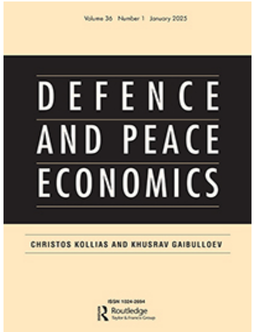

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Fertile ground for conflict: evidence revisited using spatial first differences

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ABSTRACT

In this paper, we revisit the empirical evidence regarding the effect of variations in soil fertility on violence at the local level. Recent evidence shows that as input (fertilizer) prices rise, poor soil productivity exacerbates income inequality and increases the tendency for conflict within and across ethnic groups, especially where soil fertility is more heterogeneous. However, spatial modeling with dense observational units in physical space is susceptible to spatial dependence and heterogeneity. Tackling such econometric issues requires a robust research design to address unobserved heterogeneity. Our main contribution is methodological: we use local soil nutrient availability measurements to proxy soil fertility and employ the spatial first differences (SFD) approach to investigate the effect of soil quality on local conflict. We show that soil nutrient heterogeneity is associated with conflicts and that this relationship is independent of climatic factors and fertilizer prices. Regarding policy, our results suggest that encouraging investment in agricultural practices that protect soil productivity might be important for reducing resource-related conflict in developing regions.

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Introduction

Understanding whether the decline in soil productivity increases the likelihood of civil conflict is crucial for supporting policies that improve resource redistribution for effective conflict prevention and resolution (Animashaun 2019; Ibáñez and Moya 2010). Existing research considers resource-related conflict as a form of social conflict originating from unequal access to fertile areas, thereby threatening regional peace in developing regions such as Sub-Saharan Africa (Campbell et al. 2000). This view is supported by empirical evidence; higher input prices, through the effect on income and inequality, affect appropriable rents and the opportunity costs of fighting, especially in regions with more heterogeneous soil fertility (Berman, Couttenier, and Soubeyran 2021). Although recent evidence linking soil productivity with an increased likelihood of fighting comes from advances in the empirical literature, conclusions implied from the role of input (fertilizer) prices are, at best, speculative.

Our goal in this paper is to provide credible support for recent advances in understanding the nature of conflict in relation to soil nutrient availability. Our starting point is Berman, Couttenier, and Soubeyran's (2021) paper, which investigates the effect of variation in soil fertility on civil conflict. Berman, Couttenier, and Soubeyran (2021) present a model with heterogeneous land in which

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variations in input (fertilizer) prices affect appropriable rents and the opportunity costs of fighting. The authors support this claim by using a cell-level dataset at 0.5 × 0.5 degree latitude and longitude (approx. 55 km × 55 km at the equator) covering all of Sub-Saharan Africa (SSA) from 1997 to 2013. The identification strategy employed within-cell variations in (international) fertilizer prices, conflicts over time, other unobservable cell-fixed effects, and unobserved common time shocks. They find that soil productivity, triggered by variations in fertilizer prices, is positively associated with conflicts, especially where land endowments are more heterogeneous.

Although Berman, Couttenier, and Soubeyran's (2021) underlying theory is intuitive and appealing, their findings that rely on spatial variation of fertilizer prices to identify the effect of soil fertility on conflict should be interpreted cautiously. Since the influential work of Anselin (1988), two characteristics of spatial analysis – spatial dependence and spatial heterogeneity – are important when modeling spatial and regional economic dynamics (Basile et al. 2014). Spatial dependence occurs when outcomes observed at one location depend on the values of observations at nearby locations (LeSage and Pace 2009. Spatial heterogeneity reflects the lack of spatial stability due to the difference in functional forms resulting in parameters, such as the mean, varying from point to point (Harris et al. 2010, Nakaya et al. 2005). Fertilizer prices are likely to exhibit spatial dependence and heterogeneity because agronomic practices, local input and output prices, and fertilizer investment decisions are influenced by neighborhood effects (see Bonilla Cedrez et al. (2020)).

In developing countries, substantial agricultural subsidy programs stabilize end-user input prices. Consequently, local input prices differ significantly from international market prices, and end-user input prices display enormous dispersion across locations. Berman, Couttenier, and Soubeyran (2021) circumvented some of these endogeneity concerns by computing a proxy for local fertilizer prices, given that fertilizers comprise three main nutrients (nitrogen, phosphate, and potassium) and the ideal composition of fertilizers varies across crops. More precisely, the main crop was identified for each cell. Then, using data on the world prices, a cell-specific, time-varying indicator of fertilizer price was constructed.

Nonetheless, information flow and price (or input costs) expectations between farmers across neighborhoods will likely reinforce horizontal transmissions, potentially leading to strong dependence among close neighbors. Similarly, environmental stochasticity might emphasize ecosystem constraints, agronomic response to fertilizer application, and the market's supply dynamics differently from one area to another. More importantly, Berman, Couttenier, and Soubeyran (2021) treat agricultural production activities as homogeneous in both their fertilizer requirement and the prioritization of intensification and sustainable practices. However, agricultural intensification practices vary, as does the convexity of the net benefit function, which varies by the scale of production and farm enterprise specialties. Berman, Couttenier, and Soubeyran (2021) assume that farmers assign equal importance to inorganic fertilizers to improve soil productivity, irrespective of enterprise specialization. Conversely, farmers exhibit considerable diversity in their choice of agricultural enterprises and in the importance they place on investing in fertilizer use.

Given this background, we make three methodological contributions. First, we present an empirical framework that identifies soil fertility with the local soil nutrient availability to limit the spatial dependence of fertilizer prices across locations. Second, we implement spatial first differences (SFD) to isolate variation in conflict while accounting for unobservable spatial heterogeneity. This methodology employs units of observation that are organized and densely packed across physical space, such as gridded data, and compares similar observational units. A concern with this approach is the influence of omitted variables common to neighboring units (see Döring and Mustasilta (2023); Dorff, Gallop, and Minhas (2022); Cappelli et al. (2020)). In spatial econometrics, accounting for spatial heterogeneity and spatial dependence of treatments is important for robust identification. Druckenmiller and Hsiang (2018) suggest that omitted variable bias due to this heterogeneity can be eliminated from estimates using a simple and general differencing approach. Applying SFD in this context eliminates spatially correlated unobserved heterogeneity at two levels. First, it removes the influence of all factors that vary at low spatial frequencies, meaning any factor that affects observations that are not immediately adjacent. Second, it differences all common influences that idiosyncratically affect any two observations adjacent to one another. The SFD recognizes the neighborhood effect since it allows adjacent observational units to be comparable but does not assume that distant units are comparable. By restricting comparisons to adjacent neighbors in our procedure, the influence of all omitted variables common to neighboring units is differenced out in the SFD.

Third, we implement this strategy to analyze the effect of variations in soil nutrient availability on local conflict across Africa and the Middle East. In line with Berman, Couttenier, and Soubeyran (2021), local soil nutrient variation may contribute to the occurrence of conflict. However, for empirical identification, we rely on the framework of Druckenmiller and Hsiang (2018) and regress the spatial first differences (SFD) of the outcome (conflict) on the treatment, soil nutrient availability, with and without relevant environmental covariates. When units are dense in physical space, regressing the SFD of the outcome on the treatment plausibly accounts for unobserved spatial heterogeneity, satisfying the identifying assumptions typical of other quasi-experimental designs. As in Berman, Couttenier, and Soubeyran (2021), we employ geo-referenced conflict locations within Sub-Sahara Africa (SSA) and the Middle East and North Africa (MENA) from 1997 to 2022 at a spatial resolution of 0.5×0.5 degrees. The enhanced dataset, which now includes the MENA region and extends the observation period from 1997 to 2022, improves our data points and allows for a more detailed exploration of heterogeneities than in Berman, Couttenier, and Soubeyran (2021). Our findings corroborate Berman, Couttenier, and Soubeyran (2021), showing that variations in soil quality are linked to local conflict, independent of fertilizer prices, climatic conditions, and other socioeconomic factors. The SFD analysis reveals a significant association between civil conflict and economic opportunities arising from increased soil productivity.

Broadly, our findings contribute to the understanding of this complex issue by estimating the effect of soil fertility captured through soil nutrient availability. There is a growing body of literature that seeks to understand conditions that favor conflict (see Emediegwu (2024, 2022a); Berman, Couttenier, and Soubeyran (2021, 2017); Hsiang, Burke, and Miguel (2013); Dube and Vargas 2013). Recent studies suggest that civil conflict is more likely to occur in regions with low soil fertility (i.e., where input costs are high) and is further exacerbated by inequalities in access resulting from heterogeneous soil productivity (Berman, Couttenier, and Soubeyran 2021). This view of conflict, rooted in poverty and unequal access to productive resources, is not exclusive to economics but has also been articulated in other disciplines, such as political science (Fearon and Laitin 2003) and sociology (Wimmer, Cederman, and Min 2009).

An alternative view suggests that greater land scarcity may result in less bloodshed (see Turner (2004); Breusers, Nederlof, and Van Rheenen (1998)). Arguably, where livelihoods are closely tied to land and soil productivity, the convergence in economic interests could exacerbate competition for scarce productive resources and escalate conflict. On the other hand, such scarcity might foster mutual understanding within communities, thereby enhancing their capacity to manage resource constraints and mitigate nascent conflicts effectively (Murty 1994; Runge 1986; Singleton and Taylor 1992; Turner et al. 2011). Increasing land scarcity may also drive technological and institutional reforms that stimulate social adaptations, non-farm diversification, and intensive land use (Fabbri 2021; Fabbri and Dari-Mattiacci 2021; Kugbega and Aboagye 2021). Thus, policies that internalize cooperative norms and strengthen social capital accumulation among diverse social groups could help mitigate resource-related conflict.

In contrast to Berman, Couttenier, and Soubeyran (2021), it is unclear whether variations in fertilizer prices could aggravate conflict since crop and livestock farmers do not hold the same preference for investment in soil enrichment using inorganic fertilizers. Notably, the opportunity to free-ride on the other party's investment is high due to poorly defined property rights as experienced in developing regions like SSA. Anecdotal incidences of conflict over agricultural land in SSA arise largely due to poorly defined property rights, leading to overconsumption and underinvestment by one of the parties.

The remainder of the paper is organized as follows: Section 2 describes the methodology and data, while the various results are discussed in Section 3. The paper concludes with remarks in Section 4.

Data and methodology

Data

We use geo-referenced data from two of the world's most conflict-prone regions – SSA and MENA. Both regions have historically experienced significant levels of food-related conflict. For instance, food shortages and price hikes played a role in sparking events such as the Arab Spring. Further, the contiguity of SSA and MENA makes them suitable for applying spatial first differences, as the SFD method leverages neighboring areas to account for spatial spillovers and unobserved heterogeneity. Including both regions in the study enhances the robustness and generalizability of the research findings. The list of countries is documented in Table A5 in the Appendix.

Conflict data

We utilize conflict event data from the Armed Conflict Location and Event Dataset (ACLED) (Raleigh et al., 2014), which provides detailed geo-located information on conflict events across all African countries from 1997 to 2022 and Middle East countries from 2015 to 2022.[1] ACLED is a widely recognized resource for real-time data and analysis, containing locations, dates, actors, fatalities, and types of all reported political violence and protest events globally.

Following Cunen, Hjort, and M (2020); Bertoni et al. (2019), and Jaeger and Paserman (2008), we use the total number of fatalities within a location in a given year as a proxy for conflict. We only allow for events with more than 25 casualties to reduce noise in the data and allow for a clearer focus on events with substantial and sustained impacts on development outcomes.[2] By applying this threshold, we aim to maintain comparability with other studies that focus on large-scale conflicts (see Gleditsch et al. (2002)). However, we show that the results of using unrestricted casualty figures are similar in the Appendix (Table A1). Additionally, we ensure accuracy by dropping events that are neither geo-referenced nor time-referenced.[3] Lastly, in the spirit of Berman, Couttenier, and Soubeyran (2021), we exclude events related to riots and protests from our sample, thereby focusing only on conflicts directly related to resource scarcity. We acknowledge that some measurement errors may occur in conflict reporting; however, we believe these errors are exogenous to our explanatory variables. Therefore, such errors are likely to result in imprecise rather than biased estimates.

Climate data

In the spirit of Emediegwu, Wossink, and Hall (2022) and Harari and Ferrara (2018), we use standardized precipitation evapotranspiration index (SPEI) to measure extreme weather conditions, such as drought. Developed by Vicente-Serrano et al. (2015) using temperature and precipitation data from the Climate Research Unit Time Series (CRU TS) v4.07, the SPEI has been shown to outperform other measures of extreme weather events such as self-calibrated Palmer Drought Severity Index (sc-PDSI) and standardized precipitation index (SPI) in quantifying extreme weather impacts.

The SPEI is a gridded monthly series at 0.5o resolution (approx. 56 km $\times$ 56 km across the equator) for the period January 1901 to December 2023. SPEI values range from -2 to $+2$, with high positive or negative values indicating drought or flooding, respectively.

Non-climate data

We use different geographic and edaphic characteristics to assess the impact of time-invariant factors on conflict. The choice of our fixed variables is guided by previous conflict studies and economic theory.

River distance, which measures the distance from the conflict point to the nearest river in kilometers (km), is obtained from the World Rivers dataset.[4] Elevation (in km) is considered an important indicator of conflict, as Harari and Ferrara (2018) noted. We source the data from the World Digital Elevation Model (ETOPO5) of the National Oceanic and Atmospheric Administration (NOAA). Land area dataset is obtained from the Gridded Population of the World, Version 4 (GPWv4).[5] This dataset provides estimates of the land area (in square kilometers), excluding permanent ice and water. The idea is that less (arable) land may spark or sustain conflict due to struggle for limited resources – land (see Emediegwu (2022b).

Finally, the main explanatory variable of interest is soil nutrient availability, an important soil characteristic that could impact conflict (Berman, Couttenier, and Soubeyran 2021). Spatial variation in nutrient availability might drive some societal groups, e.g., nomads, to relocate from nutrient-deficient terrains to places with higher soil quality. Such migration has been cited as one of the primary causes of conflicts in several parts of SSA (Bunei, McElwee, and Smith 2016; Okoli 2019; Sani Ibrahim et al. 2021). Data on soil nutrient availability were obtained from the Harmonized World Soil Database (Fischer et al. 2008).[6] The soil nutrient availability index (SQ1) is a composite metric that integrates factors such as soil texture and structure, organic carbon content, pH, and total exchangeable bases. Due to the intercorrelation among these soil nutrient factors, SQ1 was calculated by first identifying the most limiting soil nutrient characteristic and then combining it with the average of the remaining secondary limiting characteristics. SQ1 categorizes soil nutrient availability into several levels based on its impact on vegetation growth. Level 0, which represents water surfaces, indicates the highest constraint and the lowest nutrient availability. Conversely, Level 6 corresponds to minimal or no constraints, representing the greatest nutrient availability. Table 1 summarizes the datasets and their sources.

All datasets are structured on grids with different resolutions. We exploit this grid feature of our datasets to extract historical observations for all conflict locations in our sample; thus, observations are unique to each conflict location. We achieve this by first transforming all datasets to a uniform resolution (0.5o) using spatial software. Thereafter, we overlay a combined polygon of Africa and Middle East regions on the dataset for each grid cell. For each conflict location, we compute the average across all grid cells, except for nutrient availability, where the modal measure is used since it is qualitative data.

Although these time-invariant attributes have been cited as factors that could influence conflict occurrence, limited attention has been given to empirically estimating their effects. This hesitance could be partly due to the absence of a tractable empirical strategy that addresses unobserved heterogeneity.

Table 1. Variables description and summary statistics.

	Description			Summary statistics			
	Unit	Source	Resolution	Min	Max	Mean	SD
Conflict	Number of casualties	ACLED	0.5°	0	4581	35.43	155.39
Nutrient availability	N/A	Harmonized World Soil Database v 1.2	0.08°	1	7	2.00	1.12
SPEI	N/A	Vicente-Serrano et al. (2015)	1°	−1.51	0.90	−0.49	0.31
Distance to nearest river	Kilometers (KM)	World Rivers	Spatial lines	0.00	14.54	2.69	3.05
Elevation	Kilometers (KM)	World digital elevation model (ETOPO5)	1°	−343.5	4195.28	676.46	508.63
Land area	Kilometers (KM)	Gridded Population of the World, Version 4 (GPWv4)	1°	783.00	12391.40	10976.12	1788.03

Notes: N/A means not applicable; SD is standard deviation.

Estimation strategy

Druckenmiller and Hsiang (2018) SFD approach

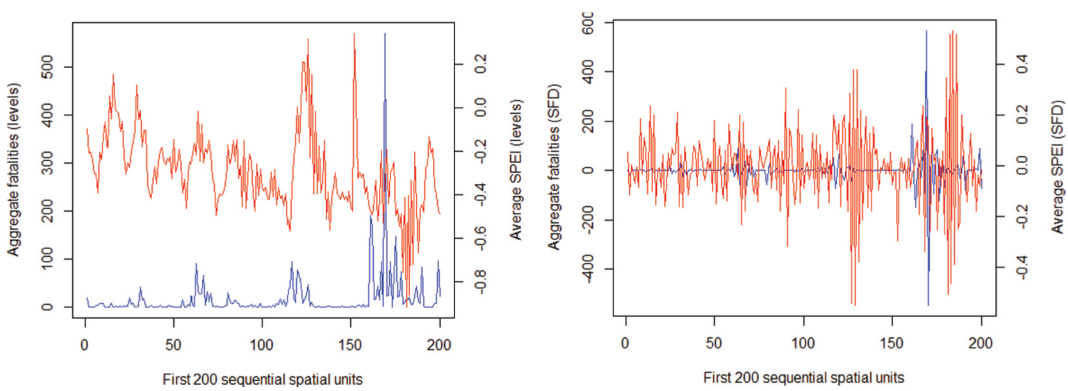
Here, we begin by transforming panel data into a cross-sectional format by collapsing the time-varying variables, resulting in a single observation per location.[7] This was achieved by aggregating fatalities and averaging SPEI. The remaining variables are already cross-sectional. Thereafter, the variables are spatially-differenced, and the resultant model is specified as

$$\Delta C_i = \alpha_0 + \Delta Soil_i \beta_{1^*} + \Delta SPEI_i \beta_{2^*} + \Delta X_i \beta_{3^*} + \Delta \varepsilon_i \tag{1}$$

where C_i is total fatalities exceeding 25 in location i, α is a vector of constants, $Soil$ is a vector representing soil nutrient availability, $SPEI$ is a vector representing SPEI, and X_i consists of important non-climate factors affecting conflict in location i. While we set the floor of our conflict variable at 25 casualties, we show in Table A1 in the Appendix that our results are robust to setting the floor to zero. We control for possible spatial correlation in the standard error terms, ε_i, using the approach described in Hsiang (2010) with an arbitrary distance of 1000 km.[8] Lastly, Δ is a spatial difference operator, and * refers to SFD estimates.

To implement the SFD approach, it is important to reorganize the data to (1) spatially difference each location from only one adjacent neighbor sequentially.[9] Hence, we adopt the generalizable approach in Druckenmiller and Hsiang (2018), which transforms the regularly shaped conflict locations into a panel-like structure. Equally, we order the spatial units, for the purpose of differencing, in the West-East direction. The steps involved in this transformation are documented in Appendix A.

Figure 1 shows the benefit of estimating spatially differenced variables rather than at levels. Using the SFD approach eliminates the low-frequency correlations inherent in the spatial history of the dependent variable. What remains after the elimination will be a cross-sectional variation used to estimate the parameters of interest.



(a) Spatial Trends in Levels (b) Spatial Trends in SFD

Figure 1. Spatial trends of conflict and SPEI data. Red lines represent aggregated fatalities, while blue lines depict the average SPEI.

Results and discussion

Main results

The main results are presented in Table 2. We find that an increase in nutrient availability is associated with a rise in conflict fatalities. The results indicate a rapacity effect, where conflict fatalities rise due to an increase in the intrinsic value of agricultural lands, independent of precipitation or prices.

Column 1 indicates that an increase in nutrient availability is associated with a rise in the number of conflict fatalities by four deaths. The estimate is statistically significant at the 5% level. Our results

Table 2. Cross-sectional estimates from the SFD model.

	(1)	(2)	(3)
Nutrient availability	4.31**	4.14**	3.42*
	(2.15)	(2.11)	(2.21)
SPEI		−39.22***	−38.15**
		(13.52)	(24.19)
Distance to nearest river			−9.06*
			(6.00)
Elevation			0.01
			(0.01)
Land area			0.0005
			(0.001)
Constant	0.17	0.18	0.53
	(0.86)	(0.88)	(0.90)
Observations	3,149	3,149	3,149

Notes: All variables are averaged over 1997-2022, except fatalities, which are aggregated, and nutrient availability, where we used the mode measure. The SFD procedures are carried out using West-East ordering. Standard errors are in brackets, adjusted for spatial (1,000km) correlation following Conley (1999).
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

align with the findings of Berman, Couttenier, and Soubeyran (2021), which show that higher fertilizer prices, moderated by soil fertility, increase conflict events. Column 2 introduces the SPEI variable, and its inclusion in the baseline model does not substantially alter the magnitude of the effect of nutrient availability. Specifically, a unit increase in SPEI is associated with a reduction of 39 conflict fatalities. The SPEI estimate aligns with the opportunity cost theory: higher agricultural productivity reduces labor supply to conflict activities. The estimated effect of SPEI on conflict fatalities is both substantial and statistically significant. Moreover, the direction, significance, and magnitude of the effect of SPEI suggest that the conflict dynamics in our sample resemble those examined in the existing economic literature (e.g., Hsiang, Burke, and Miguel (2013); Harari and Ferrara (2018)). Table A3 in the Appendix further demonstrates that the nexus between soil productivity and conflict is principally attributable to drought conditions.

The effect of nutrient availability on conflict incidence remains stable, even after adding other controls, as shown in column 3. The stable estimates for nutrient availability suggest that its relationship with conflict fatalities is not driven by changes in precipitation. The effect of land productivity on conflict remains ambiguous (Miguel, Satyanath, and Sergenti (2004); Dube and Vargas (2013); McGuirk and Nunn (2020); Berman, Couttenier, and Soubeyran (2021). Improvements in agricultural and land productivity have been shown to either decrease conflict incidence through the opportunity cost effect or increase it via the rapacity effect. On the one hand, earlier studies (Miguel, Satyanath, and Sergenti (2004); Dube and Vargas 2013) provide ample evidence of the opportunity cost effect, where agricultural productivity diverts labor supply away from conflict activities. Conversely, recent literature suggests the possibility of the opposite effect: higher land productivity may intensify competition over land resources (McGuirk and Nunn 2020); Berman, Couttenier, and Soubeyran (2021)).

Robustness

In this subsection, we apply several robustness checks that are unique to the SFD research design. First, we test our results using a spatial double difference (SDD) routine. Second, we present an alternative specification that substitutes nutrient availability with fertilizer prices as the main explanatory variable. Next, we employ extreme bounds analysis to demonstrate how SFD estimates perform relative to level estimates.

Spatial double difference (SDD)

Here, we show that our results are robust under a spatial double difference (SDD) routine, as shown in Table 3. The estimates reported in the table are qualitatively similar to the SFD estimates, albeit marginally larger. While it is understandable why the SDD estimates exhibit greater variation than the SFD estimates, the stability of both estimates implies the absence of potential bias due to omitted variables.[10]

Table 3. Cross-sectional estimates from the SDD model.

	(1)	(2)	(3)
Nutrient availability	4.31**	4.14**	3.42*
	(2.15)	(2.11)	(2.21)
SPEI		−39.22***	−38.15**
		(13.52)	(24.19)
Distance to nearest river			−9.06*
			(6.00)
Elevation			0.01
			(0.01)
Land area			0.0005
			(0.001)
Constant	0.17	0.18	0.53
	(0.86)	(0.88)	(0.90)
Observations	3,149	3,149	3,149

Notes: All variables are averaged over 1997-2022, except fatalities, which are aggregated, and nutrient availability, where we used the mode measure. The SDD procedures are carried out using West-East orderings. Standard errors are in brackets, adjusted for spatial (1,000km) correlation following Conley (1999).
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Alternative specifications

Models that emphasize opportunism and incentives for conflict in agrarian societies suggest that socially costly activities, like banditry and conflict, may increase due to a decline in agricultural productivity (Berman, Couttenier, and Soubeyran 2021). For example, we know that higher fertilizer prices substantially increase conflict, with the effect more pronounced where soil nutrient distribution is highly heterogeneous. Here, we examine how fertilizer prices sourced from Berman, Couttenier, and Soubeyran (2021) influence local conflicts.

Table 4 shows that the SFD approach recovers new cross-sectional estimates for the effects of fertilizer prices, suggesting that unobservables may confound the relationship. Including fertilizer prices and nutrient availability as independent variables, results in Table 5 pick up land's 'own'effect on conflict independent of movements in the international fertilizer price. Consistent with Berman, Couttenier, and Soubeyran (2021), intra-group and inter-group cooperation may be adversely affected, reinforcing the conclusion that land endowment heterogeneity, combined with social heterogeneity, may exacerbate inequality and impede collective action in the management of the common property. The estimate also excludes the possibility that the effect of land productivity on conflict operates through weather shocks (SPEI), fertilizer prices, or other time-invariant unobservables.

Importantly, our findings suggest that irrespective of shocks to fertilizer prices, variation in land productivity over time would still drive conflict due to the following reasons. One, many crops grown on African soils exhibit limited responsiveness to fertilizers (see Bonilla Cedrez et al. (2020)). Besides, many farmers are either unaware or skeptical of the utility of inorganic fertilizers. Additionally, limited access to fertilizers is exacerbated by widespread poverty and credit constraints. Second, rainfall variability amplifies the risk associated with fertilizer investment. An econometric issue that arises is whether identifying the effect of soil productivity on conflict is independent of other confounding factors, as the omission of these variables may result in substantial bias in inference.

Table 4. SFD estimates of the impact of fertilizer prices on conflict.

	(1)	(2)
Fertilizer price (in log)	99.44	89.61
	(109.53)	(106.87)
SPEI		−63.21
		(41.61)*
Distance to nearest river		−23.63
		(15.17)**
Elevation		0.03
		(0.03)
Land area		0.004
		(0.004)
Constant	1.22	0.52
	(6.15)	(3.13)
Observations	3,383	3,380

Notes: All variables are averaged over 1997-2022, except fatalities, which are aggregated. The SFD procedures are carried out using West-East ordering. Standard errors are in brackets, adjusted for spatial (1,000km) correlation following Conley (1999).
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 5. Alternative specification with fertilizer prices as control.

	SFD	SDD
Nutrient availability	12.31	16.73
	(6.48)**	(7.06)***
Fertlizer price	91.65	129.91
	(109.32)	(122.72)
SPEI	−68.13	−66.94
	(44.21)*	(44.22)*
Distance to nearest river	−24.99	−31.79
	(15.92)**	(17.13)**
Elevation	0.03	0.04*
	(0.03)	(0.03)
Land area	0.005*	0.007*
	(0.004)	(0.004)
Constant	1.42	0.35
	(6.39)	(11.80)
Observations	1,641	1,558

Notes: All variables are averaged over 1997-2022, except fatalities, which are aggregated, and nutrient availability, where we used the mode measure. The SFD and SDD procedures are carried out using West-East ordering. Standard errors are in brackets, adjusted for spatial (1,000km) correlation following Conley (1999).
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Given these challenges, along with their connection to other time-invariant factors of conflict and long-run agricultural productivity, it is clear that sudden movements in fertilizer prices alone may be insufficient to create an exogenous shock that drives conflict, regardless of the heterogeneity in soil productivity.

Extreme bound analysis

Since part of our objective is to demonstrate that our empirical strategy does not suffer from the conventional omitted variable bias that plagues standard cross-sectional analysis at levels, we estimate the effect of each independent variable while systematically omitting all potential groupings of controls. Said differently, for each independent variable (e.g., SPEI), we analyze a total of 16 different models, where the remaining covariates are sequentially omitted in all possible combinations. Following Druckenmiller and Hsiang (2018), we aim to determine the magnitude and extent of the omitted variable bias mitigated by spatial differencing. While variations between estimates from level and SFD models signify the presence of omitted variable bias, it is important to acknowledge that the extreme bound analysis does not dictate which is the 'right'model.

The results in Figure 2 suggest that the SFD models outperform the level cross-sectional models across all 16 models and explanatory variables. Specifically, we find that the variance is smaller for SFD models compared to level estimations. Moreover, unlike the level estimations, the SFD coefficients retain their expected signs, as shown in Table 2. Overall, the SFD model demonstrates limited sensitivity to omitted variables, making it more robust to unobserved heterogeneity.

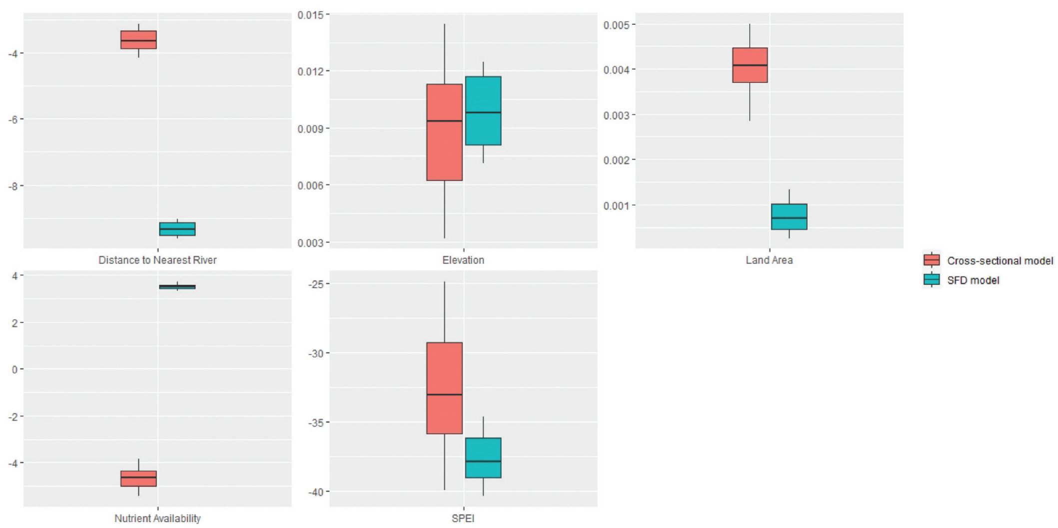


Figure 2. Marginal effect estimates from all combinations of covariates. the box plots represent the distributions of marginal effects for each variable derived by analyzing 16 models that contain the remaining independent variables as covariates. Boxes denote interquartile range of estimates, while the whiskers represent the minimum and maximum estimates. The red boxes are estimates from models in levels, and the green are estimates from SFD models.

Transmission mechanism and heterogeneity analysis

Soil productivity and income

The results in Table 6 show that increased soil nutrient availability correlates positively with improved economic outcomes, as reflected by stronger growth in nighttime light intensity compared to areas with lower nutrient availability. Many of the world's poorest populations depend largely on agriculture for their employment and income; soil fertility depletion significantly heightens the risks of poverty and low per capita food intake (Radosavljevic et al. 2020).

Documenting the nexus between increased soil productivity and economic opportunities broadens the link between competition over scarce resources and conflict. Territorial conflict is more likely and prone to escalation when (1) competition over scarce, valuable natural resources, such as fertile land, is subjected to competing interests and claims (Homer-Dixon 2010); (2) land degradation (poor soil quality) leads to forced displace- ment (Animashaun 2019), amplifying conflict between settlers and migrants, particularly where institutions and markets are weakly coordinated (Ostrom 1990; Sikor and Lund 2009); and (3) contiguous groups have shared economic and social preferences (King 2004; Resnick 2012).

Table 6. Impact of soil productivity on nighttime light.

	SFD	SDD
Nutrient availability	0.60*	0.57
	(0.41)	(0.49)
SPEI	−4.06**	−2.73*
	(2.41)	(1.77)
Distance to nearest river	0.11	0.09
	(0.31)	(0.32)
Other controls	Yes	Yes
Observations	3,379	3,038

Notes: All variables are averaged over 1997-2022, except fatalities, which are aggregated, and nutrient availability, where we used the mode measure. The SFD and SDD procedures are carried out using West-East ordering. Standard errors are in brackets, adjusted for spatial (1,000km) correlation following Conley (1999).
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Soil productivity, conflict, and regional heterogeneities

Table 7 examines the relationship between soil productivity and conflict in SSA and MENA separately. We find a similar relationship, although the coefficient and statistical significance for soil nutrients are higher in SSA. In contrast, the impact of SPEI on conflict is larger and more significant in MENA compared to SSA. When the sample is restricted to post-2015, the period from which Middle East data are available, the estimates retain their signs, although the SPEI coefficient becomes smaller and the nutrient availability coefficient is no longer significant, as shown in Table A4 in the Appendix.

Both regions exhibit plausible different mechanisms that affect conflict (Khalifa and Henning 2020).SSA is better endowed with productive soils than MENA, but the region may experience greater conflict intensity with dwindling soil nutrient profile due to lower capital investment in non-agricultural sectors relative to MENA (Williams 2015).

Table 7. Regional analysis.

	Combined	Sub-Sahara Africa (SSA)	Middle East and North Africa (MENA)
Nutrient availability	3.42*	4.11**	3.99
	(2.21)	(2.04)	(3.95)
SPEI	−38.15**	−11.93	−86.11**
	(24.19)	(13.47)	(43.46)
Distance to nearest river	−9.06*	−4.67	−16.11
	(6.00)	(6.12)	(18.23)
Elevation	0.01	0.004	0.024
	(0.01)	(0.01)	(0.025)
Land area	0.0005	0.0003	0.002
	(0.001)	(0.001)	(0.002)
Constant	0.53	−0.21	1.90
	(0.88)	(1.12)	(3.21)
Observations	3,379	1,954	1,195

Notes: All variables are averaged over 1997-2022, except fatalities, which are aggregated, and nutrient availability, where we used the mode measure. The SFD procedures are carried out using West-East ordering. Standard errors are in brackets, adjusted for spatial (1,000km) correlation following Conley (1999).
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Conclusion

This study revisits recent findings linking soil fertility to civil conflict, focusing on how higher input prices escalate civil conflict and social tension, especially where soil and productive land assets are more heterogeneous. Berman, Couttenier, and Soubeyran (2021) find that higher input (fertilizers) prices lower returns on agricultural investment and increase the likelihood of civil conflict. This finding has important implications for policies, particularly those promoting agricultural input stabilization strategies aimed at reducing local pressure on soil resources and mitigating local conflict over access to productive land.

Extending Berman, Couttenier, and Soubeyran (2021), we emphasize the importance of distinguishing between soil nutrient availability and fertilizer prices, as conflating the two can lead to misguided policy conclusions. Although fertilizer prices may vary based on local soil conditions, they can also interact in several other significant ways, requiring a more nuanced assessment to evaluate the potential impact of fertilizer price stabilization policies on the spatial spread of conflict. Several other factors, such as the prevailing local political economy situations, climatic factors, and unobservable land management practices, must be considered.

We utilize the spatial first differences (SFD) technique to remove bias caused by spatially correlated unobserved variables, which often represent most or all of the important omitted factors in many cross-sectional contexts (Cappelli et al. 2020; Döring and Mustasilta 2023; Druckenmiller and Hsiang 2018). Also, we use geo-referenced data across countries within sub-Saharan Africa (SSA) and the Middle East and North Africa (MENA) regions, with a spatial resolution of 0.5×0.5 degrees over a more extended period from 1997 to 2022. Finally, we regress the spatial first differences (SFD) of the outcome (conflict fatalities) on the treatment (soil nutrient availability) and find that soil nutrient heterogeneity is associated with conflicts, independent of climatic factors and fertilizer prices.

Regarding policy, our results suggest that effective land management practices could improve soil quality and attenuate conflicts by reducing the likelihood of internal displacement. Specifically, we recommend incentivizing farmers to implement soil management strategies. For instance, tying agricultural input subsidies to sustainable practices, such as reforestation schemes and educating farmers on proper agricultural practices, could ameliorate land degradation. Additionally, enhancing local fertilizer production could lower political economy constraints on fertilizer access. Also, effective price controls could improve fertilizer demand and application, contributing to better soil management.

Another vital consideration is the adoption of sustainable soil management practices with long-term benefits, which could be improved if mechanisms that ensure the tenure rights of small-scale farmers are implemented. Investments in agricultural research and development (R&D), particularly those focused on climate-smart technologies, combined with improved access to fertilizers, could significantly enhance soil quality and reduce inequalities in access. Moreover, private-sector-driven agricultural extension services that showcase innovative farming practices through well-established interactive learning environments are crucial for improving soil fertility in economically depressed regions. Promoting livelihood diversification away from soil-dependent agriculture could also be essential for reducing resource-related conflict in Africa and the Middle East. Finally, establishing an enforceable legal framework to limit the overuse of common-access resources could help prevent conflicts driven by natural resource exploitation (Tornell and Velasco 1992).

While this paper contributes to the literature on the causes of local and regional conflicts, certain caveats are noteworthy. First, we were unable to distinguish between different types of conflict, as our estimation procedure requires dense spatial data, limiting the feasibility of conducting a more disaggregated analysis. Besides, extending the methodology to panel data would broaden its usefulness by allowing for a larger number of observations. Addressing these issues could be a promising direction for future research.

Notes

1. Data for North African countries, a subset of both the MENA region and the African continent, is available from 1997. Therefore, the MENA data spans from 1997, initially covering only North Africa, until 2015, when data for Middle Eastern countries became available, extending through to 2022.

2. The Uppsala Conflict Data Project (UCDP) has employed this threshold to distinguish between minor skirmishes and more substantial conflicts that are likely to have broader social, political, and economic impacts (Sundberg and Melander 2013).
3. We do not expect this elimination to affect our results because only about 1.4% of events are affected, which is similar to Berman, Couttenier, and Soubeyran (2021).
4. We employ spatial tools to calculate the geodistance between a conflict unit and the nearest river boundary. World Rivers dataset is a project jointly developed by the Federal Institute for Geosciences and Natural Resources (BGR) and UNESCO. The dataset, which presents 687 rivers associated with 405 Major River Basins, can be assessed *via* http://ihp-wins.unesco.org/layers/geonode:world_rivers.
5. For more details on this dataset, see the Center For International Earth Science Information Network.
   Center For International Earth Science Information Network-CIESIN-Columbia University (2018)
6. The dataset is publicly available and accessible *via http://webarchive.iiasa.ac.at/Research/LUC/External-World-soil-database/HTML/*.
7. Unfortunately, the inability to apply this methodology to panel data is an important weakness of this paper.
8. We show estimated results using other robust standard error estimations in Table A2 in the Appendix.
9. Druckenmiller and Hsiang (2018) believe that these conditions are trivial if location boundaries follow a regular lattice (e.g. in a rectangular shape). This is the case in our work, where each conflict location is geo-referenced as a spatial point based on the reported latitude and longitude and enclosed in a rectangular box to serve as artificial boundaries.
10. Druckenmiller and Hsiang (2018) acknowledge this econometric issue with estimating SDD model, as SDD is vulnerable to attenuation bias since a large portion of the variation in the double differencing may be as a result of measurement error.

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No potential conflict of interest was reported by the author(s).

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