International Journal of Public Opinion Research

doi:10.1093/ijpor/edaa019

Devotion at Sub-National Level: Ramadan, Nighttime Lights, and Religiosity in the Egyptian Governorates

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Abstract

This study aims to construct reliable measures of religiosity and to cross-validate survey-based measures in operationalization of this central variable. We obtain measures of sub-national religiosity in the Egyptian governorates from the Arab Barometer surveys using disaggregation and multilevel regression and post-stratification techniques. Then, we use satellite imagery to compare these measures to the intensity of nighttime lights during the holy month of Ramadan. Although not designed to be fully representative, the analysis reveals that survey data at the sub-national level can provide approximate measures when aggregated. These findings contribute to scholarship by introducing a novel measure of religiosity based on nighttime activity during Ramadan and by cross-validating the reliability of survey-based measures of aggregate religiosity.

Introduction

Religion informs political attitudes and is consequential for understanding political beliefs and preferences. Typically, personal religiosity is taken as the central marker of religion in empirical studies. However, no consensus has emerged about the conceptual boundaries and the measurement strategies over this concept. In this article, we aim to introduce reliable and cross-validated measures of aggregated religiosity at the sub-national level using survey responses and satellite imagery.

Conceptualization and measurement strategies of religiosity (Ciftci, Wuthrich, & Shamaileh, 2019; Jelen & Wilcox, 2002) are greatly shaped by the availability of survey

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data that has become abundant over time, including data offered by the World Values surveys, Gallup polls, Pew Global Research Attitudes surveys, and Arab Barometer (AB). With the abundance of data and the use of scientific polling techniques (Kuriakose & Robbins, 2016), this may very well be the best available option. Given the lack of formal data in the form of membership rosters of mosques or religious organizations, students of religion and politics will be well-advised to continue to exploit survey data. We do not intend to question the suitability of survey tools for measuring religiosity. Our main contention is that there are few, if any, attempts to cross-validate survey-based measurement strategies with alternative data in the existing literature.

Macro-level studies can increase confidence in the accuracy of these measures insofar as they can compare the validity of aggregated survey measures with census data or with institutional indicators that may predict religiosity at the country or sub-national levels. Census data about religious practices, unfortunately, is extremely rare, and correlates of aggregated religiosity at the country level, while informative, do not necessarily provide conceptual validation of survey data. Can we determine the reliability of aggregated survey-based measures of religiosity using alternative data sources where formal data about religious membership and participation are missing?

In this article, our goal is to identify alternative aggregated measures of religiosity and cross-validate survey-based approaches in operationalization of this central variable. To that end, we calculate the change in nighttime light intensity in Egyptian governorates during the month of Ramadan as reported by Visible Infrared Imaging Radiometer Suite (VIIRS) based on satellite imagery. We differ from studies using aggregated measures of religiosity from individual level survey data at the *national* level (Inglehart & Norris, 2004) by focusing our attention to the *subnational* level. Subnational units are presumably less heterogeneous than cross-national units and provide leverage in comparative studies by allowing the researchers to hold country-specific indicators constant while examining substantive questions according to the variation at the sub-national units (Leemann & Wasserfallen, 2017; Snyder, 2001).

In the next section, we provide a general discussion about the conceptualization of religion. Then, we examine the three waves of AB surveys conducted in Egypt. These surveys report sub-national identifiers and interview a sufficiently large number of respondents in Egyptian governorates in waves 2, 3, and 4. We take advantage of AB questions that capture the nuances in different dimensions of religiosity at the individual level including self-reported religiosity, prayer frequency, and Qur'an readership.[1] We obtain governorate level aggregate measures of religiosity from these items. While only nationally representative, AB surveys allow us to combine responses within each governorate to obtain a sufficiently large sample at the subnational level. This is also known as *disaggregation* and has been used in American politics and other research to overcome the small-n problem at the state level (Erikson, Wright, & McIver, 1993; Miller & Stokes, 1963).

In the fourth section, we derive estimates of subnational religiosity using multilevel regression and post-stratification (MrP) (Gelman & Little, 1997; Lax & Phillips, 2009; Park, Gelman, & Bafumi, 2004; Warshaw & Rodden, 2012). MrP allows estimation of sub-national opinion using a single nationally representative sample of as small as 1,000

[1]Technically, the last variable is daily engagement in the Qur'an either by reading or listening to it. This design controls for the fact that some respondents are not literate and may not be able to read the Qur'an so they instead listen to it. However, we use readership in the manuscript for the sake of simplicity.

respondents and provides more accurate estimates than disaggregation. We run MrP models to obtain different estimates of sub-national-level religiosity and compare these to the measures we obtained with disaggregation.

In the fifth section of the article, a unique measure of sub-national religiosity is introduced, that is, the aggregate religiosity calculated from the nighttime lights data in Egypt's governorates during the holy month of Ramadan. We expect to observe an increase in the intensity of nighttime lights during Ramadan compared to the preceding month (and a decrease in the succeeding month) controlling for overall socio-economic development. We choose Egypt and Ramadan nights for several reasons. First, Egypt is a case that gives us significant variation in the level of religiosity given its long history of modernization and contentious relations between Islamist actors and the state. Second, Egypt is one of the countries that has been surveyed consistently within the last decade by polling organizations. Finally, there are macro-level data about various socio-economic indicators at the subnational level in Egyptian governorates based on extensive information available through the Central Agency for Public Mobilization and Statistics (CAPMAS) and other databases. As for Ramadan, it is a special time for religious observance where both personal (fasting and spiritual cleansing) and communal (participation in prayers and Ramadan meals) aspects of religiosity can be observed. Particularly, several rituals performed after sunset are indicative of increased activity at nighttime during Ramadan. These activities include the *iftar* (Ramadan dinner), *sahur* (night meal), and *taraweeh* (additional prayer following the *isha* [night] prayer).

After introducing the nighttime lights method, we compare aggregated religiosity calculated from Ramadan lights to the survey-based measures obtained from disaggregation and MrP. The analysis reveals the reliability of survey-based measures, with the disaggregation method achieving a slight edge. Controlling for the socio-economic indicators at the sub-national level, measures of religiosity based on nighttime lights have a strong positive correlation with survey-based measures. These results are evidence of the relative reliability of surveys and present cross-validation of the religiosity measures employed in survey research at the sub-national level.

Religiosity: An Essentially Contested Concept

Since measurement at the micro level is foundational for the aggregated measures of religiosity, it is important to examine the survey questions on various forms of piety. Studies focusing on empirical measures of religion in MENA employ four primary strategies at the individual level: (a) self-reported religiosity; (b) self-reported religious behavior; (c) religious worldview; and (d) indirect measures from various survey questions. The first and most straightforward solution is to ask respondents to categorize themselves on a scale from religious to not religious. The second strategy relies on behaviors that are associated with being religious, which in the case of Islam generally relate to the five pillars. In this vein, the two most commonly used tools to operationalize religiosity are mosque attendance and daily prayer, with special emphasis placed on prayer since it is not costly, more widely available to certain members of the faith, and a strong marker of religiosity (see Pew Research Center, 2012). However, an alternative behavioral measure of religiosity for Muslims is frequency of engaging with the Qur'an, whether it be reading Islam's holy scriptures or listening to recordings of it daily, which can serve as a second measure available to all Muslims regardless of gender or socioeconomic status.

Alternative measurement strategies also exist, including the use of religious worldviews (Ciftci, Wuthrich & Shamaileh, 2019; Tessler, 2015) and socio-religious values, or *political Islam* as a proxy for piety (Achilov & Sen, 2017; Ciftci, 2013; Driessen, 2018). Meanwhile, others measure it with the central tendency of a large number of survey responses (Tessler, 2015; Tessler, Jamal, & Robbins, 2012). To the degree that common measures are used, especially self-reported and behavioral measures, these measures are often assumed to be accurate rather than being independently evaluated. In short, measuring religiosity through public opinion surveys remains a challenge, particularly in the Arab region where relatively few respondents identify as non-religious. Aggregation strategies using these measures will likely reflect this challenge, but aggregated measures should provide approximate levels of piety in a given region.

Religiosity in Egypt: Disaggregation

The AB has implemented several questions about religiosity across MENA including self-reported piety, frequency of prayer, and engaging with the Qur'an. Here, we develop an index using the following AB questions in the case of Egypt.

Q609: In general, would you describe yourself as religious, somewhat religious, or not religious?
Q6101: Do you pray daily always, most of the time, sometimes, rarely or never?
Q6106: Do you read or listen to the Qur'an daily always, most of the time, sometimes, rarely or never?

When we combine responses from the three waves of AB and taking the Muslim-only sample in Egypt, 40% of the respondents identify as religious, 56% say they are somewhat religious, and 3% say they are not religious. Meanwhile, 69% of the Egyptian Muslims say they always pray daily, while 47% say they always read or listen the Qur'an on a daily basis. These results, however, conceal the wide variation that could be observed at the governorate level. The data demonstrate a range of 53 points for self-reported religiosity and 42 points for prayer frequency across governorates. There is again dramatic variation in engagement in the Qur'an. Aswan is the most religious by this measure, with 70% of Muslims saying they read or listen to the Qur'an daily. By comparison, just 30% in Luxor and 25% in Suez do the same.[2]

At the national level, a moderate correlation is observed between all three of these items. Likely, this is because while each of the items measures an aspect of religiosity, the measures are of different types (self-reporting vs. behavioral) and different levels of commitment (prayer vs. reading text). However, in all cases the correlations are around 0.35, suggesting that each is related but captures distinct variation (Supplementary Table O1).

To create a single measure of an underlying variable, in this case religiosity, there are multiple approaches by which we could construct an index. An additive index would weight each variable equally, which would not consider the underlying relationship between the variables. Such an approach also would provide two measures for religious

[2]Charts for cross-governorate variation in religiosity are presented in the Supplementary appendix.

Table 1.
Eigenvalues and Explained Variance, PCA

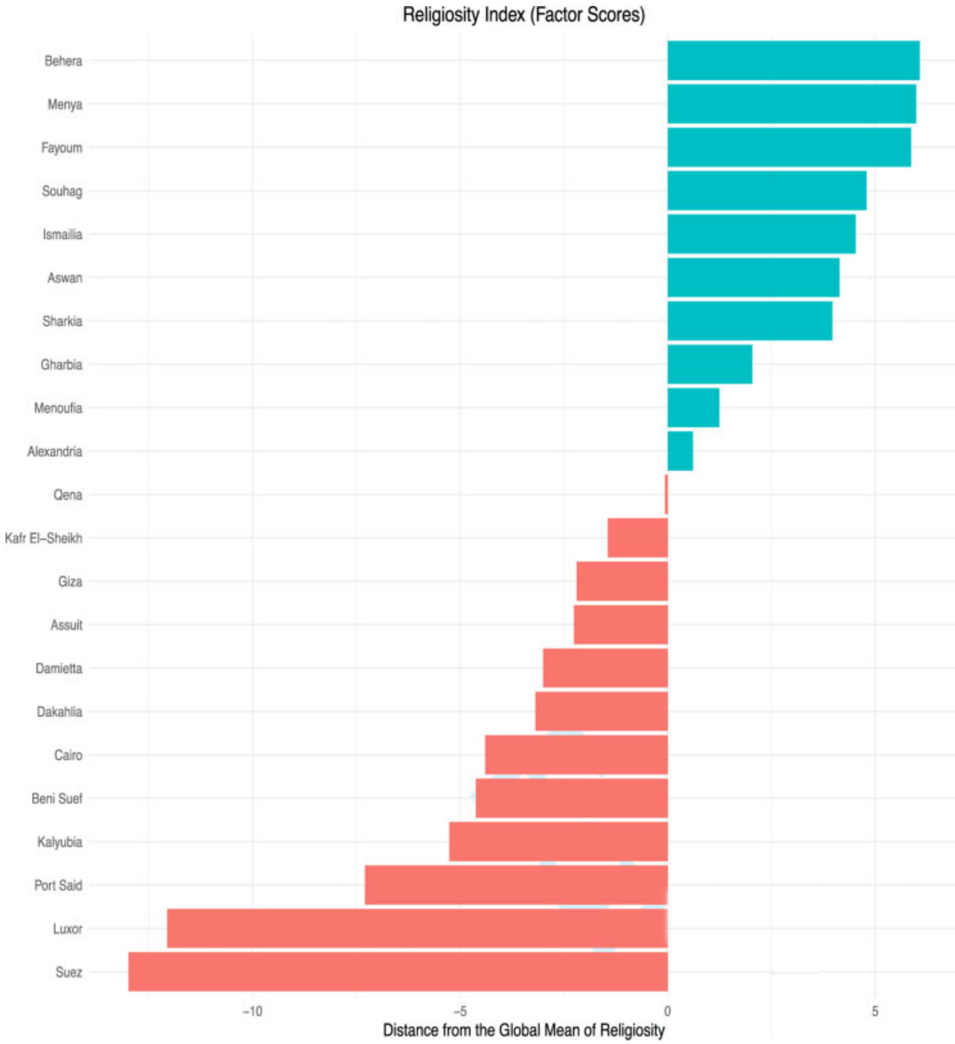
	Eigenvalue	Explained variance	Cumulative variance
1	1.6941	0.5647	0.5647
2	0.6790	0.2263	0.7910
3	0.6269	0.2090	1.0000

practice compared with only one for self-identification, so it is only employed as a robustness check. A second approach is to use principal component analysis (PCA) to develop an index based on the key underlying components shared across the three variables. This approach considers the unique variation in each of the constituent measures to yield a single overall measure. The third option is to develop an index based on item response theory (IRT), which is also designed to measure a latent variable by evaluating and ranking the consistency of responses across each respondent. Either PCA or IRT could yield a valid index, although PCA is used here. Indices using the other two approaches for construction are included in the Supplementary appendix as robustness checks. All yield similar and highly consistent results, so it is clear that the results that follow are not dependent on any single method for developing the index.

Before constructing the index, the coding was reversed for all three variables from the coding in the AB scales, meaning that higher values represent more religious. We ran a PCA analysis on these variables to reduce them to a single item. The results point to an index that is comprised roughly equally in terms of the self-identity and behavior variables, with prayer and Qur'an readership being weighted nearly equally (see Table 1). We call this variable *Religiosity Index*. Using this index, we first calculate the governorate averages across three surveys (disaggregation). Then we take the difference between these averages and the global mean of religiosity for Egypt across three surveys to show the distance from the national mean for each governorate as reported in Figure 1. Overall, we detect significant variation across Egyptian governorates. Suez, Luxor, and Port Said are among the least religious, whereas Behera, Menya, and Fayoum are the top three most religious governorates. Notably, some of these governorates carried by Mohammed Morsi in the 2012 Presidential elections by significant margins were either most religious (Menya and Fayoum) or least religious (Suez). Meanwhile, in most of the less religious governorates by this measure, including Luxor, Kalyubia, and Cairo, Morsi did not take a majority.[3]

[3]There are some governorates that stand out, however, notably Beni Suef and Suez, which have historically been Muslim Brotherhood strongholds but are on average less religious. Given the relatively low sample sizes in both governorates, it is possible that random sampling variation accounts for such differences. Despite this single result, overall levels of religiosity in the index reflect differences in vote share for Morsi. It should be noted that the vote for Morsi is not a direct measure of religiosity and support for the Brotherhood depends on a range of other factors. It is equally possible that these results are in fact a better measure of religiosity at the local level based on the full range of religiosity at the governorate level compared with vote share for Morsi.

Figure 1.
Governorate level religiosity relative to national religiosity in Egypt.



Note: The bars represent the difference between sub-national and national means of religiosity for each governorate. The index scores are standardized (0–100) factor scores from the PCA. *Source*: Arab Barometer, Waves 2–4 (2011–2016).

MrP and Sub-National Estimates of Religiosity

AB surveys provide consistent wording of questions over time inquiring about respondents' religious belief and participation. However, the disaggregation by geographic regions has its limits related to the sample size and sub-national representativeness. While one can be more confident in estimations from governorates with larger sample sizes using disaggregated results, the validity of the sub-national estimates is more problematic in governorates with relatively few data points. To derive governate-level estimates across Egypt, an alternative approach is to use multilevel regression and poststratification (MrP). This technique estimates sub-national public opinion figures from nationally representative samples in two stages. First, a multilevel regression with micro and macro correlates of the dependent variable is fitted. In the second stage, the predictions from this model are weighted by each subnational unit's actual demographic characteristics, usually obtained from census data or official statistics (i.e., poststratification) (see Gelman & Little 1997; Kastellec, 2018; Leemann & Wasserfallen, 2019; Park et al., 2004; Tausanovitch & Warshaw, 2014; Warshaw & Rodden, 2012).

In MrP estimation, the dependent variable consists of the index about self-reported religiosity, prayer frequency, and Qur'an readership obtained from PCA (see the description in Section 3). Since post-stratification requires joint distribution of demographic categories at sub-national level, we obtain micro-level data (10%) in Egyptian governorates from the 2006 census from IPUMS (2018).[4] The microdata provides the percentages for marginal and joint distributions of demographic categories in the actual population. These figures are then used for weighing the multilevel model predictions in the poststratification stage.

Before proceeding to the analysis, the demographic variables in the Census data and in the AB surveys are harmonized with the same scale to create consistent measures. These include age (four categories), education (four categories), and sex and employment status (dichotomous). We also include an interaction between education and sex to control for the joint distribution of these demographic categories.[5] We choose these variables based on their availability in both survey and census data as well as to capture the most commonly used demographic characteristics. Accordingly, in our data, each governorate has 64 different combinations for the marginal and joint distributions of these variables ($2 \times 2 \times 4 \times 4$). Since the survey data and macro variables are not consistently available for all governorates, our model includes 22 of the 27 governorates, bringing the total combinations in the census data to 1408 (64×22).[6]

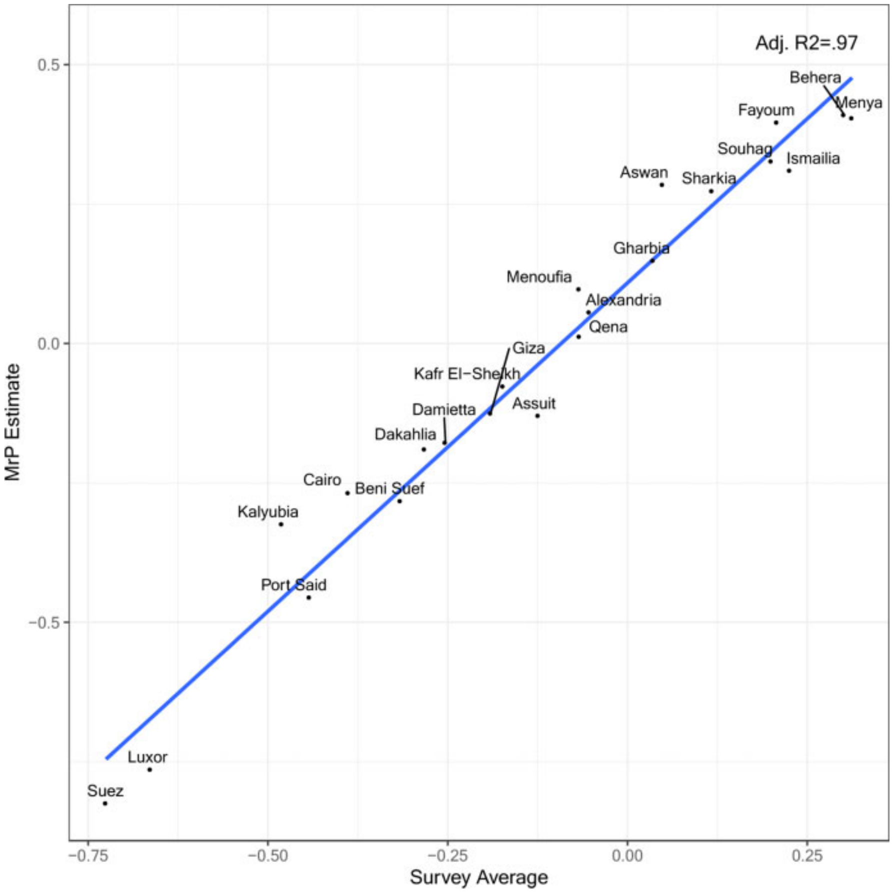
Beyond these disaggregation models, we include several controls at the governorate level. These include socioeconomic measures such as GDP and employment. Since wealth and modernization are related to the secularization hypothesis they have implications for our study. Second, we include the GINI coefficient at the governorate level, because relative inequality has been linked to overall levels of religious adherence at the societal level (Solt, Philip, & Tobin, 2011). To consider potential systematic differences in levels of religious adherence at the governorate level, we use the percentage of the vote for Mohamed Morsi in the 2012 presidential election. We also include variables for

[4]Institute for Social Research and Development, https://ipums.org.

[5]We ran alternative models, including interaction of education and age and the sub-national estimates remain very similar.

[6]The following governorates were dropped from the MrP estimation due to missing data: North Sinai, South Sinai, Red Sea, New Valley, Matrouh.

Figure 2.
MrP estimates and survey-based religiosity in Egyptian governorates based on religiosity index from PCA.



Source: Arab Barometer, Waves 2–4 (2011–2016).

regions and governorates of Egypt as well as AB survey waves to account for the possible variation in our model. While one can come up with different contextual factors in modeling, we tried our best to capture theoretical relevance and data availability in the selection of contextual variables. GDP per capita (2006) is obtained from CAPMAS, *Gini Coefficient* measuring inequality is taken from the 2014 Demographic and Health Survey, and the proportion of the Morsi vote in the first democratic presidential elections in 2012 is based on official vote totals.[7] Finally, random variation by governorate or region of Egypt could account for religiosity, so this is also included in the model.

[7]Official vote totals were obtained from http://pres2012.elections.eg/round2-results.

This approach helps provide more precise estimates. We report summary statistics for these variables in the Supplementary appendix. Our model can be expressed formally as:

Equation 1:

$$Y = \beta^{0} + \alpha_{j[i]}^{education} + \alpha_{k[i]}^{age} + \alpha_{l[i]}^{sex} + \alpha_{j[i],l[i]}^{education,sex} + \alpha_{l[i]}^{sex} + \alpha_{m[i]}^{governorate} + \alpha_{n[i]}^{employment} + \alpha_{o[i]}^{region} + \alpha_{p[i]}^{GINI} + \alpha_{q[i]}^{GDP} + \alpha_{r[i]}^{MorsiVote}$$

After we run this multilevel model (see Supplementary Table O2), we calculate the population percentages for each governorate across 64 different demographic combinations. We use these percentages to weigh the predictions obtained from the multilevel model to obtain an estimate of average religiosity in Egyptian governorates. Figure 2 shows the correlation between average religiosity as obtained from the index constructed based on AB surveys and the MrP estimates of religiosity. The average MrP estimate and *Religiosity Index* obtained from disaggregation are highly correlated, with an *R*-squared value of 97%. Most governorates remain within or very near the 95% confidence interval.

We replicated the same analysis with several alternative measures including an index constructed by IRT analysis, an additive index, and separate items most commonly used in research (frequency of prayer and frequency of engagement with the Qur'an). As reported in the Supplementary appendix, in these alternative specifications, there is a near-perfect overlap between MrP religiosity estimates and survey averages of different measures of religiosity. The high degree of overlap between MrP estimates and the survey averages (disaggregation) is encouraging for the students of religion and politics who make use of AB data but either lack a large number of surveys or necessary census data to conduct MrP. While the surveys are not sub-nationally representative at the individual level, sub-national aggregation appears to provide a good proxy for governorate level measurement. The MrP estimation confirms the validity and utility of disaggregation for the AB surveys. However, we need further justification of both methods using an indicator of religiosity exogenous to the survey data. To that end, we use the intensity of nighttime lights before and after Ramadan as a proxy for sub-national religiosity and explore its power in predicting religiosity measures obtained from disaggregation and MrP in the next section.

Ramadan Lights and Sub-National Religiosity

The wide use of nighttime lights as a reliable proxy for various socio-economic parameters dates back to the early 1990s (Elvidge, Baugh, Zhizhin, Hsu, & Ghosh, 2017; Sutton, Roberts, Elvidge, & Meij, 1997). The big advantage of using this type of data versus data gathered using traditional methods of surveying is that it can be especially useful for cross-border and subnational level regions where traditional data may be lacking (Bennett & Smith, 2017). Since 2011, the Suomi NPP satellite has made such data available through the VIIRS sensor. The VIIRS data is available from December 2011 until the present time and contains annual and monthly nighttime light composites, as compared to the DMSP-OLS data which only provides annual data for public use.

Román and Stokes (2015) used three years of VIIRS data to understand cultural patterns in energy demand during the holiday season. The authors considered the

Figure 3.
Map of Egypt's governorates.

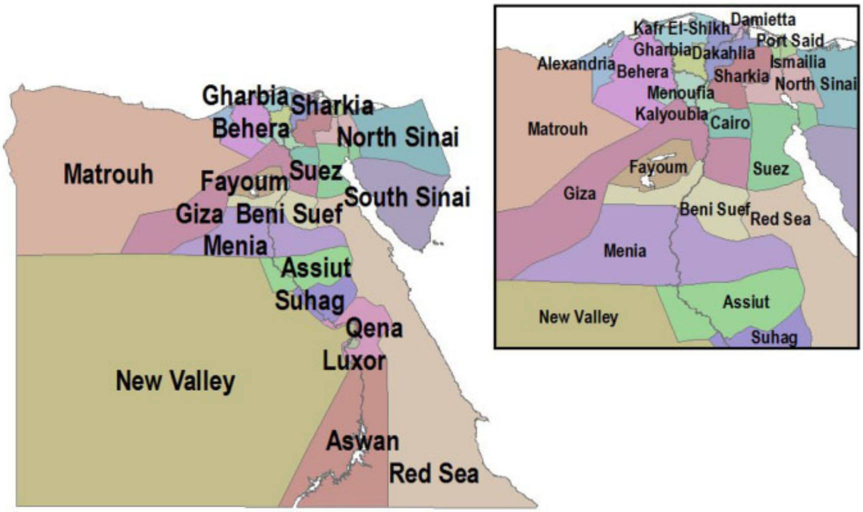


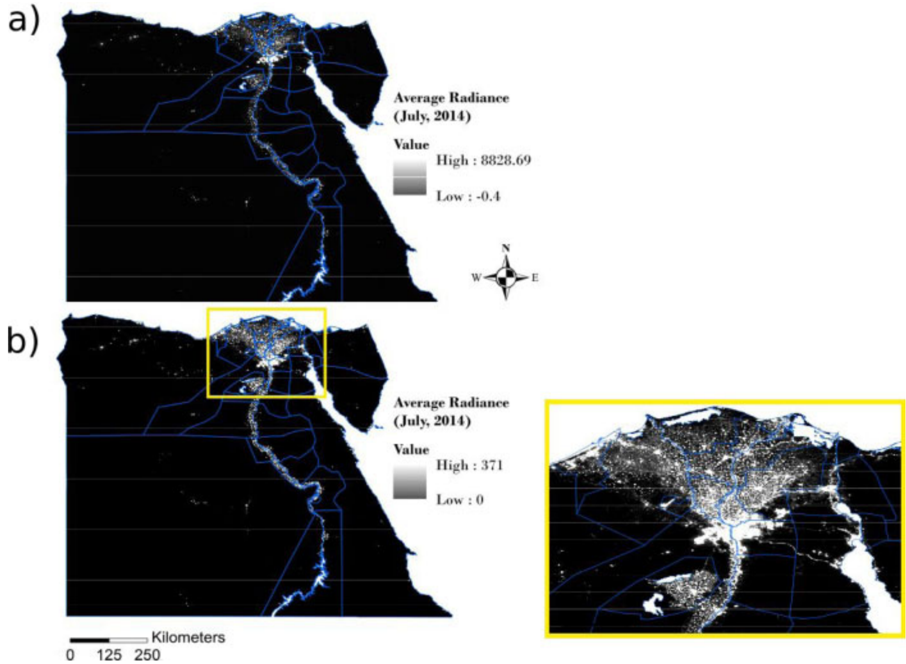
Table 2.
Data Chosen for Analysis and Corresponding Ramadan Dates

Year	Ramadan dates	VIIRS monthly composite used
2014	28th June–28th July	July
2016	5th June–6th July	June
2017	26th May–24th June	June

change in energy demands during Christmas in the United States and Mexico and during the month of Ramadan in the Middle East. A more recent study by Liu, Li, Levin, & Jendryke (2019) also used VIIRS data to investigate the correspondence between nighttime light data and behavior during Ramadan. However, the idea of incorporating nighttime lights to derive a measure of religiosity to be used on a subnational level in the Middle East was not explored fully in either of the studies.

The boundary data of administrative divisions of Egypt was obtained from the CAPMAS (see Figure 3). We downloaded 36 monthly nighttime lights composites (NPP-VIIRS) from the Earth Observation Group, NOAA National Centers for Environmental Information (NCEI). We use the data that has undergone stray-light correction to limit the degree of missing data. We focus on years 2014, 2016, and 2017 as these are the years for which the start and end dates of Ramadan are best captured using monthly data without significant information loss (see Table 2).

Figure 4.
Nighttime lights during Ramadan (2014).



Note: Map of average nighttime radiance values for Egypt for July 2014 featuring (a) raw data and (b) corrected data following procedures in Section 4. These images were retrieved from the Earth Observation Group, NOAA National Centers for Environmental Information (NCEI) (https://ngdc.noaa.gov/eog/viirs/index.html, last accessed on 6 December 2017).

The monthly nighttime lights data (a total of 36 composites) are clipped to include only the national boundary of Egypt. Finally, the data is projected into the *Africa Albers Equal Area Conic* projected coordinate system and resampled to give the spatial resolution of about 440 meters. To estimate governorate level religiosity with nighttime lights data, a series of pre-processing steps are taken. These steps include procedures that correct for extreme or unusual values caused by lights from fires, oil and gas wells, and landforms. We detail these procedures in Supplementary Box 1. It is important to note that other factors such as the variation of the satellite viewing angle (Li et al., 2019), and the impact of seasonality on nighttime brightness (Levin, 2017) have been shown to affect the quality of nighttime data. While both are important considerations, given that the focus of this study is solely on Egypt during a relatively short time window every year (1 month before and after Ramadan), the correction procedures undertaken here should be sufficient to capture the dynamics during Ramadan without affecting the analysis.

To measure the total amount of light emitted, we compute the total sum of lights (SOL), which is simply the sum of all pixel values. This is a common way to summarize light intensity for a particular area of interest (Kyba et al., 2015). We normalize the SOL values for each governorate by its respective area to arrive at an SOL index with

Table 3.
Ramadan Lights, Socio-Economic Indicators, and Religiosity: Bivariate Regression Results

	GDP per capita (1)	Gini coefficient (2)	Religiosity index (3)	MrP estimate (4)
Average light intensity	13.02	0.00	0.82**	0.74**
	(6.74)	(0.00)	(0.23)	(0.24)
Constant	5478.14**	0.12**	9.58	9.10
	(468.827)	(0.04)	(15.718)	(16.49)
Observations	22	22	22	22
R^2	0.16	0.06	0.40	0.33
Adjusted R^2	0.12	0.01	0.36	0.30

Note: *$P < 0.01$.

units of average radiance per km². A closer inspection of the data reveals that most governorates display a characteristic peak in SOL values during Ramadan (see Supplementary Figure O4). To quantify this peak, we consider the relative percent change in SOL values before and after Ramadan. The expectation is that the percent change in SOL should be positive before Ramadan begins and negative after Ramadan ends. This turns out to be the case based on the nighttime lights data as reported in the Supplementary Figure O5. This suggests that these indices accurately capture the change in the intensity of nighttime lights during Ramadan compared to other months.

Do Ramadan Lights Predict Sub-National Religiosity?

The analysis of nighttime lights demonstrates that the light intensity spikes during Ramadan for most governorates. Can we take this result at face value and use Ramadan activity as a measure of religiosity? To make the case for Ramadan lights, we pursued several strategies. First, we used several different measures of light intensity to capture the spike during Ramadan. We focus on the results using the change in nighttime light intensity from pre-Ramadan to Ramadan periods. The results from additional analyses using Ramadan to post-Ramadan change and an index that takes the sum of absolute change in light intensity before and after Ramadan corroborate our findings.[8] Second, since nighttime lights have been widely used as proxies for GDP per capita and inequality in previous studies (Li et al., 2013; Wu, Yang, Dong, Zhang, & Xia, 2018), we regressed these alternative indicators on the average change in nighttime light intensity during Ramadan (temporal mean of pre-Ramadan to Ramadan change) in 22 governorates. Third, we separately plotted the bivariate association between average change in light intensity and average religiosity index for three years to show the degree of overlap between survey-based measures (disaggregation and MrP) and Ramadan lights intensity.

Table 3 provides evidence that supports our expectations. Before we ran OLS regression models, we obtained the change in Ramadan light intensity over three years for

[8]There are some minor differences when we use this alternative measure, especially for 2017.

Table 4.
The Predictive Power of Ramadan Lights on GDP and Religiosity: Seemingly Unrelated Regression Estimations

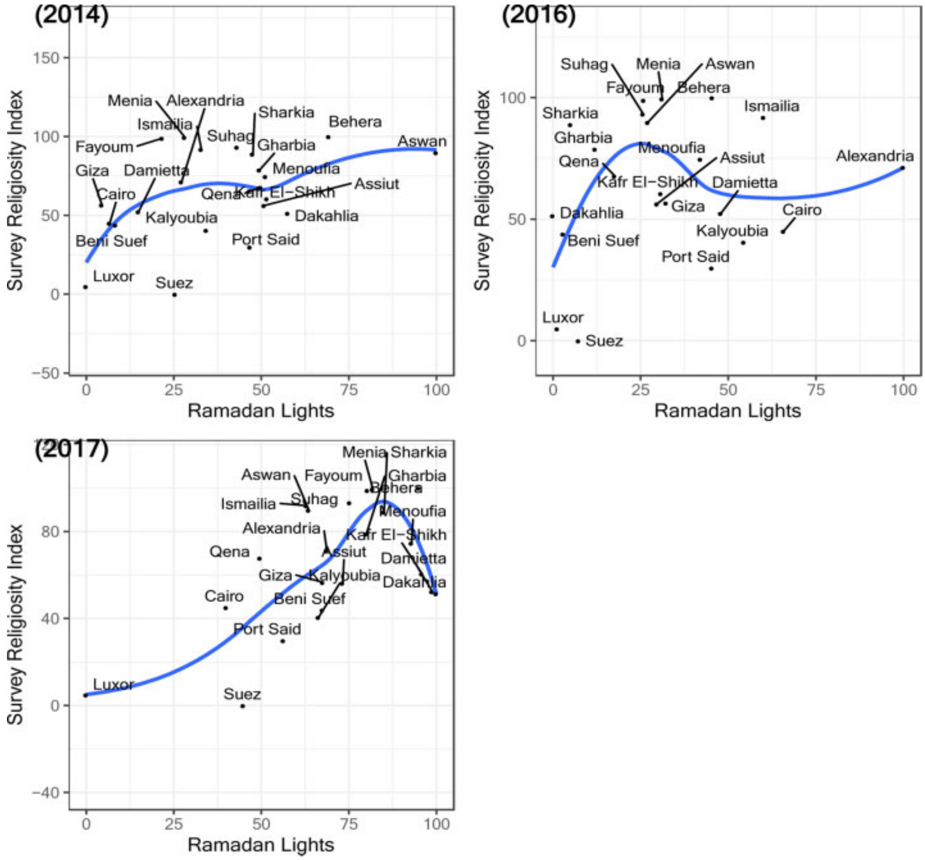
	Model 1		Model 2	
	GDP per capita	Religiosity index	GDP per capita	MrP estimate
	Equation 1	Equation 2	Equation 1	Equation 2
Average light intensity	13.02	0.82*	13.02	0.74*
	(6.74)	(0.23)	(6.74)	(0.24)
Constant	5478.15**	9.57	5478.15**	9.10
	(468.83)	(15.72)	(468.83)	(16.5)
Observations	22	22	22	22
R^2	0.16	0.40	0.16	0.33
Adjusted R^2	0.12	0.36	0.12	0.29

Note: *$P < 0.01$; **$P < 0.001$.

all governorates. We used two measures of religiosity index obtained from disaggregation and MrP estimates. Generally, average light intensity over time can be a good proxy for regional socio-economic development or inequality. However, when the Ramadan spike is considered, light intensity appears to more strongly correlate with sub-national religiosity in the Egyptian governorates than GDP per capita and inequality. Light intensity during Ramadan is not statistically significant in the models predicting GDP per capita and inequality. Average Ramadan lights intensity is positive and highly significant in both Model 3 and 4 that predict religiosity index and the MrP estimate of religiosity ($p < 0.01$). We note that disaggregation slightly outperforms the MrP estimate based on explained variance (larger R-squared in Model 3).

Despite these results, there may be considerable noise in the proposed effects of light intensity as it can predict both GDP and MrP-based religiosity estimate. In other words, it is not fully established that changes in Ramadan lights reflect varying degrees of religious intensity, as they may simply be amplifications of greater economic, social, and commercial activities in these areas. The nighttime lights data is not conducive to disentangling the religious activities from social and commercial activities during Ramadan nights. However, we should be able to separate the effects associated with lights due to economic and religious spheres. To that end, we use two strategies. First, to account for possible endogeneity between economic activity and Ramadan as drivers of light intensity, we ran *seemingly unrelated regressions* accounting for the dependency between the two equations predicting sub-national GDP and average religiosity as a function of observed light intensity spike during Ramadan. As we report in Table 4, the statistical power of light intensity in predicting the disaggregated survey measure of religiosity (Model 1, Equation 2, $p < 0.01$) and MrP estimate (Model 2, Equation 2, $p < 0.01$) outperforms the statistical certainty attributed to the prediction of governorate level GDP (Equation 2 in Model 1 and Model 2). These results, while acknowledging the random error in the predictive power of nighttime lights compared to the effect of GDP and religiosity, lend support to the instrumental utility of Ramadan lights in estimating religiosity. Second, we run a regression of GDP per capita and two measures of

Figure 5.
Performance of night lights in predicting sub-national religiosity (disaggregation method).



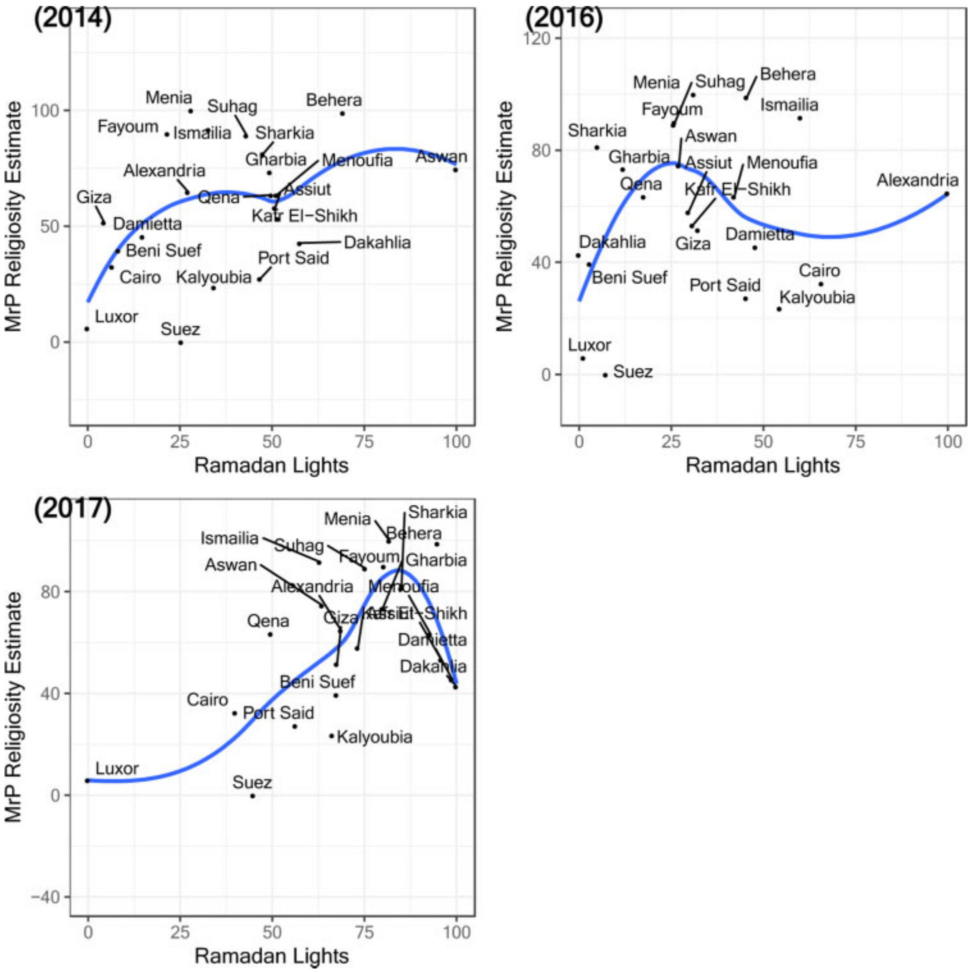
Note: Both measures are rescaled to range from 0 to 100 for better visualization.

religiosity index on the change in nighttime light intensity to show that it is religiosity and not economic development that explains the spike during Ramadan. The results confirm our expectations (Supplementary Table O3).[9]

We pursued a second strategy to further establish the robustness of Ramadan lights as a proxy for sub-national religiosity. We plot the bivariate association between the two measures of religiosity and Ramadan lights intensity for each year included in our data (2014, 2016, and 2017). In Figures 5 and 6, we present the degree of fit and the distribution of governorates with 95% confidence bonds and Loess smoothing. There are differences from year to year in the degree of overlapping and the strength of association, but, by and large, we see a curvilinear and a positive trend between Ramadan lights intensity and survey-based religiosity

[9]Dropping GDP from MrP equation does not alter the results.

Figure 6.
Performance of night lights in predicting sub-national religiosity (MrP estimates).



Note: Both measures are rescaled to range from 0 to 100 for better visualization.

measures. This indicates a high correlation between an external variable (Ramadan lights) and survey-based measures of religiosity.

Some outliers include Luxor and Port Said and less consistently Behera and Ismailia. However, this relationship may not be as strong in some of these cases. Luxor is the smallest governorate in Egypt by geographic area and one that is a major center for tourism in the country. Lights as a result of tourism activity likely mute the relatively subtle change expected during the Ramadan period in this small governorate. Suez, Ismailia, and Port Said are also consistent outliers, which is likely a result of ongoing nighttime activities related to the operation of the Suez canal, which may diminish the expected changes from Ramadan lights.[10] Meanwhile, in Suhag, a borderline case in Figure 6, Christians make up a substantial portion of the population.[11] It is also one of the poorest governorates in Egypt, with roughly half of the population living in poverty.[12] This combination may affect the predictive power of Ramadan lights, with the change expected to be relatively smaller due to the high rate of poverty and muted by the significant number of Christians in the governorate. To control for the possibility that bias may be introduced to the model from the presence of non-Muslim populations, we ran the models that include only Muslim sample. We note that the models including both Christian and Muslim respondents perform poorly in governorates with large Christian populations relative to the Muslim only models. This result increases our confidence in the validity of the measure of religiosity among Muslims.

The difference between the corresponding panels in each figure is minimal, confirming the strong correlation we observed between disaggregation and MrP estimates of religiosity. In 2014, the overall fit between the Ramadan lights and the two measures of religiosity is somehow lower. Possibly, this variation is caused by the fact that the 2014 FIFA World Cup overlapped with the first half of Ramadan. Held in Brazil, the football matches would have been shown in Egypt during the early hours of the morning. In fact, this year, it is likely that lights capture both the extent of religious activities and increased action from football fans enjoying the matches during the evening hours. The noise in the measure coming from the viewership of the World Cup can affect the nighttime lights throughout Ramadan as well as the month before Ramadan during this particular year. Accordingly, it is not unsurprising that the model is a less accurate predictor of religiosity based on survey data for 2014.

Conclusion

Taken together, these results provide several contributions to the study of religiosity. First and foremost, they make it clear that it is in fact possible to use results from existing survey data to measure religiosity in MENA. There have been concerns that self-reported measures of religiosity or behavioral measures of piety in the Arab region may not accurately capture levels of religiosity due to social desirability or misreporting. However, at least for the case of Egypt, our index of religiosity obtained by disaggregation performs admirably when examined relative to multiple models. The MrP estimates provide a second check on the power of disaggregation for the AB surveys. By and large, the survey data can accurately distinguish aggregate levels of religiosity at the provincial level. This result does not definitively prove that each individual observation does not suffer from any bias in reporting, but it does increase confidence in the measure given the robust results at a relatively small sub-unit within the survey.

This conclusion is further supported by the data from the nighttime lights. Despite a relatively small effect from the change in nighttime lights, averaging less than 10% difference from a typical month in most Egyptian governorates, there is a relatively strong correlation between the relative change in night lights during Ramadan and the

[10]These are the only three governorates in the analysis that abut the Suez Canal. Although we control for GDP in the model, the activities related to the operation of the Suez Canal may not be captured as well by this adjustment given that operations are ongoing throughout the night and they primarily concern provision of services to ships using the canal.

[11]See https://www.refworld.org/pdfid/4f4236062.pdf.

[12]See https://www.undp.org/content/dam/rbas/doc/poverty/BG_11_Poverty%20in%20Egypt.pdf.

average from the religiosity index, for both disaggregation and MrP estimate of religiosity, at this geographic level. Moreover, some of the outliers lend additional confidence to this measure given that they contain a significant Christian population, which would be expected to reduce the correlation between Ramadan lights and the religiosity index for the Muslim-majority population.

Most survey research projects in the region are designed to be representative at the national level but not at smaller geographic units such as governorates. This article demonstrates that disaggregation can be utilized to fill this gap. And when disaggregation is not possible, the MrP approach can be a useful tool for scholars seeking to estimate and better understand regional differences in countries such as Egypt where data are available from statistical organizations at the governorate level. While disaggregation slightly outperforms the MrP estimates in relation to the data from the night lights, the latter can still yield reliable estimates for public opinion at the sub-national level, opening up a range of new research possibilities for scholars.

Finally, this article demonstrates the ability to use alternative approaches such as nighttime lights innovatively in MENA to understand additional phenomena. Nighttime lights have traditionally been used as a proxy for economic development or similar indicators, but we show that these data can also be used for alternative measures such as understanding variation in levels of religiosity across Egypt. Given that these data are now widely available, this study demonstrates the power to use even relatively small differences, like the percent change during Ramadan, for measuring differences across contexts around the world.

Supplementary Data

Supplementary Data are available at *IJPOR* online.

Acknowledgments

Authors are listed alphabetically. We thank Ammar Shamaileh, the editors, and three anonymous reviewers for their valuable feedback.

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