Climatic stress, internal migration, and Syrian civil war onset

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Online Appendix

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A Random forest classification of cropland

This section expands on the method to extract cropland through random forest classification presented in the main paper. In order to construct images of cropland coverage for Syria, we use Landsat 7 satellite imagery, which captures images with a resolution of 30 meters. Existing maps to capture cropland land cover using Moderate Resolution Imaging Spectroradiometer (MODIS) satellites, are not used due to the comparably low 250-meter resolution (Lobell and Asner, 2004). Since there is no existing map of agricultural land cover using Landsat 7, we construct a classifier that distinguishes between aerial photos of cropland and non-cropland in Google Earth Engine (GEE). The classifier was trained on a set of images of cropland from Landsat 7 that were manually coded through GEE. The training set was applied to the Landsat 7 Normalized Difference Vegetation Index (NDVI)[1] layer aggregated for the year 2005 through a random forest classifier.[2] A random forest classifier uses decision trees to classify images according to independent samples from an input image. Pixels are then classified by taking the most popular voted class from all tree predictors in the forest (Pal, 2005). Using the random forest technique and the training data, the classifier categorized the remaining images as cropland or not cropland. The generated raster was converted to a shapefile in ArcGIS and used to generate average values from rasters within third-level administrative regions in Syria.

Validation against the MODIS cropland classifier was not feasible as MODIS maps of cropland did not pass a face validity test compared to satellite maps of Syria. Instead, we draw 100 random samples from the resultant cropland shapefile and visually examine images at these coordinates to determine if the points overlap with cropland. We use aerial imagery of Syria from December of

[1]NDVI utilizes the differences in light reflectance patterns of near-infrared and visible light to assess changes in the vegetation of cropland.

[2]Using 20 trees.

Figure 1: Four Samples of Cropland Shapefile. All but bottom right (16) designated as cropland.

2004 found through Google Earth Pro for the comparison. Four of the images with our randomly drawn points at the center are shown on Figure 1. Of the 100 examined coordinates, 82 were definitely identified as cropland, 14 as not cropland and 4 could not be clearly categorized based on satellite imagery. The prediction rate of approximately 82% is very high for machine learning algorithms. While there does appear to be some overprediction in our classifier, this is unlikely to induce bias, rather adding additional error to our model and making it more difficult to find significant results. Moreover, even the points that were not identified as cropland were often close to cropland, suggesting that the overpredicted values may be spillover rather than total errors.

B ICEWS sources and potential reporting bias

We generally do not expect our sources of data about protests to be systematically biased due to selective reporting. It is true that ICEWS relies on exclusively English-language sources, but this includes some sources, such as al-Jazeera or al-Arabiya, that were translated from Arabic by the media agencies themselves. There are reasons to doubt non-English language sources would include more information about protests. In March 2011, the Syrian government banned all foreign reporters from the country, including those from other parts of the Arab World, forcing journalists to rely on activists distributing information on protests through social media. As local activists were not bound by the same limitations as foreign correspondents, it is unlikely their reporting had a substantial geographic bias. Nevertheless, we use the remainder of this section to address reporting bias concerns by presenting a full accounting of the media sources used to obtain data on protests and a statistical accounting of reporting bias of protests using a zero-inflated negative binomial model.

ICEWS draws on a diverse amount of sources for information on events, ranging from traditional English language-sources to wire services such as the Associated Press and Agence France-Presse to international media sources, such as Al-Jazeera and Al-Arabiya to local Newspapers, such as The Daily Star in Lebanon or the Jerusalem Post in Israel. The sources and the corresponding amount of protests extracted from the sources are presented on Table 1.[3]

It is evident from Table 1 that a plurality of protests are coded from news agencies, primarily Agence France-Presse and Reuters, but a considerable amount are drawn from non-English or

[3]It should also be noted that ICEWS has recently been used by scholars of the Arab Spring to capture geographic variation in protest participation in other countries in the region, suggesting its reliability on the subject (Steinert-Threlkeld, 2017).

Table 1: News Sources and Number of Protests Extracted by ICEWS

Source Name	Number of Protests	Source Name	Number of Protests
AAP Bulletins	7	L' Orient-Le Jour	33
Agence France-Presse	468	L'Expression	18
Al Arabiya	10	Le Figaro	13
Al Jazeera English	45	Le Monde	9
Al-Bawaba News	12	Le Temps	25
Associated Press Newswires	26	New Straits Times	1
Australian Broadcasting Corporation	3	New Zealand Herald	2
BBC Monitoring Africa	1	O Estado de Sao Paulo	1
BBC Monitoring Asia Pacific	1	PNA (Philippines News Agency)	8
BBC Monitoring Caucasus	1	Reuters News	133
BBC Monitoring European	1	SBS World News Headline Stories	2
BBC Monitoring Middle East	88	Thai News Service	38
BBC Monitoring Newsfile	22	The Australian	4
Baltic Daily	1	The Christian Science Monitor	8
Calgary Herald	1	The Egyptian Gazette	1
Cape Times	2	The Jerusalem Post	28
China Daily	1	The Mercury	3
Daily Star	17	The Nation (Thailand)	5
Deutsche Welle	25	The New York Times	21
Dow Jones News Service	14	The Sydney Morning Herald	2
El Pais	2	The Toronto Star	12
Euronews	18	The Tripoli Post	11
Europolitique	1	The Wall Street Journal	35
Guardian Unlimited	6	The Washington Post	22
Horizons	1	Trend News Agency (Azerbaijan)	67
Interfax News Service	1	USA Today	2
Irish Times	1	Xinhua News Agency	36

sources specific to the region, such as Lebanon's Daily Star newspaper and pan-Arabic news channels such as Al-Jazeera and Al-Arabiya. Moreover, a qualitative assessment drawn from coding of protests from LexisNexis described in the following section shows that sources such as BBC Monitoring rely heavily on non-English language sources, such as blogs or YouTube videos for their reporting on the Syrian uprising, providing some evidence that non-English language sources remain represented in the ICEWS sample. Finally, the absence of Syria's domestic wire service, the Syrian Arab News Agency (SANA) is notable, but likely not substantial. SANA was indexed in LexisNexis and, once again, a qualitative accounting of the source showed that it largely ignored or minimized protests, attempting to report on as few as possible. As such, we do not believe that using only English language sources substantially affected our ability to gain an accurate geographic representation of where protests took place, nor did it affect our ability to establish an accurate picture of the number of protests that occurred in each third-level administrative district.

We follow our examination of the sources within ICEWS with a quantitative analysis that aims to statistically account for potential reporting bias. In adapting a method to account for reporting bias in events data, we follow Drakos and Gofas (2006), who utilize the zero-inflated negative binomial in order to predict systematic underreporting of events data. The zero-inflated negative binomial is a two stage model: the first stage being a logistic regression model that predicts the number of observations that have zero counts in the model and the second stage then providing corrected predictions for the number of protests in a sub-region, having accounted for any possible inflation as a result of the factors included in the first stage (Hilbe, 2011, 371-374). While cognizant of the problem of 'bad controls' mentioned in the main article, we also wanted to explore potential protest reporting bias as a result of a disproportionate share of urban population in reported protest locations. Thus, we include a measure of the share of urban population as a percentage of total population derived from the 2004 Syrian census (Central Bureau of Statistics, 2004) by De Juan and Bank (2015). In the second stages of the models, we replicated models 3 and 4 in Table 1 and model 6 in Table 3 of the main article to see if our results hold up to accounting for reporting bias.

The results of the zero-inflated negative binomial are shown in Table 2. While a greater urban population percentage has a negative effect on the amount of zeroes in the model (and thus, a positive effect on the amount of protest), there are no substantial changes from the models in the main article and the direction, magnitude and significance of the effects of climate stress and nighttime light intensity change in Sunni areas on protest. In fact, the effect of nighttime light intensity change in Sunni areas on protest become substantially stronger and more significant,

Table 2: Zero-Inflated Negative Binomial Regression on Protests in Syrian Nawahi in Jan. to July 2011

	(1)	(2)	(3)
Second Stage			
Δ Temperature (0.01 degs.)	0.990	0.749*	
	(0.033)	(0.047)	
Δ Precipitation (cms.)	0.814	25.036*	
	(0.141)	(21.197)	
Δ Temperature * Δ Precipitation		0.970*	
		(0.007)	
Mean Change in Nighttime Light Intensity			0.344*
			(0.154)
Sunni Arab Settlement			0.000***
			(0.000)
Δ Nighttime Lights * Sunni			3.534**
			(1.595)
Second Stage Constant	0.000**	5.38e+08**	0.000*
	(0.000)	(3.93e+09)	(0.000)
Governorate-Level Fixed Effects in Second Stage	Yes	Yes	Yes
First Stage			
Share of Urban Population	0.005**	0.009**	0.020***
	(0.010)	(0.014)	(0.021)
First Stage Constant	6.926***	7.713***	9.174***
	(2.566)	(2.794)	(3.206)
α	2.391***	1.745	0.338
	(0.620)	(0.582)	(0.732)
Nawahi	261	261	256

Note: *p<0.05. Incidence Rate Ratios reported in lieu of coefficients. Logged population count held constant as exposure variable in models 1 and 2. Damascus, Arbin, Hajar Aswad and Jaramana nawahi excluded from model 3 because average nighttime lights approached or were at maximum detectable levels at 63 in 2005. Standard errors clustered at second administrative level.

even when compared to a smaller baseline in the negative effect of nighttime light intensity change in non-Sunni areas.

A final concern regarding measurement of the protest variable may be in the amount of protests coded for a particular region. Once again, it is possible that the news sources are sufficient to detect at least one protest in a given location, but still inflate the count for more populated areas or areas that are more exposed to the international media. This effect may not be fully accounted for by holding population count of a given sub-region constant. As a result, we present a logistic regression model that uses a dichotomous variable that only measures whether or not a third-level administrative region in Syria experienced any protest between January and July of 2011. Otherwise, the independent variables, clustering and fixed effects are identical to those utilized in model four in Table 1 and model 2 of Table 3 of the main article.

Results are presented on Table 3. There are no substantial changes in direction, magnitude or significance in the first model. However, the positive effect of nighttime light change in Sunni areas on protest is no longer significant, suggesting that this effect does not extend to the binary specification of the variable. Broadly, however, in using both qualitative and quantitative techniques, we can be somewhat more confident that our effects are not driven by reporting bias in our protest variable.

Table 3: Logistic Regression on Protest Incidence in Syrian Nawahi in Jan. to July 2011

	(1)	(2)
Δ Temperature (0.01 degs.)	0.913*	
	(0.031)	
Δ Precipitation (cms.)	2.107*	
	(0.676)	
Δ Temperature * Δ Precipitation	0.993*	
	(0.003)	
Mean Change in Nighttime Light Intensity		0.959
		(0.160)
Sunni Arab Settlement		1.312
		(1.763)
Δ Nighttime Lights * Sunni		0.998
		(0.160)
Governorate-Level Fixed Effects	Yes	Yes
De Juan and Bank (2015) Control Variables	No	Yes
Constant	1931.715*	0.000*
	(6678.905)	(0.000)
Nawahi	257	256

Note: *p<0.05. Standard errors clustered at second administrative level. Damascus, Arbin, Hajar Aswad and Jaramana nawahi excluded from model 3 because average nighttime lights approached or were at maximum detectable levels at 63 in 2005.

C Coding for detailed protest data from LexisNexis

We desired a more in-depth look into the protests that took place from January to July of 2011 in Syria. However, due to restrictions on the sources – specifically a lack of reporting of the titles of the articles used by ICEWS – we were not able to extract information about protest size, topic or actor from the data. Thus, in order to examine demands made by protesters during the first phase of the Syrian uprising, we coded our own data on protests during the uprising using LexisNexis.

C.1 Coding Details

We used LexisNexis academic search of 'All News' sources. The search was constrained to four categories within the larger 'All News' category: Newspapers, Major World Publications, Wire Services and Blogs. The search was further constrained to focus on articles about Syria. The search term, "demonstration OR protest OR rally OR picket OR riot AND NOT sport" was used to isolate particular anti-government protests of interest for the analysis.

All gatherings of greater than 10 individuals in a public place included in the data. Protests are assumed to be anti-government in some capacity, unless the target is explicitly a foreign power or protests are explicitly pro-government (joined by members of the incumbent regime, etc.). Protests are coded at the article level (Weidmann and Rød, 2015) to avoid aggregation within coding. In other words, information from each relevant article is entered as a separate observation into the data-set. If there are multiple articles that describe the same protest, then multiple observations are entered for each article with the city and date serving as the units of analysis that aggregation is then performed on. Protests without a certain date are not coded. While this may lead to overlapping details initially, repeat observations are avoided by explicitly modeling heterogeneity in protest information, rather than aggregating it as soon as coding takes place.

When looking at each individual article, we attempt to obtain as much information on the following: date, location, number of participants (as many sources as possible are recorded), number arrested, number wounded, number killed, whether any type of repression was used, the topic or demand of the protest, the name of the actor, whether any concession were made by the state in response and the types of confessions. We also record the title and sources of the article for future reference.

C.2 Protest Demands and Migration

This section describes using our hand-coded protest data from LexisNexis to evaluate whether in-migration bolstered the claims of the already deprived or generated anti-government backlash based on the demands of protesters in the early days of the uprising. If backlash was driving protests or migrants were protesting against the state, we would expect protesters' demands to be primarily economic. Why would this be the case? In short, internal migration puts an economic strain on both locals and migrants, but those claims are substantively *different*. Migrants are constrained in economic opportunities in receiving areas (Hunter, 2009). While locals face new labor competition from new migrants (Boustan et al., 2007) Thus, given their incompatible economic preferences, it is likely that protests on economic subjects reflect contention between locals and migrants.

On the other hand, if migrants and locals coordinated or migrants otherwise bolstered the claims of politically excluded locals, we instead expect demands to have been primarily political. When migrants and locals share a relevant identity characteristic and are politically excluded, economic pressure has comparably less salience than political claims (Gaikwad and Nellis, 2017). As locals would feel emboldened by the presence of or coordination with migrants, they would likely make more political demands of the state, as both locals and migrants share political grievances against the state, but may have different and likely contradictory economic demands.

A qualitative assessment of the protests must begin on March 18, with the protests in Dara'a. While protests took place before this day, mostly in February and March in Damascus, they were fairly minimal in size, staged by human rights activists who had protested for years and were quickly dispersed.[4] The protests in Dara'a, as mentioned, were in response to the arrest and sub-

[4]However, the demands of these protesters largely matches the demands of the subsequent protests in Dara'a and

sequent torture of numerous youths that were accused of painting graffiti that called for the fall of the Assad regime. However, the protests themselves, concurrent with protests in Banias, Homs and Damascus called for "more political freedoms, less corruption, and genuine economic reforms."[5] In effect, the protesters wanted to address political, rather than economic grievances – inconsistent with the expectations of protesters that are responding to economic shocks as a result of in-migration.

The Dara'a protests were violently dispersed and at least six, likely more, people were killed. In the next days, protests continued in Dara'a during the funerals of the victims and erupted across the country in solidarity. However, once again, the protesters remained focused on political causes. Calls were made for an end of the emergency rule that had governed Syria since the Ba'ath Party coup in 1963, for reforms, for freedom and some economic changes. Some protests, including one in Madaya, made calls for the fall of the Assad regime.[6] Further repression followed in Dara'a with up to one hundred more protesters killed on March 23. These protests called for political reforms and the resignation of the governor.

The killing of at least one hundred protesters in Dara'a on March 23 triggered a Day of Dignity on March 25, where protests took place throughout the country. Nevertheless, most of the protesters continued calls for political reforms, rather than making concrete economic demands or mentioning migrants. Freedom, an end to the emergency rule and the release of political prisoners continued to be themes in the following weeks as protesters appeared, generally on Friday throughout the country, the Army or police would use force to disperse them and funerals would

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the rest of the country: democratic change, freedom and the release of political prisoners. Some protesters even made it explicit that they were not calling for the fall of the Assad regime.

[5] The Dara'a protests also called for the resignation of local officials.

[6] A video of the protest and the demands can be seen here: https://www.youtube.com/watch?v=L1fR3aYV4dQ. The protesters chant for freedom and then for the fall of the regime.

attract additional protesters. Notable at this point was anger at the Ba'ath party as several of its offices were burned down. By the time the emergency laws were repealed on April 17 and Assad appointed a new cabinet, the tone of the protests had largely shifted to demanding complete regime change and it becomes difficult to gauge the role of economic or migration-related grievances in further protests.

Enough is clear from examining the first months of protests that neither the economic demands one would expect to see from migration-related protests nor explicit mentions of migrants were present during the protests. Instead, protesters tended to make calls for democracy, freedom, or an end to corruption, Syria's long-standing emergency laws, repression, and police brutality. There were some calls for economic reforms, but these referred to long-standing grievances. Nevertheless, these issues could have been on the minds of protesters and expressed through anger against the government and demands for political reforms. However, this form of latent grievance is not something that we can discern from analysis of public demands of the state during the first month of anti-regime protests. Instead, the consistent political demands point to migration having bolstered the claims and confidence of local Sunni Arabs in demonstrating against the Syrian government.

Finally, sub-ethnic links between migrants and locals also offer support for the migrant-local coordination mechanism for Sunni Arab protesters. Specifically, there is evidence Syria's migrants and locals shared tribal, in addition to sectarian, connections. In particular, Syria's Sunni Arabs have a complex patchwork of kinship networks and these sometimes transcend regional boundaries (Tibi, 1990). Several tribes and tribal confederations have populations in both areas stricken by drought and those that received migrants: there are Baggara in both Aleppo and Deir ez-Zour, Fadan in Raqqa and Allepo's Ain al-Arab, Al-Abda in Hasakeh and Hama and Al-Harb in Hasakeh, Aleppo, Damascus and Homs (Zakariya, 1983). Boosting the link between tribal networks and protest, Leenders and Heydemann (2012) and Dukhan (2014) find tribal networks underpinned early protest mobilization against the regime in Dara'a, Idlib and Deir ez-Zour, with one protest day on June 6, 2011 being dubbed "Friday of the Tribes." As locals and migrants shared sectarian and potentially tribal bonds, it is more likely that political demands during protests came about because locals blamed the strains migrants placed on public services and labor markets on the government and coordinated to protest based on pre-existing tribal linkages.

C.3 Empirical Testing using LexisNexis Data

Hand-coded data from LexisNexis produces substantially fewer unique protests when compared to ICEWS – 641 unique protests are coded from LexisNexis, while 1333 are relayed by ICEWS. However, using data obtained through a totally independent and different coding technique in models with protests as the independent variable may demonstrate that our findings are not a product of the way in which our data was obtained. Figure 2 shows the geographic variation in protests across both sources of data (the first map replicating Figure 1 in the main paper). While there is some heterogeneity in both the number and location of reported protests, there is also considerable geographic and numeric agreement between the two figures. Moreover, the number of protests in a third-level administrative region according to ICEWS correlates with the number according to LexisNexis at about 0.85, further suggesting broad agreement across coding sources.

We run our models that use protest as a dependent variable with a count of the protests in a given Syrian nahiya between January and July 2011. The results are presented in Tables 4 and 5. The results are unchanged for the models linking drought to protest. The marginal effects of change in precipitation conditional on temperature change on the likelihood of protest are also

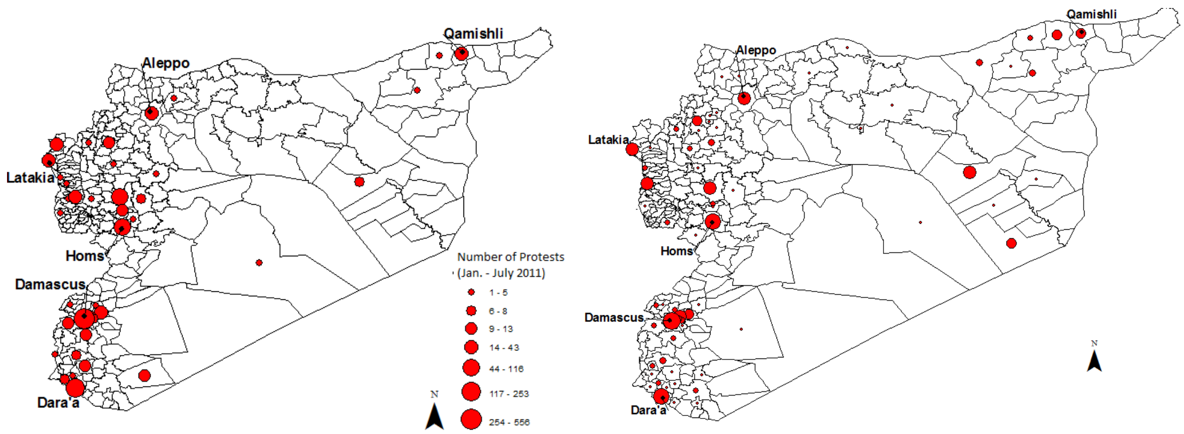

Figure 2: Protests in Syrian Third-Level Administrative Districts. Source: ICEWS (left), Lexis-Nexis (right).

largely unchanged, as shown in Figure 3. However, the effect of positive change in nighttime light intensity in Sunni regions on protest is no longer observed in the Table 5. While this conditionality is notable, we still believe that ICEWS data, with more reported protests, represents a more conclusive data source for drawing results than LexisNexis and cannot discount that the differences in findings come about due to measurement error in the LexisNexis data.

Table 4: Negative Binomial Regression on Protests from LexisNexis in Syrian Nawahi in Jan. to July 2011

	(1)	(2)	(3)	(4)
Δ Mean Temperature (0.01 degs.)	0.978*	0.905*	0.946*	0.902*
(2006-2010 from 2005-1900)	(0.006)	(0.027)	(0.022)	(0.027)
Δ Mean Precipitation (cms.)	0.875*	2.442*	1.030	2.565*
(2006-2010 from 2005-1900)	(0.047)	(0.886)	(0.202)	(1.049)
Δ Precip. $*$ Δ Temp.		0.991*		0.992*
		(0.003)		(0.004)
Governorate (First-Level) Fixed Effects	No	No	Yes	Yes
Constant	0.000*	0.329	1823.848*	2.930
	(0.000)	(1.053)	(5609.792)	(10.663)
α	4.037*	3.803*	9.212*	2.967*
	(0.779)	(0.792)	(1.969)	(0.596)
Nawahi	268	268	268	268

Note: *p<0.05. Incidence Rate Ratios reported in lieu of coefficients. Logged population count held constant as exposure variable in models 1 and 2. Standard errors clustered at second administrative level.

D Adding Control Variables to Drought-Protest Model

In the main article, we present only results of a cross-section negative binomial regression that depicts the significant effect of drought on protest. We highlight the risk of adding control variables to such a model as a 'bad control' – an endogenous covariate, could bias the exogenous coefficients of our climate variables (Hsiang, 2016). At the same time, given the cross-sectional nature of our model, it is also not possible to causally identify the effect of drought on protest. Given this trade-off, we use this space to present models including control variables derived from the 2004 Syrian Census (Central Bureau of Statistics, 2004) and utilized by De Juan and Bank (2015) in their analysis of Syrian protest repression. Specifically we include variables for the presence of Alawite residents, the presence of Sunni residents, percentage of the population living in urban areas, unemployment rate, school enrollment, percentage of government employees, electrification,

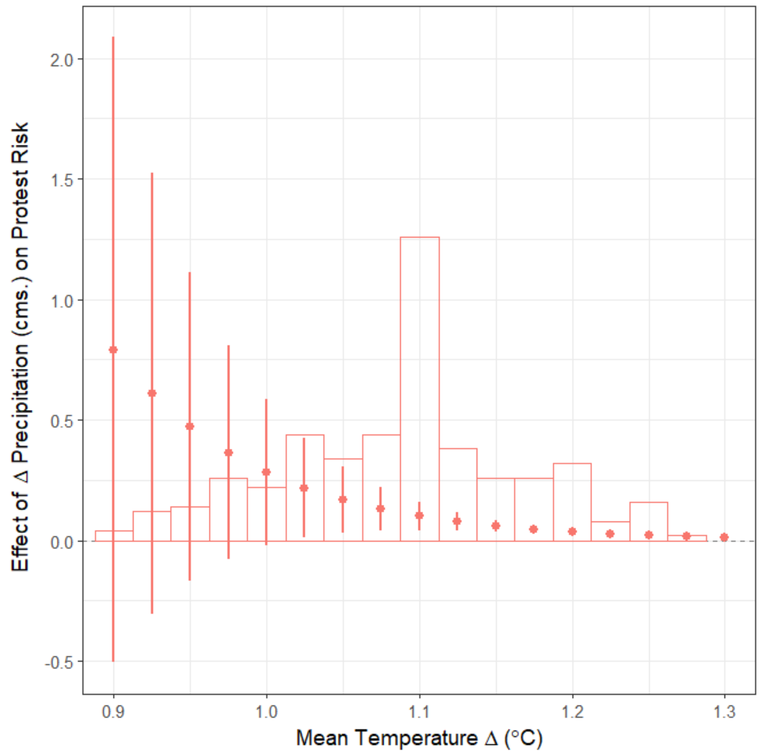

Figure 3: Marginal Effects of Interaction between Mean Temp. and Pcpt. Change on Protest (LexisNexis) Risk

percentage of home owners, road density and distance to the border. All data varies at the third administrative (or nahiya) level.

Results from the models using both ICEWS and LexisNexis protest data are presented in Table 6. Adding control variables largely leaves the magnitude and significance of the main effects of temperature and precipitation and the interaction effects unchanged, although the main effect of precipitation does lose significance at the 0.05 level in model 4. Of the controls, only a greater share of urban population in a nahiya predicted more protest. Given that controlling for urbanization did not affect the significance of the negative effect of drought on protest, we can be even more confident that our effect in the main article was not driven by a confound due to less urbanization in more drought-stricken areas.

Table 5: Negative Binomial Regression on Protests in Syrian Nawahi in Jan. to July 2011

	(1)	(2)	(3)	(4)	(5)	(6)
Mean Change in Night Light Intensity	1.088	1.130*	1.049	1.069	1.141	1.201
	(0.049)	(0.059)	(0.049)	(0.053)	(0.158)	(0.169)
Sunni Arab Settlement (Izady, 2013)			1.691	1.702	2.903	3.574
			(0.630)	(0.586)	(2.731)	(3.221)
Δ Nighttime Lights * Sunni					0.914	0.887
					(0.127)	(0.123)
Governorate-Level Fixed Effects	No	Yes	No	Yes	No	Yes
De Juan and Bank (2015) Controls	No	No	Yes	Yes	Yes	Yes
Constant	0.000*	0.000*	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
α	4.241*	2.648*	2.245*	1.318	2.247*	1.376
	(0.816)	(0.540)	(0.461)	(0.329)	(0.461)	(0.329)
Nawahi	265	265	256	256	256	256

Note: *p<0.05. Incidence Rate Ratios reported in lieu of coefficients. Logged population count held constant as exposure variable in all models. Damascus, Arbin, Hajar Aswad and Jaramana nawahi excluded from analysis because average nighttime lights approached or were at maximum detectable levels at 63 in 2005. Standard errors clustered at second administrative level. Only a greater share of urban population are consistent predictors of more protest among De Juan and Bank's 2015 control variables.

E Alternative accounting for population in climate and protest models

As mentioned in the main article, we take account of the variation in population in protest sites by holding the log of total population of a third-level administrative district constant in negative binomial regressions. This is known as an exposure variable, which allows for accounting of an upper limit in the count of certain events. The use of the variable is consistent with convention, but we desire to show that the effect we found is not contingent on the use of an exposure restriction, even if this introduces a "bad control" into our model by pairing an endogenous covariate – population – with exogenous measures of climactic variation. Nevertheless, we do this by including a control

Table 6: Negative Binomial Regression on Protests in Syrian Nawahi in Jan. to July 2011

	DV: ICEWS Protests		DV: LexisNexis Protest	
	(1)	(2)	(3)	(4)
Δ Mean Temperature (0.01 degs.)	0.962	0.755*	0.982	0.913*
	(0.040)	(0.063)	(0.011)	(0.030)
Δ Mean Precipitation (cms.)	0.738	9.975*	0.839	2.014
	(0.181)	(10.594)	(0.098)	(0.823)
Δ Precip. $*$ Δ Temp.		0.975*		0.992*
		(0.009)		(0.004)
Governorate (First-Level) Fixed Effects	Yes	Yes	Yes	Yes
De Juan and Bank (2015) Controls	Yes	Yes	Yes	Yes
Constant	0.000*	0.000	0.001	20.928
	(0.000)	(0.000)	(0.009)	(228.110)
α	5.895*	5.612*	1.306	1.279
	(1.374)	(1.321)	(0.310)	(0.324)
Nawahi	260	260	260	260

Note: *p<0.05. Incidence Rate Ratios reported in lieu of coefficients. Logged population count held constant as exposure variable in all models. Standard errors clustered at second administrative level. Only percentage of population in urban areas is a significant (and positive) predictor of protest across all models among De Juan and Bank (2015) controls.

variable of logged population rather than using it as an exposure variable.

Results are presented on Table 7. The first two models replicate the first two models from Table 1 in the main article for contrast. The results on models 3 and 4 show little substantive difference in the magnitude, direction or significance of the effects of climate stress. We can effectively rule out that our results in the models that include protest as the dependent variable are driven by the use of population count as an exposure variable.

Table 7: Negative Binomial Regression on Protests in Syrian Nawahi in Jan. to July 2011

	(1)	(2)	(3)	(4)
Δ Mean Temperature (0.01 degs.)	0.952*	0.873*	0.943*	0.862*
(2006-2010 from 2005-1900)	(0.013)	(0.028)	(0.020)	(0.035)
Δ Mean Precipitation (cms.)	0.796*	2.577*	0.777	2.612*
(2006-2010 from 2005-1900)	(0.089)	(0.909)	(0.112)	(1.224)
Δ Temperature * Δ Precipitation		0.989*		0.988*
		(0.003)		(0.005)
Natural Log of Nahiya Population			4.074*	4.207*
			(0.813)	(0.704)
Constant	0.001*	4.545	0.000*	0.092
	(0.001)	(15.297)	(0.000)	(0.474)
α	13.343*	12.657*	12.543*	11.721*
	(2.659)	(2.598)	(3.343)	(3.203)
Nawahi	268	268	268	268

Note: *$p<0.05$. Incidence Rate Ratios reported in lieu of coefficients. Logged population count held constant as exposure variable in models 1 and 2. Standard errors clustered at second administrative level.

F Fully relaxing independent observations assumption by clustering at governorate level

In our article, we primarily cluster standard errors at the second administrative level and at the year level when using time series data. We do this to account for spatial autocorrelation – that observations clustered within space are dependent on one another (**?**). By clustering standard errors at the second administrative level, we tell our regression model to assume that all observations within the same second administrative level are interdependent on one another (Greene, 2003) and that either protests or population density are spatially dependent on other observations in the same district.

This approach has limitations as it does not account for spatial autocorrelation at the governorate level or that the values of observations in one district may correlate with values in another district. This issue may be particularly problematic as our climate data is reliant on only 20 or so weather stations located in Syria. As we mention in our article, values from these weather stations are interpolated to approximately 90 0.5 by 0.5 degree quadrants using thin-plate splines. However, given the low number of weather stations that are approximately similar to the number of governorates there are in Syria, it is possible that all climatic outcomes and their correlates are not spatially independent within the same governorate.

In this section, we present alternative models which cluster our standard errors at the governorate level. By doing so, we believe we are accounting for the most spatial dependence we can in our model. As we utilize first-level administrative fixed effects, our results examine relationships are within governorates. By relaxing the assumption that observations are independent by clustering at the governorate level, we are effectively assuming that all of our observations of analysis are spatially dependent on one another. We replicate Tables 1 and 3 and Figure 4 below, with the only modeling changes being the inclusion of governorate, rather than district-clustered standard errors.

Tables 8 and 9 and Figure 4 present our findings when clustering our standard errors at the first administrative level. Results in Table 8 are largely identical to those in Table 1 of the main article. The standard errors do increase for the interaction term in Table 9 and the effect is only significant at $p<0.1$ in the drought period from 2006-2010. However, the aggregate measure for all years now shows significance. This suggests both a drought-specific and cumulative effect of temperature and lower levels of precipitation on migration. While the interaction term during the 2006-2010 period is only significant at the 0.1 level, we can be confident this is the worst-case scenario when accounting for spatial autocorrelation and unless there is full spatial dependence

Table 8: Negative Binomial Regression on Protests in Syrian Nawahi in Jan. to July 2011

	(1)	(2)	(3)	(4)
Δ Mean Temperature (0.01 degs.)	0.952*	0.873*	0.998	0.801*
(2006-2010 from 2005-1900)	(0.011)	(0.016)	(0.029)	(0.071)
Δ Mean Precipitation (cms.)	0.796*	2.577*	1.065	13.088*
(2006-2010 from 2005-1900)	(0.078)	(0.613)	(0.333)	(12.710)
Δ Precip. ∗ Δ Temp.		0.989*		0.977*
	(0.002)		(0.008)	
Governorate (First-Level) Fixed Effects	No	No	Yes	Yes
Constant	0.001*	4.545	0.000*	5.93e+05
	(0.001)	(8.452)	(0.000)	(5.96e+06)
α	13.343*	12.657*	10.068*	9.542*
	(3.346)	(3.283)	(2.300)	(2.307)
Nawahi	268	268	268	268

Note: *$p<0.05$. Incidence Rate Ratios reported in lieu of coefficients. Logged population count held constant as exposure variable in models 1 and 2. Standard errors clustered at first administrative level.

Table 9: Fixed Effects OLS Regression of Climatic Stress on Nighttime Lights

	DV: Nighttime Lights		
	All Years	Pre-Drought	Drought
	(1)	(2)	(3)
Δ Precip.	0.001	0.004	−0.022
	(0.017)	(0.016)	(0.055)
Δ Temp.	0.269	0.155	1.994
	(0.477)	(0.419)	(1.407)
Δ Precip. ∗ Δ Temp.	0.028*	0.025*	0.105
	(0.014)	(0.011)	(0.063)
Third-Level Admin FE	Yes	Yes	Yes
First-Level Admin:Year FE	Yes	Yes	Yes
Observations	4,753	3,433	1,320
R^2	0.969	0.977	0.987
Adjusted R^2	0.966	0.973	0.984
Residual Std. Error	1.680	1.385	1.301

Note: *$p<0.05$. Standard errors are multiway clustered on first-level administrative districts and years. We exclude Damascus, Arbin, Hajar Aswad and Jaramana nawahi.

within each Syrian governorate, the standard errors are likely to be closer to those shown on Table 3 of our article.

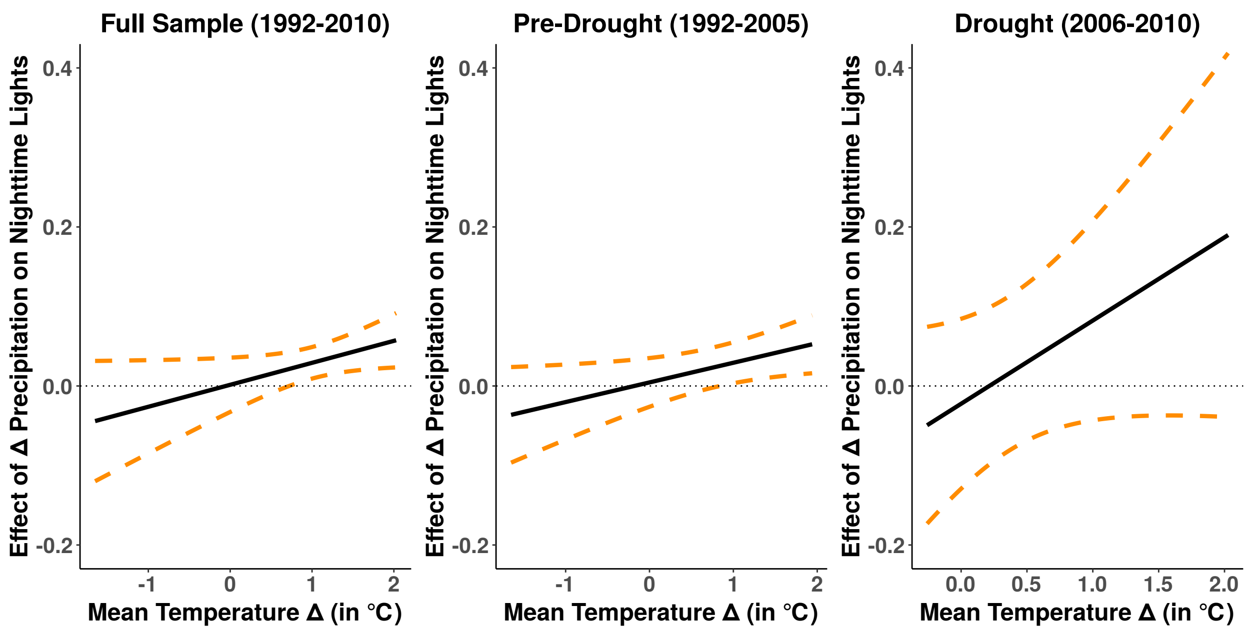

Figure 4: Effect of Annual Climatic Indicators on Nighttime Light Intensity

G Using Precipitation Data from Syrian Ministry of Agriculture

The previous section of this appendix outlines procedures taken to relax the assumption of spatial independence in our data as a way of accounting for the sparse number of weather stations from which the Climate Research Unit draws inference from Syria. In this section, we utilize an alternative source for our precipitation data: the Syrian government's Ministry of Agriculture and Agrarian Reform (MAAR). The MAAR employs data from 54 weather stations located throughout Syria and reports growing season-level data on precipitation going back to the 1981-82 rainy season (Syrian Ministry of Agriculture and Agrarian Reform, 2016). Figure 5 shows the locations of the weather stations and the relatively greater coverage afforded to Northeastern Syria, which we georeferenced based on the stated names in the data and the corresponding locations listed in Khaddour and Mazur's (2018) Syria Town Database.

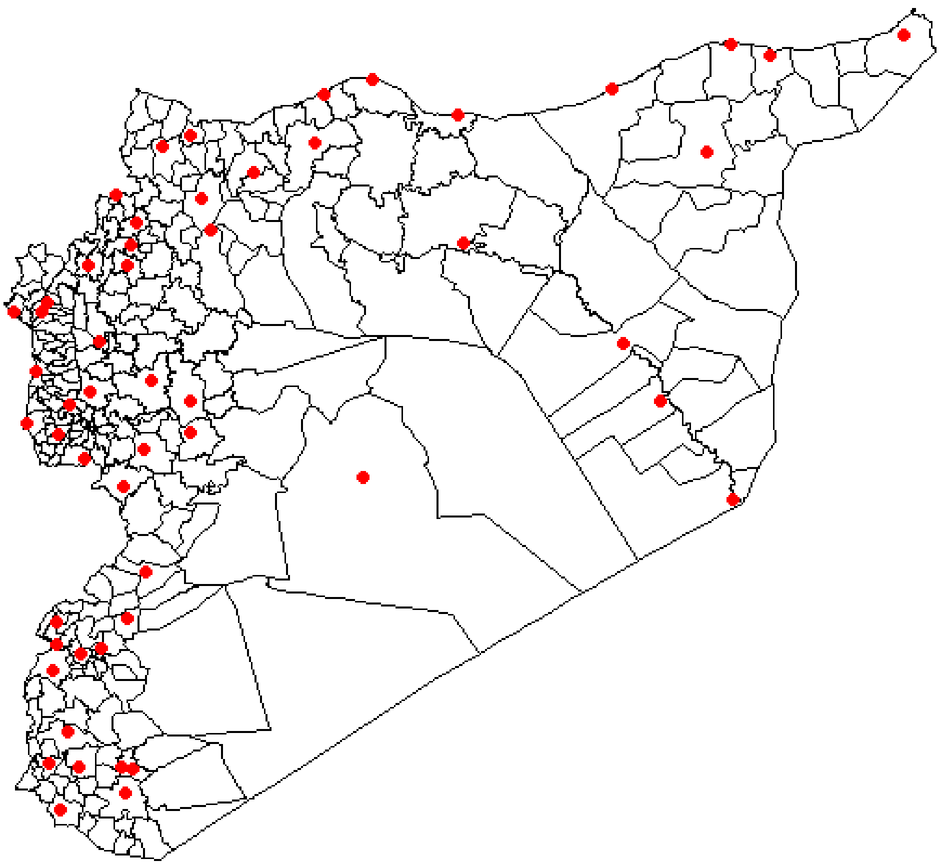

Figure 5: Location of Weather Stations used in MAAR Precipitation Measures

We take steps to interpolate data from MAAR through in a way similar to the CRU data by using bounded spline interpolation. We then take the average pixel values from each third-level administrative district's cropland boundaries to calculate annual precipitation averages. Finally, we substitute the MAAR precipitation measures for our CRU precipitation measures for models in Tables 1 and 3 of our article. For the climate-protest model, we calculate an annual deviation for each nahiya, subtracting the averages of 1981-82 to 2005-06 from 2006-07 to 2009-10. For the climate-migration model, we include averages from the preceding rainy season (i.e. 1991-92 corresponds to 1992 nighttime light averages).

There are several caveats to our use of the MAAR precipitation data. Foremost, the MAAR does not provide corresponding temperature data. As such, we must continue using the CRU temperature data in tandem with the MAAR precipitation data. This may be render it harder to find results for two reasons. First, the temperature data has a different time period than the precipitation data, covering the preceding calendar year, rather than the preceding rainy season, meaning that annual averages may not be exactly compatible with one another and sometimes reflect the previous year's events. Second, the baselines for the CRU temperature and MAAR precipitation data differ. The former represents a more-than-a-century annual average, the latter only goes back to 1981. As a result, changes in precipitation may be understated in the climate-protest model as the Levant has been experiencing a drying trend over the past several decades (Selby et al., 2017; Kelley et al., 2015).

Our results using the MAAR data are shown on Tables 10 and 11 and Figure 6. The findings in Table 10 are consistent with Table 1 in the main article. Substituting the MAAR data does not alter the effect of precipitation on protest or the direction in which the effect changes based on changes in temperature. Drought is still associated with fewer protests. The findings in Table 11 and Figure 10 somewhat differ from Table 3 in the main article. We still observe a positive relationship between precipitation and nighttime lights, but where that relationship appears temporally and its conditionality on temperature change differ from Table 3 in the main article. Specifically, the relationship is significant for the aggregate time period, but not significant for the drought, in particular. Across the distribution of temperature, there is a significant and positive relationship

Table 10: Negative Binomial Regression on Protests in Syrian Nawahi in Jan. to July 2011

	(1)	(2)	(3)	(4)
Δ Mean Temperature (0.01 degs.)	0.952*	0.921*	0.997	0.967
(2006-2010 from 2005-1900)	(0.011)	(0.026)	(0.031)	(0.030)
Δ Mean Precipitation (cms.)	1.096	2.168	1.051	2.115*
(2006-2010 from 2006-1981)	(0.067)	(0.904)	(0.068)	(0.517)
Δ Precip. $*$ Δ Temp.		0.994		0.993*
		(0.004)		(0.002)
Governorate (First-Level) Fixed Effects	No	No	Yes	Yes
Constant	0.004*	0.127	0.000*	0.000*
	(0.005)	(0.396)	(0.000)	(0.001)
α	13.617*	13.188*	10.008*	9.647*
	(2.522)	(2.492)	(1.620)	(1.591)
Nawahi	268	268	268	268

Note: *p<0.05. Incidence Rate Ratios reported in lieu of coefficients. Logged population count held constant as exposure variable in models 1 and 2. Standard errors clustered at first administrative level. Data from Syrian Ministry of Agriculture and Agrarian Reform used for precipitation.

Table 11: Fixed Effects OLS Regression of Climatic Stress on Nighttime Lights

	DV: Nighttime Lights		
	All Years	Pre-Drought	Drought
	(1)	(2)	(3)
Δ Precip.	0.017*	0.011	0.051
	(0.008)	(0.008)	(0.054)
Δ Temp.	0.245	0.211	0.661
	(0.422)	(0.327)	(0.885)
Δ Precip. $*$ Δ Temp.	-0.015^*	-0.011	-0.052
	(0.006)	(0.006)	(0.066)
Third-Level Admin FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
First-Level Admin:Year FE	Yes	Yes	Yes
Observations	4,753	3,433	1,320
R^2	0.969	0.977	0.987
Adjusted R^2	0.966	0.973	0.983
Residual Std. Error	1.680	1.387	1.309

Note: *p<0.05. Standard errors are multiway clustered on first-level administrative districts and years. We exclude Damascus, Arbin, Hajar Aswad and Jaramana nawahi. Data from Syrian Ministry of Agriculture and Agrarian Reform used for precipitation.

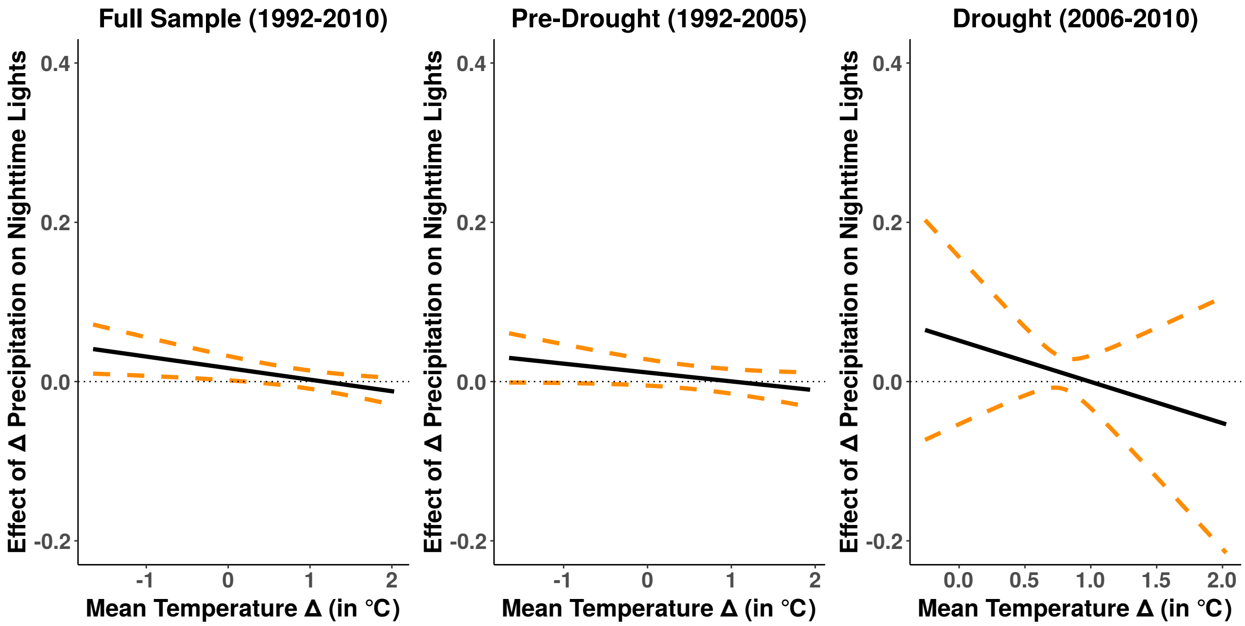

Figure 6: Effect of Annual Climatic Indicators on Nighttime Light Intensity

between precipitation and nighttime lights at lower values. Essentially, less precipitation leads to more out-migration, but only when temperatures are relatively low. We speculate that this diverging result may occur due to the incompatibility of the temperature and precipitation data, which may be introducing more error into the 2006-2010 time period, leading to a null finding there and is generally changing the values of temperature at which precipitation significantly affects population density in all three models. However, we note that the general positive association between precipitation and nighttime light intensity remains present across both the MAAR and CRU precipitation data sources.

H Regression model equations

Negative binomial: climate stress on protest

$$
\begin{aligned}
&Y_i \sim \frac{\alpha_\epsilon}{\alpha_\epsilon + \lambda_i} \\
&\text{where } \lambda_i = exp(\theta_i) * log(popcount)_i \\
&\text{and, where } \theta_i = \Delta temp_i + \Delta precip_i + \Delta temp_i * \Delta precip_i
\end{aligned}
\tag{1}
$$

Where Y_i is the number of protests in a third-level administrative region from January to June of 2011 and $\Delta temp_i$ and $\Delta precip_i$ are climate variables of interest - the variables here being changes in average precipitation during the drought period of 2006 to 2010 compared to the mean for the remainder of the available time period: 1900 to 2005. We also include an interaction of the two in some models. This linear model θ_i is then paired with an exposure variable $log(popcount)_i$ in λ_i, which is the exponential of the product of the two. We then adjust for overdispersion in the final stage by adding α_ϵ.

Fixed effects OLS: Climate stress on light intensity change

$$
Y_{ijt} = \Delta temp_{ijt-1} + \Delta precip_{ijt-1} + \Delta temp_{ijt-1} * \Delta precip_{ijt-1} + \alpha_i + \nu_{jt} + \epsilon_{ijt} \tag{2}
$$

Where Y_{ijt} represents our nighttime lights dependent variable and $\Delta temp_{ijt-1}$ and $\Delta precip_{ijt-1}$ represent our climatic variables of interest. We measure our annual climatic variables with a one period lag, as changes in nighttime lights are unlikely to occur contemporaneously with drought stress. We are interested in the marginal effects associated with the interaction of these two climatic variables. Further, because place-specific factors could bias our estimate of the effect of changes in drought on nighttime light intensity, we include α_i, which represents third-level administrative district. Finally, we include first-level administrative district-year fixed effects (ν_{jt}) to flexibly account for any broader geographic time trends that might bias our coefficient estimates.

Negative binomial: light intensity change on protest

$$Y_i \sim \frac{\alpha_\epsilon}{\alpha_\epsilon + \lambda_i}$$
$$\text{where } \lambda_i = exp(\theta_i) * log(popcount)_i \tag{3}$$
$$\text{and, where } \theta_i = \Delta NightLights_i + GasFlares_i + \Delta NightLights_i * GasFlares_i$$

The negative binomial in Equation 3 is identical to 1 apart from the independent variables in the linear stage. Here $\Delta NightLights_i$ represents the change in average light intensity in a third-level administrative region from 2005 to 2010 and $GasFlares_i$ is a dichotomous indicator of whether a given region has gas flares as a result of oil production.

I Validation of nighttime lights in Turkey

As mentioned in the main article, while Syria's government does not provide information on per capita gross regional product or time series data on population density that could be used to validate the nighttime lights measure as a proxy for population density, neighboring Turkey has more reliable data. Time-series data on both population density and per capita gross regional product at the province level[7] is available from Turkey's National Statistical Institute - the former from 2000 to 2007, the latter from 1992 to 2001 and 2004 to 2007 (Turkish Statistical Institute, 2016). Moreover, Turkey lacks the two issues that hampered validation of the indicator in Syria using census data: there are no regions where the average light intensity approaches the maximum and there are no gas flares.

As a first step and what we record in the main article, we correlate both per capita gross regional product and population density with average nighttime lights in a given first level administrative region for all available years. We obtain a 0.44 correlation with per capita GRP and a 0.88 correlation with population density. We visualize both relationships in Figure 7. In the interest of clarity, as data-points across time from the same province cluster in one space, we only use data from 2007 – the visualization is not dependent on the year. Additional panels are included excluding Istanbul for both correlations to better represent the relationship between the remaining observations – the overall correlation in both cases is unchanged.

While these correlations are strongly suggestive that nighttime lights are a reflection of population density and are simply associated, but not determined by per capita wealth in a region, it is worth conducting a more rigorous analysis. In order to do so, we conduct several OLS regression

[7] There are 81 total provinces in Turkey

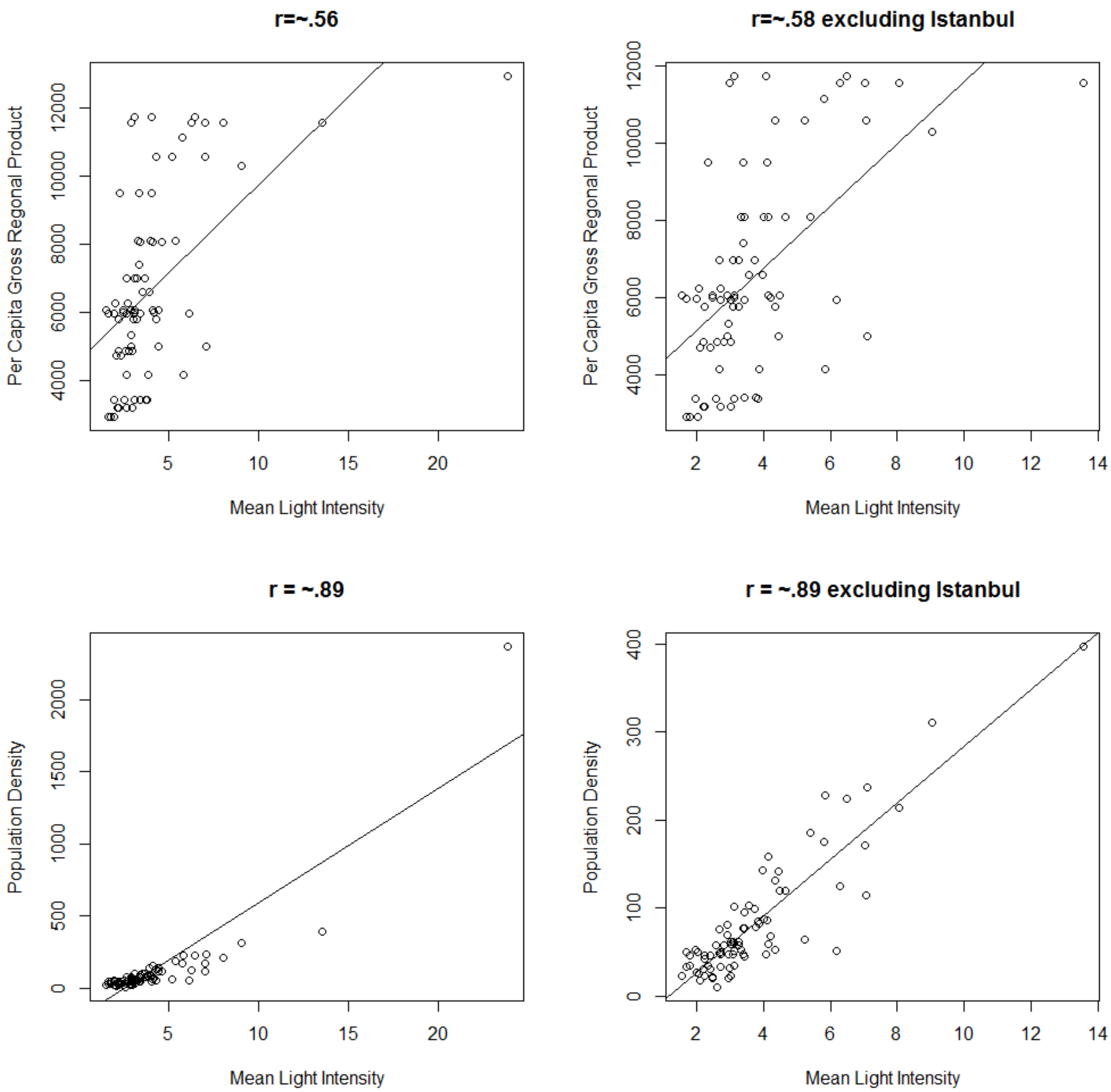

Figure 7: Correlations of Nighttime Lights, Wealth and Population in 2007

analyses to explore which of the two variables is most predictive of nighttime light intensity. To assess this relative predictive power, we standardize the coefficients for both population density and per capita gross regional product by transforming each into z-scores to measure the distance of each value, in standard deviations, from the mean (i.e. Bring, 1994). The technique allows for a comparative assessment of the relative predictive power of both population density and per capita regional income on nighttime lights.

Table 12: OLS Regression of Population and Wealth on Nighttime Lights in Turkey

	DV: Nighttime Lights			
	(1)	(2)	(3)	(4)
Population Density	0.009*	0.009*	2.133*	0.772
	(0.000)	(0.000)	(0.055)	(0.419)
Per Capita Gross Regional Product		0.000*	0.381*	-0.060
		(0.000)	(0.054)	(0.063)
Province Fixed Effects	No	No	No	Yes
Year Fixed Effects	No	No	No	Yes
Constant	2.385*	1.851*	3.290*	3.817*
	(0.052)	(0.105)	(0.057)	(0.201)
R-Squared	0.768	0.796	0.796	0.974
Number of Observations	648	468	468	468

Note: $^*p<0.05$. Models 3 and 4 employ standardized coefficients.

Results from OLS regression models are shown on Table 12. Models 1 and 2 report unstandardized coefficients. Most notable from these models is the relatively small increase in R-squared from 0.77 to 0.8 when adding per capita GRP as a coefficient, suggesting that the variable explains little additional variation when population density is already accounted for. Model 3 replicates model 2 using standardized coefficients. As evidence, relative changes in population density have an approximately 5.5 times greater effect on mean nighttime light intensity than per capita gross regional product. Again, this finding suggests that population density is far better at predicting nighttime lights than per capita income. Finally, we add year and province level fixed effects to the model, taking advantage of the panel specification of the data to account for potential omitted variable bias. While there is a decreased effect of population density, it remains positive and stronger than per capita GRP's effect in model 4 (and significant at $p<0.1$). On the other hand, per capita GRP is not significant in model 4 and changes signs to be negative. Put together, evidence from

Turkey strongly suggests that nighttime lights reflect population density in a particular region and have a substantially less influential relationship with per capita wealth.

J Validation of nighttime lights in Syria

We utilize Syrian census statistics from 1994 and 2004 on governorate level population density to assess the link between changes in population density and changes in nighttime light intensity. We expect that changes in population density between 1994 and 2004 are positively correlated to changes in average nighttime light intensity in a governorate. To derive population density, we divide the total population by the area of each governorate. The densities are compared to the average raw change in nighttime light intensity for a given region from 1994 to 2004. Two different satellite renderings are available for both years for nighttime lights: F10 and F12 for 1994 and F15 and F16 for 2004. We use the most up-to-date in each case. Understandably, it is possible that systematic bias is introduced as a result of using different satellites across time (Pandey et al., 2017). However, we would expect that such bias would make it more difficult for us to find a relationship between nighttime lights and population density as it would misrepresent populated areas on the nighttime lights maps.

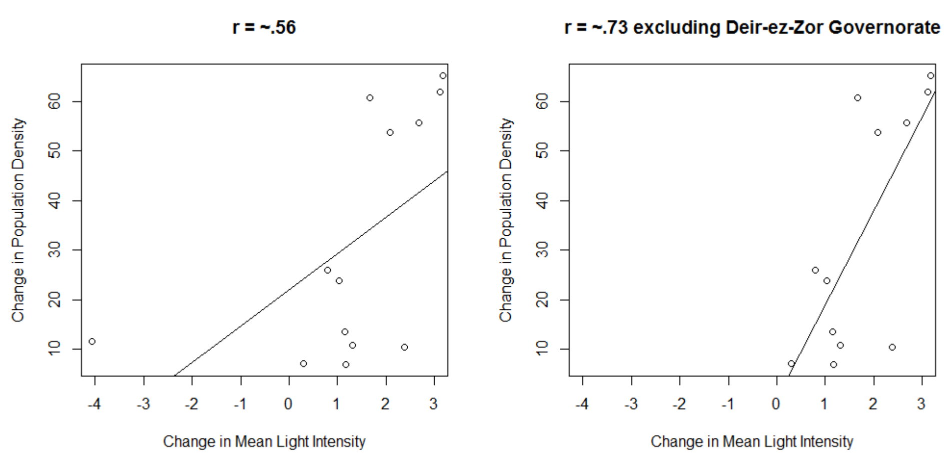

Figure 8: Changes in Population Density and Nighttime Light Intensity from 1994 to 2004

Figures 8 and 9 visualize the relationship between changes in population density and nighttime

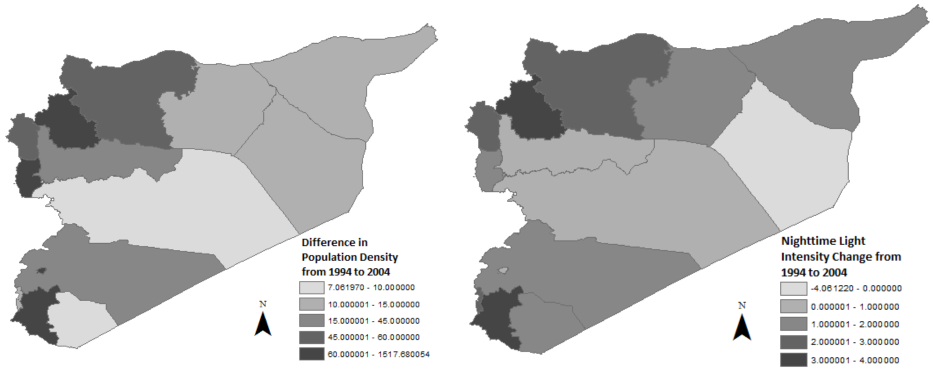

Figure 9: Map of Changes in Population Density and Nighttime Light Intensity from 1994 to 2004

lights. Due to the ceiling effect in measuring light intensity for the city of Damascus (already near the maximum 63 in 1994), we exclude Damascus Governorate from the validation analysis. Including the 13 remaining Syria governorates produces a 0.56 correlation between changes in population density and changes in nighttime lights. Notable in this correlation is the negative change in Deir ez-Zor governorate. The reason for the change is likely associated with a decline in oil production and a concordant decline in gas flares, which are visible on nighttime lights imagery, in the region. The effect of gas flares and how they are accounted for are discussed further in appendix J. We deal with the outlier in two ways. First, we exclude Deir ez-Zor altogether, improving the correlation between population density and light intensity to 0.73. Second we generate 10 kilometer buffers around locations of gas flares, obtained from Elvidge et al. (2009) and remove them from the maps we use to generate averages, obtaining a correlation of 0.67 for the changes in nighttime lights and population. Taken together, we can be confident that nighttime lights are an effective proxy for population density.

K Iraqi refugee settlement patterns and climatic stress

A potential challenge to our findings is the arrival and presence of up to 1.5 million Iraqi refugees in Syria from 2004 until the beginning of the conflict. The influx of Iraqi refugees challenges our analysis in two ways. First, Iraqi refugees could have observed the drought was taking place and sorted into areas not experiencing drought, giving the impression that greater population change in non-drought affected regions of Syria was driven by internal migration, rather than external migration. Second, Iraqi refugees could have been the underlying drivers of increased protests against the Syrian government, rather than internal migrants. We address both concerns in this section.

First, we do not think that the effect of climate on changes in population density can be explained by sorting by Iraqi migrants, as it does not appear that Iraqi migrants considered local economic conditions in deciding where to move. Instead, Iraqi refugees prioritized access to the UNHCR, the Iraqi embassy, existing Iraqi communities and even the location of bus and taxi routes to Baghdad (al Khalidi et al., 2007). As a result, around 80% of Iraqi refugees settled around Damascus (United Nations High Committee on Refugees, 2008). Even if variation in population density around Damascus was driven by Iraqi migrants, we note that our analysis of population changes mostly excludes Damascus and surrounding areas because of saturation in nighttime lights data prevents us from observing variation. Thus, we can be relatively confident that sorting did not take place among Iraqi migrants based on the drought and that our analysis linking climatic stress to population changes largely excludes Iraqi migrants.

We also do not think that Iraqi migrants were the catalysts or in any way influenced protests during the 2011 uprising. The migration of Iraqis did strain local housing markets, prices for food and household goods and created tension between the mostly Shi'a migrants and local Sunnis (Leenders, 2008). Thus, there is a possibility that some regions of Syria experiencing in-migration saw more protests during the uprising due to the presence of Iraqi migrants rather than internal migrants. We also do not believe this is the case. First, referring to findings in both the main article and earlier in this appendix, we believe the nature of the protests and their geographic distribution reflect a demographic boost in confidence for excluded Sunni Arabs from in-migration rather than anti-migrant backlash. It is unlikely that Iraqi migrants, mostly Shi'a Muslims from another country, would have in any way identified with the grievances of local Sunni Muslims and thus provided such a demographic boost to the demands that Syrian Sunni Arabs made during the uprising.

Finally, given that most Iraqis settled in the Rural Damascus governorate, our use of use of first-level administrative fixed effects likely accounts for this omitted variable, along with any other special characteristics of the governorate, in each of our statistical models. We find consistent effects across all governorates for our models, which we would not see had there been undue influence of Iraqi migrants in one part of the country.

L Deir ez-Zor, gas flares and light intensity

A puzzling outlier in the validation of the correlation between changes in population density and changes in nighttime lights from 1994 to 2004 was the governorate of Deir ez-Zor. While the governorate of Deir ez-Zor's population density increased slightly, its mean light intensity from 1994 to 2004 declined considerably from 1994 to 2004. While this appears to be a puzzling outcome that calls the validity of our measure into question, we believe the outlier comes as a result of a unique feature of Deir ez-Zor province: its oil production and refinery output. Before the civil war, Deir ez-Zor province accounted for up to 70% of Syria's domestic oil and natural gas production. However, from a production peak in 1996, petroleum production had declined significantly from 1997 into the 2000s, going from 590,000 barrels per day in 1996 to 376,000 barrels per day in 2006 (OpenOil, 2013).

The main reason why we would expect a decline in oil and natural gas production to also affect nighttime lights is the presence of natural gas flares at oil production sites. Gas flaring generally occurs when crude oil is extracted, but the natural gas that is concentrated in the crude cannot be efficiently extracted and is instead burned off on site. The flares from the burn-off are visible on satellite images of nighttime lights (Elvidge et al., 2009). It follows that a decline in oil production would also lead to a decline in gas flares and likely explains why Deir ez-Zor province is anomalous in our validation test. Figure 10 shows a measure of aggregate gas flares from 1994 and 2009 developed by Elvidge et al. (2009) for Syria.[8] Of the 51 points of gas flares on the map, 27 are in Deir ez-Zor province, with the rest scattered across Homs, Ar-Raqqa and Al-Hasakeh provinces - confirming that most of the light change as a result of gas flares would take place in

[8] Available here: https://ngdc.noaa.gov/eog/interest/gas_flares_countries_shapefiles.html.

the Deir ez-Zor governorate. A total of 15 third-level administrative regions contain some form of gas flares.[9]

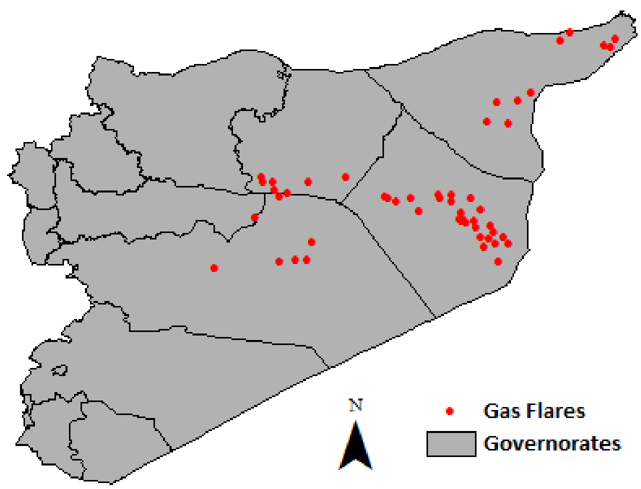

Figure 10: Aggregate Gas Flare coverage in Syria from 1994 to 2009 (Elvidge et al., 2009)

The presence of features such as gas flares could conceivably affect the accuracy of our estimation of population changes using nighttime lights data. Specifically, were a decline in nighttime lights as a result of a decline of gas-flaring occur at the same time as climate stress on a region, we may capture such a decline as a decline of population, rather than concordant with oil production. Figure 11 overlays an image of change in nighttime light intensity from 1994 to 2004 and gas flare locations showing substantial decreases in light intensity across points associated with gas flares, but especially in Deir ez-Zor province. Notably, there are also increases in the same time period that overlap with gas flares, showing a natural fluctuation in the location of domestic production, but also the possibility that change in nighttime lights may be driven by changes in oil production.

We believe that third level and first level by year administrative fixed effects sufficiently account

[9] Al-Malikeyyeh, Basira, Deir ez-Zor, Hajin, Hole, Jawadiyah, Mansura, Muhasan, Qahtaniyyeh, Sabka, Shadadah, Sokhneh, Sur, Tadmor and Thiban.

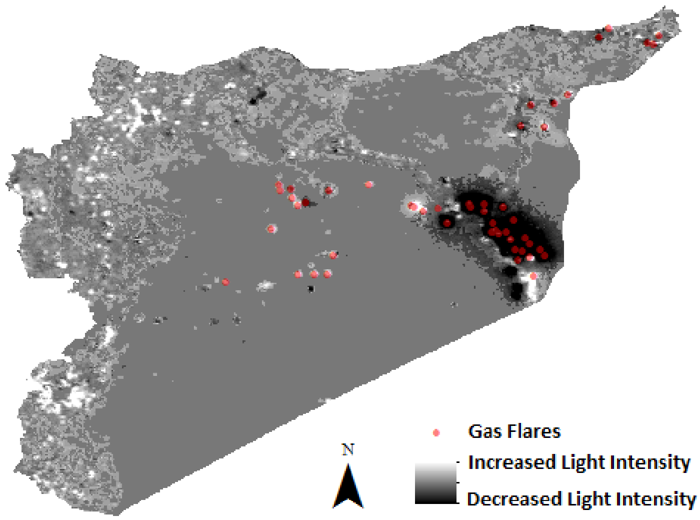

Figure 11: Change in Nighttime Lights from 1994 to 2004 overlapped with Gas Flares

for the role of gas flares in our regression of climate stress on nighttime light intensity. However, in order to insure that the effect of climate stress on nighttime lights we find is not contingent on gas flare measures, we utilize an interaction of a dichotomous variable of third-level administrative districts that have gas flares with year fixed-effects. This is intended to account for temporal variation in nighttime light intensity in third-level administrative regions that exert gas flares. The results of this analysis are shown in Table 13 and Figure 12. There is virtually no substantive differences between the results presented in the main article and those when adding the fixed effect. Lacking fixed effects at the third-administrative level, more effort was made to account for gas flares in the regression of nighttime light intensity change on protests, with those results presented in the main article.

Table 13: Fixed Effects OLS Regression of Climatic Stress on Nighttime Lights

	DV: Nighttime Lights		
	All Years	Pre-Drought	Drought
	(1)	(2)	(3)
Δ Mean Precipitation (cms.)	0.376	0.294	2.034
	(0.458)	(0.322)	(1.334)
Δ Mean Temperature (degrees)	0.001	0.004	-0.025
	(0.024)	(0.020)	(0.045)
Δ Precip. $*$ Δ Temp.	0.026	0.021	0.106^{**}
	(0.025)	(0.022)	(0.046)
Third-Level Admin FE	Yes	Yes	Yes
First-Level Admin:Year FE	Yes	Yes	Yes
Gas Flares:Year FE	Yes	Yes	Yes
Observations	4,753	3,433	1,320
R^2	0.970	0.978	0.988
Adjusted R^2	0.967	0.974	0.984
Residual Std. Error	1.652	1.361	1.301

Note: *p<0.05. Standard errors are multiway clustered on second-level administrative districts and years. We exclude Damascus, Arbin, Hajar Aswad and Jaramana nawahi.

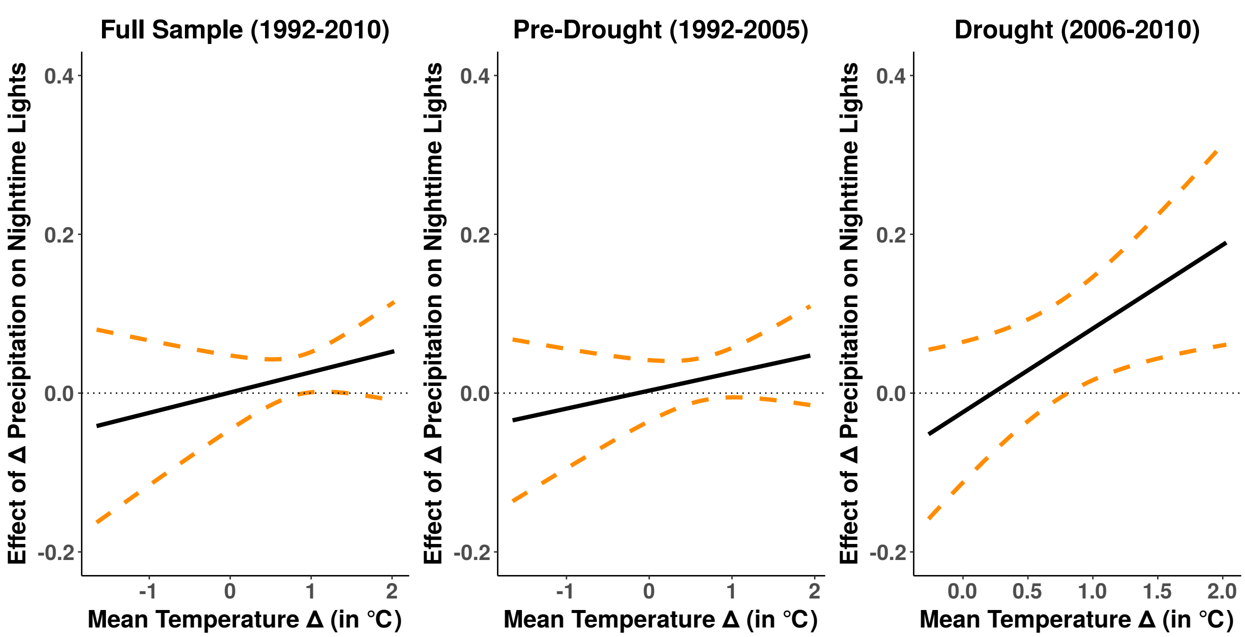

Figure 12: Effect of Annual Indicators of Drought on Nighttime Light Intensity

M Differences in Light Intensity using only F16 satellite

Pandey et al. (2017) point out that nighttime lights data taken from across multiple satellite readings may produced biased results, especially against illumination in more rural areas. This is not a concern for models where we use time-series data to look at the effect of climatic factors on changes in light intensity as we utilize year fixed effects, which should account for idiosyncrasies across individual years of nighttime lights data. It is, however, a concern for the models on Table 3 of the main article, which utilize a change variable in nighttime light intensity from 2005 to 2010. This change spans two satellites detecting light intensity, F16 for 2005 and F18 for 2010.

Additionally, as the DMSP-OLS satellite is designed to scan clouds during both day and night, light detection is generally set at the highest possible setting to detect moonlit clouds. This strategy reduces the ability to detect areas with high levels of light emission, such as cities, topping out at the highest possible light intensity value of 63 (Hsu et al., 2015). We can account for both of these issues by employing radiance-calibrated data that account for saturation by collecting data at multiple gain settings (Elvidge et al., 1999). [10] The radiance calibrated images are available for a limited number of years, but are fortuitously available for 2006 and 2010, coming from the same satellite (F16). By allowing for unsaturated imagery to be explored, we can then include four nawahi that were previously excluded from analysis in Table 4 of the main article: Damascus, Arbin, Hajar Aswad and Jaramana.

Results are presented on Table 14. The results are largely consistent with the main article, showing that Sunni Arab areas that received greater in-migration were more likely to experience protests; significant at a 0.1 level. To an extent, this confirms that our results in Table 4 were

[10] The product is freely available here: https://ngdc.noaa.gov/eog/dmsp/download_radcal.html.

Table 14: Negative Binomial Regression on Protests in Syrian Nawahi in Jan. to July 2011 using Radiance-Calibrated Imagery

	(1)	(2)	(3)	(4)	(5)	(6)
Mean Δ Night Light Intensity (2010 from 2006)	0.926	0.925	1.019	1.006	0.156	0.472
	(0.108)	(0.083)	(0.069)	(0.054)	(0.203)	(0.201)
Sunni Arab Settlement (Izady, 2013)			1.251	1.081	65.016	6.256
			(1.020)	(0.801)	(181.787)	(10.216)
Δ Nighttime Lights * Sunni					6.650	2.152
					(8.730)	(0.948)
Governorate-Level Fixed Effects	No	Yes	No	Yes	No	Yes
De Juan and Bank (2015) Controls	No	No	Yes	Yes	Yes	Yes
Constant	0.000*	0.000*	0.000*	0.000*	0.000*	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
α	16.195***	9.860***	10.982***	5.965***	10.673***	5.868***
	(3.347)	(1.577)	(3.127)	(1.358)	(2.913)	(1.369)
Nawahi	268	268	259	259	259	259

Note: *p<0.05. Incidence Rate Ratios reported in lieu of coefficients. Logged population count held constant as exposure variable in all models. Standard errors clustered at second administrative level. Higher levels of school enrollment, greater distance from the border and a greater shareof urban population are consistent predictors of more protest among De Juan and Bank's (2015). control variables.

neither driven by excluding or otherwise limiting analysis to areas without saturation and or our use of interannual data across two satellites.

N Climatic Stress and Agricultural Outcomes

While there is generally consensus, according to Ide (2018), that at least some decline in economic well-being in Syria can be explained by drought, Selby et al. (2017) question the extent to which mismanagement by the Syrian state and not climatic factors were responsible for negative economic outcomes. De Chatel (2014) goes further and states that focusing on climatic factors takes responsibility for the drought and the subsequent conflict away from the state. The goal of this section is to establish that climatic factors contributed to negative agricultural outcomes. A relationship between the role of meteorological drought and climatic stress in negative agricultural outcomes underpins the link between climatic stress and out-migration that we show in the main article. Finding such a relationship would strengthen the existing link between climatic factors and protest by providing another intervening variable in the form of negative agricultural outcomes to connect climatic stress to migration and subsequent protests. Of note, this section does not seek to disprove that government mismanagement or other manmade factors contributed to the negative agricultural outcomes in Syria prior to the uprising. Were we to find a significant association between meteorological factors and agricultural outcomes, it would simply show that climatic factors *also* contributed to agricultural outcomes.

We assess the link by looking at differences in the Normalized Difference Vegetation Index (NDVI) in Syria between pre-drought and drought time periods.[11] Like our other models, we confine our measure of NDVI to cropland, measuring fluctuation in agricultural vegetation. We measure NDVI using annual averages extracted from the Landsat 7 satellite's NDVI spectrum, which captures the degree to which an area reflects green vegetation when surveyed by the Landsat

[11] NDVI utilizes the differences in light reflectance patterns of near-infrared and visible light to assess changes in the vegetation of cropland.

7 satellite satellite. We use two growing season difference measures: one subtracts the average NDVI from 1999 to 2005 from the NDVI from 2006 to 2010, to assess the change in NDVI between drought and non-drought periods.[12] The other subtracts average NDVI from 1999 to 2005 from NDVI in 2010 – the final full year before conflict outbreak – to assess the broad agricultural impact of the meteorological drought in its final year.[13] The models we run are largely identical to those on Table 1 of the main paper in terms of clustering standard errors and fixed effects. We opt for an OLS model as average difference in NDVI is normally distributed.

Table 15: OLS Regression on Difference in NDVI (2006-2010 minus 2001-2005)

	(1)	(2)	(3)	(4)
Δ Mean Temperature (0.01 degs.)	-0.000*	-0.001*	0.000	-0.001
(2006-2010 from 2005-1900)	(0.000)	(0.000)	(0.000)	(0.000)
Δ Mean Precipitation (cms.)	-0.001	0.006*	0.000	0.008*
(2006-2010 from 2005-1900)	(0.001)	(0.002)	(0.001)	(0.004)
Δ Precip. $*$ Δ Temp.		-0.000*		-0.000
		(0.000)		(0.000)
Governorate (First-Level) Fixed Effects	No	No	Yes	Yes
Constant	-0.011	0.050*	-0.055*	0.016
	(0.012)	(0.022)	(0.018)	(0.041)
R-Squared	0.119	0.141	0.406	0.416
Nawahi	268	268	268	268

Note: *p<0.05. Standard errors clustered at second administrative level.

Results from the 2006-2010 NDVI differences are presented on Table 15, while the 2010 differences are shown on Table 16. Looking at across both measures of NDVI, negative changes

12

$$\left(\sum_{2006}^{2010}\frac{NearIR-Visible}{NearIR+Visible}\right)-\left(\sum_{1999}^{2005}\frac{NearIR-Visible}{NearIR+Visible}\right) \tag{4}$$

13

$$\left(\frac{NearIR-Visible}{NearIR+Visible}\right)_{2010}-\left(\sum_{1999}^{2005}\frac{NearIR-Visible}{NearIR+Visible}\right) \tag{5}$$

Table 16: OLS Regression on Difference in NDVI (2010 minus 2001-2005)

	(1)	(2)	(3)	(4)
Mean Temperature Change (0.01 degs.)	-0.001*	-0.002*	0.000	0.000
(2006-2010 from 2005-1900)	(0.000)	(0.000)	(0.000)	(0.001)
Mean Precipitation Change (cms.)	-0.002	0.012*	-0.002	0.002
(2006-2010 from 2005-1900)	(0.001)	(0.004)	(0.001)	(0.008)
Δ Precip. $*$ Δ Temp.		-0.000*		-0.000
		(0.000)		(0.000)
Governorate (First-Level) Fixed Effects	No	No	Yes	Yes
Constant	0.045*	0.165*	-0.081*	-0.051
	(0.022)	(0.045)	(0.031)	(0.070)
R-Squared	0.246	0.283	0.490	0.489
Nawahi	268	268	268	268

Note: *p$<$0.05. Standard errors clustered at second administrative level.

in precipitation are associated with corresponding negative changes in NDVI, whether looking at the whole drought period compared to pre-drought or at 2010 compared to 1999 to 2005. Temperature has an inconsistent, yet negative effect on NDVI, with higher temperatures leading to decreases in NDVI. There is also evidence of a joint effect of temperature and precipitation, at least when looking at 1999-2005 differenced from 2001-2005. The effect of precipitation decrease on NDVI decrease is stronger at higher temperatures, consistent with expectations for meteorological drought. The R-squared values also tell a part of the story – temperature and precipitation anomalies explain approximately 14% of the deviation in all Syrian agricultural outcomes from 1999-2005 to 2006-2010 and over 28% for the deviation of 2010 from the pre-drought period. Meteorological factors not only had a significant, but a substantial role in agricultural outcomes throughout the country.

Put together, while not our primary focus, these results show that agricultural outcomes were negatively affected by climatic stress in the period preceding the Syrian Civil War, confirming an intervening factor that would then affect subsequent migration out of areas experiencing negative outcomes.

O In-Migration and Protest in Kurdish Regions

Selby (2018) highlights that migration from Hasakeh province at the time of the Syrian drought took place among Syrian Kurds, as well as Sunni Arabs. Kurdish areas also experienced protests at the start of the Syrian uprising, albeit, based on our analysis from Appendix C, Kurdish protesters generally refrained from calling for the fall of the regime, even after Sunni protesters began to do so in August of 2011. Thus, it is worthwhile to examine whether the association of linkages between Sunni Arabs in one part of Syria to another and protest frequency that we observed in our main article extends to Kurds.

We code whether a region had Kurdish areas based on the Syria Town Database (Khaddour and Mazur, 2018), which identifies the sectarian and ethnic make-up of all populated areas in Syria; we code any nahiya with Kurdish towns or cities as having a Kurdish population. There are 26 total Kurdish nawahi. Because 14 of these nawahi also contain populations of Sunni Arabs, we must adopt a three-way interaction, looking at the effect of change in nighttime lights across areas with Sunni Arabs, Kurds and areas with both Sunni Arabs and Kurds. The models are otherwise unchanged from models 5 and 6 in Table 3 of the main article.

Table 17 shows results from the three-way interaction of Kurdish settlements and Sunni Arab settlements with changes in nighttime light intensity. While the first model shows that Kurdish, as well as Sunni Arab, areas were more likely to experience protests given in-migration, the effect is not consistent for Kurdish areas after adding fixed effects.[14] Of note, areas with Sunni Arabs and Kurds that saw in-migration were consistently less likely to experience protests, bolstering our claim that in-migration only facilitated a greater likelihood additional protests when migrating

[14]The conditional effect of Sunni Arab settlement and increase in nighttime lights on protests remains significant at $p<0.1$.

Table 17: Negative Binomial Regression on Protests in Syrian Nawahi in Jan. to July 2011

	(1)	(2)
Mean Change in Night Light Intensity	0.534*	0.684
	(0.121)	(0.183)
Sunni Arab Settlement (Izady, 2013)	0.118	0.110
	(0.207)	(0.247)
Δ Nighttime Lights * Sunni Arabs	1.640*	1.679
	(0.390)	(0.466)
Kurdish Settlement (Khaddour and Mazur, 2018)	0.000*	0.016
	(0.000)	(0.086)
Δ Nighttime Lights * Kurds	7.443*	3.494
	(7.594)	(3.103)
Sunni Arab and Kurdish Settlement	4.73e+06*	1496.826
	(3.18e+07)	(8892.830)
Δ Nighttime Lights * Kurds * Sunni Arabs	0.036**	0.145*
	(0.042)	(0.139)
Governorate-Level Fixed Effects	No	Yes
De Juan and Bank (2015) Controls	Yes	Yes
Constant	0.000*	0.000*
	(0.000)	(0.000)
α	9.474*	5.351*
	(2.300)	(1.310)
Nawahi	255	255

Note: *p<0.05. Incidence Rate Ratios reported in lieu of coefficients. Logged population count held constant count held constant as exposure variable in all models. Damascus, Arbin, Hajar Aswad and Jaramana nawahi excluded from analysis because average nighttime lights approached or were at maximum detectable levels at 63 in 2005. Standard errors clustered at second administrative level.

Sunni Arabs had a clear link to receiving regions.

P Two-Stage Model Linking Climate, Migration and Protest

To bolster our analysis linking climatic stress to migration and then to protest, we include a two-stage model that factors the uncertainty from the relationship between climatic stress and migration into our model linking migration and protest. The model combines Tables 1 and 4 from the main article into a two-stage process. The first stage is an OLS model with either change in nighttime light intensity in a given sub-district or change in nighttime light intensity in only Sunni sub-districts as the outcome variables. The independent variables in this model are the deviations in temperature and precipitation and their interaction as well as governorate level fixed effects. We then take the predicted values of nighttime lights change in all areas and nighttime lights changes in just Sunni areas and substitute them into a model predicting protest count or protest incidence. The technique is a modified version of the two-stage method used by Koubi et al. (2012), although as our data is cross-sectional we do not use their exact fixed effects vector decomposition technique.

In effect, with our two stage design, climatic stress, in the form of mean temperature and precipitation changes and their interaction functions as an instrumental variable. Instrumental variables are intended to proxy for random assignment of a predictor that takes away concerns about endogeneity. While climatic factors have extensively been utilized as instruments (i.e. Ritter and Conrad, 2016; Miguel et al., 2004), we must still ensure that we satisfy two assumptions about the instruments themselves: relevance and validity. In effect, instruments should be predictive of the independent variables in a first stage regression, mirroring some random assignment (relevance) and should not be directly predict variation in the dependent variable through any other factor, observed or unobserved (validity) (Greene, 2003).

Table 18 presents results from our first stage models and also serves as a test of the relevance

Table 18: First Stage OLS Regression on Protests in Syrian Nawahi in Jan. to July 2011

	Dependent Variable:	
	Nighttime Lights (2010-2005)	Nighttime Lights (2010-2005)*Sunni
Δ Mean Temperature (0.01 degs.)	-0.218*	-0.134
(2006-2010 from 2005-1900)	(0.066)	(0.094)
Δ Mean Precipitation (cms.)	1.606*	0.878
(2006-2010 from 2005-1900)	(0.621)	(0.880)
Δ Precip. $*$ Δ Temp.	-0.015*	-0.006
	(0.006)	(0.008)
Governorate (First-Level) Fixed Effects	Yes	Yes
Constant	25.899**	18.197
	(7.606)	(10.270)
R-Squared	0.194	0.147
F-Test of instruments	4.68	1.44
F-Test p-value	0.005	0.241
Nawahi	263	256

Note: *p<0.05. Standard errors clustered at second administrative level.

assumption. When the dependent variable is change in nighttime lights in all sub-districts, mean change in temperature and precipitation and jointly significant and point to the same link between climate and migration presented in Table 3 of the main article: increased precipitation has a positive effect on changes in nighttime light intensity, although the effect is less positive at lower temperature values. The F-test of instruments for this first model shows their cumulative significance and the instruments' relevance. The instruments in the second model, with changes in nighttime light intensity in only Sunni sub-districts as the dependent variable is not significant. However, this may have more to do with setting the values of non-Sunni sub-districts to zero – the instruments are relevant when only looking at Sunni sub-districts. Thus, we can broadly posit that in this cross sectional specification, our instruments are relevant.

We then substitute predicted values of nighttime light intensity and nighttime light intensity in Sunni areas into three specifications with protests as an outcome shown on Table 19. The first

Table 19: Second Stage Regression on Protests in Syrian Nawahi in Jan. to July 2011

	Dependent Variable:		
	Protest Count	Protest Count	Protest Incidence
Source:	ICEWS	LexisNexis	ICEWS
Specification:	Neg. Binomial	Neg. Binomial	Logit
Predicted Change in Night Light Intensity	8.127*	2.244*	4.618*
	(6.815)	(0.749)	(2.752)
Sunni Arab Settlement (Izady, 2013)	1.083	1.819	3.177
	(0.852)	(0.629)	(2.333)
Predicted Δ Nighttime Lights * Sunni	0.244	0.554	0.309
	(0.201)	(0.213)	(0.188)
Governorate-Level Fixed Effects	Yes	Yes	Yes
De Juan and Bank (2015) Controls	Yes	Yes	Yes
Constant	0.000***	0.001	0.000*
	(0.000)	(0.005)	(0.000)
α	5.638***	1.326	
	(1.401)	(0.332)	
Nawahi	256	256	246

Note: *p<0.05. Incidence Rate Ratios/Odds Ratios reported in lieu of coefficients. Logged population count held constant as exposure variable in all models. Damascus, Arbin, Hajar Aswad and Jaramana nawahi excluded from analysis because average nighttime lights approached or were at maximum detectable levels at 63 in 2005. Standard errors clustered at second administrative level.

model in this stage is a negative binomial with protest count from ICEWS as the outcome, the second is a negative binomial with protest count from LexisNexis as the outcome and the third is a logit with protest incidence from ICEWS as the outcome. The effects are consistent for all three. Change in nighttime light intensity has a positive effect on protest incidence when accounting for assignment of climatic stress in the first stage. The interaction term is significant at the 0.1 level in the first two models, indicating there remain differences between the effect of nighttime lights change on protests in Sunni and non-Sunni sub-districts. These are illustrated on Figure 13. The figure illustrates that the likelihood of protest in Sunni areas as a result of population change remains positive and at about the same magnitude as in the model in the main article. The main change is the direction, magnitude and significance of the effect of population change on protests in non-Sunni areas, which is now positive with an increase in nighttime light intensity producing up between two and eight additional protests in non-Sunni areas.

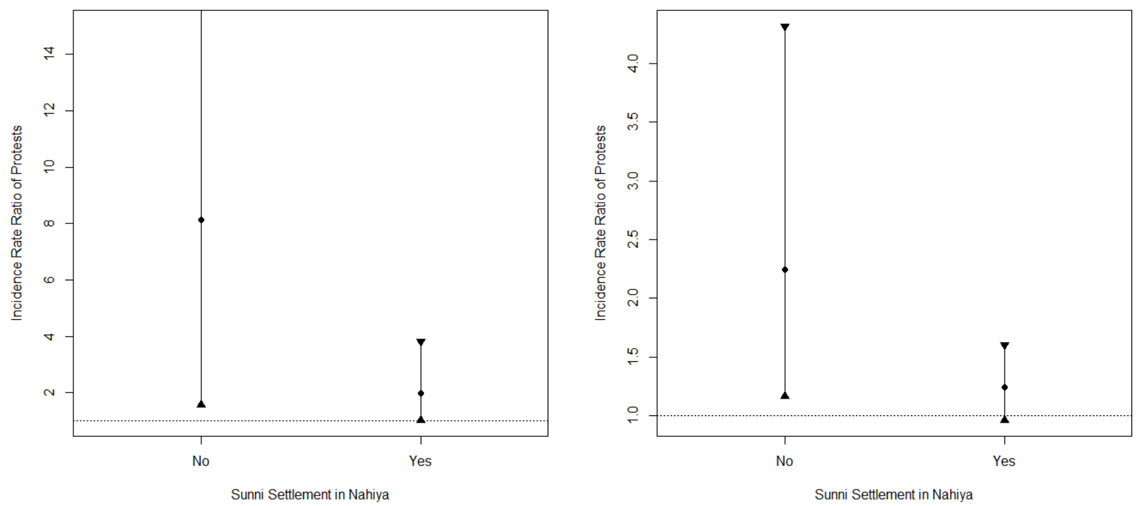

Figure 13: Effect of Change in Nighttime Light Intensity on Rate of Protest - Second Stage (ICEWS left, LexisNexis right)

While our two stage model's results reinforces our confidence regarding our findings in the main article, we remain concerned about the validity of our instruments. Specifically, while we find no reason to expect a direct positive effect of climatic stress on protests, there is a possibility of a direct negative effect, as shown on Table 1 in the main article. The results directly linking protests to climatic stress do not automatically violate the exclusion restriction; the assumption of excludability can hold as long as the effect is only through migration.

However, there is an alternative pathway for fewer protests in the form of loyalty to the regime. We cannot rule this possibility out and there is compelling evidence to think the mechanism was relevant in Syria. Specifically, Mazur (2018) finds that areas in the Northeast where Sunni tribes loyal to Assad's regime reside were less likely to protest during the uprising. It is possible that this loyalty was somehow bolstered by the regime's response to the drought, which could have provided aid through traditional patronage pathways. Thus, climatic stress could have directly decreased the likelihood of protest in the Northeast through the loyalty mechanism and not the migration measurement. Having presented this potential confound, we cannot say definitively whether it was the case or not. However, the possibility that the exclusion rule was violated is something that should be noted when evaluating the findings in this section.

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