APPENDIX for Rugged Terrain, Forest Coverage, and Insurgency in Myanmar

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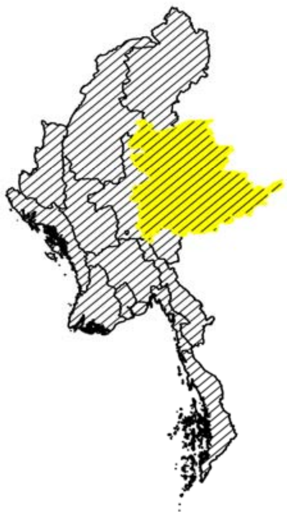
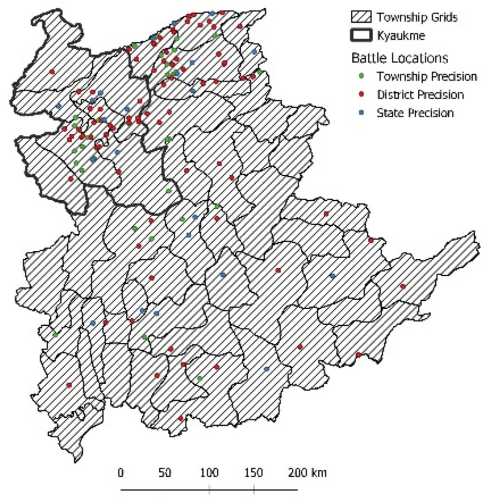
A1: Multiple Areal Scales

Figure A1: Areal Scales of Battle Location Precision in the Shan State of Myanmar

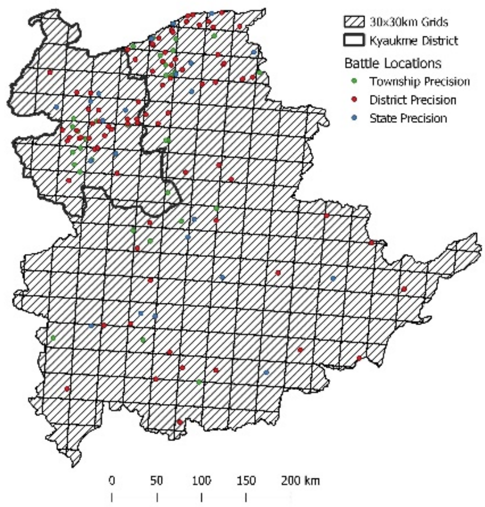
(a) Shan State (in yellow)



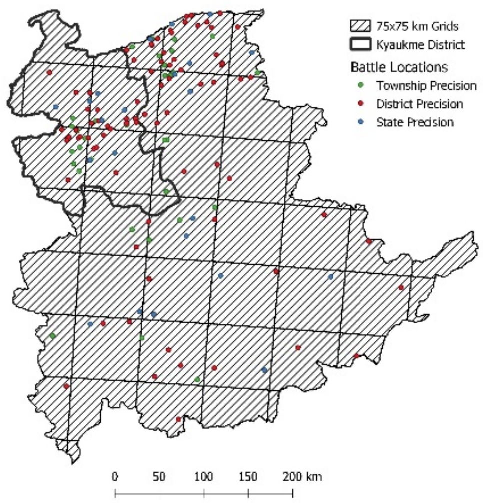
(b) Township



(c) 30x30 km.



(d) 75x75 km.



Forest data is susceptible to the Modifiable Areal Unit Problem (MAUP) or scale problems associated with aggregation (Openshaw, 1981; Wong, 2004). The selection of areal size can significantly impact the results of any statistical study. The choice of scale aggregation affects boundary delineations, which can alter results based on the selected areal size (Fotheringham et al., 2000).

In Myanmar, battle locations are recorded in the ACLED data at the administrative village level with an accuracy of 25 km. If we only analyzed the data at the village level, systematic miscoding could potentially bias our estimates. To address this issue, we randomly manipulate the geolocation sites by imposing uniform areal grids of varying sizes throughout Myanmar (e.g., 50 x 50 km. grids). By doing so, we trade-off less bias for more inefficiency in the data, as smaller grid sizes will magnify geolocation errors but be less noisy, while larger grid sizes will reduce geolocation errors but be noisier. For instance, if the true location of a battle occurs in village i but is misplaced in village j, by imposing a large grid size that encompasses both village i and j, along with accounting for forest coverage, the data may become noisier. However, we can be confident that the battle will be located within the new areal grid.

To illustrate this point, let's consider Figure A1, which depicts the use of various areal grids in the Kyaukme district of Shan state (refer to Figure A1a for the location of Shan state in Myanmar). The figure showcases different areal scales of Shan state, ranging from township (A1b), 30x30 km. grids (A1c), to 75x75 km. grids (A1d), with dots representing battle locations. The dots are color-coded to distinguish the accuracy of the battle location data, with the most accurate ones (within 25 km. of the nearest township and in red) and the least accurate ones (accurate to within the entire state itself and in blue).

If we focus on the Kyaukme district, which is highlighted in bold black in the northwest part of Shan state, Figure A1b reveals a non-trivial number of red battle locations (accurate to the nearest township by 25 km.) placed near the border of several townships. Due to the uncertainty of battle locations within 25 km., battles placed in one township could easily belong to another township. This misplacement could be systematically biased because battles with lower casualties in more remote regions may receive less media attention, resulting in the data at township or smaller areal scales such as 30x30 km. grids containing a substantial amount of noise.

Table A1: Multiple Areal Scales of Battle Frequency and Forest Coverage

	30km X 30km Grids		50km X 50km Grids	
	ACLED	UCDP	ACLED	UCDP
Forest Coverage (%)	0.096***	0.057**	0.098***	0.063**
	(0.015)	(0.019)	(0.018)	(0.020)
Forest Coverage^2	-0.001***	-0.001**	-0.001***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Deforestation Rate	-0.054	-0.023	-0.048	0.046
	(0.046)	(0.053)	(0.078)	(0.139)
Full Controls	Yes	Yes	Yes	Yes
State Dummies	Yes	Yes	Yes	Yes
Year Trend	Yes	Yes	Yes	Yes
Pseudo R-squared	0.126	0.106	0.168	0.079
Observations	8636	11522	3366	6358
	90km X 90km Grids		Townships	
	ACLED	UCDP	ACLED	UCDP
Forest Coverage (%)	0.066*	0.090***	0.047**	0.071***
	(0.028)	(0.023)	(0.015)	(0.014)
Forest Coverage^2	-0.000	-0.001*	-0.000	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Deforestation Rate	0.014	-0.094	0.024	0.111
	(0.110)	(0.123)	(0.051)	(0.102)
Full Controls	Yes	Yes	Yes	Yes
State Dummies	Yes	Yes	Yes	Yes
Year Trend	Yes	Yes	Yes	Yes
Pseudo R-squared	0.132	0.129	0.206	0.055
Observations	1206	2278	2547	4811

Robust standard errors clustered by grid or township in parentheses
* p<0.05 ** p<0.01 *** p<0.001

To address this issue, we adopt a solution used in previous studies on forest fire spread by Louvet et al. (2015) and Monjarás-Vega et al. (2020), where we analyze the results at multiple areal sizes. By examining multiple scales, we can select an optimal scale that best explains the pattern that addresses the compromise between minimizing areal scale while accounting for measurement for these effects.

To achieve this, we implement a uniform grid system throughout Myanmar, keeping in mind that the grid size must strike a balance between being too small and too large. If the grid size is too small, it could result in the same bias problem as the township-border issue. Figure 2c highlights this problem, where a 30x30 km. grid (about 625 sq. km.) in the Kyaukme district (bolded area) could potentially introduce the same bias as township data, where denser forested areas may underreport battles. Conversely, selecting too large a grid would lead to attenuation bias.

To further analyze the impact of different areal scales, we repeat the analysis using various scales ranging from 30 x 30 km. to administrative regions such as townships, as presented in Table A1. The analysis utilizes both ACLED and UCDP data. The results obtained using different scale measures for grid and administrative units are qualitatively identical to the findings in the main text, with larger marginal effects at the intermediate range.

A2: Data description and robustness checks

Figure A2: The Distribution of Forest Coverage in Myanmar

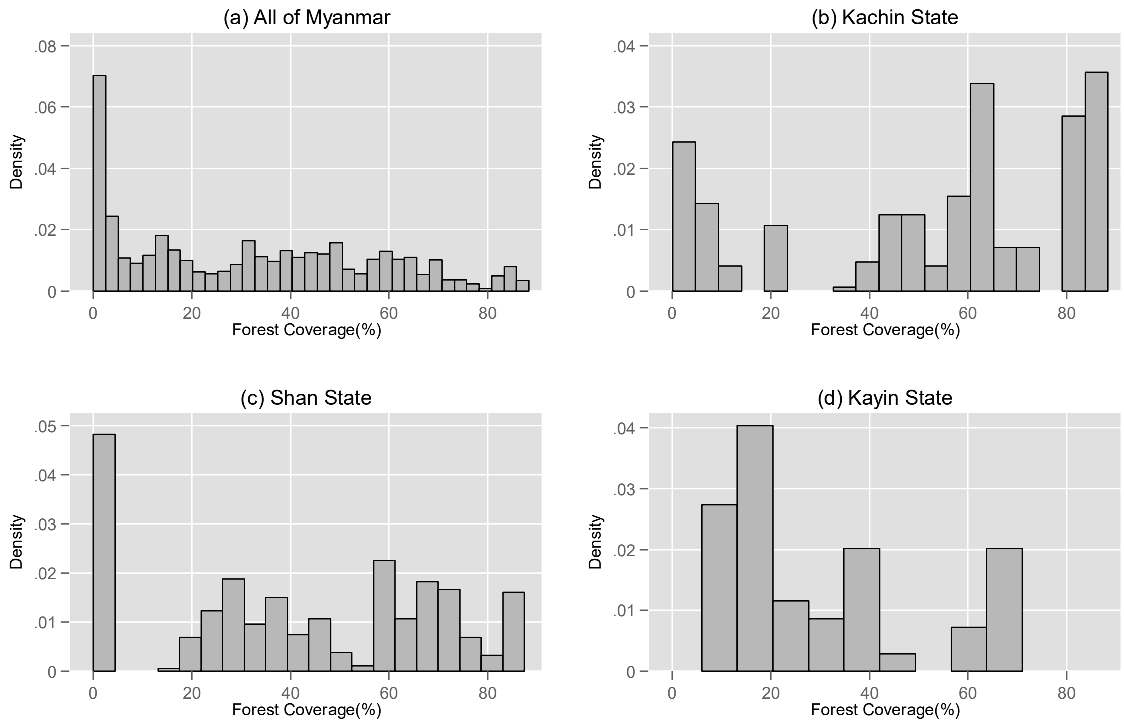


Figure A1 depicts the frequency distribution of forest coverage using a 75x75 km. grid across Myanmar (a) and three conflict-prone states: Kachin (b), Shan (c), and Kayin (d). Although Myanmar has roughly 25 percent of its landmass with forest coverage of 50 percent or higher, regions with higher forest coverage are more prevalent in conflict-prone areas. Kachin's territory has nearly 60 percent forest coverage of 50 percent or higher, while Shan territory has 35 percent, and Kayin state has 47 percent.

Furthermore, as shown in Figure 3f in the main text, the increasing effect of forest coverage on battles starting from 40 percent forest coverage suggests that conflict is not uncommon in these areas. It is worth noting that when the positive effects of forest coverage on battles begin to decrease at around 61 percent (as seen in Figure 3f, main text), 15 percent of Kayin and Shan state's territories have forest densities of these levels, while Kachin has approximately 47 percent.

Table A2: Forest Coverage and Battle Frequency with Extended Variables

	ACLED Data			UCDP Data		
	(1)	(2)	(3)	(4)	(5)	(6)
Forest Coverage	**0.11*** **	**0.10*** **	**0.10*** **	**0.08** **	**0.09*** **	**0.09*** **
	(0.02)	**(0.03)**	**(0.03)**	**(0.03)**	**(0.02)**	**(0.02)**
Forest Coverage2	**-0.00*** **	**-0.00** **	**-0.00** **	**-0.00** **	**-0.00** **	**-0.00** **
	(0.00)	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**
Deforestation Rate	-0.02	-0.07	-0.08	-0.14	-0.21*	-0.20
	(0.09)	(0.14)	(0.14)	(0.12)	(0.11)	(0.11)
Mean Elevation	-0.00**	-0.00**	-0.00**	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Variable Elevation	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
2011 Year Dummy	-0.58	-0.13	-1.89	-1.66**	-1.51**	0.55
	(0.59)	(0.58)	(1.81)	(0.52)	(0.53)	(9.56)
Mean Night Lights	-0.36	-0.17	-0.18	-2.06***	-1.64**	-1.52**
	(0.19)	(0.31)	(0.32)	(0.62)	(0.53)	(0.54)
Timber Exports	-0.54*	-0.39*	-0.80*	-1.14***	-1.07***	-1.11
	(0.24)	(0.18)	(0.37)	(0.34)	(0.26)	(0.69)
Rubber Exports	-1.43	-1.49*	-0.55	-3.19***	-3.36***	-2.98
	(0.74)	(0.70)	(1.18)	(0.97)	(0.82)	(1.72)
Mines	-5.20***	-3.94**	-3.94**	-2.15*	-1.64	-1.65
	(0.95)	(1.32)	(1.32)	(1.04)	(1.09)	(1.07)
Methamphetamines	1.18*	0.63	1.39*	1.18**	0.90*	0.42
	(0.53)	(0.67)	(0.62)	(0.40)	(0.46)	(1.37)
Opium	0.06	0.42	2.30	2.66***	2.68***	3.55
	(0.74)	(0.72)	(2.24)	(0.77)	(0.71)	(4.25)
Change in Maize Price	-0.07	0.80	-3.65	0.45	0.25	2.72
	(0.53)	(0.64)	(3.96)	(0.58)	(0.52)	(8.01)
Constant	20.78*	-190.26	-3.04	35.54**	-74.15	25.40
	(9.15)	(280.50)	(22.40)	(13.13)	(267.45)	(33.62)
Pseudo R-squared	0.122	0.150	0.150	0.124	0.163	0.166
Distance Measures	Yes	Yes	Yes	Yes	Yes	Yes
State Dummies	No	Yes	Yes	No	Yes	Yes
Year Time Trend	No	Yes	No	No	Yes	No
Year Fixed Effects	No	No	Yes	No	No	Yes
Observations	1638	1638	1638	2002	2002	2002

Standard errors clustered by grid in parentheses * p<0.05 ** p<0.01 *** p<0.001

We also consider variables that account for resource effects, including *Methamphetamines*, *Opium*, and *Timber Exports*, which are unique to Myanmar's circumstances. Myanmar has been a major center for narcotics production in the region; therefore, having data that controls for the scale of methamphetamine and opium production would be ideal. However, accurate data on illegal drug trafficking is extremely difficult to obtain. Instead, we use the number of methamphetamine tablets seized in Myanmar and neighboring Thailand in year t as our measure for methamphetamine and the estimated opium production in Myanmar in year t as our measure for opium production. For timber exports, we follow the method by Rustad et al. (2008) and use the value of timber exports per year in Myanmar, including only official government data.

We include these measures because the argument in the resource-conflict relationship literature implies that higher drug production and greater timber-related deforestation could increase the average incidence of battles as rebels obtain more financial resources from both drug and timber sales. As a result, the location of conflict in areas with dense forest coverage could be incidental to other resources, such as illicit drugs, which insurgents are willing to fight the government over. Additionally, Myanmar is well-known for its gem economy, for which we include the location data on every active mining site, ranging from jade to sapphire to ruby, etc. Finally, we include a commodity price shock measure, which is the change in global maize prices. Higher maize prices could lead to greater deforestation in Myanmar as the rising price of maize could lead to the expansion of maize plantations and the removal of forests in the country.

Our variables related to resources for conflict yield results consistent with the drug resource argument. Methamphetamine seizures are positively correlated with conflict incidences for ACLED data and are significant (p-value $<.001$). However, this relationship is not significant with UCDP data. These results suggest that perhaps more recent anti-drug campaigns on methamphetamine had a direct impact on outbreaks of fighting at the local level. On the other hand, opium production appears positively correlated and significant ($p<.001$) with battle frequency for both ACLED and UCDP data. Regarding timber exports, greater exports lead to lower battle incidences, suggesting that larger timber resources may have greater utility for the state rather than insurgents. A surge in maize prices has no relationship with battle frequency. Finally, the location of precious gems and mineral mines significantly reduces the incidence of battles for ACLED data but not UCDP data.

Table A3: Forest Coverage and Battle Frequency, by 2011 Ceasefire

	ACLED Data		UCDP Data	
	(1) 2011 and before	(2) After 2011	(3) 2011 and before	(4) After 2011
Forest Coverage	**0.090****	**0.159*****	**0.067***	**0.113****
	(0.029)	**(0.034)**	**(0.026)**	**(0.036)**
Forest Coverage^2	**-0.001***	**-0.002*****	**-0.001**	**-0.001****
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**
Deforestation Rate	-0.003	-0.167	0.008	-0.770
	(0.134)	(0.392)	(0.113)	(0.479)
Mean Elevation	-0.002**	-0.001	-0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Variable Elevation	-0.001	-0.004	-0.001	-0.008*
	(0.002)	(0.002)	(0.002)	(0.003)
Constant	1004.403	-118.242***	-774.108	81.273*
	(1152.729)	(33.014)	(2007.378)	(31.712)
Pseudo R-squared	0.155	0.218	0.187	0.229
Full Controls	Yes	Yes	Yes	Yes
Distance Measures	Yes	Yes	Yes	Yes
State Dummies	Yes	Yes	Yes	Yes
Observations	1274	364	1274	728

Standard errors in parentheses * $p<.05$ **$p<.01$ ***$p<.001$

There is an alternative explanation for the increased fighting between the government and insurgent forces, which could be due to the collapse of the 2011 ceasefire agreement between the KIO and the Tatmadaw government. To address this concern, we took two approaches. First, we included a year 2011 ceasefire dummy in Table A2, which is coded "0" for years

2011 and before and “1” for years after 2011. However, the inclusion of this dummy did not change our results. Second, we split the sample by the 2011 ceasefire dummy, as perhaps fighting was less prior to 2011 throughout most of Myanmar due to the ceasefire agreement. As shown in Table A3, this was not the case for both ACLED and UCDP data for years 2011 and before (see columns 1 and 2). These results suggest that forest coverage rather than the timing of ceasefires is driving the pattern of battles.

Table A4: Forest Coverage and Battles, by Removal of State-Specific Effects

	ACLED Data (Exclusion of the following state regions)					
	Kachin	Shan	Kayin	Rakhine	Kayah	Chin
Forest Coverage	**0.077****	**0.142*****	**0.099*****	**0.097*****	**0.101*****	**0.099*****
	(0.029)	**(0.024)**	**(0.026)**	**(0.026)**	**(0.026)**	**(0.026)**
Forest Coverage2	**-0.000**	**-0.002*****	**-0.001****	**-0.001****	**-0.001****	**-0.001****
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
Deforestation Rate	-0.117	-0.116	-0.067	-0.083	-0.076	-0.067
	(0.135)	(0.137)	(0.132)	(0.135)	(0.134)	(0.132)
Mean Elevation	-0.001	-0.002**	-0.002**	-0.002**	-0.002**	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Variable Elevation	-0.005*	-0.002	-0.002	-0.002	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Pseudo R-squared	0.152	0.160	0.150	0.150	0.149	0.150
Observations	1458	1426	1638	1629	1610	1638
	UCDP Data (Exclusion of the following state regions)					
	Kachin	Shan	Kayin	Rakhine	Kayah	Chin
Forest Coverage	**0.080****	**0.118*****	**0.090*****	**0.089*****	**0.088*****	**0.086*****
	(0.028)	**(0.026)**	**(0.026)**	**(0.025)**	**(0.025)**	**(0.026)**
Forest Coverage2	**-0.001**	**-0.001*****	**-0.001****	**-0.001****	**-0.001****	**-0.001***
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
Deforestation Rate	-0.287**	-0.277*	-0.225*	-0.246*	-0.233*	-0.278*
	(0.108)	(0.120)	(0.113)	(0.111)	(0.114)	(0.111)
Mean Elevation	0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Variable Elevation	-0.005*	-0.005	-0.003	-0.003	-0.003	-0.003
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Pseudo R-squared	0.165	0.163	0.161	0.159	0.162	0.157
Observations	1783	1741	1945	1990	1970	1875

Standard errors clustered by grid in parentheses * p<0.05 ** p<0.01 ***p<0.001

Table A4 presents an analysis of Table 1 in the main text, which removes the observations from the specific states (e.g., Kachin) to determine if battle incidences are driven by these regions or rough terrain. The results indicate that battle incidences are not driven by any specific region but rather by rough terrain.

A3: Alternate Functional Forms

Table A5: Log Regression of Forest Coverage and Battles

	ACLED Data		UCDP Data	
	(1)	(2)	(3)	(4)
Forest Coverage	**0.021****	**0.023****	**0.006***	**0.006****
	(0.008)	**(0.008)**	**(0.002)**	**(0.002)**
Forest Coverage^2	**-0.000***	**-0.000***	**-0.000***	**-0.000***
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**
Deforestation Rate	-0.003	-0.007	0.003	-0.004
	(0.012)	(0.013)	(0.005)	(0.004)
Mean Elevation	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Variable Elevation	-0.000	-0.001	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Mean Night Lights	-0.011	-0.008	-0.012	-0.008
	(0.015)	(0.019)	(0.009)	(0.008)
Timber Exports	-0.045*	0.022	0.006	0.008
	(0.021)	(0.026)	(0.011)	(0.010)
Mines	-0.374***	-0.211	-0.077**	-0.051
	(0.109)	(0.112)	(0.027)	(0.029)
Constant	1.907***	-54.109*	0.215	-10.977**
	(0.423)	(21.672)	(0.144)	(4.181)
R-squared	0.228	0.282	0.063	0.083
Distance Measures	Yes	Yes	Yes	Yes
State Dummies	No	Yes	No	Yes
Time Trend	No	Yes	No	Yes
Observations	1638	1638	3094	3094

Standard errors clustered by grid in parentheses * p<.05 ** p<.01 *** p<.001

Table A5 presents the analysis using 75 km grids with logarithmic regression, where we add 1 to the outcome variable and take the log transformation. Columns (1) and (2) show the results for battle frequency and fatalities for ACLED data, while columns (3) and (4) display the same results for UCDP data. The findings are qualitatively identical to those in Table 1 in the main text.

Table A6: Spatial Autoregressive Regression

	ACLED Data		UCDP Data	
	(1)	(2)	(3)	(4)
Forest Coverage	**0.026****	**0.026****	**0.007***	**0.008***
	(0.008)	**(0.008)**	**(0.003)**	**(0.003)**
Forest Coverage^2	**-0.000***	**-0.000***	**-0.000***	**-0.000***
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**
Year-to-year Forest Loss	-0.002	0.004	-0.002	-0.001
	(0.005)	(0.007)	(0.004)	(0.004)
Mean Elevation	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Variable Elevation	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.638	-1.689	0.001	-4.968
	(1.569)	(18.488)	(0.220)	(8.468)
Spatial ρ	0.990***	0.989***	0.917***	0.910***
	(0.032)	(0.029)	(0.050)	(0.046)
R-squared	0.233	0.276	0.065	0.081
Distance Measures	Yes	Yes	Yes	Yes
Full Controls	Yes	Yes	Yes	Yes
State Dummies	No	Yes	No	Yes
Time Trend	No	Yes	No	Yes
Observations	1638	1638	3094	3094

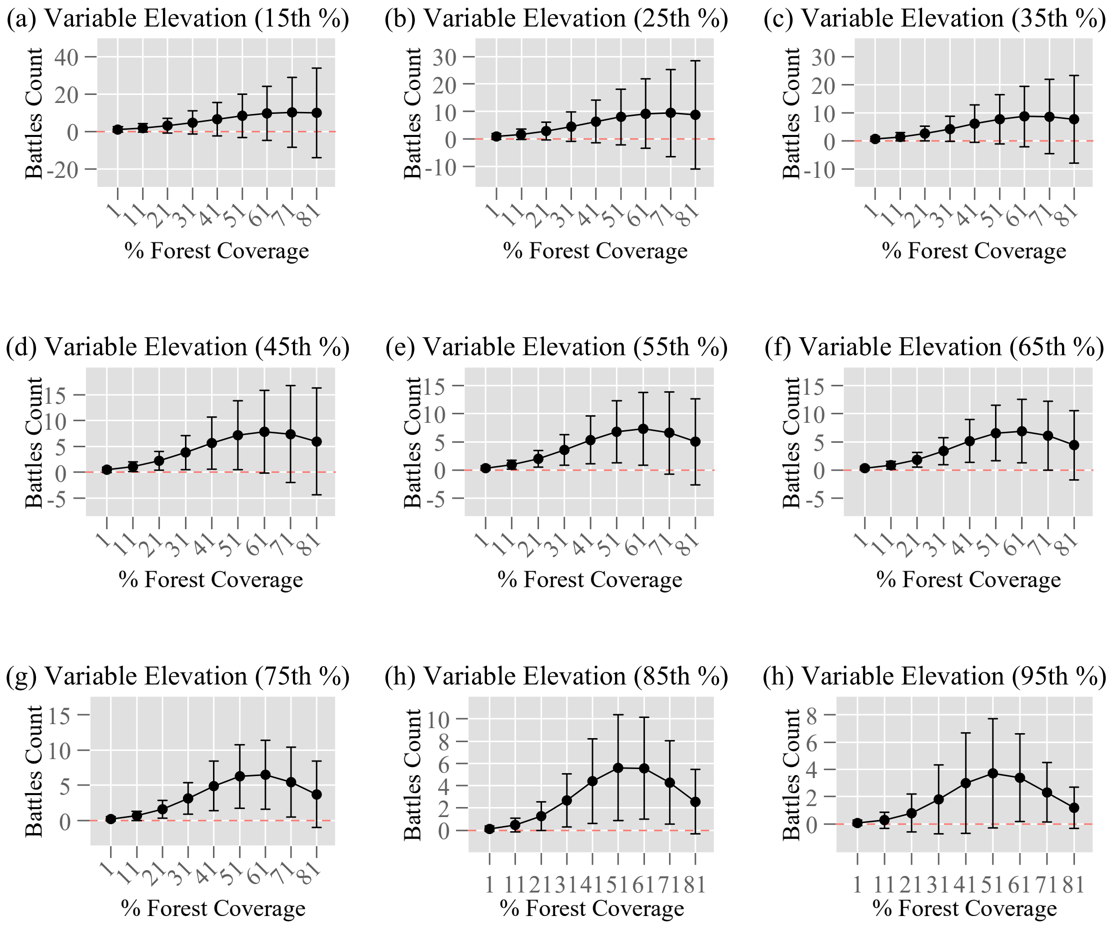
Robust standard errors in parentheses * p<.05 ** p<.01 *** p<.001

Table A6 replicates the analysis in Table 1 of the main text by controlling for global spatial autocorrelation.[1] The table presents the results for ACLED and UCDP data, with the columns under each dataset divided into two categories: with and without time trend and state dummy variables. The results are qualitatively similar, with forest coverage having an inverted U-shaped relationship with battle counts, and mean and variable elevation no longer being significant. It should be noted that the positive and significant sign for the spatial ρ indicates that battles in neighboring grid j increase battles in grid i, suggesting a global spillover effect.

[1] As in the main text, we use the log transformation of battle counts to run the spatial regression as existing literature on spatial regression has no guidance on how to model count data in a spatial context (Glaser, 2017).

A4: Interactions of Forest Density and Mountainous Terrain

Figure A3: Battle Frequency, Variable Elevation, and Forest Coverage (ACLED)

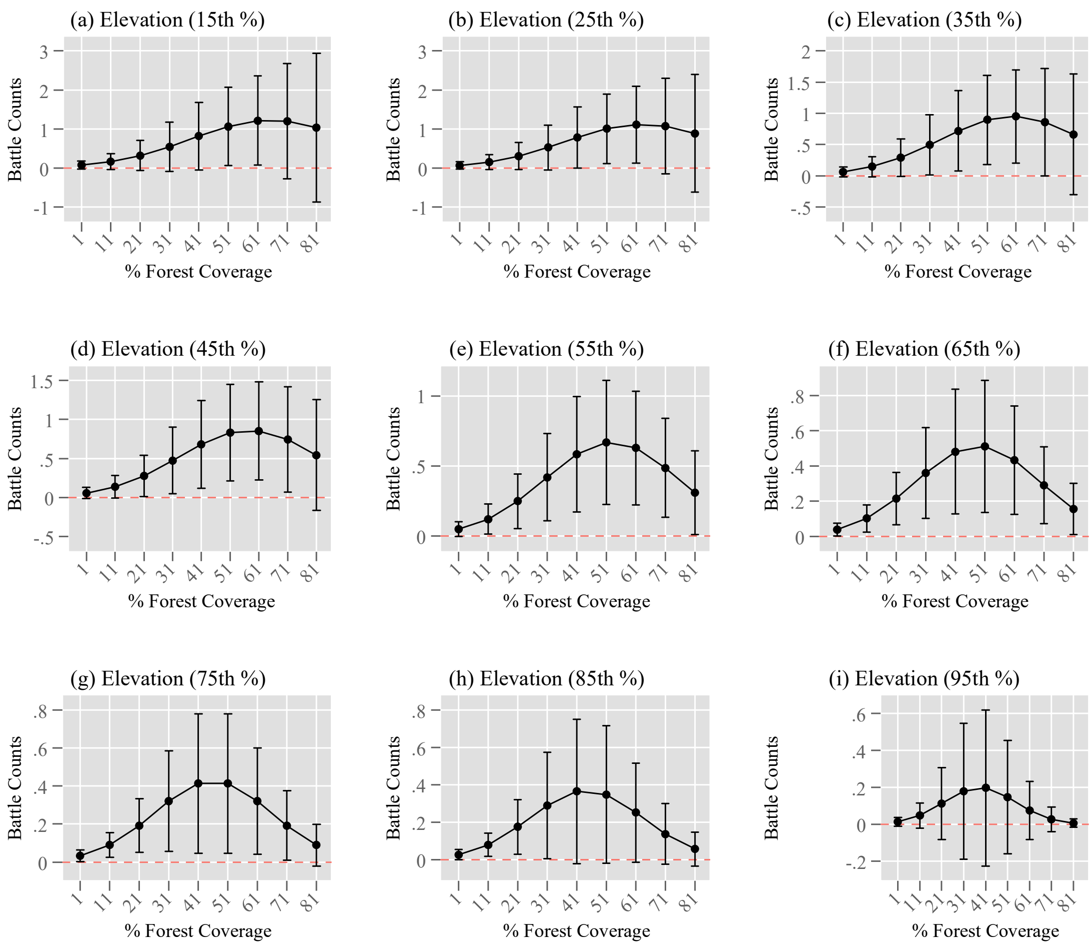


Notes: This figure plots the relationship between forest coverage and predicted battle frequency at different variable elevation levels by deciles.

Figure A3 illustrates the relationship between forest coverage and variable terrain, where the predicted battle count is shown on the vertical axis, and the percentage of forest coverage in the grid is displayed on the horizontal axis. Each subfigure shows the distribution of variable ruggedness by decile differences. Similar to the interaction effect with mean elevation, the impact of forest coverage is significant only at intermediate levels of variable ruggedness

(A3c through A3g), and it dissipates at the extreme levels of ruggedness (A3i).

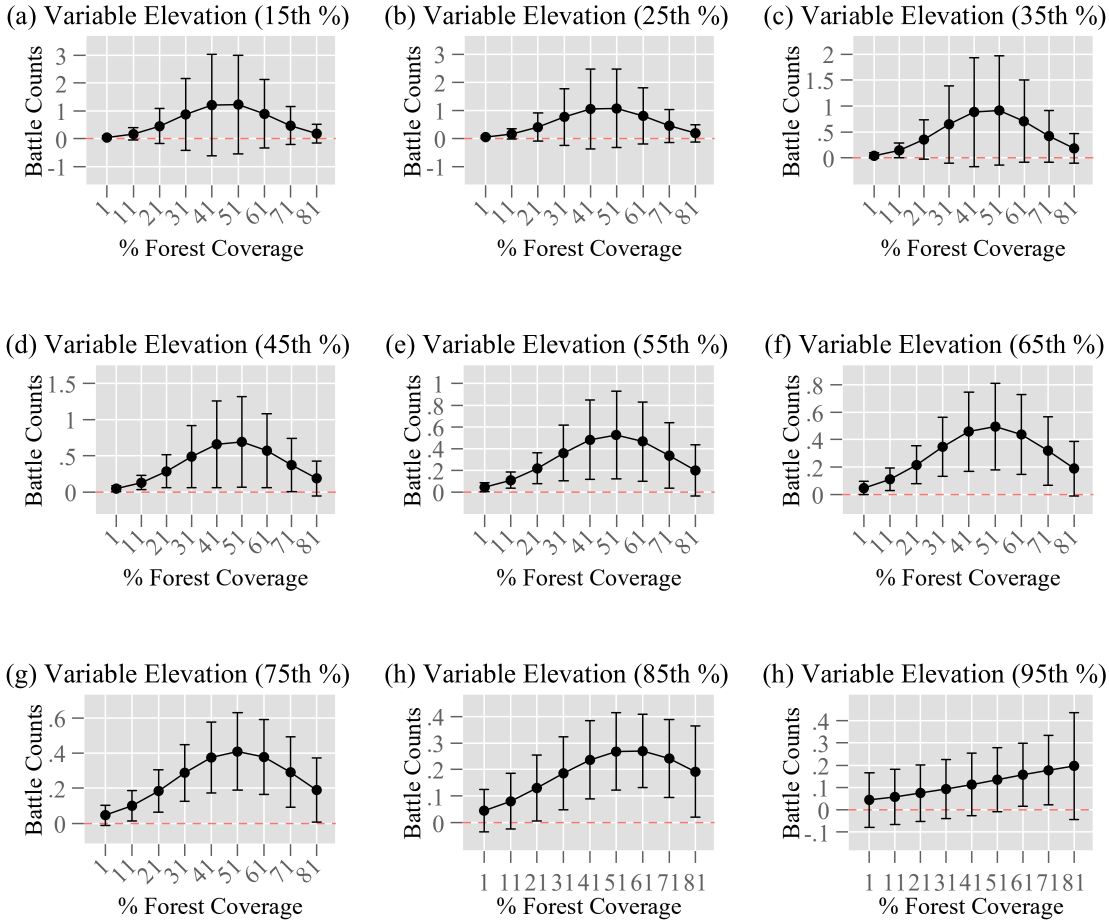
Figure A4: Battle Frequency, Mean Elevation, and Forest Coverage (UDCP)



Notes: This figure plots the relationship between forest coverage and predicted battle frequency at different mean elevation levels by deciles.

Figure A4 displays the interaction effects between forest coverage and mean elevation with the UCDP battle counts data. The results are qualitatively identical to those in Figure 3 in the main text, which uses ACLED data.

Figure A5: Battle Frequency, Variable Elevation, and Forest Coverage (UCDP)



Notes: This figure plots the relationship between forest coverage and predicted battle frequency at different variable elevation levels by deciles.

Figure A5 illustrates the interaction effects between forest coverage and variable elevation using the UCDP battle counts data. The results are qualitatively similar to those in Figure A4.

References

Fotheringham AS, Brunsdon C and Charlton M (2000) *Quantitative Geography: Perspectives on Spatial Data Analysis*. London: SAGE Publications Ltd.

Glaser S (2017) *A review of spatial econometric models for count data*. *Hohenheim Discussion Papers in Business, Economics and Social Sciences*. Hohenheim Discussion Papers in Business, Economics and Social Sciences 19–2017. University of Hohenheim, Faculty of Business, Economics and Social Sciences.

Louvet R, Aryal J, Josselin D, et al. (2015) R as a GIS: Illustrating Scale and Aggregation Problems with Forest Fire Data. *Procedia Environmental Sciences* 27. Spatial Statistics conference 2015: 66–69.

Monjarás-Vega NA, Briones-Herrera CI, Vega-Nieva DJ, et al. (2020) Predicting forest fire kernel density at multiple scales with geographically weighted regression in Mexico. *Science of The Total Environment* 718: 137313.

Openshaw S (1981) The Modifiable Areal Unit Problem. *Quantitative geography: a British view*. Routledge and Kegan Paul, Andover: 60–69.

Rustad SCA, Rød JK, Larsen W, et al. (2008) Foliage and fighting: Forest resources and the onset, duration, and location of civil war. *Political Geography* 27(7): 761–782.

Wong DWS (2004) The Modifiable Areal Unit Problem (MAUP). In: Janelle DG, Warf B, and Hansen K (eds) *WorldMinds: Geographical Perspectives on 100 Problems: Commemorating the 100th Anniversary of the Association of American Geographers 1904–2004*. Dordrecht: Springer Netherlands, pp. 571–575.