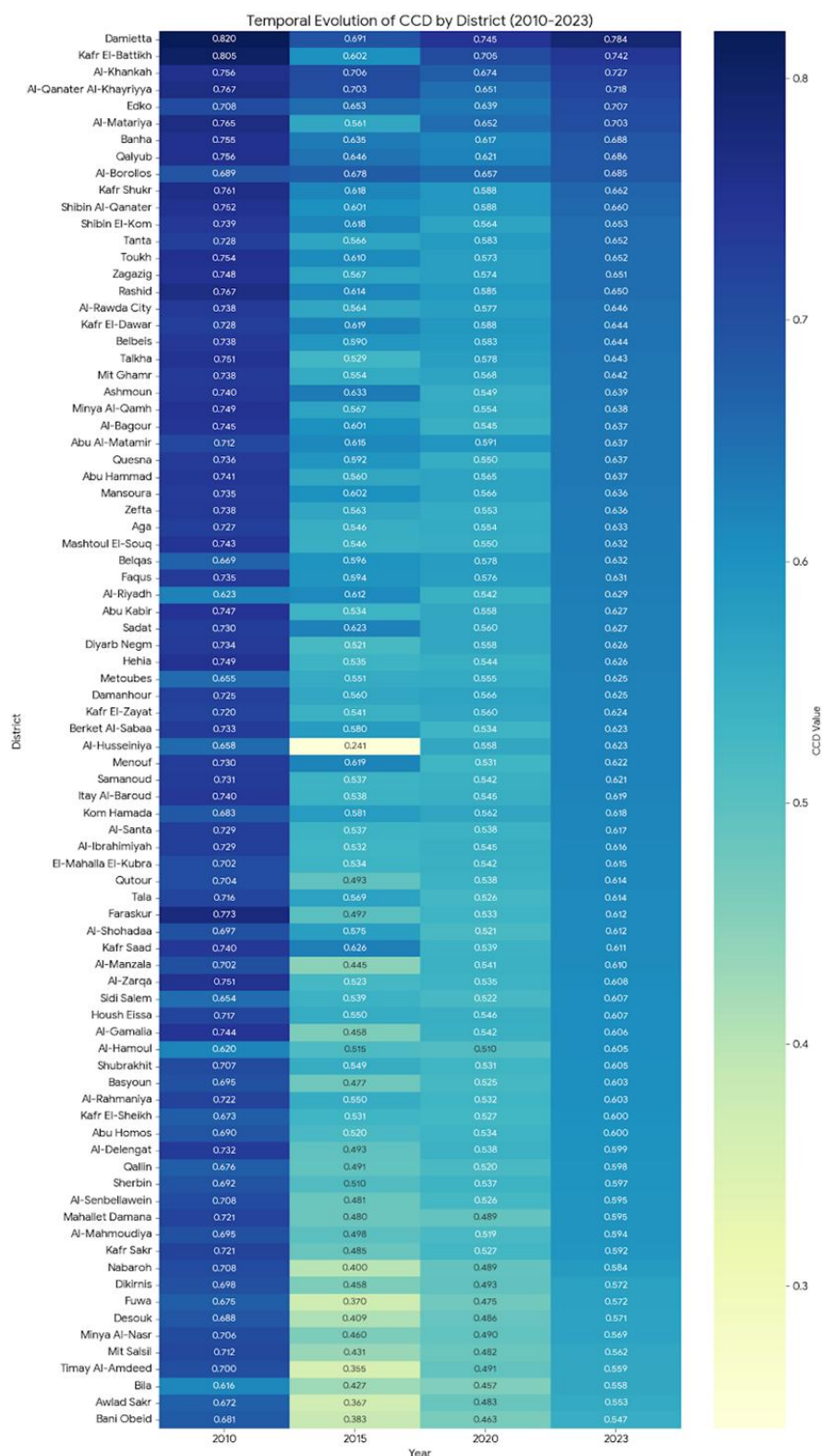


Figure 4. Temporal evolution and ranking of CCD by district (heatmap). Source: Prepared by the authors using Google Earth Engine and ArcGIS Pro (Spatial Analysis and Spatial Statistics Tools).

4.3. Spatial subtype characteristics of coupling coordination

The evolution of CCD subtypes in the Nile Delta provides a clear understanding of the shifting balance between socioeconomic and ecological systems. From 2010 to 2023, the region underwent a complex structural transformation, transitioning from a state of growth-driven environmental pressure to a widespread socioeconomic lagging condition. Detailed scientific interpretations for each diagnostic subtype are provided in Table 4.

Table 3. Coupling coordination categories, subtypes, and their scientific interpretation.

Subtype ID	Relative development type	Scientific and practical interpretation
Sub1	Socioeconomic lagging	An ecologically optimal area with high environmental quality; however, socioeconomic development remains insufficient and must be accelerated to fully utilize its ecological advantages.
Sub2	Ecological lagging	An advanced socioeconomic stage in which environmental conditions start to deteriorate, requiring immediate ecological protection measures.
Sub3	Balanced	The ideal coordination state is characterized by complete harmony between socioeconomic development and environmental protection.
Sub4	Socioeconomic lagging	Environmental quality remains very strong, while socioeconomic development progresses steadily but stays below the ecological carrying capacity.
Sub5	Ecological lagging	Rapid and successful development exceeds the environment's capacity for recovery and renewal.
Sub6	Balanced	A stable coordination state in which both systems develop synchronously and sustainably.
Sub7	Socioeconomic lagging	A resilient ecological system combined with weak or inefficient economic activities; this pattern is most common in the Nile Delta region.
Sub8	Ecological lagging	Development is improving but occurs at the expense of natural resources, leading to gradual ecological degradation.
Sub9	Balanced	A transitional stage where both systems are weak or moderately developed, and coordination remains fragile.
Sub10	Economic obstruction	Severe economic deterioration limits the socioeconomic system's ability to interact effectively with the ecological environment.
Sub11	Ecological obstruction	Even limited socioeconomic development has caused acute environmental degradation, resulting in direct system conflict.
Sub12	General rupture	The worst-case scenario is marked by a simultaneous collapse of both systems and a complete breakdown in coordination.

Source: Prepared by the authors based on the literature.

4.3.1. Phase I (2010): The era of good coordination and ecological pressure

In 2010, the Nile Delta experienced a peak in coordination, characterized by high CCD values and the dominance of the "good coordination" category. As shown in Figure 5, the spatial logic was defined by three main subtypes:

A. Sub5 (good coordination: ecological lagging): This was the most prevalent category (38 districts), concentrated in the central and southern Delta (e.g., Tanta, Mansoura, Damanshour, Benha, and Zagazig). In these regions, as historical, administrative, and industrial and agricultural hubs, intense economic activity began to outpace environmental carrying capacity ($ED > EE$).

B. Sub6 (good coordination: balanced): Approximately 20 districts, including Kafr El-Dawar, Abu Al-Matamir, and El-Mahalla El-Kubra, achieved an ideal equilibrium, primarily located in the transition zones between urban centers and agricultural peripheries, and managed to sustain growth without reaching environmental exhaustion.

C. Sub7 (basic coordination: socioeconomic lagging): This category was localized in 11 districts along the Northern Coastal belt (e.g., Edko, Rashid, and Al-Hamoul), where pristine ecological conditions existed alongside insufficient infrastructure and investment.

4.3.2. Phase II (2015–2020): Regional coordination crisis and selective recovery

The year 2015 represented a critical negative turning point in the Delta's development trajectory. The region experienced a regional coordination shock, marked by the emergence of Subtype 10 (economic obstruction) in 22 districts, particularly in the eastern Delta (Dakahlia and Sharqia governorates) and parts of the north-central region (Kafr El-Sheik governorate). This pattern reflects a near-total collapse in the socioeconomic system's ability to interact effectively with environmental resources, likely driven by institutional, technological, and economic instability. In parallel, most Delta core districts (about 55) shifted to the Sub7 pattern, where a collective spatial decline in urban centers causes the loss of their traditional role as drivers of regional development.

By 2020, the Delta experienced a cautious, selective recovery toward coordinated stability. The Sub10 pattern contracted to 11 districts in the rural northeastern hinterland, particularly in Bani Obaid and Minya al-Nas, areas with a weak economic base and a continued reliance on low-value-added activities. Notably, a spatial improvement emerged at the Delta's southern gateway (e.g., such as Banha and Al-Qanater Al-Khayriyah), which shifted to Sub9 (balanced basic coordination). In addition, the Sub7 pattern expanded to 63 districts, reflecting a general return to basic coordination. This improvement clearly reflects the impact of geographical and functional proximity to Greater Cairo, with its economic, technological, and institutional advantages, confirming that the recovery was not uniform but linked to specific locations within the national urban network.

4.3.3. Phase III (2023): Spatial homogeneity and the structural gap

By 2023, the Nile Delta reached a stage of relative spatial homogeneity, where Sub10 disappeared entirely, and 76 center districts stabilized with the Sub7 (socioeconomic lagging) pattern. While this indicates success in containing severe imbalances and promoting environmental resilience, it also reveals low-level homogeneity, where the socioeconomic system is the primary constraint.

Moreover, a significant spatial pattern shift is evident, where high-coordination centers (Sub4) are no longer found in the Delta's heart but are confined to the northern coastal margins, such as Damietta, Idku, and Kafr al-Batikh. In these areas, specialized port activities and export-driven industries have raised the coordination levels, without these improvements being reflected in the rest of the region.

Ultimately, the dominance of Sub7 confirms a crucial shift in the Nile Delta's developmental hurdles, where the primary obstacle to regional sustainability is no longer environmental degradation in isolation but rather the slow pace of socioeconomic and technological evolution. Although

ecosystem stability (U2) levels have risen, exceeding 0.7 in most districts, the socioeconomic system (U1) remains trapped by weak technological capacity, the concentration of low-value-added economic activities, and the occurrence of developmental stagnation across more than one stage of development.

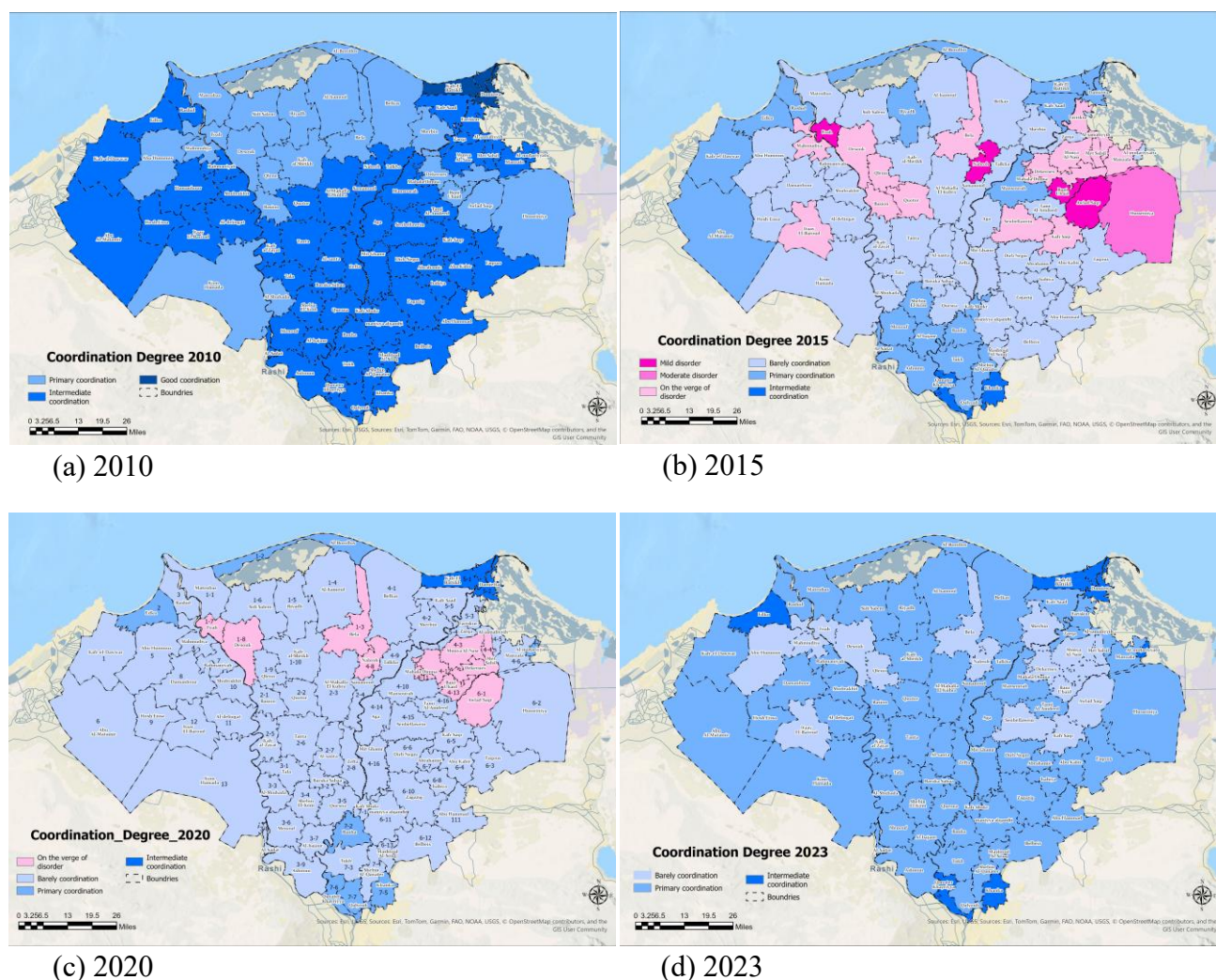


Figure 5. Spatial patterns of the coupling coordination degree (CCD) between the socioeconomic system and the ecological system in the Nile Delta districts for the years (a) 2010, (b) 2015, (c) 2020, and (d) 2023. Source: Prepared by authors using Google Earth Engine and ArcGIS Pro (Spatial Analysis and Spatial Statistics Tools).

4.4. Spatial patterns of the socioeconomic gap

This identified socioeconomic gap takes distinct spatial forms within the Nile Delta, revealing a fundamental shift from a phase of environmental pressure to a state where the environment is capable, but the system remains developmentally underdeveloped. In the coastal north, including districts such as Rosetta, Idku, Burullus, Matubas, and Kafr El-Sheik, there is an abundance of environmental resources associated with the northern lakes; however, these remain notably weak, preventing the translation of natural capital into high-level coordination. Similarly, the western Delta, encompassing Wadi El-Natron, Badr, Nubaria, Abu El-Matamir, Hosh Issa, and Delengat, represents a fragile transitional pattern that relies on modern agriculture but lacks the industrial and technological depth

required for long-term systemic resilience.

In contrast, the densely populated central core, including Damanhur, Kafr al-Dawwar, Tanta, al-Mahalla al-Kubra, Kafr al-Zayat, Zifta, al-Sunta, and Basyun, exhibits more advanced economic performance, reaching Stage 3 in several cases. Despite this progress, technological gaps continue to constrain the transition to fully balanced and high-quality coordination. Meanwhile, the eastern Delta, featuring Shebin El-Kom, Quesna, Menouf, El-Bajour, Ashmon, and Sadat, reveals a sharp contrast between relatively advanced industrial hubs and surrounding rural centers that remain stuck in transitional stages of development.

This spatial differentiation confirms that the development trajectory of the Nile Delta has undergone a transformation from a stage that exerts pressure on the environment to a stage where the environment is capable but developmentally stunted. Accordingly, the transition from basic to high-quality coordination requires a strategic redirection of development policies.

4.5. Spatial dependency and characteristics of CCD

Before establishing the spatial regression model, Global Moran's I was employed to explore whether significant spatial autocorrelation exists in the CCD across the districts of the Nile Delta. As presented in Table 5, Moran's I values for 2010, 2015, 2020, and 2023 are all positive and statistically significant ($p < 0.01$, z -scores > 2.58). This confirms that the CCD consistently exhibits a positive spatial agglomeration effect, rejecting the hypothesis of random spatial distribution. Additionally, the declining trend from 2010 to 2020, followed by a slight rebound in 2023, suggests that while the intensity of spatial clustering weakened during the regional coordination shock, it subsequently began to stabilize.

Table 4. Global Moran's I values of the CCD in the Nile Delta (2010–2023).

Year	Moran's I	z-score	p-value	Significance
2010	0.434523	9.117689	0.000000	*** ($p < 0.01$)
2015	0.344044	7.305886	0.000000	*** ($p < 0.01$)
2020	0.186773	4.106597	0.000040	*** ($p < 0.01$)
2023	0.251217	5.430331	0.000000	*** ($p < 0.01$)

Source: Prepared by the authors using ArcGIS Pro (Spatial Statistics Tools).

The spatial analysis based on the Local Moran's Index reveals a clear and persistent pattern of spatial dependence. As illustrated in Figure 6, based on LISA, the regional structure is dominated by high–high (H–H) and low–low (L–L) clusters, indicating that CCD levels are geographically anchored rather than randomly distributed. In the initial period (2010), H–H clusters formed contiguous belts in the central and southern Delta districts, while L–L clusters were largely confined to the northern coastal fringe. By 2015, these H–H clusters expanded toward the core of the Delta, reflecting a temporary but widespread strengthening of integrative coordination. This trend reversed sharply in 2020, with a marked contraction of H–H clusters, limited to five districts only, and a corresponding expansion of L–L agglomerations. This period represents the peak of spatial fragmentation in the Delta. In 2023, a limited reemergence of H–H clusters was observed in the southern gateway districts, although the L–L clusters in the northern and eastern peripheries expanded to their highest count (16 districts).

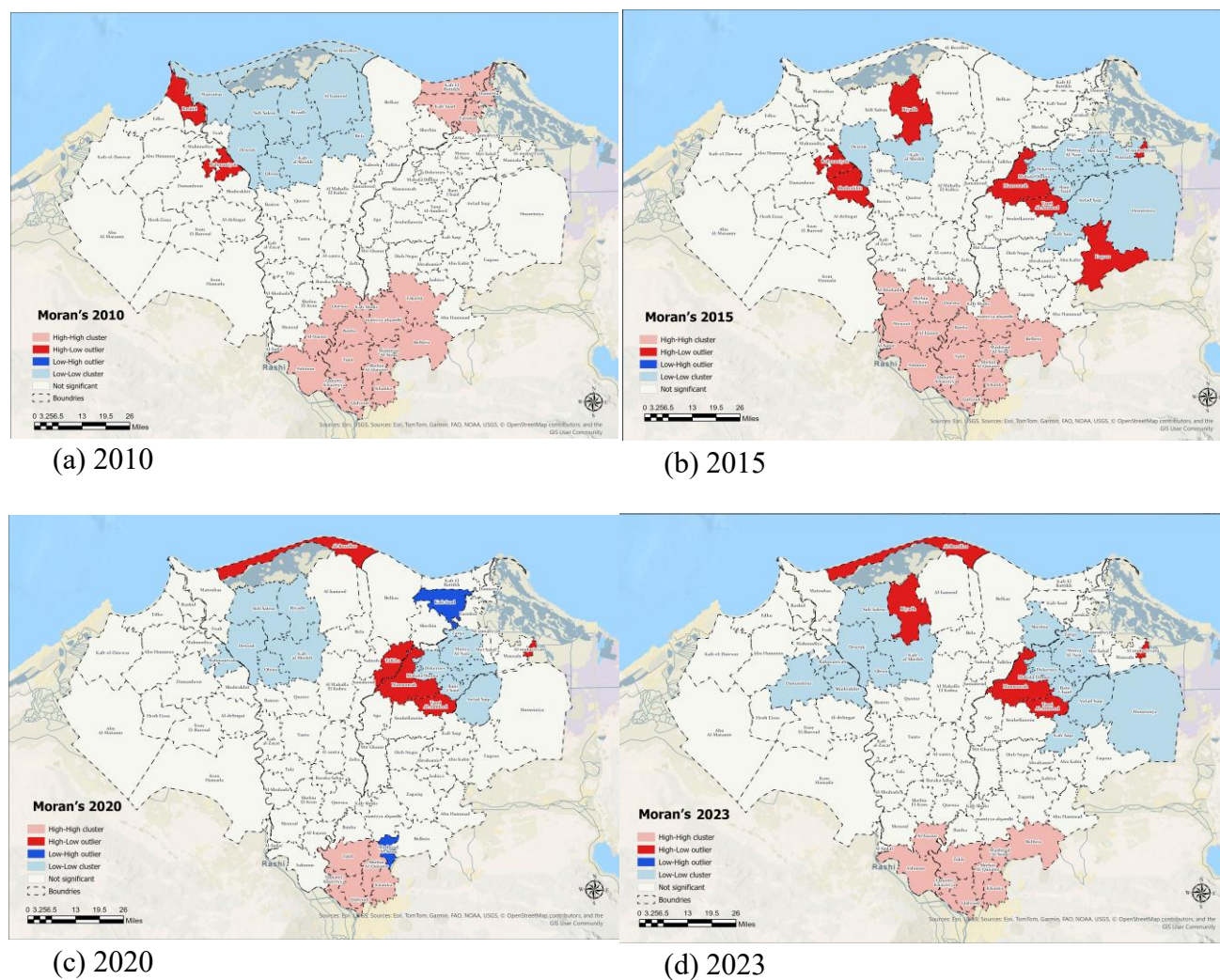


Figure 6. Moran's I maps showing spatial autocorrelation between the socioeconomic and ecological systems in the Nile Delta (2010–2023). Source: Prepared by the authors using ArcGIS Pro (Spatial Statistics Tools).

These dynamics are further supported by Moran's I scatterplot in Figure 7, which confirms the prevalence of positive local spatial autocorrelation over time. A detailed overview of the spatial cluster composition and its temporal variation is provided in Table 6, highlighting the long-term stability and path-dependent nature of CCD spatial patterns in the Nile Delta.

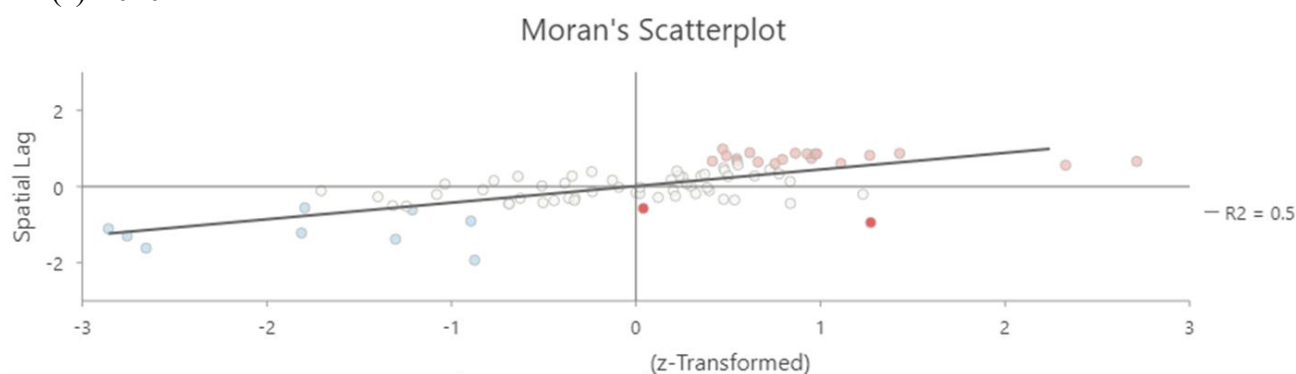
Table 5. Integrated spatial distribution and LISA cluster composition of complementary coordination (CCD) in the Nile Delta (2010–2023).

Year	High–high spatial clusters (high complementary coordination surrounded by high complementary coordination)	Low–low spatial clusters (low complementary coordination surrounded by low complementary coordination)	Spatial outliers (high surrounded by low or low surrounded by high)	Distribution of LISA cluster types (number of districts)	Overall spatial interpretation
2010	Ashmoun, Quesna, El Bagour, Faraskur, Damietta, Al Zarka, Kafr Saad, Kafr El Battikh, Zagazig, Minya Al Qamh, Kafr Shukr, Banha, Belbeis, Mashtoul Al Souq, Toukh, Shebin Al Qanater, Al Qanater Al Khayriya, Qalyub, Al Khanka	Al Hamoul, Sidi Salem, Qaleen, Biyala, Motobas, Al Riyadh, Desouk, Al Burullus, Kafr El Sheikh	Rahmaniya and Rashid (districts exhibiting high values surrounded by low values)	H–H: 19 L–L: 9 H–L: 2 L–H: 0 Not statistically significant: 53 districts; total: 83 districts	Clear formation of contiguous high-coordination spatial belts in the central and southern Delta, contrasted with persistent low-coordination zones along the northern coastal fringe
2015	Al Shuhada, Ashmoun, Menouf, Quesna, El Bagour, Shebin El Koum, Al Sadat, Minya Al Qamh, Banha, Belbeis, Mashtoul Al Souq, Toukh, Shebin Al Qanater, Al Qanater Al Khayriya, Qalyub, Al Khanka	Al Gamaliya, Mit Salsil, Dakrnes, Minyat Al Nasr, Bani Ebeid, Mahallat Damna, Desouk, Kafr El Sheikh, Al Manzala, Awlad Saqr, Kafr Saqr, Al Husseinia	Mansoura, Mit Ghamr, Al Riyadh, Al Matariya, Rahmaniya, Shubrakhit, Faqous	H–H: 16 L–L: 12 H–L: 7 L–H: 0 Not statistically significant: 48 districts Total: 83 districts	Expansion of high-coordination clusters toward the core of the Delta, accompanied by continued structural concentration of low-coordination areas in the northern and eastern Delta
2020	Toukh, Shebin Al Qanater, Al Qanater Al Khayriya, Qalyub, Al Khanka	Dakrnes, Minyat Al Nasr, Sidi Salem, Al Zarka, Qaleen, Bani Ebeid, Al Riyadh, Mahallat Damna, Desouk, Kafr El Sheikh, Rahmaniya, Awlad Saqr	Mansoura, Mit Ghamr, Talkha, Al Matariya, Al Burullus	H–H: 5 L–L: 12 H–L: 5 L–H: 2 Not statistically significant: 59 districts Total: 83 districts	Noticeable contraction of high-coordination clusters, alongside spatial expansion and consolidation of low-coordination agglomerations
2023	Ashmoun, El Bagour, Belbeis, Mashtoul Al Souq, Toukh, Shebin Al Qanater, Al Qanater Al Khayriya, Qalyub, Al Khanka	Dakrnes, Minyat Al Nasr, Sidi Salem, Al Zarka, Qaleen, Sherbin, Bani Ebeid, Mahallat Damna, Desouk, Kafr El Sheikh, Rahmaniya, Damanhour, Shubrakhit, Awlad Saqr, Kafr Saqr, Al Husseinia	Mansoura, Mit Ghamr, Al Riyadh, Al Matariya, Al Burullus	H–H: 9 L–L: 16 H–L: 5 L–H: 0 Not statistically significant: 53 districts Total: 83 districts.	Partial reemergence of high-coordination clusters in selected districts, with continued long-term dominance of low-coordination regions

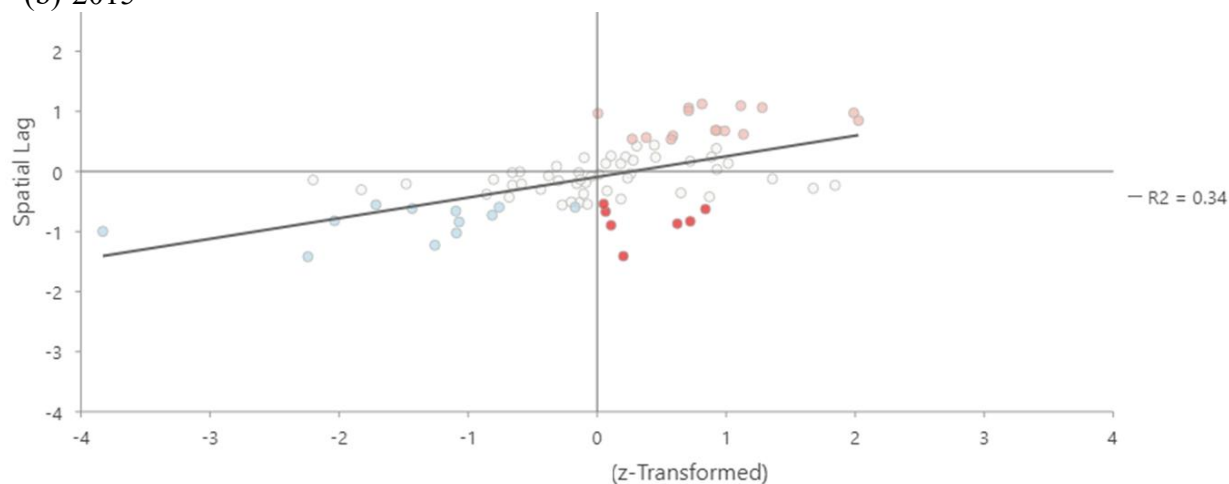
Overall trend (2010–2023)	Persistent stability of districts embedded within high-coordination regions, with limited temporal mobility	Strong path dependency and long-term persistence of low-coordination zones, particularly in the northern Delta	A limited group of structurally unstable districts acting as transitional spatial zones	Clear dominance of H–H and L–L clusters across all years, with fluctuations in their relative shares but stable total spatial structure	The spatial structure of complementary coordination is cumulative and geographically dependent, exhibiting lasting spatial heterogeneity and continuity over time
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Source: Prepared by the authors using ArcGIS Pro (Spatial Statistics Tools).

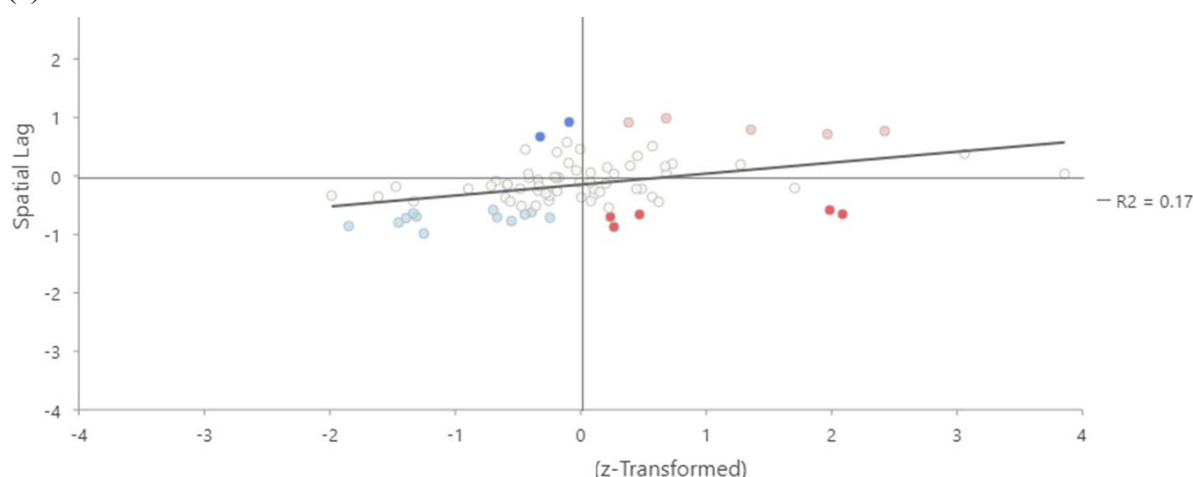
(a) 2010



(b) 2015



(c) 2020



(d) 2023

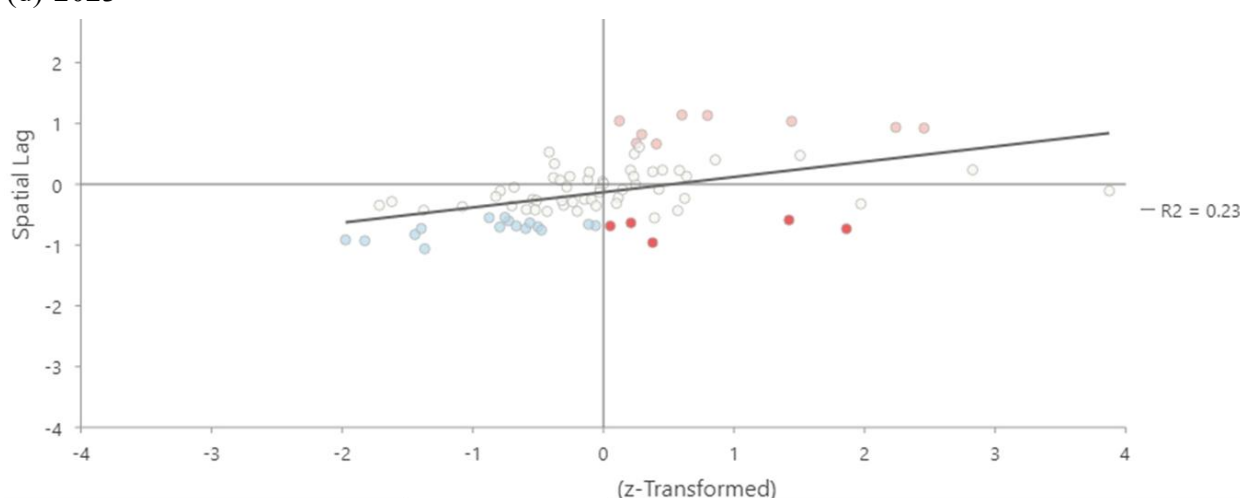


Figure 7. Moran's scatterplots of spatial autocorrelation in the Nile Delta for selected years: (a) 2010, (b) 2015, (c) 2020, (d) 2023. Source: Prepared by the authors using ArcGIS Pro (Spatial Statistics Tools).

5. Discussion

5.1. Interpreting the nonlinear temporal trajectory of coupling coordination

The nonlinear temporal trajectory identified in this study is broadly consistent with the Coordination of Interdependence Theory [11,52], which treats systemic stability as a dynamic equilibrium that remains sensitive to external shocks. The Nile Delta's pronounced vulnerability reflects its particular structural conditions: a land-intensive socioeconomic base built on smallholder agriculture and unplanned peri-urban expansion, land-use governance that is centralized yet weakly enforced, and a densely populated fertile zone with little spare capacity to absorb competing development demands. Together, these conditions heighten the ecological system's sensitivity to shifts in land use and development pressure.

The 2015 rupture coincided with the widest spatial disparities and greatest dispersion in coordination levels, which points to an uneven shock: districts differed markedly in their capacity to absorb and respond to disruption [11,32,34]. One plausible mechanism linking the broader institutional

transition to these changes is the weakening of land-use enforcement after Egypt's 2011 political transition, a period in which urban demand and informal expansion onto fertile agricultural land continued largely unchecked, at an estimated 30,000–50,000 acres annually [53]. The accelerated land conversion that followed placed further pressure on an already land-constrained ecological system during a period of institutional instability.

The partial recovery observed from 2015 to 2023 suggests that state-led interventions helped contain the crisis and restore basic stability, though they did not re-establish the pre-2010 alignment. This asymmetry points to a deeper problem: measures targeting immediate land-use and environmental pressures were not enough to overcome structural constraints rooted in limited economic diversification and technological upgrading. The finding supports the broader argument that systemic coordination depends on governance capacity and cross-sectoral planning as much as on economic growth [5,13,16,19]. In other words, coordination improved but never returned to its 2010 level.

5.2. From ecological lag to socioeconomic lag

One of the clearest findings of this study is the shift in the dominant development constraint, from Sub5 (ecological lag) in 2010 to Sub7 (socioeconomic lag) in 2020–2023. In 2010, socioeconomic development was outpacing what the ecological subsystem could support; by 2020–2023, this relationship had reversed, with ecological conditions comparatively stable while socioeconomic development had become the weaker component. The reversal indicates that the binding constraint on coordination in the Nile Delta is not fixed but changes over the course of the study period.

This trajectory echoes cases such as Xiongan New Area, the Three Parallel Rivers region, nature reserves in Western China, and the Lake Iseo Basin in Italy, where improving or stabilizing ecological conditions gave way to greater socioeconomic constraints [29,36,37,54]. The Nile Delta follows a broadly similar pattern, though within a setting where agricultural land pressure, urban expansion, and coastal environmental stress interact with a densely populated and highly developed regional system. The North China Plain and Ebinur Lake Basin, by contrast, show the opposite sequence: socioeconomic lag in the earlier period gave way to mounting ecological constraints as pressure on environmental resources continued [55–58]. The contrast between these cases shows that whether ecological or socioeconomic constraints dominate at a given time depends heavily on a region's environmental pressures, development structure, and institutional context.

For the Nile Delta, the shift toward socioeconomic lag implies that improving ecological conditions alone is unlikely to yield further gains in coordination while socioeconomic constraints remain unresolved. Economic diversification, technological upgrading, and value-added activity are thus likely to become the more decisive factors in whether the region can move beyond its current coordination level. This also sets the Delta apart from cases where continuing resource depletion remains the primary constraint, and it underscores the need to track the shifting balance between socioeconomic and ecological limitations when interpreting long-term coordination dynamics.

5.3. Driving mechanisms of socio-ecological coupling dynamics in the Nile Delta

The coupling dynamics observed in the Nile Delta appear to reflect three interacting mechanisms operating at different timescales. In the short term, the primary driver was rapid urban expansion and agricultural land conversion, which increased pressure on the ecological subsystem while sustaining socioeconomic activity. Converting fertile agricultural land to built-up uses is a direct pathway by which socioeconomic expansion erodes ecological carrying capacity, and it helps account for the

ecological lag observed in the earlier period [59–61].

A second mechanism concerns the post-2015 recovery. Improvements in environmental conditions and vegetation-related indicators emerged gradually, in line with the time that ecological systems typically need before the effects of land-use regulation and environmental intervention become measurable [40,62]. This lag helps explain why coordination did not recover immediately after the 2015 disruption. The partial recovery in spatial autocorrelation observed later in the study period further suggests that gains in individual districts were accompanied by a gradual reemergence of spatial interaction and regional synchronization.

The third mechanism operates over a longer horizon and concerns the socioeconomic subsystem itself. Limited technological upgrading, economic diversification, and value-added activity held back socioeconomic improvement even as ecological conditions stabilized [39,61]. The interventions that eased ecological pressure, in other words, did not bring about a comparable structural transformation of the socioeconomic base, a gap that helps explain the later shift from ecological lag to socioeconomic lag identified in the subtype analysis.

These three mechanisms, together, explain why the Delta did not simply return to its 2010 coordination condition. Ecological deterioration can occur quickly through land-use conversion, but ecological recovery takes several years, and structural socioeconomic transformation takes considerably longer still, requiring sustained investment and institutional change. This difference in adjustment rates produced a trajectory in which ecological conditions stabilized while socioeconomic constraints persisted. Improving coordination will accordingly require environmental and land-use regulation to be paired with sustained investment in economic diversification, technological capacity, and integrated spatial planning [61,63,64].

5.4. Spatial reconfiguration: From polarization to low-quality homogeneity

The spatial results point to three distinct coordination regimes. In 2010, coordination followed a polarized center–periphery structure, with high-coordination clusters concentrated near Greater Cairo and weaker performance in peripheral districts, a pattern consistent with the core–periphery differentiation documented elsewhere [58,65,66]. Greater Cairo’s concentration of infrastructure, investment, and institutional capacity likely gave it greater capacity to absorb land-conversion pressures; peripheral districts, with fewer such buffers, were more exposed to agricultural and environmental constraints.

By 2015, the region had entered a spatial coordination crisis, marked by expanding low-coordination clusters and widening disparities between districts. The earlier center–periphery structure appears to have broken down during this period of institutional and socioeconomic instability, as peripheral districts struggled more than others to maintain coordination under mounting environmental and land-use pressures, consistent with evidence that CCD systems can experience widening spatial disparities during periods of uneven development [23,67].

The 2020–2023 shift toward narrowed disparities and low-level spatial homogeneity is consistent with Tomal (2021) and with broader evidence that regions can settle into uniform but low-performance coordination states under shared systemic constraints [23]. In the Nile Delta, this is better read as convergence in constraint rather than convergence in development: as socioeconomic lag spread more widely across districts, differences in coordination levels narrowed without any corresponding rise in coordination itself. The reduction in spatial disparity is not, then, evidence of successful regional convergence; instead, it reflects greater spatial similarity within a generally moderate level of coordination.

5.5. Spatial dependency and the role of geographic spillovers

The consistently positive and significant Global Moran's I values confirm strong spatial dependence in Nile Delta CCD, in line with prior work [19,32,34]. Moran's I itself fluctuated over time, declining between 2010 and 2020, and then partially recovering by 2023, which indicates that the strength of spatial association was not constant across the study period. Its decline during the crisis period points to districts becoming less synchronized in their coordination trajectories, consistent with the uneven effects of weakened land-use governance and local differences in exposure to informal urban expansion. The partial recovery by 2023, concentrated particularly around Greater Cairo, points to renewed spatial association among districts more closely connected to the regional core, possibly reflecting the reemergence of regional linkages tied to infrastructure, economic activity, and administrative connections—though these specific channels were not directly tested here. This pattern of initial weakening followed by partial strengthening is consistent with what has been reported in other systems affected by policy shifts and external shocks [11,19,32]. Spatial dependence in the Nile Delta, then, appears to be shaped as much by differences in institutional capacity and regional connectivity as by geographic proximity itself.

5.6. Spatial patterns of climate vulnerability and socio-ecological resilience in the Nile Delta

The LISA analysis lends support to the Coordination of Interdependence Theory under conditions of rising climate stress, consistent with the biophysical baselines established by Dahab H M et al.[68]. By 2023, the expansion and eastward shift of low–low coordination clusters across northern Kafr El-Sheikh and Dakahlia coincide with areas exposed to intensifying maritime pressures, rising land surface temperatures, coastal erosion, shoreline loss, and increasing soil salinity. These pressures erode ecological carrying capacity in coastal districts and help account for the transitional spatial outliers that appeared in 2015 and 2020, and for the subsequent expansion of low–low clusters. Their spatial concentration makes clear that climate-related pressures are not distributed evenly across the Delta but are increasingly concentrated in exposed coastal areas.

The divergence between rural peripheries and industrialized maritime hubs such as Damietta and Kafr El-Battik offers further insight into this spatial differentiation. Robust infrastructure and targeted investment do not eliminate exposure to coastal hazards, but they can lessen socioeconomic performance's dependence on agricultural land and freshwater resources that are especially vulnerable to salinization and other coastal pressures. As a result, the socioeconomic and ecological subsystems in these industrial hubs appear less tightly coupled to the resources most affected by environmental degradation than is the case in predominantly agricultural districts. Climate change thus acts less as a uniform driver of decline in the Nile Delta than as a spatial polarizer: its ecological effects are geographically concentrated, and their implications for coupling coordination vary with the economic structure and resource dependence of individual districts. For Egypt Vision 2030, this points to a need for adaptation strategies that move beyond uniform interventions and instead target the specific resource dependencies and economic structures shaping vulnerability across districts, while strengthening linkages between exposed agricultural areas and more diversified economic centers.

The Nile Delta thus shows a coupling trajectory shaped by the interaction of agricultural dependence, coastal vulnerability, urban expansion, and uneven economic diversification. Unlike the resource depletion–driven trajectories reported in other basins, the Delta's recent pattern combines rapid ecological pressure with governance-led environmental stabilization and persistent socioeconomic constraints. Interpreting CCD in highly vulnerable delta systems should, on this basis,

take into account the specific relationship between environmental exposure, resource dependence, and the capacity of local economic structures to absorb ecological pressures.

6. Conclusions

This study evaluated the spatiotemporal dynamics of socioeconomic and environmental systems in the Nile Delta between 2010 and 2023. Integrating multi-sensor remote sensing data with the CCDM and spatial autocorrelation analysis reveals a nonlinear, spatially dependent trajectory: the Delta shifted from ecological lag in 2010 to socioeconomic lag by 2023. Although environmental conditions have improved in recent years, overall coordination remains constrained by structural weaknesses in the socioeconomic system, producing low-quality coordination across most districts. Furthermore, the results show a shift from a polarized center-periphery structure to low-quality regional homogeneity. Spatial disparities have narrowed, but convergence has occurred at moderate rather than high-performance levels. The persistence of significant spatial autocorrelation, together with the expansion of low-low clusters along the northern coastal fringe, further indicates that coordination dynamics remain spatially interconnected and path-dependent.

This study extends socio-ecological coupling research to the Nile Delta as an underrepresented African delta system, and provides a spatially explicit, longitudinal application of an established CCD framework in a socio-ecologically distinct context. By integrating multi-source remote sensing with coupling coordination and spatial analysis, the study provides evidence of how coordination patterns and dominant subsystem constraints can change across space and over time. The Nile Delta therefore provides a relevant comparative case for understanding socio-ecological coupling in other climate-vulnerable delta systems characterized by rapid urbanization, resource dependence, environmental pressures, and uneven economic development. Improving coordination in the Delta requires not only sustained environmental and land-use protection but also qualitative improvements in economic productivity, technological capacity, economic diversification, and integrated spatial planning that addresses inter-district interdependencies.

The key limitation of the present study is the reliance on remotely sensed proxies to represent the socioeconomic subsystem, without incorporating demographic, economic, employment, accessibility, and production-related dimensions available through conventional statistical data. In addition, the absence of independent external validation of the composite CCD results against socioeconomic statistics, environmental monitoring data, or field observations is another limitation. Future research could address these limitations by integrating socioeconomic datasets with consistent spatial and temporal coverage, and by validating the identified coordination patterns against empirical observations. Such integrations would provide a more comprehensive assessment of socioeconomic development and strengthen the interpretation of the mechanisms underlying socio-ecological coordination in the Nile Delta.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

Conflict of interest

The authors declare no conflicts of interest regarding the publication of this article.

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