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All Peacekeeping is Local: Measuring Subnational Variation in Peacekeeping Effectiveness

RESEARCH NOTE

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Understanding whether peacekeepers reduce fatalities at the local level is an important question. We can have increased confidence in peacekeepers' capabilities by testing whether deaths decrease in the locations where peacekeepers are present. However, commonly used modeling techniques cannot easily test peacekeepers' local effectiveness. Coefficients from methods such as linear regression, logit, and count models provide average estimates of peacekeepers' effects on violence. We argue that a solution lies in geographically weighted regression (GWR). GWR can more clearly reveal subnational spatial heterogeneity in peacekeepers' (in)effectiveness at reducing violence. We conduct an illustrative test of our argument using data on the Democratic Republic of the Congo between 2001 and 2014 and replicate an existing study to show that GWR can also help resolve seemingly contradictory findings of whether peacekeepers are better at reducing violence by government or rebel actors. The article contains important implications for how scholars can more accurately measure peacekeeping effectiveness.

Es importante entender si las fuerzas de mantenimiento de la paz reducen las muertes a nivel local. Podemos tener una mayor confianza en las capacidades de las fuerzas de mantenimiento de la paz comprobando si las muertes disminuyen en los lugares donde están presentes dichas fuerzas. Sin embargo, las técnicas de modelización comúnmente utilizadas no pueden probar fácilmente la eficacia local de las fuerzas de mantenimiento de la paz. Los coeficientes obtenidos a través de métodos como los modelos de regresión lineal, logit y de recuento proporcionan estimaciones promediadas de los efectos de las fuerzas de mantenimiento de la paz sobre la violencia. Nosotros sostenemos que la solución está en la regresión ponderada geográficamente (Geographically Weighted Regression, GWR). La GWR puede revelar más claramente la heterogeneidad espacial subnacional en la (in)eficacia de las fuerzas de mantenimiento de la paz para reducir la violencia. Llevamos a cabo una prueba ilustrativa de nuestro argumento utilizando datos sobre la República Democrática del Congo entre 2001 y 2014, y reproducimos un estudio ya existente para demostrar que la GWR también puede ayudar a resolver conclusiones aparentemente contradictorias sobre si las fuerzas de mantenimiento de la paz son mejores para reducir la violencia de los actores gubernamentales o rebeldes. El artículo contiene importantes implicaciones para que los académicos puedan medir con mayor precisión la eficacia de las fuerzas de mantenimiento de la paz.

Il est important de comprendre si les soldats de la paix réduisent les décès au niveau local. Nous pouvons avoir une plus grande confiance dans les capacités des soldats de la paix en évaluant si les décès diminuent dans les zones où ils sont présents. Cependant, les techniques de modélisation couramment utilisées ne permettent pas facilement d'évaluer l'efficacité locale des soldats de la paix. Les coefficients issus de méthodes comme les modèles de régression linéaire, les modèles de régression logistique et les modèles de régression de comptage offrent des estimations moyennes des effets des soldats de la paix sur la violence. Nous soutenons qu'une solution réside dans la régression pondérée géographiquement. Elle peut révéler plus clairement l'hétérogénéité spatiale infranationale de l'(in)efficacité des soldats de la paix dans la réduction de la violence. Nous avons mené une analyse illustrative de notre argument en utilisant des données sur la République démocratique du Congo entre 2001 et 2014, et nous avons reproduit une étude existante pour montrer que la régression pondérée géographiquement pouvait également aider à remédier aux résultats apparemment contradictoires sur la question de savoir si les soldats de la paix étaient plus efficaces pour réduire la violence perpétrée par le gouvernement ou des acteurs rebelles. Cet article recèle d'importantes implications concernant la manière dont les chercheurs pourraient mesurer plus précisément l'efficacité du maintien de la paix.

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Introduction

The study of peacekeeping effectiveness has proliferated in the last two decades following an increase in peacekeeping operations (PKOs) since the Cold War.[1] Much of this research features cross-national quantitative analyses where scholars examine how peacekeepers prevent civilians from dying (Hultman, Kathman, and Shannon 2013; Goldring and Hendricks 2018). However, peacekeeping is not a national-level endeavor. Peacekeepers are deployed to specific parts of countries (see Townsen and Reeder 2014; Powers, Reeder, and Townsen 2015). They must address local economic, geographic, and political factors, which determine whether they are successful in reducing violence (Autesserre 2010). In short, the effectiveness of peacekeepers within countries is influenced by a range of local variables that mean peacekeepers can mitigate violence in some locations but not in others.

Recognizing this, numerous scholars have conducted subnational quantitative analyses that regress measures of peacekeeping effectiveness on local-level variables.[2] These models produce coefficients that represent global effects—in plainspoken terms, average effects—of subnational factors on peacekeeping effectiveness (Cho and Gimpel 2010, 75–76). Examples of this research include Stefano Costalli's (2014, 369–76) use of logistic regression to show that peacekeepers do not affect the severity of violence, Deniz Cil and her co-authors' (2020, 367) use of negative binomial regression to show that peacekeepers reduce battle deaths in areas with high road density, and Anup Phayal and Brandon Prins' (2020, 326–33) use of Poisson regression to show that more United Nations (UN) military peacekeeping units help protect civilians.

Understanding the average effects of subnational factors on peacekeeping effectiveness can be instructive. As Wendy Cho and James Gimpel write, if the effect of the independent variable (peacekeepers) is "uniform or randomly scattered across geographic regions, then the average effect would not be hiding much" (2010, 76). However, in the case of subnational peacekeeping effectiveness, peacekeepers are deployed to different degrees in some locations, but they are absent in others. Thus, relying exclusively on models that estimate global effects risks obscuring a key inference about peacekeepers' abilities to mitigate violence locally: peacekeepers are effective to varying degrees at mitigating violence in some locations but not others. The coefficients from models employed thus far in quantitative subnational analyses do not capture spatial heterogeneity in peacekeeping effectiveness, thereby ignoring this important geographic pattern.

We show the utility of an alternative method to examine subnational peacekeeping effectiveness: geographically weighted regression (GWR). GWR is a spatial regression technique that fits a model for each unit in the dataset to examine the local relationships between the independent and dependent variables (Brunsdon, Fotheringham, and Charlton 1996; Calvo and Escolar 2003; Cho and Gimpel 2010; Brass et al. 2020). GWR more easily reveals subnational spatial heterogeneity in the effectiveness of peacekeepers at reducing violence. It better models empirical patterns where peacekeepers simultaneously reduce violence in some locations but not in others.

By improving measures of subnational peacekeeping effectiveness, we can have greater confidence in tests of theories about why peacekeepers are effective at the subnational level. The value of this contribution is illustrated by contradictions in current studies, which rely on models that estimate global effects, about how certain subnational factors influence peacekeeping effectiveness. Overall, we are far from achieving scholarly consensus about how different local-level factors influence peacekeepers' effectiveness. Although we do not claim to rectify this in our research note—such work requires further theory and empirical analysis—by more accurately measuring peacekeepers' effectiveness using GWR, we can have increased confidence in whether peacekeepers are able to reduce violence in specific locations. As Phayal and Prins write, "[w]e would have more confidence in the ability of peacekeepers to limit harm and protect non-combatants if the reduction in violence occurred locally where blue helmets were positioned" (2020, 311). The main contribution of this research note, therefore, is to demonstrate how GWR can more accurately capture local patterns of peacekeeping effectiveness, despite its limitations.[3]

While our contribution is empirical, it is important to highlight that failing to understand geographic patterns of peacekeeping effectiveness has implications for vulnerable populations on the ground. If we do not measure peacekeeping effectiveness accurately, then we cannot have an informed understanding of why peacekeepers are (un)successful. This hinders policymakers' abilities to ensure that PKOs are adequately and appropriately resourced, neither under- nor over-deployed to certain locations, or that they use appropriate engagement strategies with local communities. Echoing Cil et al.'s point, accurately measuring peacekeeping effectiveness can improve "the design, composition, and conduct of peacekeeping missions" (2020, 361).

We demonstrate the value of GWR through the following sections. First, we describe the existing quantitative research on subnational peacekeeping effectiveness, noting contradictory findings from studies that rely on models that estimate global effects. Second, we introduce GWR using an illustrative analysis of the United Nations Organization Stabilization Mission in the Democratic Republic of the Congo (MONUSCO). Third, we replicate local-level research on civilian protection, showing the value of GWR in reconciling contradictory findings in the literature. Finally, we discuss potential limitations and caveats of applying GWR to future research on subnational peacekeeping effectiveness.

Prior Scholarship on Local-Level Peacekeeping Effectiveness

First, then, we review subnational quantitative literature on peacekeeping effectiveness, highlighting potential concerns about substantive inferences in previous studies. In sum, although many scholars find that peacekeepers have broadly positive effects on the subnational level, when scholars

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The data underlying this article are available on the ISQ Dataverse, at https://dataverse.harvard.edu/dataverse/isq.

[1] Among past PKOs, thirteen were launched before the end of the Cold War, starting with United Nations Emergency Force I in the Middle East in November 1956; forty-six were launched from 1991 onward. See https://peacekeeping.un.org/en/past-peacekeeping-operations.

[2] There are many qualitative subnational studies on peacekeeping effectiveness (e.g., Autesserre 2010), but we restrict our focus to quantitative research since our recommendation concerns a quantitative modeling technique.

[3] We acknowledge that GWR is not perfect; see the "Limitations and Caveats" section at the end of this research note.

Table 1. Quantitative subnational research on peacekeepers and violence

Author (year)	*Modeling technique*	*Data*	*Key findings*
Dorussen and Gizelis (2013)	Probit	UN PKOs in Africa, 1989–2005	Rebels are more likely to react to peacekeepers with hostility, while government authorities are more likely to cooperate with peacekeepers.
Costalli (2014)	Logit	Bosnia, 1992–1995	UN troops do not affect the severity of violence.
Ruggeri et al. (2017)	Logit	UN PKOs in sub-Saharan Africa, 1989–2006	Peacekeepers reduce the length of conflict but may not affect conflict onset.
Fjelde et al. (2019)	Logit	UN PKOs in Africa, 2000–2011	UN troops prevent rebel violence against civilians, but not by government actors.
Phayal (2019)	Difference-in-differences	UN PKO in Darfur, 2005–2010	Peacekeepers protect civilians, with a slightly greater effect on government than rebel perpetrators.
Cil et al. (2020)	Negative binomial regression	UN PKOs in Africa, 1994–2014	UN troops reduce battle deaths in areas with high road density.
Di Salvatore (2020)	Negative binomial regression	Sierra Leone, 1997–2001	UN troops reduce civilian deaths, but with diminishing returns when power asymmetries grow.
Hunnicutt and Nomikos (2020)	Logit	UN PKOs in sub-Saharan Africa, 1999–2018	Unclear if UN troops or police protect civilians from rebels; UN troops and police are positively related to reducing government violence against civilians.
Phayal and Prins (2020)	Poisson regression	Four UN PKOs, varying dates between 2006–2016	More UN military peacekeeping units protect civilians; however, in areas without violence between government and rebel forces, peacekeepers are more likely to focus on civilian targeting by rebels than government authorities.
Smidt (2020a)	Ordered logit	UN PKO in Côte d'Ivoire, 2011–2015	Peacekeeping election education events reduce violent protests and riots.
Smidt (2020b)	Probit	UN PKO in Côte d'Ivoire, October 2011–May 2016	Peacekeepers reduce communal violence among civilians and by armed groups through intergroup dialogues.
Fjelde and Smidt (2021)	Two-way fixed-effects linear regression	UN PKOs in sub-Saharan Africa, January 1994-December 2017	Peacekeepers make election violence less likely.

examine the effects of peacekeepers on certain types of violence, they unearth contrasting findings. These contradictions could be due to spatial or temporal differences in the data analyzed, but it is plausible that they are also driven by modeling techniques that produce coefficients that represent misleading global effects.

Table 1 summarizes findings from the subnational quantitative literature on peacekeeping effectiveness, the modeling techniques used, and the data analyzed. This body of work finds, on average, that peacekeepers are effective.[4] They can help reduce the length of conflict (Ruggeri, Dorussen, and Gizelis 2017), diminish violent protests and riots (Smidt 2020a), reduce communal violence among civilians and by armed groups (Smidt 2020b), and reduce civilian deaths under various circumstances (Fjelde, Hultman, and Nilsson 2019; Phayal 2019; Cil et al. 2020; Di Salvatore 2020; Hunnicutt and Nomikos 2020; Phayal and Prins 2020).

However, there are contradictory findings on the relationship between peacekeeping and violence by rebel versus government actors. Examining UN PKOs in Africa between 1989 and 2005, Dorussen and Gizelis (2013) find that rebels are more likely to respond to peacekeepers with hostility whereas government actors tend to cooperate with peacekeepers. Conversely, in their analysis of UN PKOs in Africa between 2000 and 2011, Fjelde, Hultman, and Nilsson (2019) find that UN troops are better at preventing rebel violence against civilians than they are at preventing government violence. Despite the five-year overlap, these contrasting findings could be driven by temporal differences in the data analyzed.

Related studies have not clarified the picture. In contrast to Fjelde, Hultman, and Nilsson (2019), Phayal (2019) finds that peacekeepers have a greater effect on reducing violence by government actors. This finding is based on data from the UN PKO in Darfur between 2005 and 2010. In this instance, spatial differences in the data analyzed could influence the divergent findings.

However, like Phayal (2019) but in contrast to Fjelde, Hultman, and Nilsson (2019), Hunnicutt and Nomikos (2020) find that peacekeepers can reduce government violence against civilians, but they are unsure whether peacekeepers can protect civilians from rebels. Recall that Fjelde, Hultman, and Nilsson (2019) study UN PKOs in Africa between 2000 and 2011. Hunnicutt and Nomikos (2020) also studied UN PKOs in Africa but between 1999 and 2018.

[4] One exception is Costalli (2014), who finds that UN troops do not affect the severity of violence.

Given the temporal and spatial overlap in the data analyzed by Fjelde, Hultman, and Nilsson (2019) and Hunnicutt and Nomikos (2020), it is reasonable to question whether an alternative factor is behind these diverse findings. Specifically, we consider whether the modeling techniques used in the studies described above mask spatial heterogeneities in peacekeeping effectiveness at reducing government or rebel violence by producing coefficients that represent the average effects of peacekeepers at reducing these different kinds of violence.

We investigate this possibility in the following sections. We begin with an overview of GWR and compare this approach to stationary models that currently dominate the literature. This is followed by a replication of Fjelde, Hultman, and Nilsson (2019), where we assess whether GWR can help bridge the gap between divergent findings in the subnational study of peacekeeping effectiveness.

The Utility of Geographically Weighted Regression: An Illustration

GWR extends stationary regression models by allowing parameters to change locally, thereby capturing heterogeneity in effect. The presence of local parameters shifts the model away from a stationary process to a nonstationary one that allows the influence of predictors on the dependent variable to vary across geographic space. To illustrate, we briefly describe the nonstationary GWR model and apply it alongside a stationary model (linear regression model, hereafter LRM) to MONUSCO in the Democratic Republic of Congo (DRC) from 2001 to 2014.

Consider the following global regression model:

$$y_i = a_0 + \sum_k a_k x_{ik} + \varepsilon_i$$

In this model, one parameter is estimated for the relationship between each covariate and the dependent variable. Because only one parameter is estimated, the model is stationary; the influence of x on y is assumed to be universal across the study area (averaged).[5] In our context, this means that at every location in the DRC the values of β_0 and β_1 are assumed to be the same and are not allowed to vary. The parameter is:

$$a = (X^t X)^{-1} X^t y$$

where a is a vector of global parameters to be estimated, X a matrix of covariates with the elements of the first column set to 1, and y a vector of observations. The potential problem with this approach is that the residuals from the model (ε_i) should be independent and normally distributed with a mean of zero. When this is not the case, GWR is useful as it adapts this framework by replacing the global-only parameter with local parameters. This transforms the technique into a local nonstationary model because the influence of x varies across the entire study area. For our purposes, this means that a universal effect of peacekeeping (either negative or positive based on the average) is not imposed across the study area. Formally, this adaption is:

$$y_i = a_0(u_i, v_i) + \sum_k a_k(u_i, v_i) X_{ik} + \varepsilon_i$$

where (u_i, v_i) represents the geographic coordinates of point i and $a_k(u, v_i)$ is a realization of the continuous function $a_k(u, v)$ at point i. This allows parameter values to be taken across a continuous surface at specified points, resulting in a local nonstationary estimate because the result varies across the study area. This contrasts with the single parameter generally identified in prior research exploring the influence of peacekeeping on patterns of violence.

GWR assumes that observed data near i will have more of an influence in the estimation of $a_k(u_i, v_i)$ relative to observed data that is farther removed. In practice, this equates to a distance-decay function whereby the influence of observed data on the estimation of $a_k(u_i, v_i)$ decreases as the distance from point i increases. This is based off the noncontroversial assumption that factors that are nearby have more influence than those that are further away. Thus, weighted least squares provides the foundation to understand the GWR estimator:

$$a(u_i, v_i) = (X^t W(u_i, v_i) X)^{-1} X^t W(u_i, v_i) y$$

where $W(u_i, v_i)$ denotes a matrix with diagonal elements that refer to the geographical weighting of the observed data at each location (point i). All other values are set at 0, per the following $n \times n$ matrix:

$$W(u_i, v_i) = \begin{matrix} w_{i1} & 0 & 0 & \dots & 0 \\ 0 & w_{i2} & 0 & \dots & 0 \\ 0 & 0 & w_{i3} & \dots & 0 \\ . & . & . & \dots & . \\ 0 & 0 & 0 & \dots & w_{in} \end{matrix}$$

where w_{in} is the weight of observed data at point n on the calibration of the GWR estimator at point i. This is where the GWR estimator differs from traditional weighted least squares because the weight applied is not constant; in GWR, the weights vary across point i (1, 2, 3, …). To calibrate the weight at point i, one can use an adaptive weighting function that protects against the possibility that the GWR model is estimated on relatively few data points. This is especially useful when units differ in sizes (such as districts or states) because the size of the bandwidth (h) will be smaller when data points (j) are densely distributed and larger when data points are sparse. In our illustrative example using the DRC presented below, this is not necessary because our units are identical in size. As such, we utilize a fixed weighting function using a Gaussian scheme:

$$w_{ij} = \exp\left(-\frac{d_{ij}^2}{h^2}\right)$$

where d_{ij} is the distance from point i to data point j, and h is the bandwidth. This results in a weight in which sampled observations near point i are granted more influence during estimation vis-à-vis data points that are further away, via the distance decay function described above.

To summarize, GWR can be viewed as a localized multivariate regression whereby the parameters of the equation change locally, accounting for local context. Unlike LRMs (and other stationary models such as negative binomial and logit), which produce a single regression equation to summarize global relationships among a dependent variable and a set of predictors, GWR detects spatial variation in relationships and uses nearby values. In other words, GWR captures local relationships while LRMs assume homogeneity in effect across the study area. This makes GWR particularly advantageous to study the effectiveness

[5] An interaction term would permit the effect of the independent variable to vary across space, but this would merely produce an average effect of how the independent variable can differ based on one factor rather than the myriad of interrelated subnational factors that might influence how peacekeepers affect violence.

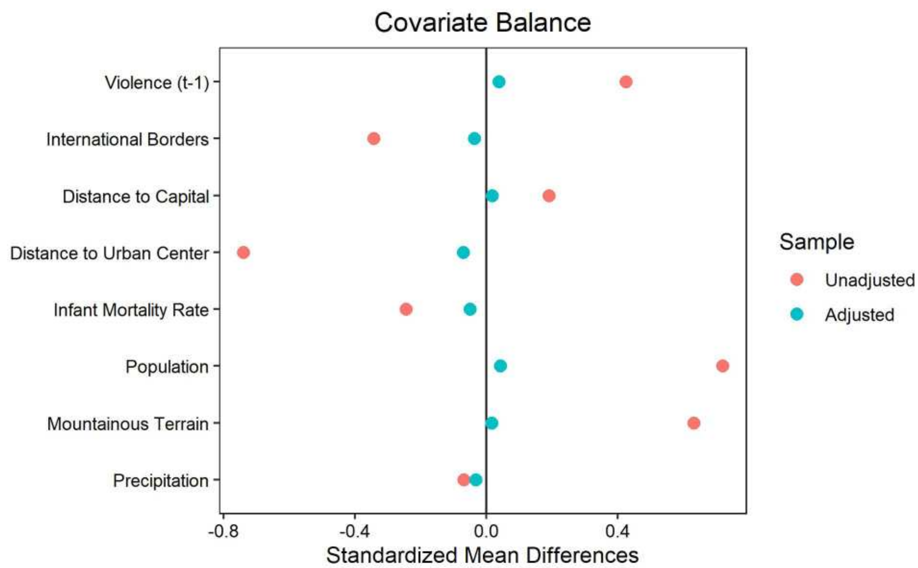

Figure 1. Standardized mean differences in adjusted and unadjusted samples.

of PKO deployments, as we know that notable variation in effectiveness occurs across geographical space.

To illustrate this, we use GWR to examine peacekeepers' effectiveness at stopping violence, using data on MONUSCO in the DRC from 2001–2014. For comparison, we also estimate LRMs for the same period.

Our primary dependent variable is the total number of fatalities (natural log) resulting from battles between governments and rebels, battles between rebels, and one-sided attacks targeting civilians, created using the UCDP Geo-Referenced dataset (Sundberg and Melander 2013; Pettersson and Oberg 2020).[6] We use total fatalities rather than an alternative indicator—civilian fatalities, for example—because peacekeeping aims to help countries move from conflict to peace, which cannot happen without a reduction in all fatalities (UN 2020).[7]

As predictors, we include a count of UN peacekeeping forces and its lagged version (Cil et al. 2020),[8] a lagged version of the dependent variable, distance to international borders,[9] distance to the capital city,[10] travel time to the nearest urban center,[11] infant mortality rate,[12] mountainous terrain,[13] the amount of precipitation,[14] and a spatial lag accounting for the number of UN forces and one-sided battle deaths in neighboring grid cells during the prior period. The control variables largely mirror the model specifications of previous studies (see table 1), while the spatial lags account for spatial dependence.

Because peacekeeping deployments are not random and may be selecting into locations more prone to violence, we preprocess our data using coarsened exact matching (CEM; Iacus, King, and Porro 2012). We do this for both the LRM and GWR models. CEM is useful because it creates weights that can subsequently be used in regression models to account for selection. For our purposes we use five cut-points for each of our variables across the 2,353 hexagons, which function as our unit of analysis.[15] Figure 1 presents the mean differences in the pre- and postprocessed data. As is evident, applying CEM greatly reduces differences across all covariates used in the analysis.[16]

We visualize the results from the stationary (LRM) and nonstationary (GWR) models below. The visualizations show whether peacekeepers $(t-1)$ are associated with a reduction or increase in violence. For the LRMs, the effect of peacekeepers is calculated by first setting the lagged number of peacekeepers at 0 and predicting the levels of violence across the country. A second prediction is then made by setting the level of peacekeepers $(t-1)$ at the observed levels, making the difference between the baseline (peacekeepers = 0) and this second prediction the estimated effect of peacekeepers on violence. These effects are then plotted graphically at the local level across the DRC. Red indicates increasing violence (ineffective peacekeeping), whereas blue indicates decreasing violence (effective peacekeeping). The shades of reds and blues display the strength of effects, while white indicates no effect.

For GWR, we plot the localized coefficients. This produces a "neighborhood effect" whereby the presence of UN forces in a hexagon can influence violence in a more extensive geographic area, including hexagons where UN forces were not deployed.[17] Theoretically, it is possible (and

[6] See online Appendix A for the Local Moran's I statistic in the DRC as well as a local indicator of spatial association (LISA) map.

[7] We also estimate GWR models on each type of violence. Online appendix B contains visualizations of these results.

[8] We overlay the locations of forces for each year across the study area and count the number in each hexagon. We then take the natural log of the variable to correct for skew.

[9] The natural log of spherical distance in kilometers to international borders per Weidmann et al. (2010).

[10] The natural log of spherical distance in kilometers to the capital city per Weidmann et al. (2010).

[11] The natural log of the estimated travel time to the nearest major city, defined as having a population of at least fifty thousand (Uchida and Nelson 2009).

[12] The natural log of infant mortality rates, operationalized as the number of children per ten thousand live births that die before their first birthday (Storeygard et al. 2008). Infant mortality rate is a measure that varies annually.

[13] The natural log of the proportion of a hexagon that is deemed to be mountainous based on elevation, slope, and local elevation range (Blyth et al. 2002).

[14] The total yearly precipitation across weather stations (Willmott and Matsuura 2012).

[15] Hexagons are chosen for illustrative purposes. Note that grid cells would be appropriate as well. That said, we choose hexagons because neighbors are more clearly delineated (grid cells have two types of neighbors: those who share a vertex and those who share an edge). Clearer neighbors make defining the bandwidth in GWR clearer, while also allowing for a better accounting of UN forces and one-sided deaths in neighboring units at time $t-1$.

[16] We perform CEM for each month. This reported improvement is the aggregate: all hexagon-years together.

[17] As noted above, we use a fixed kernel because our units are identical in size. Because our data points are equally distributed, there is no need to

probably likely) that the presence of peacekeepers in nearby hexagons changes incentives for violence, thus having the effect GWR reveals. That said, a researcher employing GWR for this purpose may, if she chooses, focus on the estimated effect in individual hexagons or smaller geographic areas and/or adjust the weighting function to match their proposed theoretical framework. We do this in the subsequent section, for example, where we replicate research on civilian protection.

Prior to reporting our findings, two details require mention. First, for GWR to be appropriate the parameters must vary across the study area, which in our case, they do given the geo-referenced data we have at our disposal. Second, and less obvious, GWR must perform better than LRM. In the literature, there are four different tests that directly examine the null hypothesis that GWR and LRM describe variability in the data equally: the Brundson et al. (1999) F test, the Leung, Mei, and Zhang (2000) F1 test, the Leung, Mei, and Zhang (2000) F2 test, and the Fotheringham, Brundson, and Charlton (2002) F3 test. Running these tests on each year included in this illustrative analysis shows that GWR performs better than LRM, further justifying our chosen bandwidth and the application of GWR to peacekeepers' influence on violence.[18]

Figure 2 shows the estimated effect of peacekeepers at the local level based on the LRMs across 2001–2014 in the DRC in grid cells where UN forces were located.[19] The main pattern that we wish to highlight is the homogeneity of effect conveyed by the coefficients of the LRMs. In 2001 for example, peacekeepers were supposedly exclusively ineffective (to varying degrees) at reducing violence (only red shades are visible), while in 2002, they were only effective (to varying degrees) in reducing violence (only blue shades). In each year, if the relationship between violence and UN deployments was estimated to be effective (ineffective), it is deemed to be effective (ineffective) across the entirety of the DRC. This homogeneity in effect is inconsistent with knowledge about peacekeeping in the DRC and other UN missions. For example, in 2002, peacekeeping in the DRC was effective in many instances with regional and national peace agreements formed to end the civil and international wars that were plaguing the nation (Autesserre 2010). However, UN peacekeepers in the DRC also failed, for instance, to protect the population of Kisangani from violence (Autesserre 2010, 90). Thus, the heterogeneity of effectiveness by peacekeepers in 2002 in the DRC is misrepresented by the coefficients produced by LRM and other stationary modeling choices (logit, probit, negative binomial, etc.).

Figure 3 visualizes the substantive effects of peacekeepers at the local level from 2001 to 2014 in the DRC based on estimates from GWR, preprocessed with CEM. Unlike results from the LRM in figure 2, figure 3 reveals heterogeneity in the effect of peacekeepers in reducing violence across the DRC in each year, especially in 2002–2004, 2007, 2010, 2012, and 2014. This is consistent with knowledge about UN deployments: they are often more effective in some locations than others during the same period. Further, the success of peacekeepers in mitigating violence in the same locations varied year to year. This implies that the factors driving variation in effectiveness are not static (such as mountains or distance to international borders); instead, local-level peacekeeping effectiveness is likely the result of dynamic processes. Explaining these local-level variations in peacekeeping effectiveness requires explicit theorizing, beyond the scope of this article.

While we have cited some qualitative evidence that illustrates the value of GWR in more accurately capturing spatial variations in peacekeeping effectiveness, there is also anecdotal evidence that initially appears to contradict our findings. For example, in 2008, figure 3 suggests peacekeepers were effective in the DRC's Kivu and Orientale provinces, whereas Autesserre (2010) notes that violence against civilians escalated here in 2008. However, peacekeepers may have prevented an even worse situation from arising. For instance, Autesserre (2010) also discusses how local conflict-resolution structures increased with international interveners beginning to acknowledge the role of local tensions. The UN took several measures to try and stabilize this region. In January 2008, the Congolese government with support from the UN held a peace conference in Goma on the issues plaguing the Kivus. In November 2008, the UN Security Council provided three thousand more troops to alleviate violence and tension in Kivu and Orientale. Thus, although violence escalated, the shifting strategies of MONUSCO may have prevented a worse situation from emerging.

Applying Geographically Weighted Regression to Civilian Protection

The illustrative analysis on the DRC highlights the advantage of GWR in more clearly measuring spatial heterogeneity in peacekeeping effectiveness. We now further demonstrate GWR's utility to the subnational study of peacekeeping effectiveness, by reanalyzing an existing study's data to probe why prior research has found different relationships between peacekeepers and violence against civilians perpetrated by governments or rebel groups (Dorussen and Gizelis 2013; Fjelde, Hultman, and Nilsson 2019; Phayal 2019; Hunnicutt and Nomikos 2020). Specifically, we use the replication data provided by Fjelde, Hultman, and Nilsson (2019) to estimate the effect of UN troops on patterns of civilian victimization (one-sided violence) using stationary (LRMs) and nonstationary (GWR) models. Their dataset is useful to probe this question due to its broad spatial (twelve UN PKOs in eight African countries) and temporal (2000–2011) coverage.

We estimate two sets of models to analyze Fjelde, Hultman, and Nilsson's (2019) data. The dependent variable is coded as one where at least five civilians were killed in a grid cell in a given month (Fjelde, Hultman, and Nilsson 2019, 112). We first replicate Fjelde, Hultman, and Nilsson's (2019) analysis by estimating LRMs, in this case, linear probability models (LPMs) given the binary dependent variable. Fjelde, Hultman, and Nilsson (2019, 119) estimate logit models, but we use LPMs to ease comparison with the GWR estimates since GWR is an extension of linear regression. We estimate 144 LPMs, one for each month,[20] and directly compare the results to our second set of models:

employ an adaptive weighting scheme. In choosing our bandwidth, we sought to keep the GWR regressions as localized as possible while still maintaining proper model fit (comparing Akaike Information Criterion (AIC) from ordinary least squares (OLS) to GWR models). This led to a specified bandwidth encompassing the ninety *k*-nearest neighbors, which in practice led to an average of eighty-two neighbors per hexagon due to border regions.

[18] Online appendix C contains the results of these tests.

[19] A small number of cells are either blue or red in figure 2, compared to figure 3, because unlike GWR, a "neighborhood effect" is not produced via LRM. However, this should not detract from the key point in figure 2: in each year, LRM suggests that peacekeepers have a singularly positive or negative effect on violence. Additionally, most studies cluster standard errors on the panel (grid cell) to account for nonindependent observations. This is not necessary in our case because we estimate a separate model for each year.

[20] In these models, the algorithm scores the root mean square predictor error for the GWR model and minimizes this value via cross validation to select an appropriate bandwidth (Paez et al. 2011).

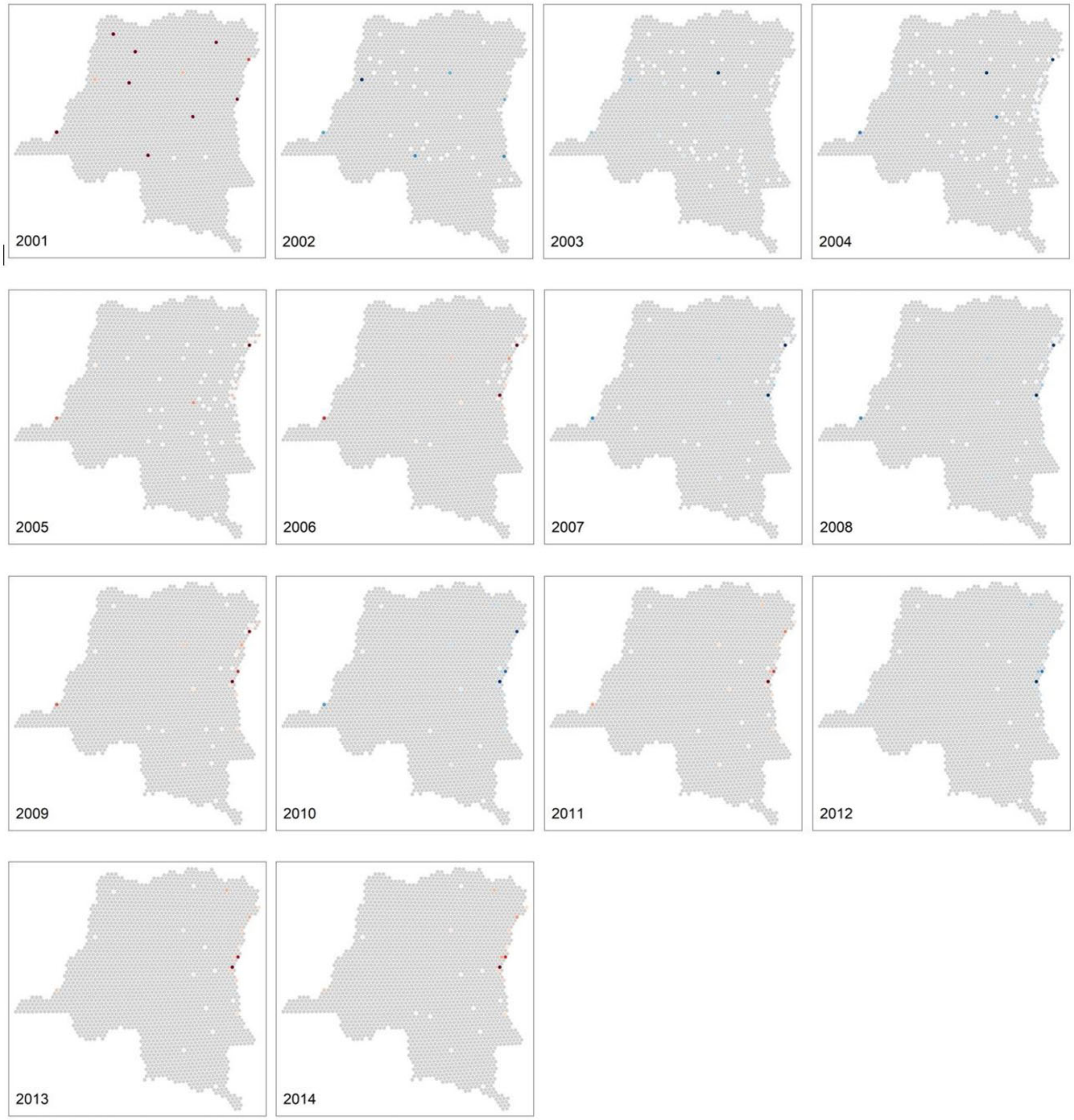

Figure 2. The local-level effects of UN peacekeeping forces estimated using linear regression following the application of CEM.

Notes: Blue hexagons indicate effectiveness, red hexagons indicate ineffectiveness, white hexagons indicate UN forces present but no effect. More intense colors indicate more (in)effectiveness.

144 GWR models. We then summarize the results by visually isolating grid cells that experienced UN deployments and determine whether UN forces were associated with a reduction, increase, or no change in patterns of civilian victimization.[21]

We use the identical independent and control variables employed by Fjelde, Hultman, and Nilsson (2019). The independent variable of interest is the number of UN troops in each grid cell, while the following controls are introduced to account for confounding variables: total population, mountainous terrain, distance to nearest city, and the number of battle deaths observed the prior month. Like Fjelde, Hultman, and Nilsson (2019), we also control for temporal and spatial dependence with decay functions that capture the time since one-sided violence in a grid cell, and the number of UN troops present in neighboring cells during the prior month.[22]

[21] Effects from the LPMs were calculated by taking a baseline prediction (predicted probability using observed values) and comparing this to the predicted probability absent UN troops. If the baseline prediction was greater than the absence prediction without overlapping confidence intervals, this indicates UN troops were associated with an increase in violence. Similarly, if the baseline prediction was less than the absence prediction, peacekeepers mitigated violence.

[22] See Fjelde, Hultman, and Nilsson (2019, 113–14) for more details on these variables, including the data sources and summary statistics.

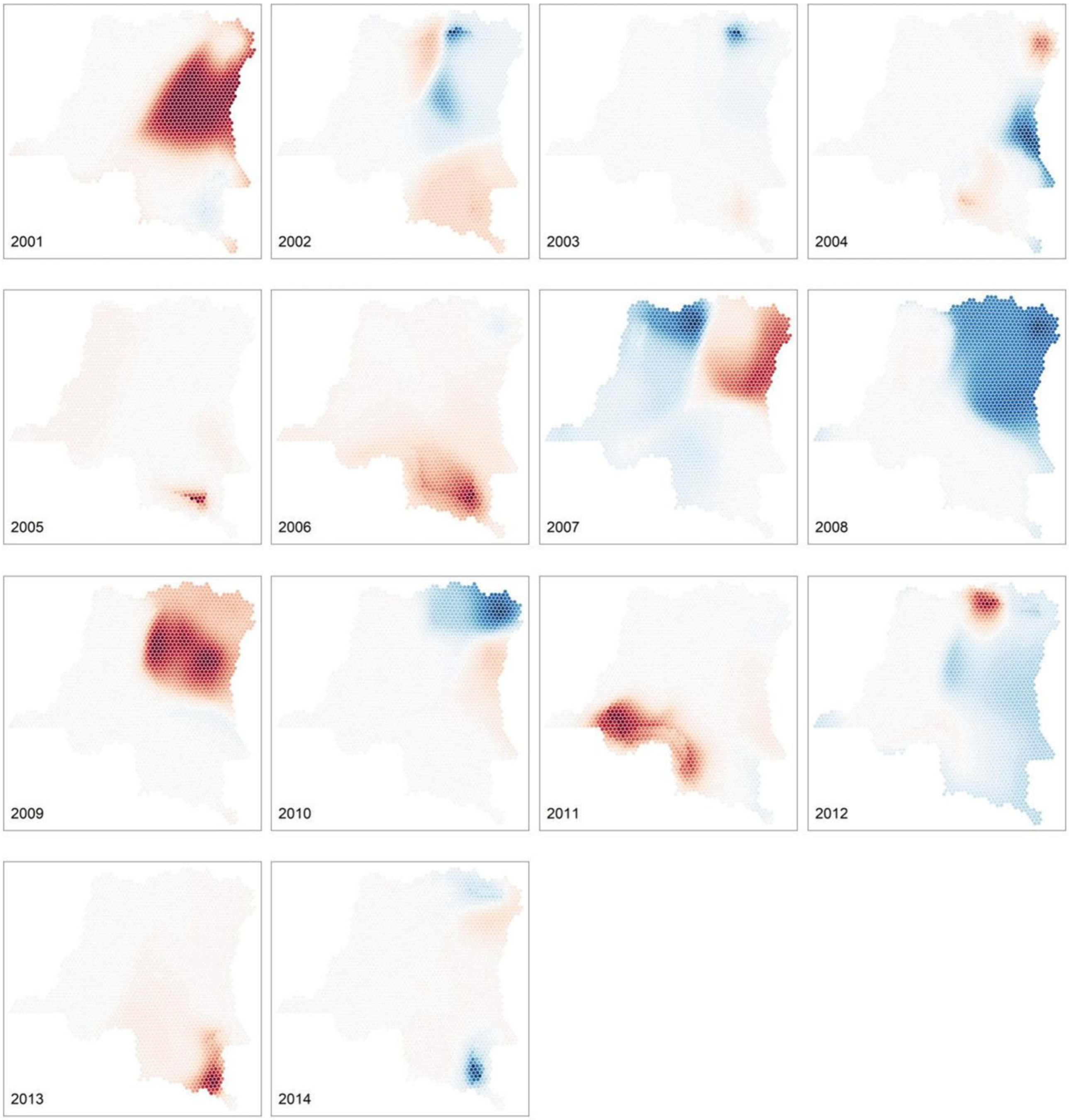

Figure 3. The local-level effects of UN peacekeeping forces estimated using GWR following the application of CEM.
Notes: Blue hexagons indicate effectiveness, red hexagons indicate ineffectiveness. More intense colors indicate more (in)effectiveness.

To reiterate, we estimate these two sets of models for civilian victimization when rebels and the government are perpetrators. Fjelde, Hultman, and Nilsson (2019) find UN troops to be effective in deterring rebel violence, but not government violence. This is contrary to what others have found, such as Phayal (2019) and Hunnicutt and Nomikos (2020), who find UN troops reduce government attacks targeting civilians.

Figure 4a (rebels as perpetrators) and 4b (governments as perpetrators) present differences between the LPMs (2019) and GWR, when using the same dependent variable and predictors. The different colors of the grids in figure 4a and 4b indicate the following:

- Blue: both approaches find that UN troops reduce violence.
- Purple: both approaches find that UN troops increase violence.
- Cyan: GWR finds that UN troops reduce violence while the LPMs suggest that troops increase violence.
- Yellow: GWR finds that UN troops increase violence, whereas the LPMs find that troops reduce violence.
- Gray: GWR and the LPMs fail to find a statistically significant relationship ($p < 0.05$) between UN troops and violence.

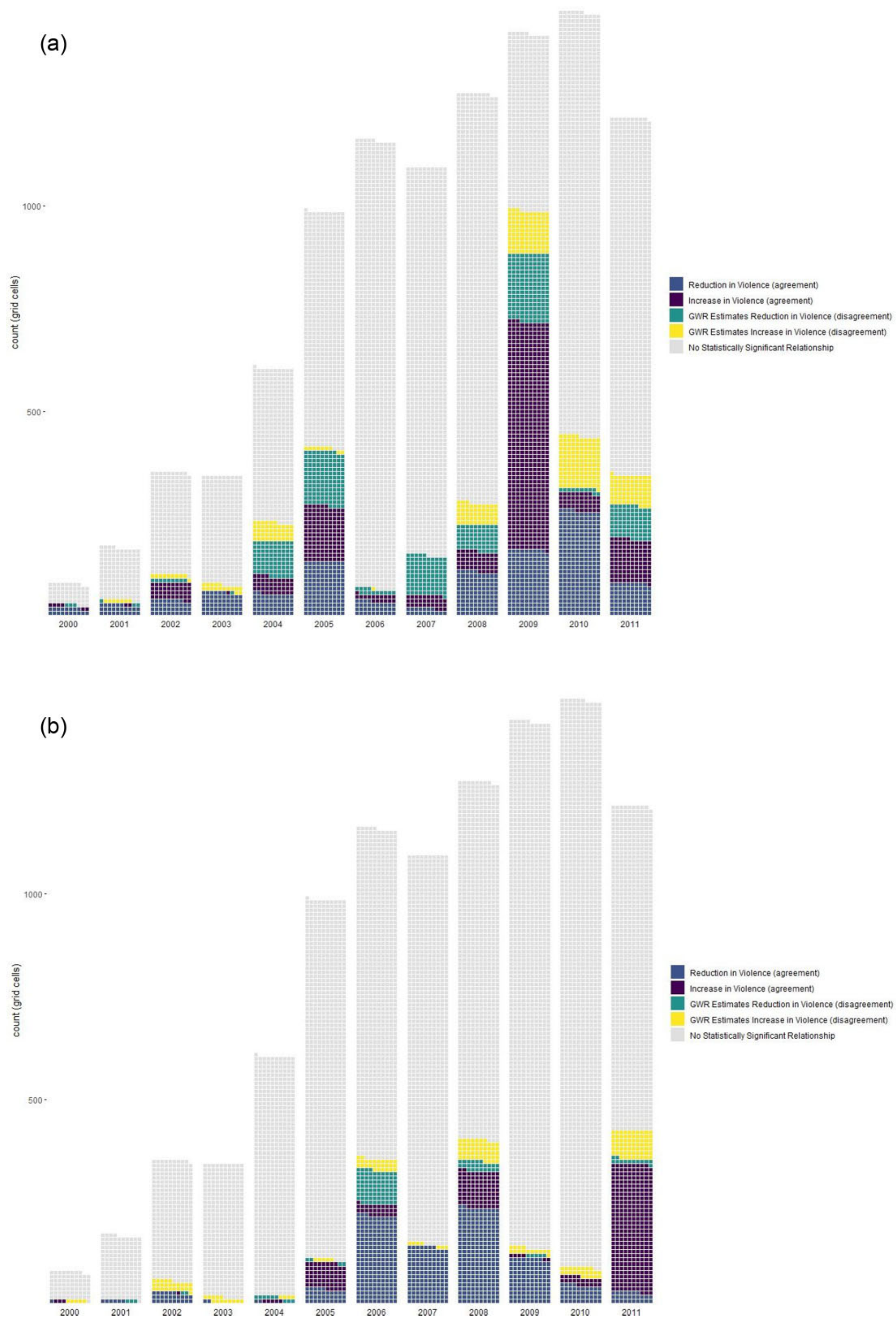

Figure 4. a. (Rebel violence): Comparing stationary (LPM) and nonstationary regression (GWR) models on patterns of civilian victimization across Africa, 2000–2011. **b.** (Government violence): Comparing stationary (LPM) and nonstationary regression (GWR) models on patterns of civilian victimization across Africa, 2000–2011.

The total number of grids, and the increase observed over time, reveals the growing presence of UN troops across Africa.

First, looking at rebels as perpetrators (4a), we find notable agreement until we see a surge of UN troops into conflict zones in 2004. The GWR models then reveal a noteworthy pattern: while the LPMs indicate that UN troops can deter rebel-perpetrated violence against civilians, as Fjelde, Hultman, and Nilsson (2019) find, GWR suggests they underestimate the strength of this effect. This is especially true in 2005–2009, where GWR identifies a substantial number of grid cells that, when accounting for local conditions (via

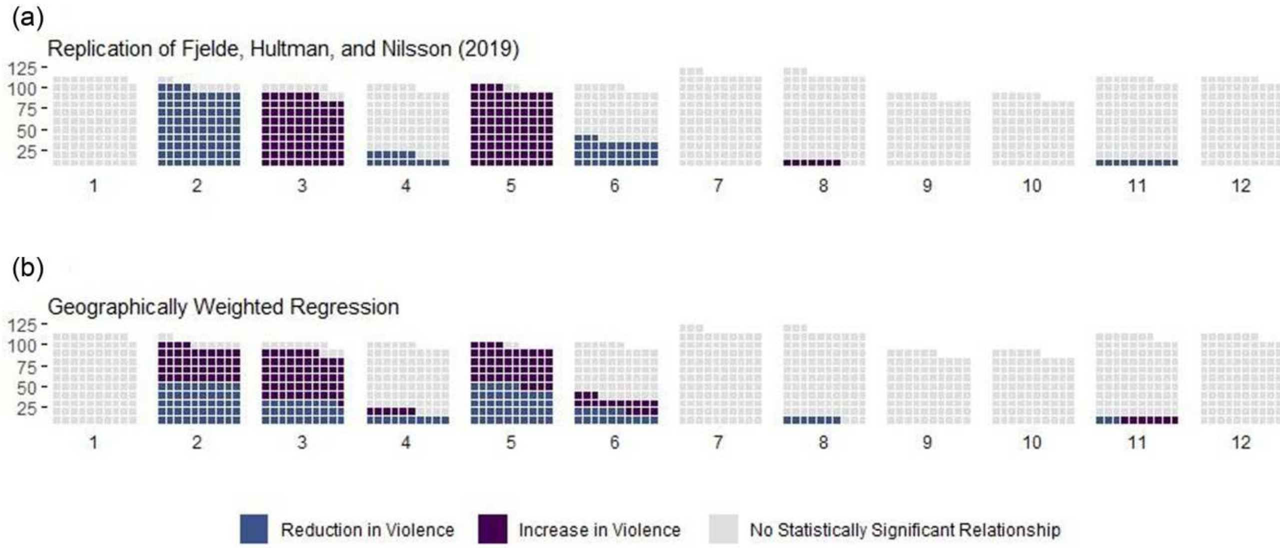

Figure 5. Influence of UN troops on rebel violence targeting civilians, 2006.

localized regression), saw UN troops reduce violence, while the LPMs reveal troops to be associated with an increase in violence. This shifts briefly after 2009, when we return to a period of agreement (majority of grid cells) between the two approaches. In sum, however, GWR not only produces findings that generally agree with Fjelde, Hultman, and Nilsson (2019) but also finds the effect to be stronger than anticipated. Thus, UN troops do deter violence against civilians perpetrated by rebel forces. There is, however, notable variation across years in effectiveness, which warrants further investigation by scholars in the future. In particular, the difficulty deterring civilian attacks by rebel forces in 2009 requires explanation.

When looking at locations where governments are perpetrators (4b), we find much more agreement between the two methods.[23] The exception to this appears to be 2005 and 2008, where we find GWR estimates that UN troops lead to lower levels of civilian victimization in a notable number of grid cells, contrary to the LPMs, but consistent with Phayal (2019) and Hunnicutt and Nomikos (2020). In the aggregate during these years, UN troops are more likely to reduce violence, implying that under some circumstances, they can be effective. This continues from 2007 to 2010, where we find most grid cells to be associated with fewer civilian attacks, even when including locations where GWR finds increases compared to the LPMs. This shifts drastically in the final year included in the study, as we find UN troops to be ineffective, corresponding to patterns reported by Fjelde, Hultman, and Nilsson (2019). This reveals that, in total, UN troops were effective in deterring civilian targeting by government forces, at most locations most of the time.

In sum, GWR reveals that UN troops are effective at protecting civilians from rebel forces, even more so than reported by prior research (Fjelde, Hultman, and Nilsson 2019). GWR also reveals that UN troops can deter government attacks in most locations during a majority of months included in the analysis, consistent with Phayal (2019) and Hunnicutt and Nomikos (2020). This reveals, in effect, that both competing findings found in the literature are correct: UN troops can protect civilians from rebels and government forces most of the time.

This begs the question: where does GWR differ from the stationary approaches currently employed in the literature? As noted in the illustrative case of MONSUCO in the DRC, one significant advantage of GWR is that it allows for the influence of UN forces to vary across the study area during the same period. Stated differently, unlike stationary regression models, which take the average effect, localized approaches such as GWR use local context to assess local effects. What this means in practice is that the differences we find between the replication of Fjelde, Hultman, and Nilsson (2019) and GWR are likely due to the ability of GWR to vary across space.

To illustrate this further, consider figures 5 and 6, which present monthly differences during 2011 for rebel violence and government violence, respectively, in grid cells where UN peacekeepers were deployed. The numbers correspond to months; blue indicates that UN troops are associated with a reduction in violence, purple indicates an increase in violence, and gray-shaded grid cells are those with no statistically significant relationship. As expected, we see the differences stem from the ability of GWR to have different effects in different places during the same period (month). Stationary models, such as linear regression, probit, and logit, among others, impose homogeneity across the study area during a period by estimating global (average) effects. This further highlights the potential power of GWR when applied to peacekeeping deployments, as we know that during a given period, these forces are effective in some locations but not others. GWR allows us to capture this effect.

Limitations and Caveats

GWR provides several advantages to the study of peacekeeping effectiveness. However, certain limitations warrant mention. The first was evident when applying GWR to civilian protection: GWR is not well suited to easily deal with time-series data; reporting effects can, therefore, be difficult as it is best done visually. In our case, replicating the existing work that covers a twelve-year time-period necessitated estimating, in total, 288 models (144 for the replication; 144 GWR models for comparison). Additionally, we had to derive a way to visualize the findings, which entailed creating a specialized function that could extract the information we needed. Thus, at the moment, there is a significant cost to

[23] Notably, both the LPMs and the GWR models find a reduction in government violence in most years, except in 2003, 2005, and 2011.

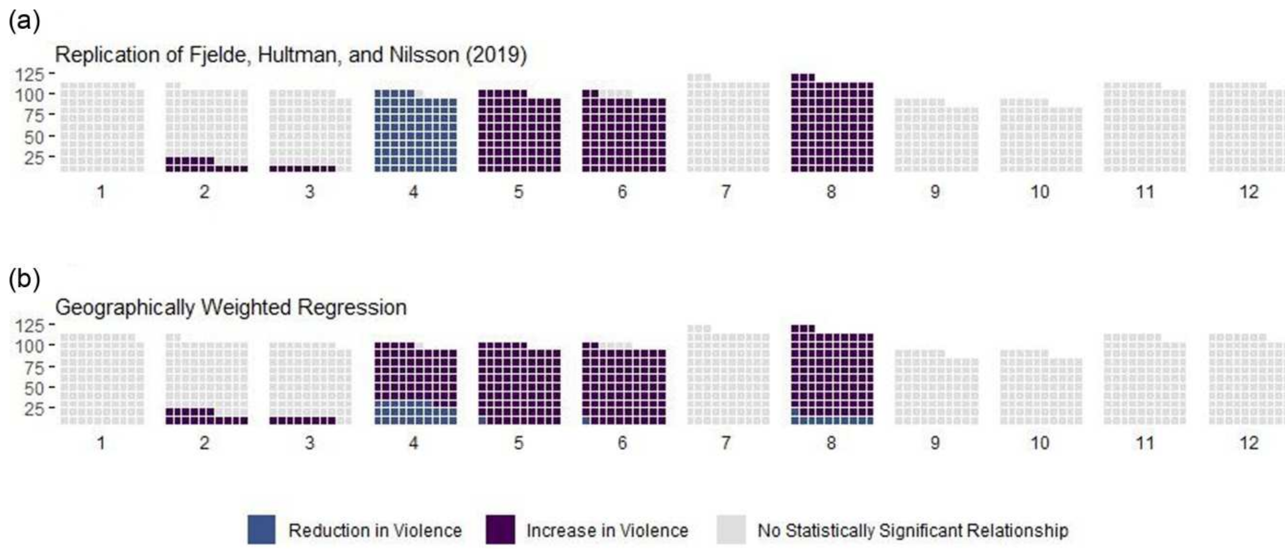

Figure 6. Influence of UN troops on government violence targeting civilians, 2006.

researchers who may need to learn new tools to use GWR to study the subnational dynamics of PKOs. We hope that our contribution can help alleviate some of these costs; our replication code, including the visual displays of our results, can be adapted by scholars interested in using GWR to answer their research questions.

Second, the power of GWR is the localized regression models, which use local context to estimate local effects (as opposed to global effects). This process, however, requires *reliable* and *valid* covariates that vary across geographic space. While data exist that make this possible (as illustrated in this study), geo-referenced data, especially event data, are prone to bias and often require significant processing to ensure that this bias is not driving results, especially when collected from conflict zones (Woolley 2000; Earl et al. 2004; Weidmann 2015, 2016; Reeder 2018; von Borzyskowski and Wahman 2021). This creates more uncertainty when compared to state-level studies, as having confidence in where and when events occurred, and how they were reported is an issue that is unlikely to be resolved in the near-term. This problem is not unique to GWR, of course, but any local-level research relying on observational data needs to be keenly aware of potential bias.

Finally, researchers must make important decisions about the nuances of GWR. To take one example, in our illustration using MONUSCO in the DRC, we chose to use a bandwidth producing a "neighborhood effect," whereby the influence of UN forces was extended beyond areas where they were deployed. Contrary to this, in our exploration of civilian protection, we focused only on grid cells where UN troops deployed because this was consistent with the theoretical logic proposed by studies of civilian protection. The decision to allow for a "neighborhood effect" or focus on isolated grid cells, however, is not always clear and researchers must take care to match these decisions with theory.

Conclusion

Relying on modeling techniques that estimate average (global) effects could mask an important inference about peacekeepers' abilities: peacekeepers are effective to varying degrees at mitigating violence in some locations but not others. The coefficients produced by models utilized in previous analyses imply spatial homogeneity in peacekeeping effectiveness. To help solve this issue, we put forth GWR—an alternative method for measuring and visualizing spatial heterogeneity in local-level peacekeeping effectiveness.

To highlight the utility of GWR in capturing these effects as compared to stationary models, we conducted two illustrations. First, we used MONUSCO in the DRC to assess how GWR models differ from LRMs. We found that while the models did agree in some instances, GWR could more easily display locations of effective and ineffective peacekeeping during the same period. Coefficients from LRMs, on the other hand, implied homogeneity in effectiveness across the country, inconsistent with what we know about the local-level dynamics of these missions. Furthermore, the GWR results highlighted the year-to-year variance in the success of peacekeepers at mitigating violence, which indicates that the factors contributing to the variation in effectiveness are nonstationary and likely the result of dynamic processes. Hence, one obvious advantage of GWR is that it allows for the influence of peacekeepers to vary across the study area during the same period, better matching the reality on the ground.

Second, we engaged research on civilian protection, replicating the important work of Fjelde, Hultman, and Nilsson (2019). While GWR agreed with the findings produced via the replication in many cases, notable differences emerged. Specifically, the GWR approach further strengthened the findings reported by Fjelde, Hultman, and Nilsson (2019), as more instances of successful civilian protection from rebel forces were identified with GWR. Contrary to Fjelde, Hultman, and Nilsson's (2019) conclusions, however, GWR also revealed that UN troops protected against government attacks at most locations during a majority of months included in the sample. Thus, apparent contrary findings from Phayal (2019) and Hunnicutt and Nomikos (2020) were confirmed, as well. In sum, the contrasting findings found in the literature may both be correct: peacekeepers can protect civilians against rebel and government forces under certain conditions.

Based on the utility of GWR, we recommend that scholars use it to improve the measurement of peacekeeping effectiveness at the local level. As part of this research note, we provide our GWR estimates created as part of the replication of Fjelde, Hultman, and Nilsson (2019). Included is a hopefully intuitive R-script that will allow scholars to adjust the model parameters, add new variables, and make other changes they see fit. With improved measures of subnational peacekeeping effectiveness, we can increase our confidence in tests of theoretical assumptions about why peacekeepers are (in)effective at the subnational level while also creating the ability to visualize patterns of effectiveness across time and space. However, GWR is not a panacea. It is a model like any other that has its own limitations and should be used with care (see the previous section). Thus, scholars should only utilize GWR if it is appropriate to examine their research questions.

Supplementary Information

Supplementary information is available at the *International Studies Quarterly* data archive.

References

Autesserre, Severine. 2010. *The Trouble with the Congo: Local Violence and the Failure of International Peacebuilding*. New York: Cambridge University Press.

Blyth, Simon, Brian Groombridge, Igor Lysenko, Lera Miles, and Adrian Newton. 2002. "Mountain Watch: Environmental Change & Sustainable Development in Mountains." *UNEP-WCMC Biodiversity Series 12*.

Brass, Jennifer N., Justin Schon, Elizabeth Baldwin, and Lauren M. MacLean. 2020. "Spatial Analysis of Bureaucrats' Attempts to Resist Political Capture in a Developing Democracy: The Distribution of Solar Panels in Ghana." *Political Geography* 76: 1–13.

Brunsdon, Chris, A. Stewart Fotheringham, and Martin E. Charlton. 1996. "Geographically Weighted Regression: A Method for Exploring Spatial Nonstationarity." *Geographical Analysis* 28 (4): 281–98.

———. 1999. "Some Notes on Parametric Significance Tests for Geographically Weighted Regression." *Journal of Regional Science* 39 (3): 497–524.

Calvo, Ernesto, and Marcelo Escolar. 2003. "The Local Voter: A Geographically Weighted Approach to Ecological Inference." *American Journal of Political Science* 47 (1): 189–204.

Cho, Wendy K. Tam, and James G. Gimpel. 2010. "Rough Terrain: Spatial Variation in Campaign Contributing and Volunteerism." *American Journal of Political Science* 54 (1): 74–89.

Cil, Deniz, Hanne Fjelde, Lisa Hultman, and Desirée Nilsson. 2020. "Mapping Blue Helmets: Introducing the Geocoded Peacekeeping Operations (Geo-PKO) Dataset." *Journal of Peace Research* 57 (2): 360–70.

Costalli, Stefano. 2014. "Does Peacekeeping Work? A Disaggregated Analysis of Deployment and Violence Reduction in the Bosnian War." *British Journal of Political Science* 44 (2): 357–80.

Di Salvatore, Jessica. 2020. "Obstacle to Peace? Ethnic Geography and Effectiveness of Peacekeeping." *British Journal of Political Science* 50 (3): 1089–1109.

Dorussen, Han, and Theodora-Ismene Gizelis. 2013. "Into the Lion's Den: Local Responses to UN Peacekeeping." *Journal of Peace Research* 50 (6): 691–706.

Earl, Jennifer, Andrew Martin, John D. McCarthy, and Sarah A. Soule. 2004. "The Use of Newspaper Data in the Study of Collective Action." *Annual Review of Sociology* 30: 65–80.

Fjelde, Hanne, Lisa Hultman, and Desirée Nilsson. 2019. "Protection through Presence: UN Peacekeeping and the Costs of Targeting Civilians." *International Organization* 73 (1): 103–31.

Fjelde, Hanne, and Hannah M. Smidt. 2021. "Protecting the Vote? Peacekeeping Presence and the Risk of Electoral Violence." *British Journal of Political Science* 1–20.

Fotheringham, Alexander, Chris Brundson, and Martin Charlton. 2002. *Geographically Weighted Regression: The Analysis of Spatially Varying Relationships*. Chichester: Wiley.

Goldring, Edward, and Michael Hendricks. 2018. "Help is Close at Hand? Proximity and the Effectiveness of Peacekeepers." *Research & Politics* 5 (4): 1–9.

Hultman, Lisa, Jacob Kathman, and Megan Shannon. 2013. "United Nations Peacekeeping and Civilian Protection in Civil War." *American Journal of Political Science* 57 (4): 875–91.

Hunnicutt, Patrick, and William G. Nomikos. 2020. "Nationality, Gender, and Deployments at the Local Level: Introducing the RADPKO Dataset." *International Peacekeeping* 27 (4): 645–72.

Iacus, Stefano M., Gary King, and Giuseppe Porro. 2012. "Causal Inference without Balance Checking: Coarsened Exact Matching." *Political Analysis* 20 (1): 1–24.

Leung, Yee, Chang-Lin Mei, and Wen-Xiu Zhang. 2000. "Statistical Tests for Spatial Nonstationarity Based on the Geographically Weighted Regression Model." *Environment and Planning: Economy and Space* 32 (1): 9–32.

Paez, Antonio, Steven Farber, and David Wheeler. 2011. "A Simulation-Based Study of Geographically Weighted Regression As a Method for Investigating Spatially Varying Relationships." *Environment and Planning: Economy and Space* 43 (12): 2992–3010.

Pettersson, Therese, and Magnus Oberg. 2020. "Organized Violence, 1989–2019." *Journal of Peace Research* 57 (4): 597–613.

Phayal, Anup. 2019. "UN Troop Deployment and Preventing Violence against Civilians in Darfur." *International Interactions* 45 (5): 757–80.

Phayal, Anup, and Brandon C. Prins. 2020. "Deploying to Protect: The Effect of Military Peacekeeping Deployments on Violence against Civilians." *International Peacekeeping* 27 (2): 311–36.

Powers, Matthew, Bryce W. Reeder, and Ashly Townsen 2015. "Hot Spot Peacekeeping." *International Studies Review* 17 (1): 46–66.

Reeder, Bryce W. 2018. "The Political Geography of Rebellion: Using Event Data to Identify Insurgent Territory, Preferences, and Relocation Patterns." *International Studies Quarterly* 62 (3): 696–707.

Ruggeri, Andrea, Han Dorussen, and Theodora-Ismene Gizelis. 2017. "Winning the Peace Locally: UN Peacekeeping and Local Conflict." *International Organization* 71 (1): 163–85.

Smidt, Hannah M. 2020a. "Mitigating Election Violence Locally: UN Peacekeepers' Election-Education Campaigns in Côte D'ivoire." *Journal of Peace Research* 57 (1): 199–216.

———. 2020b. "United Nations Peacekeeping Locally: Enabling Conflict Resolution, Reducing Communal Violence." *Journal of Conflict Resolution* 64 (2–3): 344–72.

Storeygard, Adam, Deborah Balk, Marc Levy, and Glenn Deane. 2008. "The Global Distribution of Infant Mortality: A Subnational Spatial View." *Population, Space and Place* 14 (3): 209–29.

Sundberg, Ralph, and Erik Melander. 2013. "Introducing the UCDP Georeferenced Dataset." *Journal of Peace Research* 50 (4): 523–32.

Townsen, Ashly, and Bryce W. Reeder. 2014. "Where Do Peacekeepers Go When They Go? Explaining the Spatial Heterogeneity of Peacekeeping Deployments." *Journal of International Peacekeeping* 18 (1-2): 69–91.

Uchida, Hirotsugu, and Andrew Nelson. 2009. "Agglomeration Index: Towards a New Measure of Urban Concentration." *Background Paper for the World Bank's World Development Report*.

United Nations. 2020. "What is Peacekeeping." Accessed November 24, 2021. https://peacekeeping.un.org/en/what-is-peacekeeping.

von Borzyskowski, Inken, and Michael Wahman. 2021. "Systematic Measurement Error in Election Violence Data: Causes and Consequences." *British Journal of Political Science* 51 (1): 230–52.

Weidmann, Nils. 2015. "On the Accuracy of Media-Based Conflict Event Data." *Journal of Conflict Resolution* 59 (6): 1129–49.

———. 2016. "A Closer Look at Reporting Bias in Conflict Event Data." *American Journal of Political Science* 60 (1): 206–18.

Weidmann, Nils B., Doreen Kuse, and Kristian Skrede Gleditsch. 2010. "The Geography of the International System: The CShapes Dataset." *International Interactions* 39 (1): 86–106.

Willmott, C.J., and K. Matsuura. 2012. "Terrestrial Precipitation: 1900–2010 Gridded Monthly Time Series." Version 3.02. Accessed November 24, 2021. http://climate.geog.udel.edu/~climate/html_pages/download.html#P2011rev.

Woolley, John T. 2000. "Using Media-based Data in Studies of Politics." *American Journal of Political Science* 44 (1): 156–73.