# Spatial Coupling of Greenhouse Gas Emissions, Vegetation Activity, Groundwater Nitrate Occurrence, and Soil Environments Across Denmark: A 5-km Spatial Association and Soil-Stratified Analysis

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**Abstract**

Integrated environmental assessment increasingly requires the joint analysis of atmospheric emissions, vegetation dynamics, groundwater quality, and soil context rather than isolated thematic mapping. We developed a Denmark-wide 5-km analytical grid in EPSG:25832 containing 1,803 cells and harmonized four continuous environmental indicators: $CO_2$ and $CH_4$ emissions from EDGAR, vegetation activity represented by 2024 MODIS NDVI, and groundwater nitrate occurrence derived from national GEUS observations. Soil information from the GEUS Digital Soil Map was used to stratify environmental associations into five broad environmental groups. Global Pearson, Spearman, and Kendall associations were complemented by global Moran's $I$, directional bivariate Moran's $I$, local bivariate spatial association, an upper-1% $CO_2$ sensitivity analysis, and soil-stratified statistics. $CO_2$ and NDVI showed the strongest national association (Pearson $r = -0.2621$), while

$CH_4$ was positively associated with $CO_2$ ($r = 0.0898$) and nitrate occurrence ($r = 0.0792$). All four continuous variables exhibited significant positive spatial autocorrelation under both Queen and Rook contiguity, with the strongest structure for $CH_4$ and $CO_2$ and the weakest for nitrate. Bivariate Moran analysis supported a negative $CO_2$–NDVI cross-association and positive $CH_4$–$CO_2$ and $CH_4$–nitrate cross-associations. Soil-stratified results showed substantial heterogeneity; the strongest Pearson $CO_2$–NDVI association occurred in Human-affected & Technological environments ($r = -0.6208$), whereas Sandy & Poor and Sedimentary & Clay-rich environments displayed the clearest positive $CH_4$–$CO_2$ associations. The study is explicitly associative rather than causal. Its principal contribution is a spatially explicit national screening framework that reveals where environmental indicators co-occur, where relationships are spatially organized, and where targeted process-based investigation and monitoring may be most informative.

**Keywords:** Denmark; greenhouse gases; $CO_2$; $CH_4$; NDVI; groundwater nitrate; soil stratification; spatial autocorrelation; LISA

# 1 Introduction

Climate mitigation, agricultural intensification, vegetation dynamics, and groundwater protection are commonly addressed as separate environmental policy domains, although the underlying processes are spatially coupled. Greenhouse gas emissions are unevenly distributed because sources follow population density, transport, industry, energy use, agriculture, and land management. Vegetation activity is likewise spatially structured by land cover, climate, soil properties, management intensity, and urban development. Groundwater nitrate is additionally shaped by nitrogen inputs, recharge, hydrogeological vulnerability, and the temporal legacy of agricultural practices. Treating these indicators independently can therefore obscure geographically coherent combinations of environmental pressure and environmental response. A national-scale analysis that places these variables on a common spatial support can provide a more informative screening layer for subsequent process-based research.

Denmark is particularly suitable for this type of analysis because intensive agriculture, groundwater dependence, heterogeneous soils, and ambitious climate and water-quality policies coexist within a compact national territory. Long-term Danish monitoring has documented systematic relationships between agricultural nitrogen surplus and nitrate in oxic groundwater, including a reversal of nitrate trends following reductions in nitrogen surplus and improved nitrogen management (Hansen et al., 2011, 2012). At the policy level, the European Union Nitrates Directive explicitly aims to reduce and prevent water pollution caused by agricultural nitrates (European Commission, 1991), while Denmark's 2024 Green Tripartite agreement establishes a long-term framework linking agricultural land use, greenhouse-gas mitigation, nitrogen management, nature restoration, and drinking-water protection (SGAV, 2024). These policy developments make spatially explicit environmental screening particularly relevant, but they also increase the need for analyses that distinguish observed co-occurrence from causal mechanisms.

Remote sensing and gridded emission inventories provide spatially consistent information that can be integrated with national environmental observations. The EDGAR framework provides harmonized spatial estimates of anthropogenic greenhouse-gas emissions and documents the spatial disaggregation of national and subnational emissions (Crippa et al., 2024). MODIS MOD13Q1 provides 16-day, 250-m vegetation-index observations designed for consistent monitoring of vegetation condition (Didan, 2015). Danish soil mapping has a long methodological history, including digital soil mapping approaches that demonstrate strong spatial contrasts between sandy western environments and more loamy eastern environments (Adhikari et al., 2014). The integration of these data products is therefore scientifically defensible as a screening framework, provided that their differing spatial and temporal supports are explicitly acknowledged.

The statistical challenge is that spatial environmental observations are rarely independent. Positive spatial autocorrelation can inflate apparent information content and can alter inference when conventional correlation or regression is applied without considering spatial dependence (Moran, 1950; Dormann, 2007). Global Moran's $I$ provides a formal measure of spatial autocorrelation, while local indicators of spatial association (LISA) identify geographically concentrated local configurations (Anselin, 1995). Consequently, the present study was designed as a hierarchy rather than a single correlation exercise: descriptive characterization was followed by global association, spatial autocorrelation, bivariate spatial association, robustness testing, and soil-stratified analysis.

The objectives were fivefold: (1) to construct a common national 5-km spatial framework for four continuous environmental indicators and soil context; (2) to quantify global associations using complementary parametric and rank-based measures; (3) to determine whether each indicator is spatially clustered; (4) to identify directional cross-variable spatial associations and local configurations; and (5) to determine whether principal associations vary among broad soil-environment groups. The study deliberately does not infer causality. Instead, it asks a more defensible national-scale question: where and under which soil contexts do environmental indicators exhibit statistically coherent spatial co-occurrence?

# 2 Materials and Methods

## 2.1 Study area and analytical framework

The study covered Denmark using a common 5-km spatial grid in EPSG:25832. The final master dataset contained 1,803 grid cells intersecting the national study area. A common spatial support was used because the input products have different native resolutions, geometries, sampling structures, and temporal characteristics. Harmonizing them to the same analytical cells does not eliminate source-data uncertainty, but it ensures that all reported associations are calculated on the same set of spatial units rather than mixing incompatible supports.

The analytical hierarchy comprised five stages. First, descriptive statistics characterized the distributions and scale of each indicator. Second, Pearson, Spearman, and Kendall statistics were used to evaluate global pairwise associations. Third, global Moran's $I$ was calculated under Queen and Rook contiguity to determine whether each indicator was spatially structured. Fourth, directional bivariate Moran statistics and local bivariate classifications were used to determine whether cross-variable relationships extended across neighboring cells. Fifth, an upper-1% $CO_2$ sensitivity analysis and soil-stratified associations were used to evaluate robustness and environmental heterogeneity. This sequence was designed to prevent a statistically significant global correlation from being interpreted without first establishing the spatial structure of the underlying variables.

## 2.2 Environmental datasets

$CO_2$ and $CH_4$ were derived from EDGAR 2024 greenhouse-gas emission data. EDGAR provides harmonized global emission estimates and a documented spatial disaggregation framework, making it appropriate for national-scale screening, although the product should not be interpreted as direct measurement of fluxes at the 5-km cell scale (Crippa et al., 2024). Vegetation activity was represented by the 2024 annual NDVI summary derived from MODIS MOD13Q1. The MOD13Q1 product is a validated 250-m, 16-day vegetation-index product based on quality-controlled compositing (Didan, 2015). The annual aggregation was used to provide a single vegetation-activity indicator compatible with the national cross-sectional framework.

Groundwater nitrate occurrence was derived from national GEUS groundwater observations and the national Jupiter/GRUMO infrastructure, which provides nationwide groundwater chemical observations and monitoring data (GEUS, 2026a,b). In each grid cell, nitrate occurrence represents the proportion of wells with nitrate-related observations meeting the study's positive-occurrence criterion relative to the wells represented in that cell. It therefore describes observed monitoring prevalence rather than a continuous modeled groundwater concentration surface. This distinction is essential because monitoring density is heterogeneous and because groundwater response can lag land-surface nitrogen management by years or decades (Hansen et al., 2011, 2012). Soil information was derived from the GEUS Digital Soil Map of Denmark at 1:25,000 scale (dataset version 7.1, January 2026) (GEUS, 2026c) and grouped into five environmental classes: Organic & Waterlogged, Sandy & Poor, Sedimentary & Clay-rich, Developed & Dense, and Human-affected & Technological. The grouping is an analytical stratification rather than a replacement for the original pedological classes.

### 2.3 Global association analysis

Pearson correlation was used to quantify linear association. Spearman's rho and Kendall's tau were included as rank-based measures that are less dependent on a strictly linear relationship and less sensitive to extreme values (Spearman, 1904; Kendall, 1938). Reporting all three statistics allows the direction and relative strength of an association to be assessed across different statistical representations of the same spatial observations. This is particularly important for $CO_2$ and $CH_4$, both of which showed pronounced right-skew in the national descriptive statistics.

Multiple testing was controlled where multiple statistical hypotheses were evaluated using the Benjamini–Hochberg false discovery rate procedure (Benjamini and Hochberg, 1995). Statistical significance was not treated as a proxy for environmental importance. With 1,803 cells, even small coefficients can produce very small $p$-values. Accordingly, interpretation emphasized effect magnitude, agreement across Pearson/Spearman/Kendall statistics, persistence under sensitivity analysis, and consistency with spatial statistics rather than $p$-values alone.

### 2.4 Global spatial autocorrelation

Global Moran's $I$ was calculated under Queen and Rook contiguity. Queen contiguity defines neighboring cells through shared edges or vertices, whereas Rook contiguity requires a shared edge. Using both specifications provides a simple sensitivity assessment of whether the estimated spatial structure depends strongly on the neighborhood definition. The expected Moran value under randomization was calculated from the observed graph structure, and significance was assessed using 999 permutations. Therefore, the smallest reportable permutation $p$-value is 0.001.

Spatial autocorrelation is not treated here merely as a nuisance. In environmental systems, clustering can contain substantive information because climate, soil, land use, infrastructure, agricultural systems, and hydrogeology themselves vary spatially. Nevertheless, strong spatial dependence means that neighboring grid cells should not be treated as independent replicates for causal inference. The Moran analysis therefore functions as a diagnostic and a bridge to spatially explicit association analysis rather than as a substitute for mechanistic modeling (Moran, 1950; Dormann, 2007).

### 2.5 Bivariate spatial association and local clustering

Directional bivariate Moran's $I$ was used to distinguish ordinary cell-level correlation from spatial cross-association. In this formulation, the value of one variable in a focal cell is related to the spatially lagged values of another variable in neighboring cells. Three principal directions were evaluated: $CO_2$–NDVI, $CH_4$–$CO_2$, and $CH_4$–nitrate. This distinction matters because a global Pearson coefficient describes paired values within the same cell, whereas bivariate Moran's $I$ asks whether high or low values of one indicator tend to be surrounded by systematically related values of another indicator.

Local bivariate association was evaluated using LISA concepts following Anselin (Anselin, 1995). The resulting High–High, Low–Low, High–Low, and Low–High configurations were interpreted as spatial configurations rather than causal hotspots. A High–High classification means that a focal cell with a relatively high value of the first variable is located in a neighborhood characterized by relatively high values of the second variable. Because local classifications are more sensitive to sampling variation and multiple testing, non-significant cells were retained as a distinct category rather than being forced into a hotspot class.

### 2.6 Robustness and soil-stratified analysis

$CO_2$ displayed a pronounced right tail, with a maximum far above the upper quartile. To test whether the principal associations depended on a small number of extreme observations, the upper 1% of $CO_2$ values were excluded in a sensitivity analysis. The 99th-percentile threshold was 6.158261, reducing the dataset from 1,803 to 1,784 cells. The purpose was not to remove potentially meaningful emission hotspots from the principal analysis, but to determine whether the direction and approximate magnitude of the main associations were stable when the most extreme observations were excluded.

The four continuous indicators were then analyzed separately within each soil-environment group. The five groups contained 37, 422, 893, 279, and 120 cells, respectively. Because sample size varies markedly among groups, especially for Organic & Waterlogged environments, soil-stratified coefficients were interpreted as contextual associations rather than formal tests that soil mediates an environmental mechanism. The stratification is nevertheless valuable because a national coefficient can conceal strong relationships in one environmental context and weak or absent relationships in another.

## 3 Results

### 3.1 National environmental structure

The final dataset contained 1,803 cells. Mean $CO_2$ was 0.569817 kg $CO_2$ $m^{-2}$ $yr^{-1}$, with a median of 0.302261 and a standard deviation of 1.403115. Values ranged from 0.020495 to 33.452141 kg $CO_2$ $m^{-2}$ $yr^{-1}$. The large separation between the mean and median and the very high maximum indicate a strongly right-skewed distribution. $CH_4$ showed a similar but less extreme pattern, with a mean of 0.005702, median of 0.003598, standard deviation of 0.006078, and a maximum of 0.052822 kg $CH_4$ $m^{-2}$ $yr^{-1}$. These distributions demonstrate why rank-based statistics and sensitivity analysis are important complements to Pearson correlation.

NDVI was comparatively constrained, with a mean of 0.556367, median of 0.564921, standard deviation of 0.054808, and a range of 0.204799–0.670345. Groundwater nitrate occurrence was substantially more variable, with a mean of 20.788925%, median of 11.111111%, standard deviation of 26.102789 percentage points, and a full range from 0 to 100%. The contrast among these distributions is scientifically important: the emissions indicators contain strong high-end heterogeneity, vegetation varies within a narrower range, and nitrate occurrence has a bounded but highly heterogeneous prevalence structure. Figure 1 visually confirms that the environmental system is spatially patterned rather than homogeneous.

Table 1: Descriptive characteristics of the four continuous environmental indicators across the 1,803-cell Denmark analytical grid.

| Variable | N | Mean | Median | SD | Min | Max | Q25 | Q75 |
|---|---|---|---|---|---|---|---|---|
| $CO_2$ | 1803 | 0.569817 | 0.302261 | 1.403115 | 0.020495 | 33.452141 | 0.194299 | 0.505233 |
| $CH_4$ | 1803 | 0.005702 | 0.003598 | 0.006078 | 0.000001 | 0.052822 | 0.001703 | 0.007641 |
| NDVI | 1803 | 0.556367 | 0.564921 | 0.054808 | 0.204799 | 0.670345 | 0.533333 | 0.591758 |
| Nitrate (%) | 1803 | 20.788925 | 11.111111 | 26.102789 | 0 | 100 | 0 | 33.333333 |

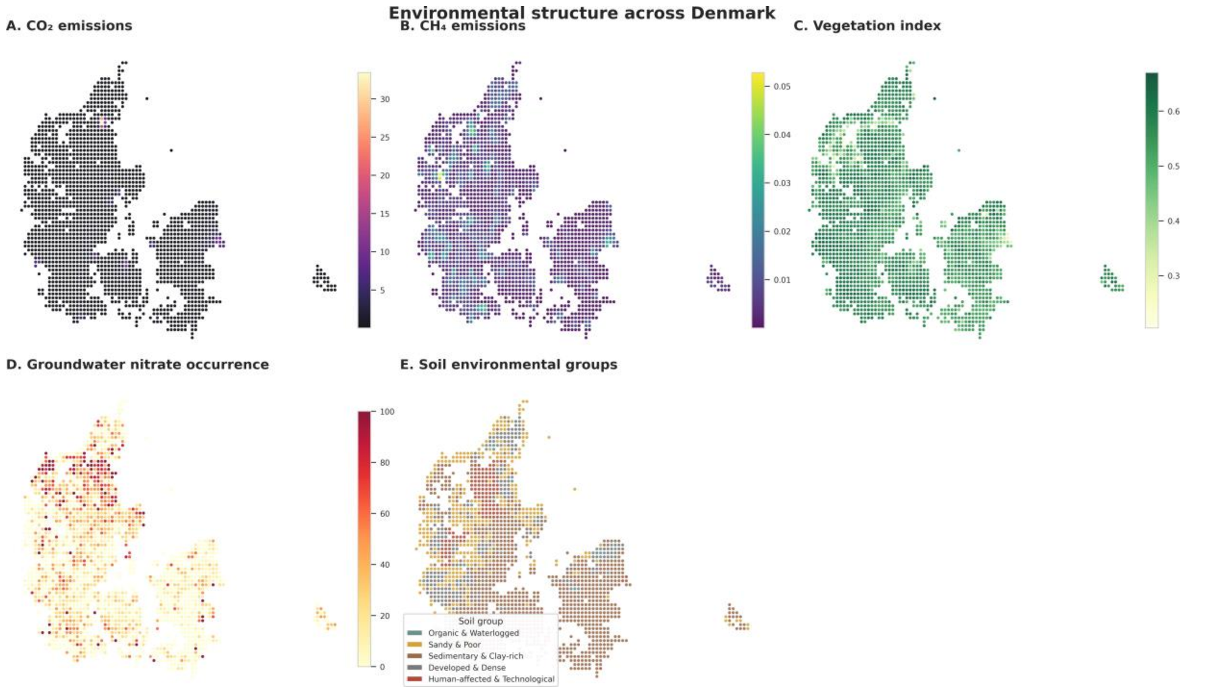


Figure 1: National spatial distribution of $CO_2$, $CH_4$, NDVI, groundwater nitrate occurrence, and the five soil-environment groups. The maps illustrate the common 5-km analytical support used for all subsequent statistics.

## 3.2 Global environmental associations

The strongest and most consistent global association was the negative relationship between $CO_2$ and NDVI. Pearson correlation was $r = -0.262121$ ($p = 1.03 \times 10^{-29}$), while Spearman's rho and Kendall's tau were $-0.173444$ and $-0.125247$, respectively. The agreement in direction across three statistics is more informative than the very small Pearson $p$-value alone. Figure 2 also shows that the relationship is visually dominated by the concentration of observations at low-to-moderate $CO_2$ values, with a smaller number of high-$CO_2$ cells extending the horizontal distribution. The association should therefore be interpreted as a national spatial pattern rather than as evidence that $CO_2$ directly suppresses vegetation.

$CH_4$ was positively associated with both $CO_2$ and nitrate occurrence, but the effect sizes were modest. $CH_4$–$CO_2$ produced Pearson $r = 0.089840$, Spearman $\rho = 0.183211$, and Kendall $\tau = 0.125196$; $CH_4$–nitrate produced Pearson $r = 0.079156$, Spearman $\rho = 0.128816$, and Kendall $\tau = 0.092211$. The stronger rank-based coefficients relative to Pearson are consistent with the skewed distributions of the emission variables and indicate that monotonic co-ordering is more evident than a simple linear relationship. In contrast, the magnitude of the coefficients demonstrates that these are weak associations in practical terms, even though they are statistically detectable in the national dataset.

Table 2: Global associations among the three principal environmental relationships.

| Relationship | N | Pearson $r$ | Pearson $p$ | Spearman $\rho$ | Spearman $p$ | Kendall $\tau$ |
|---|---|---|---|---|---|---|
| $CO_2$–NDVI | 1803 | -0.262121 | 1.03e-29 | -0.173444 | 1.21e-13 | -0.125247 |
| $CH_4$–$CO_2$ | 1803 | 0.089840 | 1.34e-04 | 0.183211 | 4.49e-15 | 0.125196 |
| $CH_4$–Nitrate | 1803 | 0.079156 | 7.68e-04 | 0.128816 | 4.05e-08 | 0.092211 |

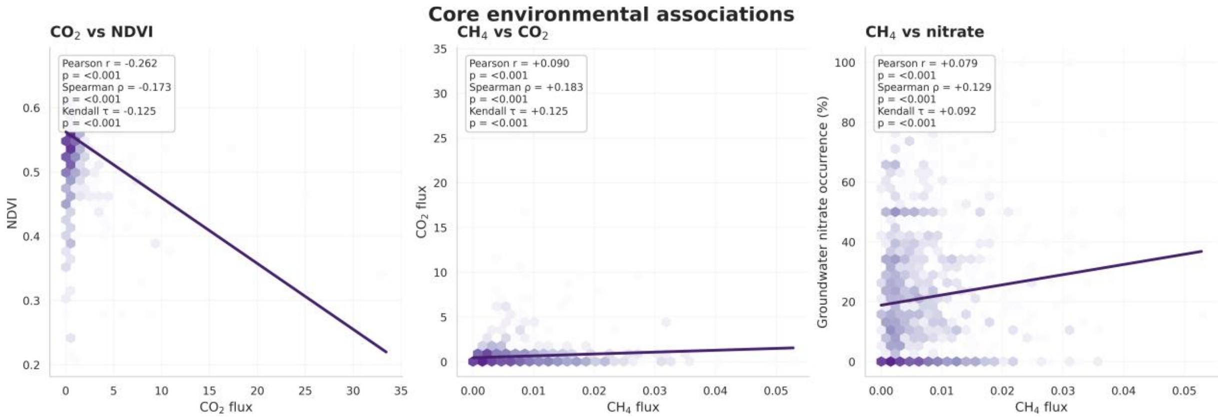


Figure 2: Global environmental associations across the Denmark 5-km grid. The three panels show the principal $CO_2$–NDVI, $CH_4$–$CO_2$, and $CH_4$–nitrate relationships with fitted linear trends and complementary rank statistics.

### 3.3 Spatial autocorrelation of the environmental indicators

All four continuous variables exhibited positive global spatial autocorrelation under both Queen and Rook contiguity. Under Queen weights, Moran's $I$ was 0.464621 for $CO_2$, 0.487511 for $CH_4$, 0.493691 for NDVI, and 0.285720 for nitrate. Under Rook weights, the corresponding values were 0.559944, 0.578364, 0.534447, and 0.304885. Every statistic was significant at the permutation limit ($p = 0.001$ after 999 permutations; FDR-adjusted $p = 0.001$). The positive signs mean that similar values occur closer together than expected under spatial randomness.

The difference between variables is more informative than the common significance level. Nitrate showed the weakest spatial structure, whereas $CH_4$ and $CO_2$ exhibited particularly strong clustering. The higher Rook values for $CO_2$ and $CH_4$ indicate that their spatial organization remains pronounced even under the more restrictive edge-sharing neighborhood definition. Figure 3 summarizes this contrast. These results establish that the 1,803 cells are not independent spatial replicates, reinforcing the need to interpret the correlation results together with spatial statistics rather than in isolation.

Table 3: Global Moran's $I$ under Queen and Rook contiguity weights.

| Variable | Weights | Moran $I$ | Expected $I$ | Z | Permutation $p$ | FDR $p$ |
|---|---|---|---|---|---|---|
| $CO_2$ | Queen | 0.464621 | -0.000555 | 38.199522 | 0.0010 | 0.0010 |
| $CO_2$ | Rook | 0.559944 | -0.000555 | 34.777674 | 0.0010 | 0.0010 |
| $CH_4$ | Queen | 0.487511 | -0.000555 | 40.079268 | 0.0010 | 0.0010 |
| $CH_4$ | Rook | 0.578364 | -0.000555 | 35.920583 | 0.0010 | 0.0010 |
| NDVI | Queen | 0.493691 | -0.000555 | 40.586776 | 0.0010 | 0.0010 |
| NDVI | Rook | 0.534447 | -0.000555 | 33.195654 | 0.0010 | 0.0010 |
| Nitrate | Queen | 0.285720 | -0.000555 | 23.508447 | 0.0010 | 0.0010 |
| Nitrate | Rook | 0.304885 | -0.000555 | 18.951836 | 0.0010 | 0.0010 |

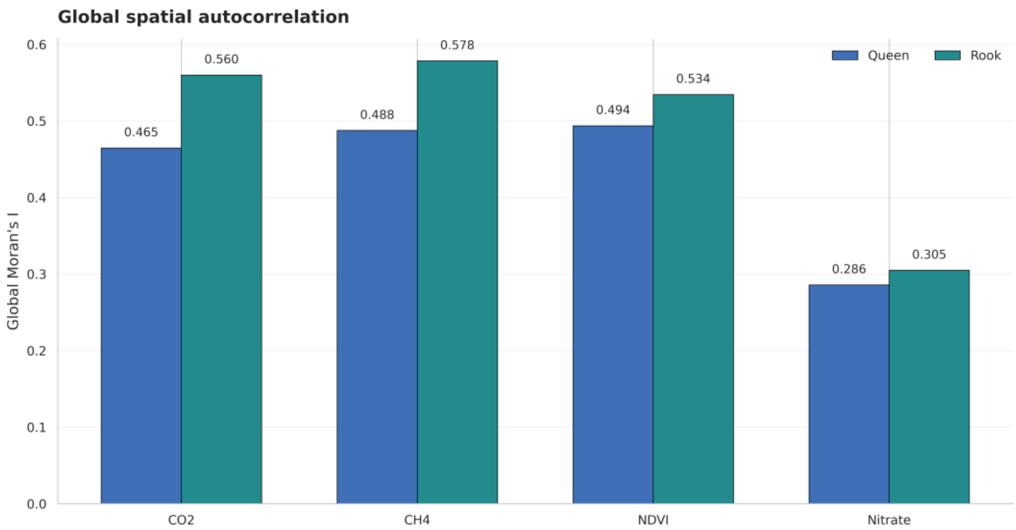


Figure 3: Global Moran's $I$ for the four continuous environmental indicators under alternative spatial-weight specifications.

### 3.4 Bivariate spatial associations and local configurations

Directional bivariate Moran analysis identified a negative $CO_2$–NDVI spatial cross-association ($I = -0.186210$, permutation $p = 0.001$), together with positive $CH_4$–$CO_2$ ($I = 0.059268$, $p = 0.003$) and $CH_4$–nitrate ($I = 0.064922$, $p = 0.001$) cross-associations. The magnitudes are smaller than the strongest univariate Moran statistics, which is expected because bivariate Moran's $I$ measures cross-variable spatial organization rather than clustering of a single variable. The direction nevertheless agrees with the global correlations, providing an independent spatial line of evidence for the main environmental patterns.The local bivariate maps reveal that these relationships are geographically concentrated rather than uniform across Denmark. For $CO_2$–NDVI, most cells are non-significant, with localized Low–Low, High–Low, and Low–High configurations. For $CH_4$–$CO_2$ and $CH_4$–nitrate, the maps similarly show spatially coherent patches interspersed with large non-significant areas. This is an important distinction from a conventional correlation coefficient: a national association can be driven by a limited number of geographically organized configurations. Accordingly, the local results are better described as candidate zones for targeted monitoring and process investigation than as national-wide environmental hotspots.

Table 4: Directional bivariate Moran's $I$ statistics.

| X | Y | Weights | $I$ | Expected $I$ | Permutation $p$ | FDR $p$ |
|---|---|---|---|---|---|---|
| $CO_2$ | NDVI | Queen | -0.186210 | 0.000179 | 0.0010 | 0.0015 |
| $CH_4$ | $CO_2$ | Queen | 0.059268 | -0.000497 | 0.0030 | 0.0030 |
| $CH_4$ | Nitrate | Queen | 0.064922 | 0.000590 | 0.0010 | 0.0015 |

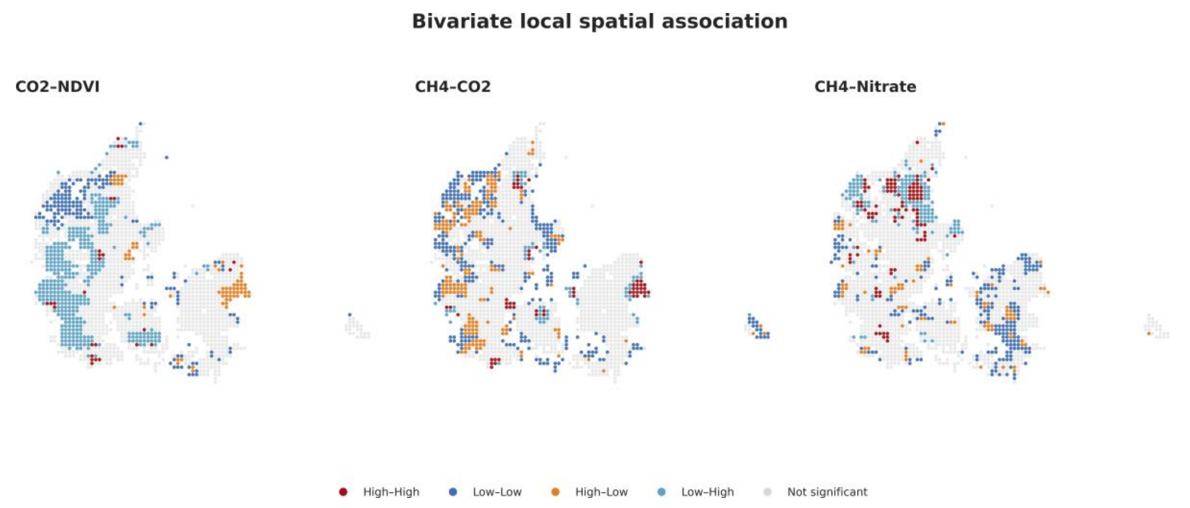


Figure 4: Local bivariate spatial association patterns for $CO_2$–NDVI, $CH_4$–$CO_2$, and $CH_4$–nitrate. Non-significant cells are retained explicitly to avoid interpreting all spatial differences as local hotspots.

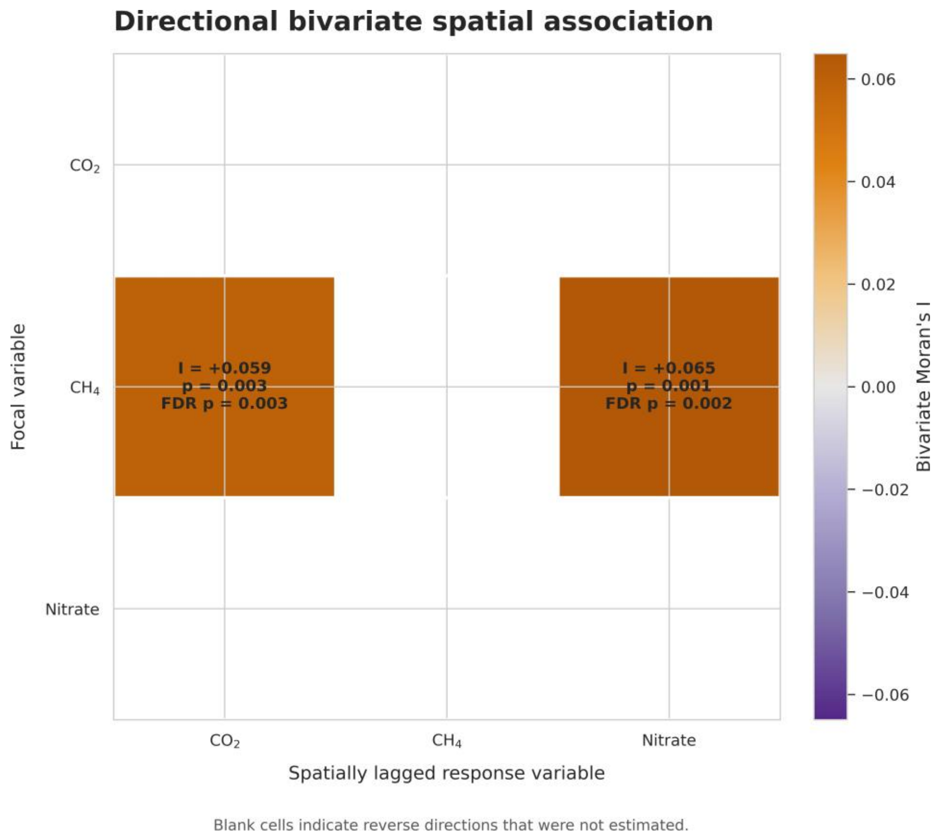


Figure 5: Directional bivariate Moran associations reported in the analysis. Blank cells indicate directions that were not estimated in the supplied output.

### 3.5 Robustness to extreme $CO_2$ values

The upper 1% of $CO_2$ observations was removed to assess whether the main associations were artifacts of a small number of extreme emission cells. The cutoff was 6.158261 and the sample declined from 1,803 to 1,784 cells. The $CO_2$–NDVI Pearson coefficient changed from -0.262121 to -0.213301, while the Spearman coefficient changed from -0.173444 to -0.153744. The relationship therefore weakened in magnitude but retained its negative direction and remained highly significant.

The $CH_4$–$CO_2$ relationship was especially stable in Pearson form, changing only from 0.089840 to 0.092789; its Spearman coefficient changed from 0.183211 to 0.172042. $CH_4$–nitrate also retained its positive direction, with Pearson changing from 0.079156 to 0.083913 and Spearman from 0.128816 to 0.129806. Taken together, the sensitivity results indicate that the principal directions are not generated solely by the most extreme $CO_2$ cells. The robustness analysis does not mean that emission extremes are unimportant; rather, it shows that the reported national associations are not dependent on those extremes alone.Table 5: Sensitivity of the principal associations after removing the upper 1% of $CO_2$ observations.

| Relationship | Pearson full | Pearson trimmed | Spearman full | Spearman trimmed | $N$ full | $N$ trimmed |
|---|---|---|---|---|---|---|
| $CO_2$–NDVI | -0.262121 | -0.213301 | -0.173444 | -0.153744 | 1803 | 1784 |
| $CH_4$–$CO_2$ | 0.089840 | 0.092789 | 0.183211 | 0.172042 | 1803 | 1784 |
| $CH_4$–Nitrate | 0.079156 | 0.083913 | 0.128816 | 0.129806 | 1803 | 1784 |

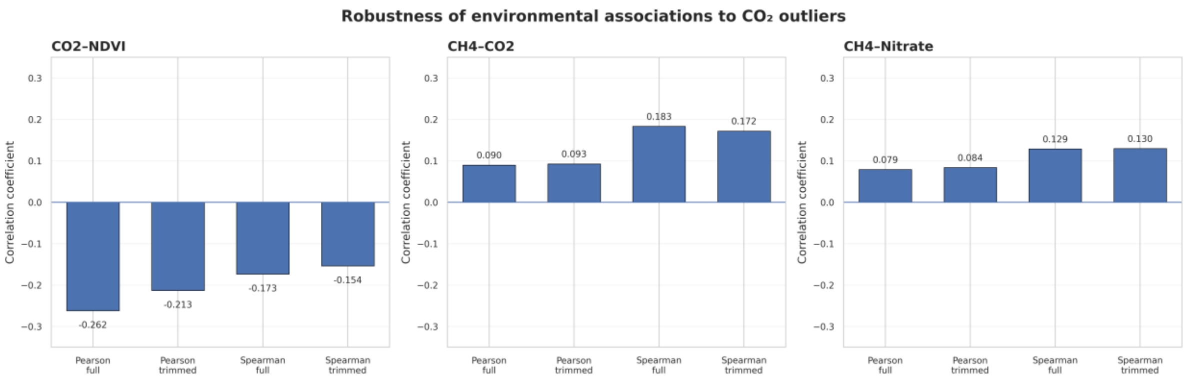


Figure 6: Sensitivity analysis after removing the upper 1% of $CO_2$ observations. The direction of all principal associations is preserved.

### 3.6 Soil-stratified heterogeneity

Soil context substantially modified the magnitude of environmental associations. $CO_2$–NDVI was negative in all five soil-environment groups. The strongest Pearson association occurred in Human-affected & Technological environments ($r = -0.620785$, $p = 3.93 \times 10^{-14}$), followed by Sedimentary & Clay-rich environments ($r = -0.403328$, $p = 2.94 \times 10^{-36}$). The broad consistency in direction suggests that the negative $CO_2$–NDVI pattern is not restricted to one soil class, although its magnitude varies greatly among contexts.

The strongest positive $CH_4$–$CO_2$ associations occurred in Sedimentary & Clay-rich environments (Pearson $r = 0.174966$) and Sandy & Poor environments (Pearson $r = 0.027550$, with a stronger rank-based association, Spearman $\rho = 0.287930$). $CH_4$–nitrate was positive in Organic & Waterlogged, Sandy

& Poor, Sedimentary & Clay-rich, and Human-affected & Technological groups, but the strongest and most consistently supported association was in Sandy & Poor environments (Pearson $r = 0.122778$, Spearman $\rho = 0.181009$, Kendall $\tau = 0.128734$). Developed & Dense environments showed weak or negative $CH_4$ relationships. The contrast demonstrates why national averages can hide environmentally meaningful heterogeneity.

Table 6: Soil-stratified associations among the principal environmental variables.

| Soil group | Relationship | N | Pearson $r$ | Pearson $p$ | Spearman $\rho$ | Kendall $\tau$ | Kendall $p$ |
|---|---|---|---|---|---|---|---|
| Organic & Waterlogged | $CO_2$–NDVI | 37 | -0.374710 | 0.0223 | -0.267188 | -0.186186 | 0.1049 |
| Organic & Waterlogged | $CH_4$–$CO_2$ | 37 | -0.073010 | 0.6676 | -0.289948 | -0.198198 | 0.0843 |
| Organic & Waterlogged | $CH_4$–Nitrate | 37 | 0.019817 | 0.9073 | 0.181481 | 0.123690 | 0.3136 |
| Sandy & Poor | $CO_2$–NDVI | 422 | -0.178180 | 2.34e-04 | -0.122452 | -0.088537 | 0.0066 |
| Sandy & Poor | $CH_4$–$CO_2$ | 422 | 0.027550 | 0.5725 | 0.287930 | 0.197823 | 1.29e-09 |
| Sandy & Poor | $CH_4$–Nitrate | 422 | 0.122778 | 0.0116 | 0.181009 | 0.128734 | 2.20e-04 |
| Sedimentary & Clay-rich | $CO_2$–NDVI | 893 | -0.403328 | 2.94e-36 | -0.164668 | -0.113972 | 3.42e-07 |
| Sedimentary & Clay-rich | $CH_4$–$CO_2$ | 893 | 0.174966 | 1.43e-07 | 0.296540 | 0.211894 | 2.58e-21 |
| Sedimentary & Clay-rich | $CH_4$–Nitrate | 893 | 0.085453 | 0.0106 | 0.109451 | 0.079357 | 8.84e-04 |
| Developed & Dense | $CO_2$–NDVI | 279 | -0.184520 | 0.0020 | -0.205575 | -0.141006 | 4.47e-04 |
| Developed & Dense | $CH_4$–$CO_2$ | 279 | -0.009692 | 0.8720 | -0.080348 | -0.057871 | 0.1497 |
| Developed & Dense | $CH_4$–Nitrate | 279 | -0.064769 | 0.2810 | -0.061433 | -0.044343 | 0.2883 |
| Human-affected & Technological | $CO_2$–NDVI | 120 | -0.620785 | 3.93e-14 | -0.242425 | -0.171909 | 0.0054 |
| Human-affected & Technological | $CH_4$–$CO_2$ | 120 | 0.075539 | 0.4122 | 0.038146 | 0.037982 | 0.5387 |
| Human-affected & Technological | $CH_4$–Nitrate | 120 | 0.034602 | 0.7075 | 0.049653 | 0.033024 | 0.6039 |

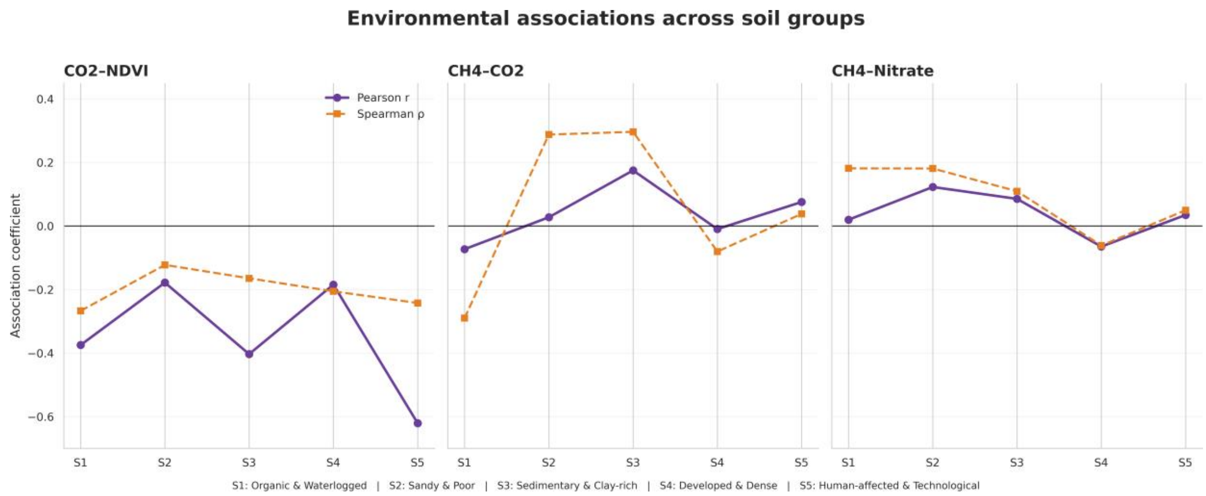


Figure 7: Soil-stratified environmental associations. The figure shows Pearson and Spearman coefficients across the five environmental soil groups. The strongest contextual contrast is observed for $CO_2$–NDVI, while $CH_4$–$CO_2$ and $CH_4$–nitrate are most evident in Sandy and Poor and Sedimentary and Clay-rich settings.

# 4 Discussion

## 4.1 From thematic mapping to spatial environmental coupling

The principal contribution of this study is methodological as much as empirical. A conventional national mapping exercise would produce separate surfaces for emissions, vegetation, groundwater nitrate, and soil and would then describe their visual similarities. The present framework instead treats the 5-km grid as a common spatial support and progressively asks whether environmental indicators co-vary, whether each indicator is spatially clustered, whether cross-variable relationships extend into neighboring cells, whether the main directions survive sensitivity analysis, and whether they differ by soil environment. This progression is important because spatially structured environmental data contain information that ordinary correlation cannot represent. The very strong Moran statistics demonstrate that Denmark's environmental indicators are geographically organized, so a national coefficient without spatial diagnostics would be incomplete.

The results also show why statistical significance alone is insufficient. The $CH_4$–$CO_2$ Pearson coefficient of 0.0898 and the $CH_4$–nitrate coefficient of 0.0792 are small, despite highly significant $p$-values. In contrast, the $CO_2$–NDVI coefficient of -0.2621 is materially larger and is supported by Pearson, Spearman, and Kendall statistics. The difference is not merely numerical: the $CO_2$–NDVI pattern remains negative after extreme $CO_2$ values are removed and appears as a negative bivariate spatial association. The paper should therefore be framed around a hierarchy of evidence rather than a list of significant correlations.

### 4.2 Interpreting the $CO_2$–NDVI association without causal overreach

The negative $CO_2$–NDVI association is the strongest empirical signal in the study, but several mechanisms can generate such a pattern. High $CO_2$ values in an inventory can reflect fossil-fuel use, transport, industrial activity, energy demand, or other anthropogenic source structures, while NDVI is sensitive to vegetation cover and activity. Urbanized or heavily developed areas can therefore simultaneously exhibit higher anthropogenic emissions and lower vegetation indices. Agricultural structure can also contribute to spatial covariance, and differences in land cover can affect both emission estimates and vegetation signals. The observed coefficient is consequently best interpreted as a geographically organized contrast between anthropogenic emission intensity and remotely sensed vegetation activity, not as a direct physiological response of vegetation to $CO_2$ emissions.

The soil-stratified results strengthen this interpretation because the magnitude of the relationship changes substantially among environmental contexts. The Human-affected & Technological group produced the largest Pearson coefficient in magnitude ($r = -0.6208$), while Sedimentary & Clay-rich environments showed a substantial negative association ($r = -0.4033$). Developed & Dense environments also retained a negative relationship, whereas Organic & Waterlogged environments were based on only 37 cells. Such heterogeneity is compatible with the idea that land-use and environmental context jointly organize the observed association. A process-based study should therefore test land cover, population density, transport, industrial sources, crop type, management intensity, and meteorological conditions before attempting causal interpretation.

### 4.3 $CH_4$–$CO_2$ as a spatial co-location signal

The positive $CH_4$–$CO_2$ relationship is weaker in simple linear terms than the $CO_2$–NDVI relationship, but its spatial behavior is informative. Pearson correlation was 0.0898, while Spearman correlation was 0.1832 and Kendall's tau was 0.1252. The positive direction persisted after the upper 1% of $CO_2$ observations was removed, and bivariate Moran analysis also produced a positive spatial cross-association. This combination suggests that cells with relatively high $CH_4$ tend to occur in broader spatial settings where $CO_2$ is also elevated, even though the relationship is not sufficiently strong to imply a single common source mechanism.

The soil-stratified analysis provides an important refinement. Sedimentary & Clay-rich environments showed a positive $CH_4$–$CO_2$ Pearson coefficient of 0.1750 and a stronger rank-based coefficient of 0.2965. Sandy & Poor environments showed little linear association but a substantially stronger positive Spearman coefficient of 0.2879. This divergence between Pearson and rank statistics indicates that monotonic ordering may exist even where a linear model is a poor summary. The finding is scientifically useful because it identifies soil environments in which a future process-based analysis of emission sources, moisture, drainage, land use, and agricultural management could be especially informative.

## 4.4 $CH_4$–nitrate: an exploratory but policy-relevant spatial signal

The positive $CH_4$–nitrate association is the weakest of the three principal relationships at the national scale. Pearson $r = 0.0792$, Spearman $\rho = 0.1288$, and Kendall $\tau = 0.0922$ all point in the positive direction, and bivariate Moran analysis also identifies positive cross-association. However, the effect size is small, and the present study does not establish that nitrate enrichment and methane emissions share a common process. The relationship can arise from common land-use structures, hydrogeological context, agricultural intensity, monitoring density, or spatially correlated environmental conditions. It should therefore be presented as an exploratory signal that motivates targeted investigation rather than as evidence of a nitrate-driven methane mechanism.

The soil results nevertheless make the signal more interesting. Sandy & Poor environments show the strongest positive $CH_4$–nitrate relationship among the major groups, whereas Developed & Dense environments show a weak negative coefficient and Human-affected & Technological environments show a near-zero coefficient. Sandy environments can be environmentally important because soil hydraulic properties, recharge, and nitrogen transport may differ from those in finer-textured settings. However, the present nitrate indicator is based on monitoring occurrence rather than a process-based groundwater concentration model. The appropriate next step is therefore not to infer causality from the coefficient, but to integrate aquifer vulnerability, recharge, depth-to-water, nitrogen surplus, land use, soil hydraulic properties, and groundwater age in a spatially explicit model.

## 4.5 Why spatial autocorrelation changes the interpretation

The Moran results provide one of the strongest arguments for retaining spatial statistics as a central contribution of the manuscript. $CO_2$, $CH_4$, and NDVI all have Moran's $I$ values around 0.46–0.58 depending on the neighborhood rule, while nitrate is also positively clustered. These are not marginal spatial effects. They indicate that neighboring cells share environmental similarity, which can arise from spatially continuous land cover, infrastructure, climate, geology, hydrology, and source distributions. In such a system, 1,803 cells should not be mentally treated as 1,803 independent experimental units.

This observation also explains why local bivariate analysis is valuable. The global $CO_2$–NDVI association does not mean that every part of Denmark follows the same relationship; the LISA map shows that a large majority of cells are locally non-significant. Similarly, $CH_4$–$CO_2$ and $CH_4$–nitrate have localized configurations surrounded by broad non-significant areas. The spatial pattern therefore supports a targeted monitoring strategy: national statistics identify candidate relationships, while local spatial statistics identify where those relationships deserve field-level or catchment-level investigation.

This is more defensible than constructing a single composite “risk” score from arbitrary thresholds.Implications for Danish environmental policy

The policy relevance of the framework lies in spatial targeting rather than in prescribing fertilizer rates from a cross-sectional correlation study. Denmark’s long monitoring history demonstrates that nitrogen regulation can influence groundwater nitrate trajectories, while the current Green Tripartite framework links land conversion, agricultural climate mitigation, nitrogen reduction, and protection of water and nature (Hansen et al., 2011; SGAV, 2024). A spatial screening framework can complement these policies by identifying areas where multiple indicators show coherent environmental pressure or unusual cross-variable configurations.

The most defensible management application is therefore a tiered monitoring framework. First, national maps can identify areas with persistent or unusually high emission indicators. Second, local bivariate spatial analysis can identify places where emission, vegetation, and nitrate patterns co-occur. Third, soil stratification can prioritize areas where the same relationship is repeatedly observed under a particular environmental context. Finally, high-priority areas can be evaluated with field observations, groundwater chemistry, farm nutrient balances, land-use records, and temporal remote sensing. Such a workflow would support precision monitoring and targeted mitigation while avoiding the scientifically unsafe claim that the present correlations alone identify farms responsible for emissions or nitrate pollution.

# 5 Limitations and methodological boundaries

Several limitations constrain interpretation. First, the study is ecological and spatially aggregated. A 5-km association cannot be translated directly to field, farm, aquifer, or individual well scales because of the modifiable areal unit problem and ecological inference constraints. Second, the input products have different native spatial and temporal supports. EDGAR provides inventory-based emissions, MODIS provides remotely sensed vegetation observations, and GEUS nitrate data arise from a monitoring network with heterogeneous sampling density. Aggregating them to a common grid improves spatial comparability but does not remove uncertainty inherited from the source products.

Third, groundwater nitrate occurrence is not equivalent to a continuous groundwater concentration field. A cell with zero observed positive wells can represent a sampled zero-prevalence observation rather than an unsampled absence, and the number of wells per cell varies. Fourth, soil groups have highly unequal sample sizes, especially Organic & Waterlogged environments, so the corresponding coefficients are less precise and should not be used as strong evidence of environmental mediation. Fifth, spatial autocorrelation is diagnosed but not fully incorporated into a causal regression model. The current analysis therefore should be regarded as a spatial screening and hypothesis-generation framework rather than a final predictive model.

A further limitation is temporal alignment. $CO_2$, $CH_4$, and NDVI are represented for the 2024 analytical period, whereas groundwater nitrate observations have a different temporal structure and may integrate legacy nitrogen inputs over substantially longer periods. The observed spatial associations therefore cannot be interpreted as contemporaneous cause-and-effect relationships. Future work should use multi-year emission and vegetation time series, groundwater age or recharge information, nitrogen-surplus data, precipitation/recharge variables, land use, and aquifer vulnerability. Spatial cross-validation would also be preferable to random train/test splitting for any subsequent machine-learning phase because spatial autocorrelation can otherwise produce overly optimistic predictive performance.

# 6 Conclusions

This study moves the analysis of Denmark's environmental indicators beyond independent thematic maps by placing greenhouse-gas emissions, vegetation activity, groundwater nitrate occurrence, and soil context on a common national spatial framework. The strongest result is a robust negative $CO_2$–NDVI association that is supported by multiple correlation measures, survives removal of the upper 1% of $CO_2$ observations, and is also expressed as a negative bivariate spatial association. A second, weaker but spatially coherent signal links $CH_4$ and $CO_2$, while $CH_4$–nitrate represents a positive but exploratory association that requires stronger process-based evidence before mechanistic interpretation.

The study also demonstrates that spatial structure is fundamental rather than incidental. All four continuous indicators are positively spatially autocorrelated, and local bivariate analysis shows that cross-variable relationships are concentrated in specific geographical configurations. Soil stratification further reveals that environmental associations are context-dependent, with particularly strong $CO_2$–NDVI patterns in Human-affected & Technological and Sedimentary & Clay-rich environments and more evident $CH_4$ relationships in Sandy and Poor and Sedimentary and Clay-rich settings. The scientific value of the framework therefore lies not in claiming causality, but in identifying where spatially coherent environmental combinations occur and where more detailed monitoring can most efficiently test competing mechanisms.

For Danish environmental management, the framework provides a reproducible screening layer that can support targeted monitoring under the broader objectives of nitrogen reduction, groundwater protection, land-use transition, and agricultural climate mitigation. The next methodological step should be a spatially cross-validated predictive model incorporating land use, soil hydraulic properties, recharge, groundwater vulnerability, nitrogen surplus, and temporal remote-sensing indicators. Such an extension would transform the present national association framework into a genuinely predictive decision-support system while retaining the central principle established here: spatial patterns are evidence for where mechanisms should be investigated, not proof of what causes them.

# Data availability

The analysis uses publicly available environmental datasets and national geospatial information sources. The derived 5-km analytical dataset and analysis scripts can be made available by the author upon reasonable request, subject to source-data licensing conditions.

# Competing interests

The author declares no competing interests.

## Author contributions

Avideh Asadollahi: conceptualization, methodology, data curation, spatial analysis, statistical analysis, visualization, and manuscript preparation.

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