

“Cross-border impact of agricultural fertilizer use: Environmental spillovers and healthcare costs in European countries”

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CROSS-BORDER IMPACT OF AGRICULTURAL FERTILIZER USE: ENVIRONMENTAL SPILLOVERS AND HEALTHCARE COSTS IN EUROPEAN COUNTRIES

Abstract

This study empirically examines the cross-border environmental and health impacts of mineral fertilizer use in European countries by applying spatial panel models. Specifically, it evaluates how nitrogen and phosphate fertilizers affect public health expenditures and water quality within national borders and adjacent countries. To accurately capture transboundary influences, the analysis uses a spatial weights matrix based on shared land borders constructed from geospatial data (Natural Earth shapefiles), enabling the assessment of spillover effects between neighboring countries. The models cover the timespan 2006–2021 for 29 European nations, except those that do not have common land borders (island countries), with available and comparable data. The results confirm significant spatial effects. The spatial lag model revealed strong direct and spillover effects for health expenditure, particularly for nitrogen and pesticide use, indicating that increased agricultural intensity in one country can raise health costs in neighboring states. Phosphate and potash use were associated with reductions in health expenditure, though the interpretation may reflect regional differences in environmental management. In contrast, the spatial error model best explained unsafe drinking water outcomes, highlighting the role of unobserved, spatially correlated environmental pressures. Nitrogen and pesticide use were linked to increased water contamination, while phosphate showed a strong but context-dependent negative association.

Keywords

mineral fertilizers, healthcare expenditures, water resource safety, cross-border pollution, sustainable agriculture, sustainable water management, sustainable development policies

JEL Classification

Q15, Q18, I18, C33

INTRODUCTION

The use of mineral fertilizers remains a fundamental component of modern agricultural practices, significantly contributing to increased crop yields and food security. However, intensive and often excessive application of fertilizers, especially nitrogen, phosphate, and potash compounds, leads to critical environmental and public health issues. The runoff of nitrates and phosphates into aquatic ecosystems causes eutrophication, reduces oxygen levels, and disrupts aquatic biodiversity. Additionally, prolonged chemical use negatively impacts soil health by diminishing its biological productivity and microbial diversity.

Beyond ecological impacts, excessive fertilizer use imposes considerable direct and indirect economic costs, particularly on public health systems. Exposure to nitrate-contaminated water has been linked to

increased risks of cancer, respiratory diseases, and cardiovascular conditions, leading to escalating healthcare expenditures. This effect is notably pronounced in European countries, where healthcare costs often exceed 10% of GDP (OECD/European Union, 2020). Consequently, environmental degradation due to agricultural practices significantly strains public finances and resource allocation.

The transboundary nature of agricultural pollution further complicates these economic and environmental challenges. Shared river basins, such as the Danube and Rhine, facilitate the transmission of agricultural pollutants from upstream nations like Germany and Austria to downstream countries, including Romania and Bulgaria, adversely impacting water quality and public health at a regional scale, ultimately affecting ecosystems like the Black Sea (EEA, 2018). Such cross-border spillovers complicate national policymaking, as the financial and health burdens resulting from environmental mismanagement are rarely contained within national borders, thus disproportionately affecting countries downstream.

Despite recognizing these cross-border environmental spillovers, there remains limited empirical understanding of how agricultural fertilizer use affects healthcare expenditures across national boundaries in Europe. Therefore, this study seeks to address this scientific gap by investigating how mineral fertilizer application contributes to environmental degradation and subsequent healthcare costs domestically and in neighboring European countries.

1. LITERATURE REVIEW

The environmental and fiscal consequences of mineral fertilizer use are becoming increasingly relevant as policymakers and researchers confront global challenges related to sustainable agriculture, food security, and public health financing. Fertilizers such as nitrogen, phosphate, and potash are essential for crop yields but pose severe risks to ecosystems and contribute to economic burdens through environmental degradation and increased healthcare expenditures.

A substantial body of research confirms that excessive fertilizer use negatively impacts water resources. Bartram et al. (2002) and Glavan et al. (2019) show that runoff from agricultural lands introduces nitrates and phosphates into rivers and groundwater, causing eutrophication and degrading drinking water quality. This concern is magnified in Europe, where river systems like the Danube transcend borders and transmit pollution downstream (European Environment Agency, 2018; European Commission, n.d.). The EU Nitrates Directive, analyzed by van Grinsven et al. (2012) and de Vries et al. (2021), has improved water quality in some areas but remains limited in scope due to regional heterogeneity in agricultural practices and enforcement. Similarly, Supriyanto et al. (2024) demonstrate how ecosystem service

valuation models can guide efficient environmental management by quantifying the economic value of water conservation efforts.

Beyond environmental degradation, there is growing recognition of the public health and economic costs associated with fertilizer overuse. Lyeonov et al. (2021) and Kuzior et al. (2022a, 2022b) have documented how polluted environments, particularly in rural areas, correlate with increased incidence of disease and strain on health systems. Ukpe and Mohamadou (2024) extend this conversation by showing linkages between agricultural productivity and out-of-pocket healthcare spending, underscoring how poor environmental practices can worsen food insecurity and personal health expenditures.

Huzenko and Kononenko (2024) and Ai et al. (2024) emphasized the difficult trade-offs between maximizing food production and managing environmental and health consequences. This trade-off is particularly relevant in low- and middle-income countries, where state capacities to absorb public health costs are limited (Benbekhti et al., 2024).

The economic dimensions of agriculture and environmental practices are also explored through the lens of sustainability and policy reform. Baidala

et al. (2024) assess the state of organic farming in Europe, while Zegunis and Balezentis (2024), Eidukaitis and Balezentis (2022), and Machova et al. (2022) examine agricultural production risks shaped by regional climate and economic factors. Bilan et al. (2023) connect these themes with the long-term effects of global shocks such as COVID-19 on food systems, illustrating the interdependence between public health and sustainable agriculture. Similarly, Guliyev et al. (2024), Juhászová et al. (2023), and Bilan et al. (2018) stress the importance of national and transnational strategies to secure both food supply and environmental protection. For instance, Richardson (2023) illustrates how pesticide use indirectly affects food systems by endangering pollinators, while Ray (2023) and Hnatenko and Konieczny (2023) highlight the need for flexible public support systems that consider evolving social and environmental demands.

Technological and policy innovations also influence fertilizer efficiency and environmental resilience. Bai et al. (2020) use spatial models to explore determinants of fertilizer use, while Dong et al. (2023) apply efficiency models to water use in agriculture. Ma and Zheng (2021) and Hadouga (2023) show that digital technology adoption reduces fertilizer and pesticide overuse by enabling more precise input application. This is echoed by Guemidi et al. (2024), who propose decision-support systems for fertilizer regulation. In addition, Mongi (2023) highlights ICT's role in sustainable water governance. Broader policy frameworks that promote innovation, such as those recommended by Jarzębowski et al. (2024), are essential for scaling such tools across rural economies.

Agricultural sustainability's financial, behavioral, and institutional aspects are increasingly studied in diverse regional contexts. Chapagain et al. (2024) investigate farmers' satisfaction with agricultural insurance, linking it to risk perception and awareness. Cao Dinh and Phan Thanh (2025) analyze contract farming disputes, a key issue in managing production practices and incentives. Handayani Amaliah (2025) links farmer performance to knowledge sharing, cultural norms, and traditions, suggesting that capacity-building efforts are critical to improving environmental outcomes.

At the same time, the role of foreign investment and financing is not to be overlooked. Bhowmik (2022) underlines how foreign direct investment in agriculture can support and challenge sustainable practices depending on regulatory conditions. Relatedly, Clark et al. (2024) explore technical innovations for recovering phosphate and nitrogen from wastewater, representing a circular economy solution to fertilizer pollution.

The transboundary impact of agricultural fertilizer use in Europe poses significant environmental and public health challenges. Sumets et al. (2022) stress the need for robust environmental risk management in agrohholdings, while Dvigun et al. (2022) highlight how fertilizer runoff threatens freshwater resources, increasing health risks and costs. Prokopenko et al. (2020) advocate for sustainable land-use practices like agroforestry to limit cross-border spillovers. Shvets et al. (2023) emphasize region-specific agricultural strategies through smart specialization, and Nifatova et al. (2024) link these efforts to the broader green and bioeconomy agenda.

Finally, cross-border cooperation and governance remain central. Steiner et al. (2024) and Makarenko et al. (2024) discuss transparency in agri-food systems, while Bozhenko et al. (2023) highlight monitoring gaps in climate-related finance. Investment strategies that integrate environmental risk, as proposed by Starchenko et al. (2021), are essential for responsible agricultural development across borders. Additionally, Singh and Pandey (2023) provide a comprehensive review of how nations, using India as a case study, attempt to balance public health, poverty alleviation, and environmental goals within the Sustainable Development Goals (SDGs) framework. Their findings underscore the complexity of achieving economic resilience and public health improvements in parallel with environmental sustainability, a core dilemma echoed in the European context of this study.

The reviewed literature confirms the multidimensional impact of fertilizer use on environmental quality, public health, and economic outcomes. While much has been studied about environmental degradation and health risks,

less attention has been paid to the economic burden on public healthcare systems, particularly in a cross-border context. There is a clear need to integrate environmental and economic perspectives using spatial methods that reflect the interconnected nature of European ecosystems and economies.

This study aims to empirically test the assumption that the intensive use of mineral fertilizers in agriculture contributes to environmental degradation that, in turn, leads to increased public health expenditures not only within the country of origin but also in neighboring countries. Using spatial panel models, this paper empirically tests the following hypotheses:

H1: Increased mineral fertilizer use significantly raises public healthcare expenditures through negative environmental impacts, specifically water pollution, within European countries.

H2: A positive and significant relationship exists between fertilizer-driven water pollution and health-related public expenditures across European countries.

H3: Agricultural fertilizer use has measurable transboundary effects, significantly increasing environmental degradation and associated healthcare costs in neighboring countries.

2. METHODOLOGY

The study uses two spatial panel models. Both of these models allow for considering spatial dependencies, i.e., to determine how the values of a variable in one region may depend on the values of the same variable or other factors in neighboring regions. The difference between the models is where the spatial effect is considered: in the dependent variable itself or the residuals (Anselin, 1988; Baltagi et al., 2003; Elhorst, 2014):

- the spatial lag model is used when it is assumed that the dependent variable in one region depends on the values of the same variable in neighboring regions;

- the spatial error model is chosen when the dependence is due to the correlation of residuals between neighboring regions, i.e., unaccounted-for spatial factors affect all regions.

2.1. Data collection

The sample includes all European countries except those that do not share common land borders (island countries) and those for which the necessary statistical data are unavailable in the international databases of the World Bank, EPI, and FAO.

The island countries (Cyprus, Iceland, Ireland, Malta, and the United Kingdom) that do not have land borders with other countries, which is mandatory for spatial analysis, were excluded. Montenegro was excluded from the analysis due to the limited data on this country.

Thus, the sample of countries is represented by:

- European countries that are part of the EU (Austria, Belgium, Bulgaria, Croatia, the Czech Republic, Denmark, Estonia, France, Germany, Greece, Hungary, Italy, Latvia, Lithuania, Luxembourg, the Netherlands, Poland, Portugal, Romania, the Slovak Republic, Slovenia, Spain, and Sweden);
- countries that have harmonized legislation with the EU (Switzerland);
- countries on the way to joining the EU (Albania, Bosnia and Herzegovina, Moldova, Serbia, Türkiye, and Ukraine).

Finland, Norway, and Sweden were excluded from the sample while conducting the spatial analysis, as they share borders only with each other and not with the other countries in the sample.

The time period was chosen in order to obtain balanced panel data, which means the same number of observations for each country over time. Thus, the time period is 2006–2021.

Indicators that give an idea of the dependent (y) and independent (x) variables used in the study are presented in Table 1.

Table 1. Variables and their sources

Variable	Indicator	Source
y1	Current health expenditure per capita, PPP (current international USD)	World Bank database
y2	Current health expenditure (% of GDP)	World Bank database
y3	Environmental Performance Index: Unsafe drinking water	EPI database
x1	Fertilizers nutrient nitrogen N use per area of cropland	FAO database
x2	Fertilizers nutrient phosphate P2O5 use per area of cropland	FAO database
x3	Fertilizers nutrient potash K2O use per area of cropland	FAO database
x4	Pesticides use per area of cropland	FAO database

2.2. Creating a matrix of spatial weights

The matrix W defines the spatial dependence between regions. The elements of the matrix W_{ij} show the degree of neighborhood or spatial influence between regions i and j .

Data from the Natural Earth (n.d.) file – ne_10m_admin_0_countries.shp were used to construct the geographical neighborhood matrix of countries in this study. The list of neighboring countries was converted into a neighborhood matrix.

2.3. Spatial Panel Fixed Effects Lag Model (SLM)

The spatial lag model considers spatial dependence directly in the dependent variable:

$$y_{it} = \rho \sum_j W_{ij} y_{jt} + x_{it} \beta + \alpha_i + \mu_t + \varepsilon_{it}, \quad (1)$$

where y_{it} is the value of the dependent variable for region i at time t ; ρ is a spatial lag parameter that shows the strength of dependence on the values of the dependent variable in neighboring regions; W is the matrix of spatial weights; x_{it} is the matrix of independent variables for region i at time t ; β is the vector of coefficients for the independent variables; α_i are the fixed effects of regions (to control for time-constant characteristics of regions); μ_t are the time fixed effects (to control for the effects common to all regions at any given time); ε_{it} is a random error.

2.4. Spatial Panel Fixed Effects Error Model (SEM)

The spatial error model considers spatial dependence in the residuals, but not in the dependent variable itself:

$$y_{it} = x_{it} \beta + \alpha_i + \mu_t + u_{it}, \quad (2)$$

$$u_{it} = \lambda \sum_j W_{ij} u_{jt} + \varepsilon_{it}, \quad (3)$$

where λ is a spatial error parameter that reflects the spatial correlation in the residuals; other notations are the same as in the spatial lag model.

In this model, the spatial effect is due to an error. u_{it} , that is, there are unaccounted factors that affect the spatial interaction between the studied neighboring countries.

Maximum Likelihood (ML) methods are most commonly used to estimate models with spatial effects, but for some models, the Generalized Method of Moments (GMM) can also be used. The GMM method was used in this study.

2.5. Testing and model selection

The AIC (Akaike Information Criterion) was used to compare the models, where a lower criterion value indicates a better model. The residuals were also tested for spatial autocorrelation, which helps to assess how well the model captured spatial effects.

3. RESULTS

3.1. Spatial analysis of the cross-border impact of fertilizers and pesticides on current health expenditure per capita

The estimation results of the spatial panel fixed effects lag model are summarized in Table 2. This specification incorporates spatial dependence by

Table 2. Results of the spatial panel fixed effects lag model of the estimation of the impact of fertilizer and pesticide use on current health expenditure per capita

Source: Calculations in R Studio.

Spatial panel fixed effects lag model				
Call:				
spml(formula = y1 ~ x1 + x2 + x3 + x4, data = pdata, listw = lw, model = "within", effect = "individual", lag = TRUE, spatial.error = "none")				
Residuals:				
Min.	1st Qu.	Median	3rd Qu.	Max.
-1603.9939	-196.7786	-1.5295	162.0150	1775.6716
Spatial autoregressive coefficient:				
	Estimate	Std. Error	t-value	Pr (> t)
lambda	0.681901	0.031094	21.93	< 0.0001***
Coefficients:				
Variables	Estimate	Std. Error	t-value	Pr (> t)
Fertilizers nutrient nitrogen N use per area of cropland	1.8495	1.5419	1.1995	0.23034
Fertilizers nutrient phosphate P2O5 use per area of cropland	-6.0632	3.6704	-1.6519	0.09855.
Fertilizers nutrient potash K2O use per area of cropland	-9.6644	3.9340	-2.4566	0.01402*
Pesticides use per area of cropland	-2.3475	32.7932	-0.0716	0.94293

Note: *** – 0.001; ** – 0.01; * – 0.05; ‘’ – 0.1; ‘No symbol’ – insignificant.

including a spatially lagged dependent variable and fixed effects to control for unobserved heterogeneity across units. The model demonstrates a statistically significant spatial autoregressive coefficient ($\lambda = 0.6819$, $p < 0.001$), indicating strong spatial spillover effects in the dependent variable across neighboring countries.

In contrast, the spatial panel fixed effects error model, presented in Table 3, accounts for spatial autocorrelation through the error term rather than the dependent variable. This approach is appropriate when spatial dependence arises from omitted variables or latent processes shared across neighboring regions. The spatial error coefficient ($\lambda =$

Table 3. Results of the spatial panel fixed effects error model of the estimation of the impact of fertilizer and pesticide use on current health expenditure per capita

Source: Calculations in R Studio.

Spatial panel fixed effects error model				
Call:				
spml(formula = y1 ~ x1 + x2 + x3 + x4, data = pdata, listw = lw, model = "within", effect = "individual", lag = FALSE, spatial.error = "b")				
Residuals:				
Min.	1st QU.	Median	3rd Qu.	Max.
-2069.255	-361.250	-95.754	278.717	2352.387
Spatial autoregressive coefficient:				
	Estimate	Std. Error	t-value	Pr(> t)
lambda	0.69521	0.03055	22.757	< 0.0001 ***
Coefficients:				
Variables	Estimate	Std. Error	t-value	Pr(> t)
Fertilisers nutrient nitrogen N use per area of cropland	2.6073	1.5779	1.6524	0.098453 .
Fertilisers nutrient phosphate P2O5 use per area of cropland	-5.0742	3.7678	-1.3467	0.178073
Fertilisers nutrient potash K2O use per area of cropland	-11.0379	4.0428	-2.7303	0.006328**
Pesticides use per area of cropland	-5.1766	33.5390	-0.1543	0.877336

Note: Signif. codes: *** – 0.001; ** – 0.01; * – 0.05; ‘’ – 0.1; ‘No symbol’ – insignificant.

0.6952, $p < 0.001$) is statistically significant, indicating notable spatial correlation in the residuals.

Although the spatial error model (Table 3) reveals significant spatial dependence in the error terms, indicating that healthcare expenditures exhibit spatial autocorrelation, the model selection diagnostics suggest that the spatial lag model offers a superior fit. Specifically, the residual variance of the spatial lag model (188,562.5) is markedly lower than that of the spatial error model (422,068.5), suggesting a more accurate representation of the variation in the dependent variable, i.e., per capita healthcare expenditures.

Model comparison criteria further reinforce this conclusion. The Akaike Information Criterion (AIC), a standard measure of model fit, favors the spatial lag specification, which reports a lower AIC value (7,031.93) relative to the spatial error model (8,560.255). This implies that accounting for spatial dependence directly in the dependent variable provides a more efficient and robust estimation framework in the context of this analysis.

These results indicate that spatial spillovers in healthcare expenditure are not merely due to unobserved regional effects but reflect a substantive interaction whereby changes in one country influence outcomes in neighboring ones. The spatial autoregressive coefficient ($\lambda = 0.6819$) is statistically significant at the 1% level ($p < 0.0001$), confirming that a one-unit increase in healthcare spending in neighboring countries is associated with a 0.6819-unit increase in the country under analysis.

The analysis of covariates in the spatial lag model yields further insights. The coefficient for nitrogen fertilizer use (x_1) is 1.8495 but is not statistically significant ($p = 0.23034$), suggesting no clear relationship between nitrogen application per unit of cropland and per capita healthcare expenditures.

Conversely, the coefficient for phosphate fertilizer use (x_2) is -6.0632 and marginally significant at the 10% level ($p = 0.09855$), indicating a weak inverse relationship between phosphate application and healthcare spending. While counterintuitive, this finding may reflect non-causal associations influenced by confounding factors. Regions with higher phosphate use may also benefit from supe-

rior infrastructure, better agronomic practices, or greater economic development. These characteristics can mitigate health risks and reduce public health expenditures.

The coefficient for potassium fertilizer use (x_3) is -9.6644 , which is statistically significant at the 5% level ($p = 0.01402$), suggesting that increased potassium fertilizer use may be associated with lower healthcare spending, though causality remains uncertain. The coefficient for pesticide application (x_4) is -2.3475 and statistically insignificant ($p = 0.94293$), indicating no meaningful influence on healthcare costs in this model.

The residual distribution of the lag model ranges from -1603.9939 to 1775.6716 , indicating that while the model captures much of the variance, substantial deviations remain, likely due to omitted variables or unobserved region-specific characteristics.

It is important to cautiously interpret the weak or inverse associations observed in some fertilizer variables. These may reflect confounding factors rather than causal effects. For instance, regions with higher phosphate or potassium use may also enjoy better economic conditions, stronger environmental regulation, or more advanced agricultural practices, all of which can improve health outcomes indirectly and reduce healthcare expenditures.

Figure 1 maps country-specific fixed effects from a spatial panel model of health expenditure per capita, showing baseline differences after accounting for agricultural inputs like fertilizers and pesticides. Darker blue countries, such as Turkey and Spain, spend more on health than expected based on input use, likely due to stronger healthcare systems or higher income levels. Lighter-shaded countries, including parts of Eastern Europe and France, spend less than expected, possibly reflecting limited health infrastructure or funding. The map highlights where unobserved structural factors, beyond agriculture, drive health investment differences across countries.

The spatial panel analysis explores how agricultural input use influences health expenditure per capita within countries and borders. Nitrogen fer-

Source: Calculations in R Studio.

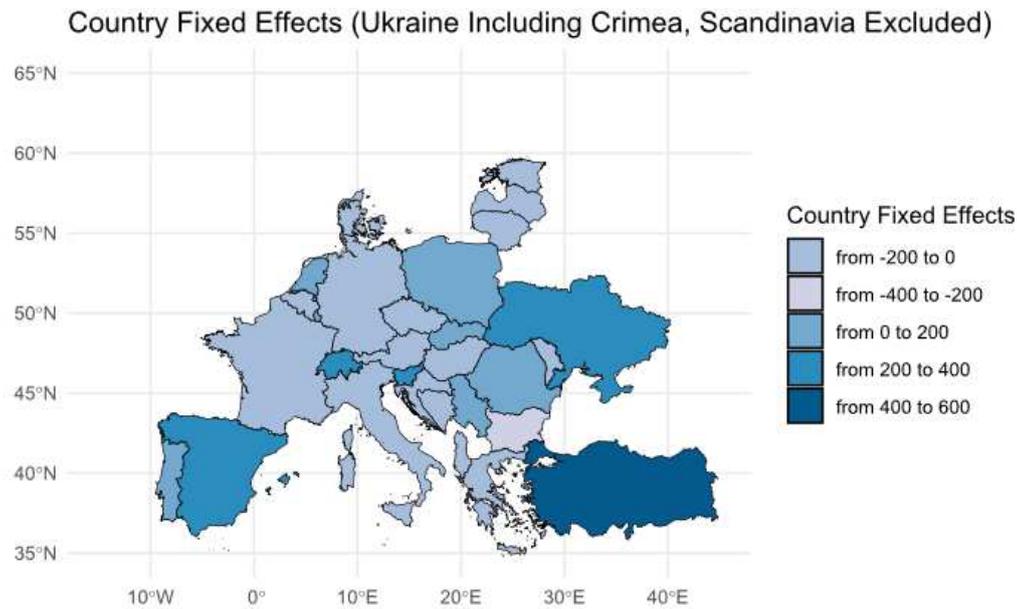


Figure 1. Country-specific fixed effects from a spatial panel model of health expenditure per capita

tilizer use shows a strong, statistically significant positive effect (Table A1, Appendix A), increasing domestic health spending by around USD 4.2 and neighboring countries' spending by USD 6.6, suggesting that greater agricultural productivity may boost health investment. In contrast, phosphate use is linked to a significant decline in health expenditure locally and regionally, potentially due to environmental harm or reduced returns. Potash use also shows a negative, though less specific, impact. Pesticide use is associated with a significant increase in health spending – over USD 90 regionally – but with high uncertainty, possibly reflecting economic gains and increased health risks. Overall, nitrogen use appears beneficial, phosphate and potash may have adverse effects, and pesticides require careful, context-specific interpretation due to their mixed implications.

3.2. Spatial analysis of the cross-border impact of fertilizers and pesticides on current health expenditure as a percentage of GDP

The results of the spatial panel fixed effects models, using current health expenditure as a percentage of GDP (y_2) as the dependent variable, are pre-

sented in Tables 4 and 5. The explanatory variables include nitrogen use per hectare of cropland (x_1), phosphate use (P_2O_5 , x_2), potassium use (K_2O , x_3), and pesticide use per hectare (x_4). Both the spatial lag model and the spatial error model (SEM) were estimated to assess the robustness of spatial dependence structures in explaining variation in health expenditure across European countries.

Both models identify statistically significant spatial dependence, with the spatial coefficients (λ) being positive and significant at the 1% level in both cases. In the lag model, λ is 0.138030 ($p = 0.009526$), while in the error model, λ is 0.13882 ($p = 0.00$), indicating that they partially influence healthcare expenditure patterns in one country and neighboring countries. Model diagnostics favor the spatial lag model. The Akaike Information Criterion (AIC) for the lag model is 928.18, which is substantially lower than the AIC for the spatial error model at 2460.96. This indicates that the lag model better balances model complexity and explanatory power.

In the spatial lag model, nitrogen use (x_1) is positively associated with healthcare expenditure and statistically significant, with an estimated coefficient of 0.00666 and a p -value of 0.00508. This supports the hypothesis that nitrogen-related pol-

Table 4. Results of the spatial panel fixed effects lag model of the estimation of the impact of fertilizer and pesticide use on health expenditure as a percentage of GDP

Source: Calculations in R Studio.

Spatial panel fixed effects lag model				
Call:				
spml(formula = y2 ~ x1 + x2 + x3 + x4, data = pdata, listw = lw, model = "within", effect = "individual", lag = TRUE, spatial.error = "none")				
Residuals:				
Min.	1st Qu.	Median	3rd Qu.	Max.
-2.374837	-0.345773	-0.043442	0.260585	4.719269
Spatial autoregressive coefficient:				
	Estimate	Std. Error	t-value	Pr(> t)
lambda	0.138030	0.053241	2.5926	0.009526 **
Coefficients:				
Variables	Estimate	Std. Error	t-value	Pr(> t)
Fertilizers nutrient nitrogen N use per area of cropland	0.0066565	0.0023758	2.8018	0.005082
Fertilizers nutrient phosphate P2O5 use per area of cropland	-0.0141488	0.0055014	-2.5719	0.010115
Fertilizers nutrient potash K2O use per area of cropland	-0.0078403	0.0061030	-1.2847	0.198906
Pesticides use per area of cropland	0.0077057	0.0548916	0.1404	0.888360

Note: *** – 0.001; ** – 0.01; * – 0.05; ‘’ – 0.1; ‘No symbol’ – insignificant.

Table 5. Results of the spatial panel fixed effects error model of the estimation of the impact of fertilizer and pesticide use on health expenditure as a percentage of GDP

Source: Calculations in R Studio.

Spatial panel fixed effects error model				
Call:				
spml(formula = formula, data = panel_data, listw = listw, model = "within", lag = TRUE, spatial.error = "b")				
Residuals:				
Min.	1st Qu.	Median	3rd Qu.	Max.
-2.36025	-0.35481	-0.05622	0.24697	4.72912
Spatial autoregressive coefficient:				
	Estimate	Std. Error	t-value	Pr(> t)
lambda	0.13882	0.05374	2.5832	0.00 *
Coefficients:				
Variables	Estimate	Std. Error	t-value	Pr(> t)
Fertilizers nutrient nitrogen N use per area of cropland	0.0067861	0.0024043	2.8225	0.004765 **
Fertilizers nutrient phosphate P2O5 use per area of cropland	-0.0144059	0.0056258	-2.5607	0.010446 *
Fertilizers nutrient potash K2O use per area of cropland	-0.0080526	0.0061654	-1.3061	0.191516
Pesticides use per area of cropland	0.0247116	0.0545045	0.4534	0.650270

Note: *** – 0.001; ** – 0.01; * – 0.05; ‘’ – 0.1; ‘No symbol’ – insignificant.

lution contributes to increased healthcare costs. Phosphate use (x2) is negatively associated with healthcare expenditure and statistically significant (estimate = -0.01415, $p = 0.01012$). Although this may seem counterintuitive, it could reflect confounding regional characteristics such as stronger environmental governance, infrastructure, or healthcare systems. Potassium use (x3) and pesticide use (x4) are not statistically significant in this model, with p -values of 0.19891 and

0.88836, respectively, suggesting no meaningful impact on health expenditure from these inputs.

The spatial error model shows similar results. Nitrogen and phosphate use remain statistically significant predictors, with similar effect sizes and p -values of 0.00477 and 0.01045, respectively. Potassium and pesticide use again show no significant associations with healthcare expenditure, with p -values above 0.19 and 0.65.

The distribution of residuals is relatively narrow in both models, ranging from approximately -2.375 to 4.719 in the lag model and -2.360 to 4.729 in the error model. This suggests that the models explain a substantial portion of the variance in the dependent variable, though some unexplained heterogeneity remains.

The findings highlight the role of spatial interdependencies in shaping national healthcare expenditures and suggest that agricultural inputs such as nitrogen and phosphate fertilizers may influence public health costs. The statistically significant spatial coefficients emphasize the need for coordinated policy responses across countries. However, caution is warranted in interpreting the observed relationships as causal, particularly in the case of the negative association with phosphate use, which may reflect underlying structural or institutional differences rather than direct health effects.

The spatial panel analysis (Table A2, Appendix A) explores how agricultural input use affects health expenditure as a share of GDP within and across borders. Nitrogen fertilizer use has a small but consistent positive effect, suggesting that increased productivity may slightly boost public health investment. In contrast, phosphate and potash use are linked to lower health spending, pos-

sibly due to inefficiencies or negative externalities. Pesticide use shows a weak positive effect, though results are uncertain and may reflect both productivity gains and health-related costs. Overall, agricultural practices appear to influence national and regional health expenditure patterns.

3.3. Spatial analysis of the cross-border impact of fertilizers and pesticides on current health expenditure as a percentage of GDP

The estimation results for the relationship between the Environmental Performance Index indicator for unsafe drinking water (y_3) and agricultural input variables are presented in Tables 6 and 7. These models assess the influence of fertilizer and pesticide use, specifically nitrogen (x_1), phosphate (x_2), potassium (x_3), and pesticide application (x_4) per hectare of cropland, on water quality across European countries, using both a spatial lag model and a spatial error model with fixed effects.

Both models reveal statistically significant spatial dependence, with the spatial autoregressive coefficients highly significant ($p < 0.0001$) in both the spatial lag model ($\lambda = 0.681901$) and the spatial error model ($\lambda = 0.533434$). This confirms the

Table 6. Results of spatial panel fixed effects lag model: Impact of fertilizer and pesticide use on unsafe drinking water (Environmental Performance Index)

Source: Calculations in R Studio.

Spatial panel fixed effects lag model				
Call:				
spml(formula = $y_1 \sim x_1 + x_2 + x_3 + x_{12}$,				
data = pdata, listw = lw, model = "within", effect = "individual", lag = TRUE, spatial.error = "none")				
Residuals:				
Min.	1st Qu.	Median	3rd Qu.	Max.
-1603.9939	-196.7786	-1.5295	162.0150	1775.6716
Spatial autoregressive coefficient:				
	Estimate	Std. Error	t-value	Pr(> t)
lambda	0.681901	0.031094	21.93	< 0.0001 ***
Coefficients:				
Variables	Estimate	Std. Error	t-value	Pr(> t)
Fertilizers nutrient nitrogen N use per area of cropland	3.3424	1.5678	2.1318	0.03302*
Fertilizers nutrient phosphate P2O5 use per area of cropland	-9.0190	3.6325	-2.4828	0.01303*
Fertilizers nutrient potash K2O use per area of cropland	-3.7445	4.0228	-0.9308	0.35194
Pesticides use per area of cropland	27.4412	36.1696	0.7587	0.44804

Note: *** - 0.001; ** - 0.01; * - 0.05; ' - 0.1; 'No symbol' - insignificant.

Table 7. Results of spatial panel fixed effects error model: Impact of fertilizer and pesticide use on unsafe drinking water (Environmental Performance Index)

Source: Calculations in R Studio.

Spatial panel fixed effects error model				
Call:				
spml(formula = y3 ~ x1 + x2 + x3 + x4,				
data = pdata, listw = lw, model = "within", effect = "individual", lag = FALSE, spatial.error = "b")				
Residuals:				
Min.	1st Qu.	Median	3rd Qu.	Max.
-3.879740	-0.347767	0.012458	0.456527	2.029785
Spatial autoregressive coefficient:				
	Estimate	Std. Error	t-value	Pr(> t)
lambda	0.533434	0.040006	13.334	< 0.0001 ***
Coefficients:				
Variables	Estimate	Std. Error	t-value	Pr(> t)
Fertilizers nutrient nitrogen N use per area of cropland	-0.0033156	0.0024553	-1.3504	0.176896
Fertilizers nutrient phosphate P2O5 use per area of cropland	-0.0151640	0.0058386	-2.5972	0.009398**
Fertilizers nutrient potash K2O use per area of cropland	0.0076392	0.0062501	1.2223	0.221611
Pesticides use per area of cropland	0.0571508	0.0528394	1.0816	0.279433

Note: *** – 0.001; ** – 0.01; * – 0.05; ' – 0.1; 'No symbol' – insignificant.

presence of spatial spillovers in water quality outcomes, likely reflecting transboundary water systems, shared pollution sources, or regional environmental policy dynamics.

Model selection criteria favor the spatial error model over the spatial lag specification. The AIC for the spatial error model is 2522.609, which is substantially lower than the AIC of 7031.93 reported for the lag model. This suggests the spatial error model offers a better trade-off between explanatory power and complexity when modeling unsafe drinking water outcomes.

In the spatial lag model, phosphate use per hectare (x2) has a statistically significant negative association with water quality (estimate = -9.0190, $p = 0.01303$), suggesting that higher phosphate fertilizer use contributes to deterioration in drinking water safety. Nitrogen use (x1) is also statistically significant in this model (estimate = 3.3424, $p = 0.03302$), indicating a positive relationship with the unsafe drinking water index, which reflects better water quality. However, this direction of the relationship appears counterintuitive, as excessive nitrogen application is typically associated with water contamination; further analysis is needed to assess whether this reflects a spurious correlation or omitted variable bias. Potassium use (x3) and pesticide use (x4) are statistically insignifi-

cant in the lag model, with p -values of 0.35194 and 0.44804, respectively, suggesting no measurable effect on water quality in this specification.

In the spatial error model, phosphate use remains statistically significant (estimate = -0.01516, $p = 0.009398$), reinforcing the association between phosphate application and water quality degradation. Nitrogen use (x1) is not significant in this model ($p = 0.1769$), and neither are potassium (x3) or pesticide use (x4), with p -values of 0.2216 and 0.2794, respectively.

The residual range is narrower in the spatial error model (from -3.8797 to 2.0298) than in the spatial lag model (from -1603.9939 to 1775.6716), further supporting the better fit of the error specification. These results underscore that drinking water safety outcomes are not determined solely by local agricultural practices but are also shaped by broader spatial interactions. This highlights the importance of integrating spatial dependence into environmental quality assessments, especially when dealing with shared ecological resources like water systems.

Phosphate fertilizer use shows a consistent and significant link to poorer drinking water quality, while nitrogen's role is more ambiguous and model-dependent. The spatial error model appears to

capture the structure of the data more effectively, as indicated by lower AIC and tighter residuals. These findings support the utility of spatial econometric models in evaluating cross-border environmental effects and call for cooperative regional policy measures to manage water quality risks effectively.

The spatial panel fixed effects lag model estimates (Table A3, Appendix A) how agricultural input use affects the Environmental Performance Index related to unsafe drinking water (y_3) across countries and their neighbors. The model includes spatial dependence, as indicated by the highly significant spatial autoregressive coefficient ($\lambda = 0.68$), showing that neighboring conditions strongly influence countries' environmental outcomes.

Nitrogen fertilizer use (x_1) shows a statistically significant positive effect. A one-unit increase in nitrogen use raises the unsafe water index by about 4.2 units directly and an additional 6.6 units indirectly in neighboring countries, for a total increase of 10.8 units. This implies that nitrogen use may worsen water quality locally and regionally, potentially through runoff and leaching.

Phosphate fertilizer use (x_2) has a significant negative impact. It indirectly decreases the unsafe water index by around 11.1 and 17.6 units, resulting in a total reduction of approximately 28.7 units. While counterintuitive, this might reflect substitution effects, reporting anomalies, or broader agricultural practices in countries using phosphate more efficiently.

Potash (x_3) shows a negative but statistically insignificant effect, while pesticide use (x_4) has a significant total positive effect of about 92.7 units, though with wide confidence intervals. This suggests a strong potential link between pesticide use and poor water quality but also highlights uncertainty in the estimates.

4. DISCUSSION

The results of this study confirm the presence of significant spatial interdependencies in how agricultural input use affects public health and environmental outcomes across European countries.

Using spatial panel fixed effects models, the paper demonstrates that mineral fertilizer and pesticide application in one country can influence health expenditure levels and drinking water quality in neighboring countries. The spatial error model, which best captures the structure of spatial dependence in water pollution data, reveals that shared, unobserved regional factors, such as standard water basins or environmental governance gaps, drive similarities in unsafe drinking water indicators across borders.

For health expenditure outcomes, spatial lag models perform better, suggesting that the level of healthcare spending in one country is directly influenced by spending in neighboring states. This result aligns with the transboundary nature of environmental degradation and healthcare challenges discussed in the literature, particularly by Bartram et al. (2002) and the European Environment Agency (2018). The significant and positive spatial lag coefficient reinforces the view that nitrate pollution and related health burdens extend beyond national borders, as also observed by Glavan et al. (2019) and Lyeonov et al. (2021).

The study further finds that nitrogen fertilizer use is positively associated with increases in health expenditure, both per capita and as a share of GDP, supporting earlier evidence by Huzenko and Kononenko (2024) on the public health risks of nitrate contamination. In contrast, phosphate fertilizer use is negatively associated with healthcare costs but has a substantial, statistically significant negative impact on drinking water quality. This divergence may reflect differences in how countries internalize environmental risks. As noted by Bilan et al. (2023), wealthier nations may offset environmental exposure through infrastructure and public health investment, resulting in lower observed health costs despite environmental damage.

Potassium fertilizer and pesticide use show less consistent effects. Potash is generally associated with lower healthcare expenditure, though the relationship may be confounded by regional agricultural efficiency or economic conditions. While not always statistically significant in fixed-effects regressions, pesticide use shows a substantial total effect in the impact decomposition analysis. These mixed results mirror findings from Ai et al. (2024)

and Singh and Pandey (2023), who describe the complex trade-offs between agricultural intensification and its long-term environmental and health consequences.

Overall, this study supports the argument advanced by Supriyanto et al. (2024) and Dong et al. (2023) that spatial spillovers require coordinated regional policy solutions. The impact of agricultural practices extends beyond national borders, and unilateral efforts are insufficient to mitigate environmental and public health risks. The findings underscore the need for integrated, cross-border regulation of fertilizer use, investments in environmental monitoring infrastructure, and regional cooperation in health and water policy to address shared challenges in sustainable development.

While this study provides meaningful insights into the cross-border environmental and economic impacts of mineral fertilizer use in European agriculture, several limitations must be acknowledged.

First, the analysis is constrained by data availability and consistency across multiple international databases, necessitating a fixed time period of 2006–2021. This timespan was chosen to ensure temporal and geographic compatibility of data on fertilizer use, healthcare expenditures, and environmental indicators across all countries included in the sample. As a result, the model may not fully capture more recent developments, particularly those arising after 2021.

Second, the geopolitical and economic consequences of the war in Ukraine, which began in

2022, are not reflected in the dataset. The war has significantly disrupted agricultural production and trade in the region. Ukraine, one of the world's leading grain exporters, has experienced substantial losses in harvest volumes, stored crops, and arable land, impacting its food security and influencing production strategies in neighboring and trading countries. Many European countries have increased the intensity of their crop production in response to decreased Ukrainian exports, which could lead to increased fertilizer use and greater environmental stress. Furthermore, sanctions on agricultural exports from Russia, a major fertilizer producer, have disrupted global supply chains, likely affecting fertilizer pricing, availability, and application patterns across Europe.

Third, while spatial econometric methods help reveal structural interdependencies between countries, causal inference remains limited. The study identifies statistical associations between fertilizer use and public health/environmental outcomes but cannot definitively establish causation without more granular, time-sensitive, and country-specific data.

Lastly, although the models control for spatial effects, the analysis does not explicitly include other non-agricultural drivers of public health expenditure and water quality, such as industrial pollution, healthcare policies, or climate variability. Future research could benefit from integrating these additional variables and examining how environmental policies, trade dynamics, and technological changes mediate the observed relationships.

CONCLUSION

This study aimed to assess how agricultural input use, specifically nitrogen, phosphate, potash fertilizers, and pesticides, affects public health and environmental outcomes, particularly health expenditure and unsafe drinking water, across European countries. To achieve this, the analysis applied spatial panel fixed effects models using both spatial lag and spatial error specifications to account for spatial dependencies and spillover effects between countries over time.

The results demonstrate clear spatial dynamics. For health expenditure, the spatial lag model provided the best fit, with a highly significant spatial autoregressive coefficient ($\rho = 0.68$), indicating that increases in health spending in one country are associated with higher health spending in its neighbors. Nitrogen fertilizer use (x_1) significantly positively affected health expenditure per capita, increasing it by approximately 10.8 international dollars (4.2 direct, 6.6 indirect). In contrast, phosphate (x_2) and

potash (x3) fertilizers significantly negatively affected health expenditure, with phosphate showing a total reduction of nearly 28.7 dollars. Pesticide use (x4) had the most significant total effect on health expenditure (~92.6 dollars), though wide confidence intervals indicate uncertainty.

In the case of unsafe drinking water, the spatial error model showed better model fit (AIC = 2,522.6 vs. 7,031.9 for the lag model), suggesting that unobserved spatially structured factors – rather than direct interactions between countries – are the main drivers of spatial dependence in environmental outcomes. Moran's I statistic ($I = 0.16$, $p = 0.09$) on the model residuals revealed mild residual spatial clustering, confirming that shared regional factors still affect water quality despite the controls. Among the inputs, nitrogen use was again positively associated with higher unsafe water scores, while phosphate use showed a strong negative relationship, suggesting regional environmental management or reporting variation.

These findings reinforce the need for cross-border policy coordination. The significant spillover effects of nitrogen and pesticide use on health outcomes and the shared spatial drivers of unsafe water highlight that national policies alone are insufficient to manage these challenges. Governments should pursue harmonized regulation of fertilizer and pesticide use, regional water monitoring frameworks, and shared investment in sustainable agricultural practices. Coordinated policies at the EU level or among neighboring countries are essential to mitigate transboundary environmental risks and reduce their public health impacts.

AUTHOR CONTRIBUTIONS

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APPENDIX A

Table A1. Spatial spillover effects of agricultural fertilizers and pesticides on current health expenditure per capita

Variable	Direct	Indirect	Total
x1	4.105357	6.401898	10.50726
x2	-11.077736	-17.274635	-28.35237
x3	-4.599269	-7.172105	-11.77137
x4	33.705231	52.559977	86.26521

Simulation results (variance matrix): Direct: Iterations = 1:200; Thinning interval = 1; Number of chains = 1; Sample size per chain = 200

Empirical mean and standard deviation for each variable, plus standard error of the mean				
Variable	Mean	SD Naive	SE Time-series	SE
x1	4.192	1.919	0.1357	0.1357
x2	-11.686	4.561	0.3225	0.3225
x3	-4.279	4.540	0.3210	0.2322
x4	35.563	43.902	3.1043	2.4807

Quantiles for each variable					
Variable	2.5%	25%	50%	75%	97.5%
x1	0.4716	2.878	4.253	5.370	7.999
x2	-21.0529	-14.660	-11.702	-8.723	-2.914
x3	-12.7073	-7.279	-4.354	-1.228	4.361
x4	-43.9261	4.977	37.343	65.425	113.249

Indirect: Iterations = 1:200; Thinning interval = 1; Number of chains = 1; Sample size per chain = 200

Empirical mean and standard deviation for each variable, plus standard error of the mean:				
Variable	Mean	SD Naive	SE Time-series	SE
x1	6.553	3.102	0.2194	0.2194
x2	-18.307	7.547	0.5337	0.5337
x3	-6.660	7.180	0.5077	0.3622
x4	55.306	68.113	4.8163	4.8163

Quantiles for each variable					
Variable	2.5%	25%	50%	75%	97.5%
x1	0.7088	4.462	6.452	8.510	12.534
x2	-33.2495	-23.762	-17.839	-12.708	-4.804
x3	-19.6637	-11.584	-6.913	-1.858	6.832
x4	-74.1418	7.705	55.252	103.062	176.279

Total: Iterations = 1:200; Thinning interval = 1; Number of chains = 1; Sample size per chain = 200

Indirect: Iterations = 1:200; Thinning interval = 1; Number of chains = 1; Sample size per chain = 200

Empirical mean and standard deviation for each variable, plus standard error of the mean:				
Variable	Mean	SD Naive	SE Time-series	SE
x1	10.74	4.98	0.3522	0.3522
x2	-29.99	11.99	0.8475	0.8475
x3	-10.94	11.69	0.8264	0.5916
x4	90.87	111.70	7.8985	7.8985

Quantiles for each variable					
Variable	2.5%	25%	50%	75%	97.5%
x1	1.18	7.524	10.76	13.796	20.53
x2	-53.30	-38.681	-29.70	-21.541	-7.71
x3	-32.14	-19.361	-11.03	-3.173	11.02
x4	-119.11	12.682	94.66	170.770	289.85

Table A2. Spatial spillover effects of agricultural fertilizers and pesticides on current health expenditure (% of GDP)

Variable	Direct	Indirect	Total
x1	0.006695607	0.001026810	0.007722417
x2	-0.014231964	-0.002182555	-0.016414519
x3	-0.007886384	-0.001209423	-0.009095806
x4	0.007750947	0.001188653	0.008939600

Simulation results (variance matrix): Direct: Iterations = 1:200; Thinning interval = 1; Number of chains = 1; Sample size per chain = 200

Empirical mean and standard deviation for each variable, plus standard error of the mean				
Variable	Mean	SD Naive	SE Time-series	SE
x1	0.006503	0.002429	0.0001718	0.0001718
x2	-0.014169	0.005723	0.0004047	0.0004047
x3	-0.007949	0.006086	0.0004303	0.0004303
x4	0.009518	0.052893	0.0037401	0.0037073

Quantiles for each variable					
Variable	2.5%	25%	50%	75%	97.5%
x1	0.002237	0.004774	0.006557	0.008382	0.011088
x2	-0.025650	-0.017958	-0.014124	-0.010059	-0.003913
x3	-0.019942	-0.012168	-0.007534	-0.003475	0.002149
x4	-0.090524	-0.033108	0.014634	0.047044	0.106477

Indirect: Iterations = 1:200; Thinning interval = 1; Number of chains = 1; Sample size per chain = 200

Empirical mean and standard deviation for each variable, plus standard error of the mean:				
Variable	Mean	SD Naive	SE Time-series	SE
x1	0.0009696	0.0005743	4.061e-05	4.061e-05
x2	-0.0021157	0.0013063	9.237e-05	9.237e-05
x3	-0.0011799	0.0012010	8.492e-05	8.492e-05
x4	0.0016867	0.0091693	6.484e-04	5.197e-04

Quantiles for each variable					
Variable	2.5%	25%	50%	75%	97.5%
x1	9.159e-05	0.0005416	0.0008890	0.0013521	0.0022497
x2	-4.914e-03	-0.0028676	-0.0018885	-0.0011229	-0.0002049
x3	-4.557e-03	-0.0018007	-0.0009246	-0.0004103	0.0003417
x4	-1.409e-02	-0.0040212	0.0015179	0.0065651	0.0191527

Total: Iterations = 1:200; Thinning interval = 1; Number of chains = 1; Sample size per chain = 200

Indirect: Iterations = 1:200; Thinning interval = 1; Number of chains = 1; Sample size per chain = 200

Empirical mean and standard deviation for each variable, plus standard error of the mean:				
Variable	Mean	SD Naive	SE Time-series	SE
x1	0.007473	0.002817	0.0001992	0.0001992
x2	-0.016285	0.006664	0.0004712	0.0004712
x3	-0.009129	0.007096	0.0005018	0.0005018
x4	0.011205	0.061453	0.0043454	0.0038446

Quantiles for each variable					
Variable	2.5%	25%	50%	75%	97.5%
x1	0.002513	0.005472	0.007276	0.009463	0.012405
x2	-0.028842	-0.020639	-0.016135	-0.011727	-0.004684
x3	-0.024981	-0.013745	-0.008570	-0.004056	0.002463
x4	-0.103427	-0.037475	0.016470	0.052137	0.121200

Table A3. Spatial spillover effects of agricultural fertilizers and pesticides on Environmental Performance Index: Unsafe drinking water

Variable	Direct	Indirect	Total
x1	4.105357	6.401898	10.50726
x2	-11.077736	-17.274635	-28.35237
x3	-4.599269	-7.172105	-11.77137
x4	33.705231	52.559977	86.26521

Simulation results (variance matrix): Direct: Iterations = 1:200; Thinning interval = 1; Number of chains = 1; Sample size per chain = 200

Empirical mean and standard deviation for each variable, plus standard error of the mean				
Variable	Mean	SD Naïve	SE Time-series	SE
x1	4.204	1.920	0.1358	0.1358
x2	-11.149	4.595	0.3249	0.3709
x3	-4.685	5.015	0.3546	0.3546
x4	35.813	45.242	3.1991	2.9543

Quantiles for each variable					
Variable	2.5%	25%	50%	75%	97.5%
x1	4.204	1.920	0.1358	0.1358	4.204
x2	-11.149	4.595	0.3249	0.3709	-11.149
x3	-4.685	5.015	0.3546	0.3546	-4.685
x4	35.813	45.242	3.1991	2.9543	35.813

Indirect: Iterations = 1:200; Thinning interval = 1; Number of chains = 1; Sample size per chain = 200

Empirical mean and standard deviation for each variable, plus standard error of the mean:				
Variable	Mean	SD Naïve	SE Time-series	SE
x1	6.614	3.170	0.2241	0.2241
x2	-17.565	7.863	0.5560	0.6270
x3	-7.359	8.178	0.5783	0.5783
x4	56.842	74.241	5.2496	4.8381

Quantiles for each variable					
Variable	2.5%	25%	50%	75%	97.5%
x1	0.8468	4.471	6.657	8.705	12.671
x2	-34.8025	-22.731	-16.891	-11.420	-4.802
x3	-24.3518	-11.975	-6.803	-2.375	6.643
x4	-75.0503	2.182	59.756	103.419	206.004

Total: Iterations = 1:200; Thinning interval = 1; Number of chains = 1; Sample size per chain = 200

Indirect: Iterations = 1:200; Thinning interval = 1; Number of chains = 1; Sample size per chain = 200

Empirical mean and standard deviation for each variable, plus standard error of the mean:				
Variable	Mean	SD Naïve	SE Time-series	SE
x1	10.82	5.046	0.3568	0.3568
x2	-28.71	12.326	0.8716	0.9875
x3	-12.04	13.153	0.9301	0.9301
x4	92.65	119.140	8.4244	7.7597

Quantiles for each variable					
Variable	2.5%	25%	50%	75%	97.5%
x1	1.357	7.286	10.96	14.145	20.902
x2	-54.390	-37.387	-28.45	-19.633	-7.985
x3	-37.261	-19.755	-11.26	-4.028	10.501
x4	-120.029	3.691	99.31	170.248	321.348