ABSTRACT

Title of Dissertation:	BUILDING A BASELINE: UNIFYING SPATIAL AND TEMPORAL METHODOLOGIES TO UNDERSTAND ARCHAEOLOGICAL LOOTING IN EGYPT
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Archaeological looting – the illegal excavation or removal of an antiquity from the ground or structural complex of an archaeological site – is a persistent issue in many countries. National and international laws, agreements, conventions, and statutes all proscribe the looting transporting, possession, and sale of antiquities illegally removed from archaeological sites. Looting has also generated a lot of academic attention, with scholarship developing in archaeology, sociology, criminology, and law (among others). Despite such legal proscriptions and scholarly contributions to understanding this phenomenon, current efforts have been unable to produce tangible solutions for preventing this crime. Not only has there not yet been extensive scholarship to understand the link between looting and contextual forces, there is a dearth of research on the most effective ways to study these interconnected variables. Using a framework of routine activity theory, this dissertation proposes a new possible approach that considers spatial, temporal, and spatio-temporal relationships to establish baseline data on patterns of archaeological looting attempts in Lower Egypt from 2015 to 2017 relative to sociopolitical, economic, and environmental stress — and to begin to address this research gap. Specifically, this dissertation proposes a methodology for collecting and coding data on archaeological looting attempts from satellite imagery. It then applies a series of spatial (clustering, proximity), temporal (SEM, VAR, ARDL), and spatio-temporal methods (clustering, hot spots analysis, spatial time series) to these data to demonstrate the importance of analyzing this phenomena multidimensionally.

BUILDING A BASELINE: UNIFYING SPATIAL AND TEMPORAL METHODOLOGIES TO UNDERSTAND ARCHAEOLOGICAL LOOTING IN EGYPT

by

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Dedication

This dissertation is dedicated to my husband, who has supported me throughout this journey and to whom I am eternally grateful.

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List of Abbreviations

ACLED – Armed conflict location and event data

ARDL – Autoregressive distributed lag model

CAPMAS – Central agency for public mobilization and statistics

GTD – Global terrorism database

IOM – International organization for migration

RAT – Routine activity theory

SEM – Structural equation modeling

UCDP – Uppsala conflict data program

UNESCO – United nations educational, scientific, and cultural organization

VAR – Vector autoregression

VEC – Vector error correction

Chapter 1: Introduction

Archaeological looting – the illegal removal of antiquities from the ground of an archaeological site – is a recognized and persistent crime in many countries. Antiquities, here defined as any object over 100 years old located in the ground or structural complex of an archaeological site, are valuable as potential sources of income for individuals.[1] They require few skills to remove from the ground, are often easily concealable, and are in high demand on the art market. Further, they maintain their market value even if not sold immediately and looted objects are difficult to trace, making them ideal forms of revenue (Hardouin & Weinchhardt, 2006). This also makes them potentially good sources of currency on the illicit market (e.g., for munitions) (Wilford, 2003). These benefits make looting difficult to control and reduce through laws.

National and international laws, agreements, conventions, and statutes proscribe looting, transporting, possessing, and selling antiquities illegally removed from archaeological sites (Ulph & Smith, 2012). Internationally, the oldest legal precedent establishing looting as a crime is the 1954 Convention for the Protection of Cultural Property in the Event of Armed Conflict (UNESCO, 1954). Nationally, laws establishing archaeological looting as a crime are much older. Egypt's earliest law, for example, dates from 1884 when they were ruled by the Ottoman Empire and made illegally excavating archaeological sites and withholding objects a crime (Kersel,

[1] This definition distinguishes an antiquity from other related terms such as cultural property or cultural heritage, whose definitions are broader and at times overlapping. Consensus does not exist on how to define key concepts related to cultural property crime. For a discussion on the debate surrounding definitional clarity, see Fabiani (2018).

2010). The most recent law, a 2010 update to the 1983 Antiquities Protection law, which establishes that the Egyptian government owns all antiquities. These laws have been reinforced and expanded through more recent legislation and international resolutions, such as the United Nations Security Council resolutions 2347 and 2368 in 2017, which call for the protection of heritage from destruction and looting and to stop sources of terrorist financing, including antiquities (UN Resolution 2347, 2017; UN Resolution 2368 2017). Many countries also have local efforts to curb and prevent the looting of archaeological sites. For example, Egypt engages both police and security personnel to protect archaeological sites from potential looting or destruction (El-Aref, 2016).

Archaeological looting and related criminal activities (trafficking, sale, etc.) have also generated a lot of academic attention. Scholars across multiple fields have called for increased involvement in stopping looting and the subsequent trafficking and sale of antiquities (Casey, 2006; Dobovšek & Slak, 2011; Hardy, 2016; Hill, 2008; Mackenzie & Green, 2009; Mazza, 2018; Ojedokun, 2012; Passas & Proulx, 2011; Polk, 2009). In response, several lines of scholarship have developed over the last decade. Some scholars have identified societal factors that would motivate persons to loot, including economic hardship (e.g., due to famine, drought, hyperinflation, etc.) (Hardy, 2015; Korka, 2014; Lane et al., 2008; Lawler, 2003), disease (Lane et al., 2008), and armed conflict (Lostal et al., 2017, Teijgeler, 2013). Other scholars have delineated the possibility of targeted looting and cultural destruction by organized groups, especially in areas of armed conflict (Fabiani, 2018; Lostal et al., 2017; Van der Auwera, 2012; Williams & Coster, 2017). Additionally, because it is difficult to document looting, scholars have used a variety of creative methods to identify looted sites, including in-person monitoring (Parcak et al., 2016) and monitoring the media for reports of looting (Fabiani, 2018). Recently, scholars have been using satellite imagery to record and quantify archaeological looting, particularly in the Middle East (Bowen et al., 2017; Casana & Laugier, 2017; Contreras & Brodie, 2010; Cunliffe, 2014; Fradley & Sheldrick, 2017; Isakhan, 2015; Lauricella et al., 2017; Parcak et al. 2016).

Despite the legal proscriptions against looting and the scholarly contributions to our understanding of this crime, current efforts have been unable to offer any tangible solutions to reduce or prevent looting. One need look no farther than the recency of anti-looting legislation and relevant publications to conclude that fast enough progress is not being made to prevent the theft of or to recover these items of cultural heritage.

To develop effective interventions and laws to reduce crime it is necessary to have an empirical understanding of the underlying patterns of the criminal activity in question. This has proven an effective approach with other forms of crime that are spatially concentrated (e.g., burglary, robbery, homicides, etc.). Through the analysis of spatial and temporal patterns, police have been able to more effectively allocate their resources to combat and prevent crime. Hot spots policing, which relies on a continual feed of information on the spatial and temporal patterns of crime, is one of the most effective ways to reduce crime and use resources effectively (Braga et al., 2014).

Like other forms of crime, archaeological looting varies in both space and time in response to different influences (e.g., environmental, economic, social, political). Therefore, developing solutions to reduce and prevent looting requires empirically looking at the underlying patterns in relation to a variety of stressors. Yet, there is a dearth of scholarship seeking to understand these patterns, making it difficult to identify tangible solutions for preventing and reducing looting. Existing scholarship has looked at both subsistence-based and targeted or intentional looting, but much of it is focused on descriptions of offender motivation and do not provide a baseline for developing actionable solutions (for exception see Fabiani, 2018).

Similarly, efforts with satellite imagery have accumulated large quantities of data on looting events; however, there have not been any attempts to use these data to look at patterns in looting in response to opportunistic and strategic factors such as those identified above. These data have also been collected with varying methodologies, which makes it difficult to translate results to tangible solutions. Cunliffe (2014) recorded 18 forms of site damage at two sites in Syria over a 50-year period (images from the late 1960s, 2003-2004, and 2009-2010) and compared site damage during conflict to times of peace. However, she only recorded one form of damage explicitly connected to looting and her comparisons were qualitative in nature. This kind of research is important; however, on their own, these studies cannot identify underlying patterns in archaeological looting or offer tangible solutions to looting.

Identifying the methodological frameworks that will allow the field to begin uncovering these underlying patterns in archaeological looting is a key first step in the current research. Not only has there not yet been extensive scholarship to understand the link between looting and contextual forces, there is a dearth of research on the most effective ways to study these interconnected variables. Using a framework of routine activity theory, this dissertation proposes a new possible approach that considers spatial, temporal, and spatio-temporal relationships to establish baseline data on patterns of archaeological looting attempts in Egypt — and to begin to address this research gap.[2]

As a case study, Egypt has several characteristics that make it a good candidate for this research. Egypt has a long cultural heritage, with many archaeological sites that are situated in geographically diverse landscapes (desert, marsh, cities, etc.). Egypt's population is also ethnically diverse, which can lead to or contribute to social and political tensions or conflict (TIMEP, 2018a). Further, Egypt's economy relies heavily on agriculture and tourism, both of which are sensitive to environmental, political, and economic changes over time and space (TIMEP, 2018b). Egypt's recent instability as a result of the Lotus Revolution (Teijgeler, 2013) affected the economy, politics, and social cohesion differently across the governorates as the instability spread through the country. Finally, climate change has affected the weather in Egypt and may have resulted in environmental stress in some parts of the country, depending on the season. Each of these influences varies over space and time in Egypt and so may affect the likelihood of archaeological looting.

The next chapter provides the theoretical framework for this study – Cohen and Felson's (1979) routine activity theory. The third chapter provides a more in-depth discussion of Egypt as a case study as well as an overview of the country's economy, environment, politics, and demographics and an overview of Egypt's archaeological landscape. The fourth chapter outlines the data sources, collection and coding strategy

[2] The term looting implies that something was taken. Since not all pits are "successful," meaning that not all result in an antiquity being removed, this dissertation uses the term "looting attempts" instead of the more generic term "looting."

and methods. Results are presented in the fifth chapter. The sixth chapter presents a detailed discussion of the advantages and disadvantages to the analytic strategies used. This dissertation ends with a discussion of recommendations for improving future research in this area.

Chapter 2: Spatial and Temporal Theories of Crime

Both spatial and temporal dimensions of crime are important for understanding the underlying patterns of archaeological looting attempts. A site may experience looting attempts in close spatial proximity to an incident of armed conflict, but the events may have occurred several years apart. Or, a site may experience looting attempts immediately following a poor harvest, but the attempts could have occurred several thousand kilometers away in an area unaffected by environmental hardship. Which sites are targeted, when, and by whom are all influenced by and should be understood through spatial, temporal, and macro-level factors, such as: spatial proximity; opportunity; and stress in a country's economic, environmental, and sociopolitical conditions. Among criminological theories, Cohen and Felson's (1979) routine activity theory (RAT) incorporates spatial and temporal variation explicitly into their explanation of crime. As such, it provides a useful approach to delineating the dynamics of archaeological looting.

Routine activity theory suggests that a complete understanding of which archaeological sites in Lower Egypt are more likely to have looting attempts and when requires a consideration of both spatial and temporal variables. As later discussed in Chapter 5, this requires a more robust exploration of potential methodologies to understand the impact and interdependence of these variables. The framework presented here both allows for an initial understanding of forces affecting archaeological looting in Egypt but allows for the identification of potential methodologies to best identify these patterns. This section first discusses the theory in more depth and then applies RAT to archaeological looting attempts in Lower Egypt.

Routine Activity Theory

Cohen and Felson's (1979) routine activity theory argues crime is more likely to occur when there is a confluence of three elements in both *space* and *time*: (1) a motivated offender, (2) a suitable target, and (3) a lack of capable guardianship. Because crime can affect a person or a place, they use the term "target" instead of victim, which usually only refers to people. The theory assumes that there will be a motivated offender, focusing instead on the role of situational opportunity. In particular, Cohen and Felson (1979) specify that crime is unevenly distributed in time and space and that the routine activities of suitable targets create opportunities for crimes. The routinization of a target's activities creates times and places where there is less guardianship, which in turn increases the suitability of the target for a crime. It is when the assumed motivated offender interacts with these periods of vulnerability that crime is more likely to occur. This idea of situational opportunity is central to Cohen and Felson's theory and has informed many applications of the theory.

Many studies apply routine activity theory to individual-level topics, such as patterns of victimization (Mustaine & Tewksbury, 1999), the effect of individual characteristics on crime (Kang, Tanner, & Wortley, 2017), and identifying offender information for criminal investigations (Rossmo & Summers, 2015). However, the theory itself focuses on larger, macro-level routines and their effects on crime. Cohen and Felson's (1979) original study looked at the macro-level changes in routines after World War II, including the movement of women entering the workforce at a national level and the shift of people staying out in public locations longer. Assuming a motivated offender allowed Cohen and Felson (1979) to focus on the ways in which the routine activities or targets, guardianship, and offenders interact in different times and places to produce crime.

Routine activity theory has been used as a theoretical framework for examining several lines of criminological research. For example, some studies look at just the role of guardianship in crime (Pratt & Cullen, 2005). Others use RAT to examine why some are more likely to be victimized than others (i.e., target selection) (Fisher et al., 2010; Wittebrood & Nieuwbeerta, 2000). A third line of research looks more specifically at how differences in locations affect routine activities, and by extension, crime (Andresen, 2006). These lines of research generally find support for the conclusion that routine activities influence crime rates across different settings. Although RAT implies a convergence in time and space down to the minute, in practice, time and space are not operationalized at such a granular level. For example, Andresen (2006) and Wittebrood and Nieuwbeerta (2000) both only look cross-sectionally at one year of data for a single city.

Because of this, routine activity theory is well suited to investigating the spatial and temporal patterns of archaeological looting attempts. Similar to houses with portable electronics, archaeological sites do not themselves have routine activities. However, the locations and people around them do have routines that affect guardianship of archaeological sites. Combined with the assumed motivated offender, routines (and by extension guardianship) influences whether specific archaeological sites are suitable targets for attempted looting.

Many (but not all) sites are located in or nearby populated areas, but do not have equal guardianship. If an archaeological site is a tourist destination then there may be a lot of security, making the site less accessible and possibly less attractive as a target. A site that is on the edge of a populated center or that is not a tourist destination will have fewer people around it. Similar to often empty houses, archaeological sites in less trafficked areas may have less guardianship and may be more attractive targets. The Egyptian government also offers varying degrees of legal protection to archaeological sites, which may be reflected in the extent of guardianship at the site. Sites with fewer legal protections may have less guardianship.

Relatedly, the routines around archaeological sites may vary by time of day or time of year affecting when and which sites are considered "suitable" targets for attempted looting. The "tourist" season in Egypt depends on when other countries have their holiday season (e.g., August in France, June – August in the US, or April, July, & September in Australia). During the tourist season, sites may be less attractive targets because the increased traffic could increase the risk of getting caught. Similarly, archaeological sites near areas with high rates of unemployment or that have experienced crop failure (a main source of income for the agriculture-dominated economy) may be more suitable as targets than those in areas with low rates of unemployment and good harvests.

Routine activity theory therefore provides a strategic framework for looking at variations of archaeological looting attempts in time and space. By assuming that there is a motivated offender, RAT shifts the focus to the patterns of when and where the crimes occur, which are necessary for creating a baseline of understanding around a given phenomenon. Offender motivation is an important element in understanding why a particular type of crime occurs; however, it is a complex and difficult concept to accurately measure. Studies looking at archaeological looting have identified several possible motivations for looting by both individual perpetrators and more organized groups (Balcells, 2018; Campbell, 2013; Matsueda, 1998; Teijgeler, 2013). One set of motivations stems from the assumption that for some, archaeological sites also provide a means of support for potential offenders (Balestrieri, 2018; Matsueda, 1998; Teijgeler, 2013). Subsistence digging has been a way to make a living or at least a quick buck in archaeologically "rich" countries for many years (Matsueda, 1998; Teijgeler, 2013). Another set of motivations view looting as a more organized activity. For organized individuals and groups, archaeological looting may be just one source of income in a portfolio of illegal activity (Balcells, 2018; Balestrieri, 2018; Campbell, 2014). Other motivations discussed in this literature include economic hardship (e.g., due to famine, drought, hyperinflation, disease etc.) (Hardy, 2015; Korka, 2014; Lane et al., 2008; Lawler, 2003), and conflict (Fabiani, 2018; Lostal et al., 2017, Teijgeler, 2013; Van der Auwera, 2012; Williams & Coster, 2017). While important theoretically and essential for any causal analysis, it is difficult to accurately capture and measure individual or group motivation.

Whether scholars view looters as "victims" of circumstance or "criminals" (Balestrieri, 2018) may also reflect the practice of separating the action of looting from the perpetrator (something not often done with other crimes). Such separations may hinder rather than help to identify patterns if they reflect assumptions about who should be looting at which sites and when.[3] Without any baseline knowledge of the patterns

[3] See Balestrieri (2018) for a more in-depth discussion of the potential consequences of distinguishing between what she calls "victim-looters" and "criminal-looters."

of archaeological looting attempts, such an analysis could reflect the assumptions of the literature rather than the actual patterns of looting attempts. As the focus of this dissertation is on developing a methodology for analyzing spatial and temporal patterns of looting attempts, the behaviors of the offenders are beyond the scope of this study. Further, in assuming the motivated offender, RAT provides a way to examine patterns in archaeological looting attempts in space and time without making assumptions about causal relationships. The next section identifies in more detail how the theoretical framework can be applied to archaeological looting attempts.

A Spatial and Temporal Theoretical Framework for Archaeological Looting Attempts

Routine activity theory can help understand which archaeological sites in Lower Egypt are more likely to be targeted for attempted looting and when. Archaeological sites are prevalent in Egypt and tend to cover large geographic areas, providing an ample supply of potentially suitable targets. Given how large some sites can be (e.g., an ancient city would be one site), adequate protection through capable guardianship is difficult.

Additionally, Egypt's population has been concentrated along the Nile Delta for millennia and much of Egypt's current economy relies on tourism related to their cultural heritage (Joffe, 2011). Since archaeological sites tend to be located around areas of historical settlements and many of the larger temples/sites are tourist locations, potential offenders are likely aware of archaeological sites. As such, there is ample opportunity for motivated offenders, suitable targets, and a lack of capable guardianship to combine in space and time, and it is the area and context surrounding the site that influences when and where these three converge to produce looting attempts. Furthermore, viewing archaeological looting in Egypt under this framework suggests specific spatial and temporal relationships associated with both guardianship and target suitability. It is important to note that although discussed separately, lack of guardianship and target suitability overlap conceptually and therefore some hypotheses may relate to both theoretical elements.

Formal and Informal Guardianship

Archaeological sites cover large amounts of territory and are both difficult to police and typically areas of low priority. This is in part due to the sheer number of sites in a country like Egypt. Like other countries in the Middle East, Egypt has a long cultural heritage. Though there has not been a complete count of archaeological sites in Egypt, recent studies have used satellite remote sensing to map and identify archaeological sites across Iraq, Syria, and Lebanon (Casana & Panahipour, 2014; Danti et al., 2017). These studies have identified tens of thousands of archaeological sites in these countries. For example, Syria has at least 15,000 sites, including both previously published sites and probable sites (not excavated or previously discovered) (Casana & Panahipour, 2014). Given its long cultural heritage, it is reasonable to expect Egypt to have a similarly high number of archaeological sites. It would require a sizable police force to monitor all archaeological sites with any degree of efficiency and efficacy.

Though it is difficult to police archaeological sites, there are both informal and formal forms of guardianship around archaeological sites.[4] Informal guardianship generally takes the form of locals who care about an archaeological site nearby and who can offer protection in the form of watching or reporting looting. In some cases,

[4] Guardianship in this dissertation is defined as any type of oversight or maintenance of an archaeological site that would serve as a form of protection against activities like looting or vandalism that could damage the site and its contents.

informal guardianship reflects the mores of a community that takes pride in their cultural heritage. Which sites have local guards varies spatially and the degree to which an individual can guard an archaeological site depends on their routine activities. If they are a farmer, there may only be an hour or two when they can watch, or certain months when they are not required elsewhere.

Formal guardianship can include security guards or police presence, an active archaeological dig, or a declaration of ownership by the State. Active archaeological digs provide a presence of archaeologists during the day to dissuade would-be looters and security guards at night. When an active dig site is operational, that site may receive extra guardianship and protection from the presence of the excavation. The most formal mechanism for guardianship is ownership. Not all archaeological sites in Egypt are considered eligible for "ownership" by the state and there are varying degrees of ownership. Sites can be fully owned by the Supreme Council of Antiquities (SCA), under the protection of the Antiquities Law but not owned by the SCA (i.e. in the process of becoming fully owned), submitted for protection, or not covered (SCA, 2009).[5] For some sites, the Supreme Council of Antiquities appoints a *gafir*, or local guard, for some archaeological sites (Wilson, 2007). They typically live next to the site for which they are responsible – if the site is very large, there may be more than one *gafir*. When people visit these sites, they must explain why they are there, or they will be turned away (Wilson, 2007). However, it is unclear whether all sites have these guards or just some sites designated by the SCA. Though unclear, it is possible that

[5] These four categories represent a continuum of protections, with full ownership providing the most protection and not covered providing the least. However, it is unclear what types of protections are afforded each category or how long it takes for a site to go from being submitted for protection to being fully owned.

these degrees of ownership also align with varying degrees of protection of archaeological sites and thus guardianship.

Both active dig sites and official ownership have spatial and temporal variation. Not all sites will receive active digs; in fact, a small percentage of sites are excavated at any time and usually not year-round. Common times for international archaeologists in the Northern hemisphere to participate in active excavations are May to August, when they can leave for fieldwork. Similarly, sites owned by the government are unevenly distributed within or across governorates; however, it is unclear whether there is a pattern behind which sites are owned or not. Though there is no way to directly measure a lack of guardianship, this theoretical framework does suggest a hypothesis using the proxy of ownership. If sites that are owned have more protection, then they may be less likely to experience looting attempts because of a greater perception of guardianship compared to other sites.

> ***Hypothesis 1:*** *Archaeological sites that are owned by the Supreme Council of Antiquities will experience less evidence of looting attempts.*
>
> > ***Hypothesis 1a:*** *The degree of ownership of an archaeological site (submitted for protection vs. protected under the law vs. owned by the SCA) will determine which sites experience looting attempts.*

A site's proximity to urban areas or cities may also affect how frequently and well-guarded it is. For example, a site that is in the middle of a city may be more likely to be a tourist destination and thus more likely to be well-guarded. By contrast, a site in a more remote location may be less of a priority and so have less guardianship. This would suggest that sites closer to urban and populated areas will less likely to experience looting than those that are more remote. Yet, proximity to populated areas may also influence a target's suitability. An archaeological site's proximity to an urban area may make it more accessible and thus attractive as a target for looting for individuals or organizations.

Thus, a site close to an organization's headquarters makes it a potentially good source of revenue. Or, if a particular region is experiencing high rates of inflation, proximity to urban areas may make sites more suitable targets as a means of quickly increasing an individual's income. Proximity to urban or populated areas, then, suggests two competing hypotheses. Sites close to such key locations may be less likely to experience looting if they have increased guardianship as a result of their location. Or, such sites may be more likely to experience looting attempts if they are seen as more suitable targets than those that are further away (i.e., more difficult to reach).

> ***Hypothesis 2:*** *Proximity to key locations (e.g., to populated centers, farms, etc.) affects whether or not an archaeological site will have evidence of looting attempts.*

Archaeological Sites as Suitable Targets

The suitability of an archaeological site as a target may also vary depending on the economic, socio-political, and environmental context of the area. The presence of socio-political stress (e.g., protesting, terrorism, sustained conflict), economic stress (e.g., high rates of unemployment, inflation, etc.), or environmental stress (e.g., drought, poor harvest) may make archaeological sites more suitable as targets. Archaeological sites in an area experiencing high rates of unemployment or inflation may increasingly become attractive options for looting as people seek alternative sources of income. Areas faced with a poor harvest or drought may see similar outcomes as individual livelihoods are jeopardized. Similarly, archaeological sites in areas with a lot of protests, terrorism, and unrest may become increasingly attractive targets as either the social order constraining illegal behaviors breaks down and looting increases in general or sites become targets as sources of financing. This suggests that conditions in the larger geographic region may influence which sites are targeted.

> ***Hypothesis 3:*** *Archaeological sites with evidence of looting attempts will be co-located with areas experiencing sociopolitical, economic, or environmental stress.*

Temporal variation also exists where sites are seen as "suitable" for attempted looting, depending on socio-political, economic, or environmental stress. Some types of conflict may last only a day or a few days (protests, riots, terrorism) while others are more prolonged affairs (organized group conflicts). Whether the result of socio-political stress (e.g., the vacuum in social order created by conflict) or as a means of financing future stress, it is possible that a site will be seen as suitable for looting because socio-political stress is building, or an incident has recently occurred. Similarly, in months where there is high unemployment there may be an increase in looting attempts at sites because of the potential monetary gain. Yet, the influence of such stressors may not be immediate. In areas experiencing environmental or economic stress, the effects may not be felt by individuals or groups immediately. It may take several months for looting a site to become a viable or suitable option. This suggests that there may be both immediate and long-term influences of duress on target suitability.

> ***Hypothesis 4:*** *The proportion of archaeological sites with evidence of looting attempts will increase during months where there is a stressor (e.g., sociopolitical, economic, or environmental).*

> ***Hypothesis 5:*** *The longer the stressor persists, the more archaeological sites will have evidence of looting attempts.*

Spatio-Temporal Influences on Looting

Egypt has a complex history of economic, socio-political, and environmental factors that could influence the likelihood that which archaeological sites are targeted and when. Because Egypt is administered largely on a governorate-level[6] and there is a lot of variation in their composition, changes in the broader socio-political, environmental, and economic conditions may vary spatially and temporally. Some of Egypt's largest governorates are the least densely populated because most of the land is desert, whereas the governorates in the Nile Delta (in Lower Egypt) are small and densely populated, surrounded by the Nile and its distributaries. Variation in landscape can translate into variation in environmental conditions and by extension economic conditions. Much of the arable land in Egypt is set aside for agriculture. For those governorates with extensive croplands, changes in the environment can have significant economic impacts (e.g., locally high unemployment or bad crop yields). Similarly, there is variation in the ethnic composition of Egypt' governorates, which may lead to differing levels of tension or conflicts. Finally, each of these "stressors" (political, economic, social, and environmental) vary over time. Economic hardship is temporary and environmental conditions change with the seasons. All this variation impacts which archaeological sites are likely to be targeted for looting attempts and when.

It is the broader societal context that influences capable guardianship and target suitability of archaeological sites. The specific conditions in an area may determine how well guarded a site is and its viability as a suitable target. In armed conflict, capable

[6] Governorates are the first-level administrative division in Egypt. They are roughly equivalent to states in the United States; however, each governorate has its own governor that is appointed by the president.

guardianship is difficult to maintain as the priorities of the government shift to address the greatest need. Archaeological sites are more likely to be overlooked during conflict as local law enforcement is deployed elsewhere and active dig sites are shut down. Internationally, existing regulations are both easy to bypass and ineffective at stopping looted objects as they leave the country and after they reach the market. This makes archaeological sites more accessible if they are no longer guarded and reduces the likelihood that guardianship will resume in the near future. While it is a useful heuristic to think of spatial and temporal variation separately, realistically the two are inextricably intertwined. Too many dynamics influence the complex pattern of economic, social, political, and environmental factors to truly separate spatial and temporal influences on looting attempts. As such, this theoretical framework suggests one spatio-temporal hypothesis regarding archaeological looting (see Hypothesis 6).

> ***Hypothesis 6:*** *Archaeological sites with evidence of looting attempts will be clustered in time and space with sociopolitical, economic, or environmental stress.*

Table 1, below, provides an overview of the hypotheses presented above as well as the type of variation to which each relates.

Table 1. Hypotheses based on the theoretical framework

Hypothesis		Type of Variation
1	Archaeological sites that are owned by the Supreme Council of Antiquities will experience less evidence of looting attempts.	Spatial
1a	The degree of ownership of an archaeological site (submitted for protection vs. protected under the law vs. owned by the SCA) will determine which sites experience looting attempts.	Spatial
2	Proximity to key locations (e.g., to populated centers, farms, etc.) affects whether or not an archaeological site will have evidence of looting attempts.	Spatial
3	Archaeological sites with evidence of looting attempts will be co-located with areas experiencing sociopolitical, economic, or environmental stress.	Spatial
4	The proportion of archaeological sites with evidence of looting attempts will increase during months where there is a stressor (e.g., sociopolitical, economic, or environmental).	Temporal
5	The longer the stressor persists, the more archaeological sites will have evidence of looting attempts.	Temporal
6	Archaeological sites with evidence of looting attempts will be clustered in time and space with sociopolitical, economic, or environmental stress.	Spatio-temporal

Chapter 3: Lower Egypt as a Case Study

The modern Arab Republic of Egypt ("Egypt") is a unified country of 27 governorates, each with its own governor appointed by the president (see Figure 1). Egypt appears to be a relatively ethnically homogenous country; however, there are no current published statistics on the country's ethnic composition.[7] Religiously, Egypt is very diverse – most of the country is Muslim; only ten percent of the population is Christian (Coptic and Catholic), and they are dispersed throughout the country (TIMEP, 2018a; Ragab et al., 2016).

Egypt's governorates can be roughly divided into two regions – "Upper" Egypt and "Lower" Egypt – that reflect differences in elevation and the flow of the Nile rather than cardinal direction. The Nile flows north from Lake Tana in Northern Ethiopia and Lake Victoria on the border of Tanzania to the Mediterranean Sea (Bard, 2015). Upper Egypt is "up river" and corresponds to the south where there is a higher elevation, while Lower Egypt is "down river" and corresponds to the north where the Nile meets the Mediterranean Sea (see Figure 2). This division dates back millennia to when Ancient Egypt was two separate geo-political regions. Between 8000 BCE and 3000 BCE Upper and Lower Egypt developed separately without much contact (Brewer, 2012).

[7] In 2018, the International Organization for Migration (IOM) and CAPMAS began a survey of foreigners living in Egypt; however, the results have not been made publicly available yet.

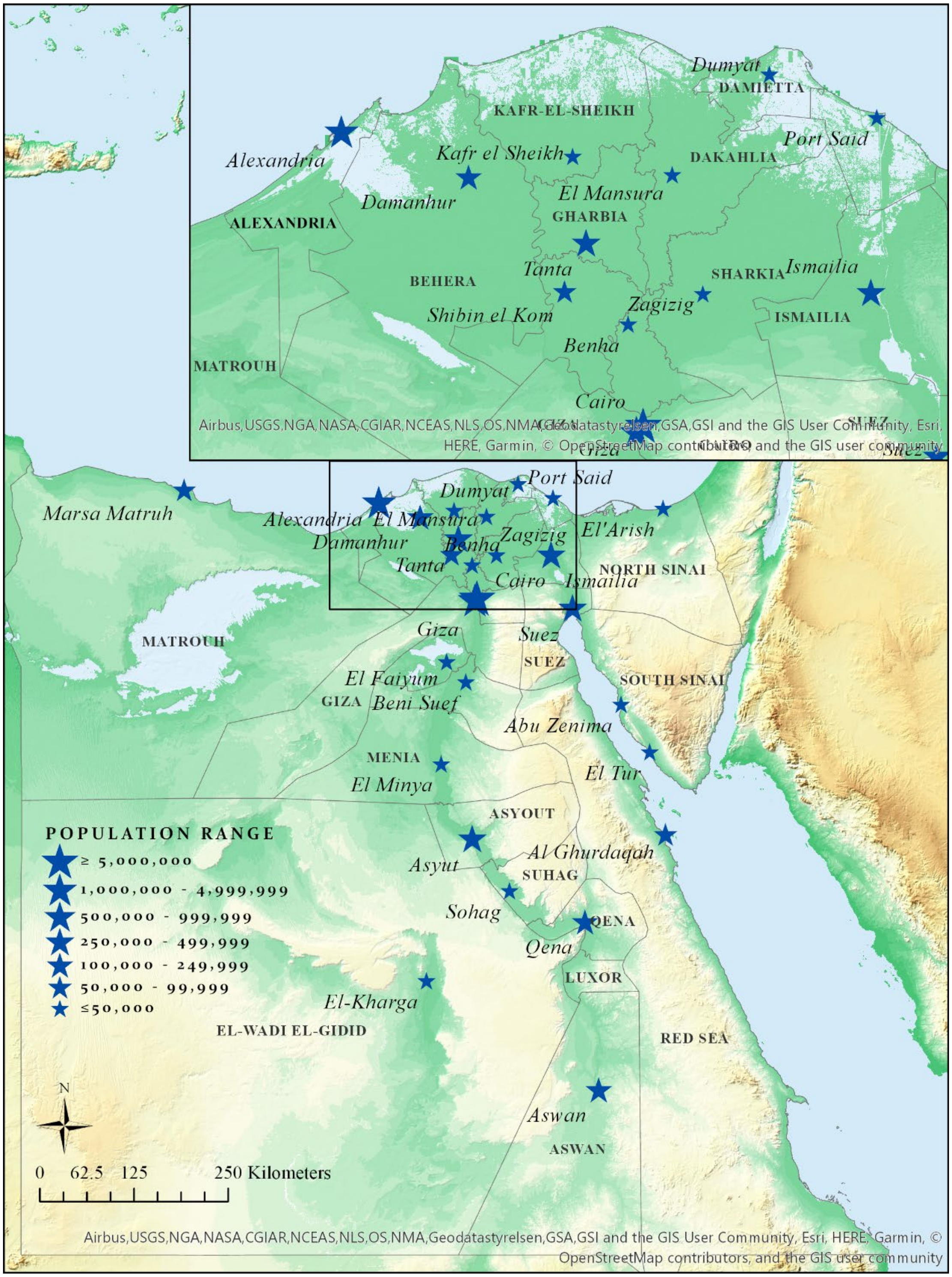

Figure 1. Map of Egypt with all 27 governorates labeled.

Figure 2. The Extent and Flow of the Nile with Upper and Lower Egypt Labeled. The Nile originates at Lake Victoria and Lake Tana and flows downriver to the Mediterranean Sea. Lighter colors indicate higher elevation. Yellow indicates desert terrain, green indicates arable land.

Though they are no longer separate geo-political regions, regional differences remain between Upper and Lower Egypt in terms of access to wealth, resources, and land use, and more (see Ragab et al., 2016; World Bank, 2009). Lower Egypt contains most of the country's population and produces most of its agricultural goods (Ragab et al., 2016). By contrast, Upper Egypt is mostly desert terrain and so is less populated, though it has larger concentrations of poverty than Lower Egypt. Economic, health, conflict, and environmental indicators are often collected and analyzed for Upper and Lower Egypt separately in addition to the national-level analyses (Ragab et al., 2016; World Bank, 2012). As such, it is possible to look at either Upper or Lower Egypt on its own.

This dissertation considers only Lower Egypt,[8] which encompasses 13 governorates in the Nile Delta (see Figure 1): Alexandria, Beheira, Cairo, Damietta, Daqahliyah, Al Gharbiyah, Ismailia, Kafr es Sheikh, Al Minufiyah, Port Said, Qalyubiyah, Al Sharqiyah, and Suez. Three important characteristics distinguish Lower Egypt as an ideal case study for examining the spatial and temporal patterns of archaeological looting.

First, it has both spatial and temporal variation in its demographic, economic, environmental, and socio-political conditions. For example, the Nile floods each year following the Indian monsoon seasons' schedule (Parcak, 2010). Monsoon rain feeds the Nile at its origin – Lake Tana (see Figure 2) and floods the river. In a year with strong monsoons, flooding is likely to extend all the way down river to the Delta in

[8] Lower Egypt is sometimes broken down into "Lower Egypt" and "Metropolitan" or "Urban" governorates. The Urban governorates include Alexandria, Cairo, Port Said, and Suez (CAPMAS, 2018b). To avoid confusion, this dissertation will use the more general grouping of "Lower Egypt."

Lower Egypt, the furthest point of the Nile. In a drier year, flooding may be more concentrated in the governorates closer to the Nile's origin, in Upper Egypt (near the border with Sudan). Which and how many governorates bordering the Nile that are affected by flooding depends on how much rain there is each year and how far down river they are (Parcak, 2010). Variation in environmental conditions could impact archaeological looting geographically and across time by affecting access to archaeological sites (e.g., due to population expansion, conflict, etc.) and the suitability of sites as targets (e.g., their value and ease of disposability, ability to use as currency, etc.).

The second reason that Lower Egypt is a good case study is that it has an incredibly long, rich cultural landscape dating back to 8000 BCE (Brewer, 2012). The region not only has a plethora of archaeological sites but a variety of archaeological material from many cultures. This cornucopia of cultures makes the governorates in the Nile Delta a potentially important source of antiquities for illegal art and antiquity markets, increasing the likelihood of archaeological looting. From 8000 BCE to 1000 CE, Lower Egypt had at least 20 different cultures that could be represented at archaeological sites (Lloyd, 2010). Upper Egypt's cultural landscape contains some of the same cultures; however, the Delta's proximity to the rest of Mesopotamia and the ocean made Lower Egypt more likely to encounter other cultures before Upper Egypt.

Finally, Egypt as a country – and by extension the governorates in Lower Egypt – has a long history of trying to protect its cultural heritage through legislation, guardianship, and international agreements. New programs and policies are regularly designed to improve upon existing measures for protecting cultural heritage in Egypt.

For example, beginning in 2005, Egypt increased security measures at antiquities storehouses and set up additional check-points at ports (El-Aref, 2005). In July 2018, Egypt passed an amendment to the Antiquities Protection Law of 1883 that increased the punishments for all crimes associated with cultural heritage (Egypt Today, 2018). While the whole country is affected by such efforts, Lower Egypt contains most of the country's ports and so these efforts may disproportionately impact sites in the Delta. These three characteristics (a complex set of macro-level conditions, rich cultural landscape, and history of protecting cultural heritage) combine to make Lower Egypt compelling choice as a case study and are discussed in turn below.

Macro-level Conditions in Lower Egypt

The Nile Delta, which occupies most of Lower Egypt, includes the fertile Delta, desert, and marshland. The western side of the delta extends into a desert plateau that ultimately leads to the Western Desert with an oasis on the far side (Wilson, 2007). The east side of the delta extends to the Suez Canal and features marshland and lakes (Wilson, 2007). In between the desert and marshland are the Nile tributaries, which create a large area of arable land (see Figure 3). This diverse landscape has given rise to unique demographic, economic, environmental, and socio-political contexts, each of which is discussed below.

Figure 3. Landscape of Lower Egypt

Demographics

Lower Egypt contains both the largest area of fertile land and many of the country's largest cities (e.g., Alexandria, Cairo), which concentrates the majority of Egypt's population in the Delta governorates (CAPMAS, 2018a; Wilson, 2007). Nationally, more than 90 percent of Egypt's population lives on approximately eight percent of the land – the fertile land in the Nile Valley and the Nile Delta (Ghafar, 2018; Ragab et al., 2016). This land is also historically where agriculture developed, creating concentrations of urban and "rural" areas in close proximity. According to the 2017 census, approximately 60 percent (60.1%) of the country's population lives in and around the Delta, with the largest concentrations in the Cairo (10%), Al Sharqiyah (7.6%), and Daqahliyah governorates (6.8%) (CAPMAS, 2018a). As Table 2 demonstrates, governorates also vary by how urban or rural their population is. Cairo, Alexandria, Port Said, and Suez have almost entirely urban populations, whereas the other nine governorates are split between urban and rural (CAPMAS, 2018a). As of 2015 (the most current numbers), almost thirty percent (29.4%) of Lower Egypt lives in poverty, 9.7% in urban areas and 19.7% in rural areas (CAPMAS, 2018b).

Table 2. Distribution of Lower Egypt's Population by Governorate (2017)

Governorate	Total Pop.	Rural	Urban	Percent of National Pop.
Alexandria	5,163,750	1.5%	98.5%	5.4%
Beheira	6,171,613	81.3%	18.7%	6.5%
Cairo	9,539,673	0.0%	100.0%	10.1%
Damietta	1,496,765	60.4%	39.6%	1.6%
Daqahliyah	6,492,381	71.2%	28.8%	6.8%
Al Gharbiyah	4,999,633	71.4%	28.6%	5.3%
Ismailia	1,303,993	55.4%	44.6%	1.4%
Kafr es Sheikh	3,362,185	76.0%	24.0%	3.5%
Al Minufiyah	4,301,601	79.0%	21.0%	4.5%
Port Said	749,371	0.0%	100.0%	0.8%
Al Qalyubiyah	5,627,420	57.3%	42.7%	5.9%
Al Sharqiyah	7,163,824	75.4%	24.6%	7.6%
Suez	728,180	0.0%	100.0%	0.8%

Note: All numbers come from the 2017 Census (CAPMAS, 2018a)

The average household size is approximately 3.94 people and between 8 and 23 percent of the population live in an overcrowded household (one or two rooms for all inhabitants) across all governorates. Roughly half of each governorate's population is between 15 and 44 years of age, with the next largest group between five and 14 years of age (See Table 3, CAPMAS, 2018a). More than half of the population is also male, and men occupy much of the labor force.

Table 3. Age and Sex Distribution as Percent of Total Population by Governorate

Governorate	Total Pop.	0 – 4	5 – 14	15 - 44	45 - 59	60+	Male	Female
Alexandria	5,163,750	12%	17%	47%	14%	9%	51%	49%
Beheira	6,171,613	14%	21%	46%	12%	6%	52%	48%
Cairo	9,539,673	10%	17%	49%	15%	9%	52%	48%
Damietta	1,496,765	13%	21%	46%	13%	7%	51%	49%
Daqahliyah	6,492,381	13%	21%	45%	13%	7%	51%	49%
Al Gharbiyah	4,999,633	12%	20%	46%	14%	8%	51%	49%
Ismailia	1,303,993	15%	20%	46%	12%	6%	52%	48%
Kafr es Sheikh	3,362,185	14%	20%	46%	13%	7%	51%	49%
Al Minufiyah	4,301,601	14%	21%	46%	12%	7%	52%	48%
Port Said	749,371	10%	17%	48%	15%	10%	51%	49%
Al Qalyubiyah	5,627,420	13%	22%	48%	12%	6%	52%	48%
Al Sharqiyah	7,163,824	14%	21%	46%	12%	6%	51%	49%
Suez	728,180	13%	19%	48%	13%	7%	51%	49%

Note: All numbers come from the 2017 Census (CAPMAS, 2018a)

Employment rates (for ages 15 to 64) have remained stable over the last five years in the Nile Delta governorates, while unemployment[9] rates have increased (see Table 4). Among the unemployed, females have a higher rate of unemployment than males (23.1% vs 8.2% in 2017) and unemployment rates for both have increased steadily over the last five years, peaking in 2013 and 2015, respectively (CAPMAS, 2018a).

[9] CAPMAS (2018a) defines unemployment as individuals ages 15 to 64 who have the ability to work, want to work, and search for work but who do not find it.

Table 4. Employment and Unemployment for Males and Females by Governorate

Governorate	Employed		Unemployed	
	Males	*Females*	*Males*	*Females*
Alexandria	83%	17%	9.6%	29.6%
Beheira	70%	30%	11.9%	21.6%
Cairo	78%	22%	11.4%	26.1%
Damietta	81%	19%	5.4%	23.9%
Daqahliyah	82%	18%	76.0%	23.3%
Al Gharbiyah	77%	23%	8.8%	23.4%
Ismailia	79%	21%	6.0%	28.4%
Kafr es Sheikh	77%	23%	9.7%	18.1%
Al Minufiyah	72%	29%	6.3%	8.3%
Port Said	75%	25%	12.1%	28.2%
Al Qalyubiyah	79%	21%	9.1%	23.7%
Al Sharqiyah	78%	22%	9.0%	28.1%
Suez	84%	16%	16.5%	42.9%

Note: All numbers come from the 2017 Census (CAPMAS, 2018a)

Over the last decade, Egypt as a whole and Lower Egypt regionally have experienced challenges associated with rapid population expansion. Egypt's total population grew from 72.8 million in 2006 to 97 million in 2017 (CAPMAS, 2018a; Ghafar, 2018; Ragab et al., 2016). This expansion has not occurred uniformly across the country – it has concentrated in the Delta area. Lower Egypt's population expansion has led to the construction of over 30 new villages and towns (compared to six additional villages and towns in Upper Egypt) (CAPMAS, 2018a). Much of this growth is due to increasing birth rates and unsuccessful efforts by the government to implement family planning policies (Ghafar, 2018).

Rapid population expansion has also increased the density of already densely populated areas. Egypt's total population density per square kilometer increased from 78.1 in 2010 to 92.4 in 2017, putting strain on the existing infrastructure (CAPMAS, 2018b). More land must be cultivated for crops to feed the growing population, which has led to draining marshland to increase the amount of irrigated land (CAPMAS, 2018a; Ghafar, 2018). The recent movement by the military and government to cultivate the desert plateau area of the Delta has also increased strain on the water supply and put archaeological sites in danger of looting (Saleh, 2018). The construction of new urban areas and the push to create more arable land with irrigation systems in an arid climate strains the water supply in Delta, often requiring farmers to use untreated ground water ("dirty water") for their crops (see more on the environment below, Saleh, 2018). This puts strain on the already high unemployment rate and makes it more difficult for people to make a living wage (see more on the economy below).

Economics

Egypt's economy depends on a range of economic activities. In the 2016 fiscal year, almost 70 percent of Egypt's gross domestic product (GDP) was comprised of: manufacturing industries (17.1%); wholesale and retail trade (14.0%); agriculture, forestry, and fishing (11.9%); and other[10] (26.1%) (Bank Audi Sal, 2017). Tourism contributed less than two percent (1.8%) of the country's GDP. Egypt's military also plays a significant role in the economy, conscripting people to work in many of the industries in Egypt with little or no pay (Boukhari, 2017; Home Office, 2017; Marshall, 2015). Lower Egypt's economy depends on many of the same sectors as the country overall. The governorates in the Nile Delta employ individuals across a wide range of industries with most employed in agriculture, tourism, manufacturing, construction, wholesale and retail sale of vehicles, transportation, education, and defense (CAPMAS,

[10] Note, Bank Audi Sal does not discuss what activities the "other" category includes.

2018a, b). Of these, agriculture and manufacturing are the largest public sector paying employers.

Over the last seven years, Egypt has experienced economic hardship related in part to three factors: (1) the 2011 revolution, (2) the role of the military in the economy, and (3) environmental changes.[11] In 2011, Egypt experienced a large-scale uprising (the Lotus Revolution) that led to three regime changes in a year. President Mubarak was ousted in early 2011 and was replaced when Mohammed Morsi won the election later that year. The military then ousted Morsi and held power until the election of President Sisi in 2012. The Lotus Revolution affected the economy through changes in leadership, reductions in tourism, and strain on the ability of the government's domestic and international reserves. The changes in leadership from 2012 to 2014 negatively impacted the GDP and reduced tourism. The frequent changes in leadership also affected the government's ability to create an economic policy to address the situation (Ghafar, 2018). The percent of GDP growth plummeted in 2011 and has only slowly recovered. It dropped from 5.1% growth in 2010 to 1.8% growth in 2011 and in 2016 only reached 3.8% growth (Bank Audi Sal, 2017). This growth is in part due to the government's investment in its main economic sectors – for example, agriculture and construction both received increases in investment over the last two years (Bank Audi Sal, 2017).

[11] The causes of Egypt's current socio-political and economic situation are the subject of debate. Some argue that the current situation is the consequence of the 2011 revolution and that Egypt has started to improve (Bank Audi Sal, 2017). Others argue that the situation reflects some long-standing issues in the country rather than being solely the result of the 2011 revolution and, importantly, that Egypt's economy continues to suffer (TIMEP, 2017).

Although tourism is not currently a large contributor to Egypt's GDP, Egypt's economy has historically depended heavily on it (TIMEP, 2017). In the wake of the 2011 revolution, tourism suffered, and this trend has continued. Tourism decreased by over a third from 2010 to 2011 (32.4%) and Egypt reported half as many tourists in 2016 as the country had during the same period in 2015 (TIMEP, 2017). Terrorist attacks and regional differences in security concerns have influenced the international perception that the country is not safe to visit (Bank Audi Sal, 2017).

The revolution also affected Egypt's ability to pay its debts domestically and internationally. Government debt is currently around 90 percent of GDP and continues to rise (TIMEP, 2017). Since 2013, Egypt has faced shortages of foreign currency required to import goods and basic supplies due to unfavorable exchange rates and a lack of reserves, resulting in a black market for commodities (Boukhari, 2017; Hauslohner, 2013; TIMEP, 2017). This culminated in 2016 when the government decided to revalue the Egyptian pound. As a result, the country experienced extreme inflation (24% in December 2016), shortages in essential products (e.g., food, medicine, and other basic supplies), increased poverty, and increased unemployment (12.8% overall and 37% for youth) (Boukhari, 2017; TIMEP, 2017).

Lower Egypt was more affected by the high rates of inflation, increases in poverty, and reductions in tourism compared to Upper Egypt after the revolution (Ghafar, 2018). Inflation and shortages of basic supplies affected the production of crops (a primary economic output for the region) and increased poverty. Through new initiatives and financial restructuring, some say Egypt's economy has started to recover in the last two years (Bank Audi Sal, 2017).

The second source of economic hardship relates to the military's role in Egypt's economy. The Egyptian Armed Forces (EAF) played a key role in reshaping the economy after the Revolution and continues to affect whether there is economic hardship (see more in socio-political below). All male Egyptians between 18 and 30 years of age are required to serve up to three years in the military (Home Office, 2017). Additionally, the military can conscript free labor for construction projects (Boukhari, 2017). For most, military service involves working in a factory or another industry owned and operated by the military for a very small, unlivable wage (Boukhari, 2017; Home Office, 2017).

Over the last seven years, the military has increased its influence on the economy. In 2015, President Sisi passed a law allowing the military to set up companies with the participation of domestic and foreign capital (Ghafar, 2018). Currently, the military is involved with approximately 80 percent of the market (Home Office, 2017). It is involved in many sectors of the economy, including: manufacture of construction materials, construction services, management of the road system, importation of medicine and wheat, and manufacture of domestic appliances (Boukhari, 2017). Much of this expansion occurred during the recent economic crisis as the military took over production of key items previously imported. For example, Egypt faced a medicine shortage in 2016 due to lack of access to dollars. In response, the military received authorization to establish their own lab to develop and produce cancer medication (Boukhari, 2017). Yet the extent of military involvement in the economy contributes to high unemployment rates by preventing local companies from competing for government contracts (Ghafar, 2018). Those who refuse to participate in their military service can also be blocked from getting jobs elsewhere (Home Office, 2017).

Finally, water shortages, soil degradation, and pollution have affected the quality and quantity of crops produced in the Nile Delta, one of the primary producers of crops in Egypt (see more on the environment below Saleh, 2018). This has impacted governorate economies to varying degrees (Saleh, 2018) and forced Egypt to continue to import more than they export (CAPMAS, 2018a). This is discussed in more depth in the following section.

Environment

Egypt has a unique environment that makes it highly dependent on the Nile river and Nile Delta governorates for water and agriculture, respectively. Egypt's landscape is largely comprised of desert, arid, and semi-arid areas with concentrated pockets of fertile land around the Nile river. Annual rainfall ranges from a maximum of 200mm in the northwest coast to no rainfall in the south, making the Nile river the largest supply of water for the country. Historically, the combination of desert with concentrated pocket areas of fertile land led to an almost exclusive focus on agriculture as Egypt's primary industry.

Agriculture remains a key element of Egypt's economy, accounting for 20 percent of the GDP, a third of exports, and provides employment for about a third of the labor force (Ghafar, 2018). Agricultural production in Lower Egypt comes from three main zones: (1) "ancient" irrigated lands that have been farmland for generations (2.3 million hectares, or 5 million acres); (2) "newly" reclaimed lands including desert areas with poor soil quality (up to 0.8 million hectares); and (3) rain-fed areas with sandy soil (about 0.1 million hectares) (El-Hadi & Marchand, 2013, see Figure 4). Egypt's proximity to the equator makes it ideal for cultivating a wide variety of goods, including wheat, barley, maize, sorghum, rice, beans, lentils, linen, peanuts, sesame, soya beans, sunflowers, sugar beets, onions, citrus fruits, and palm dates (CAPMAS, 2018b).

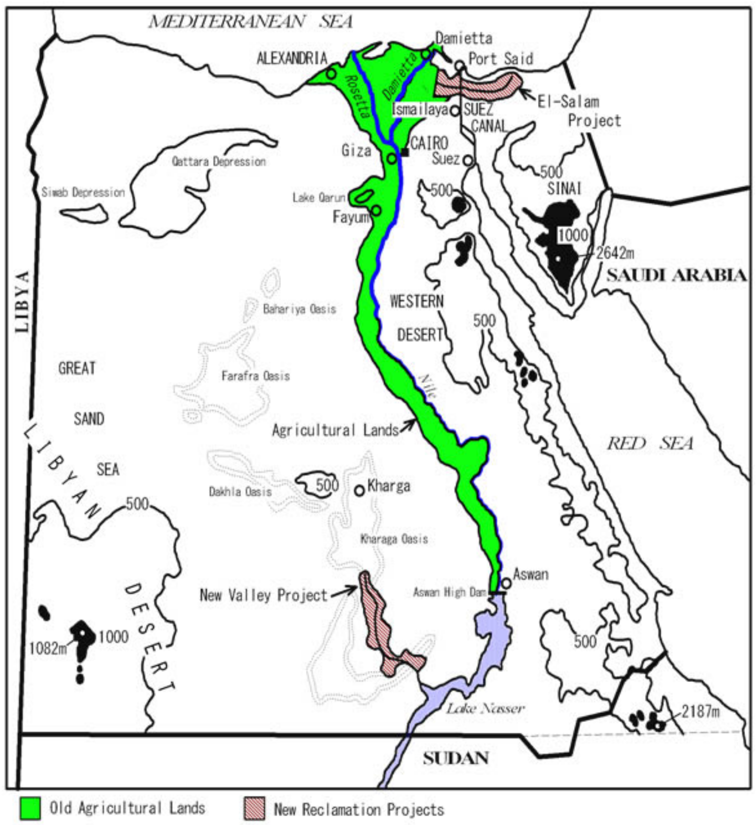

Figure 4. "Ancient" irrigated lands vs "newly" reclaimed land (El-Hadi and Marchand, 2013: 15).

Lower Egypt produces most of Egypt's domestic agriculture (Ghafar, 2018). All governorates in the delta cultivate wheat, many of them grow rice and cotton, and some grow sugar cane as well (CAPMAS, 2018). Those governorates in the heart of the delta (Beheira, Damietta, Daqahliyah, Al Gharbiyah, Kafr es Sheikh, Al Minufiyah, Qalyubiyah, Al Sharqiyah), tend to produce all four crops, requiring large quantities of water (CAPMAS, 2018b). Lower Egypt primarily uses ancient irrigated lands for agriculture, though there is a growing area of reclaimed land in the Port Said governorate and some rain-fed land on the northwest coast (El-Hadi & Marchand, 2013). Water for the Delta's crops comes primarily from the Nile River and underground water in the area, which – since 1950 – has been supplemented with re-used agricultural drainage water and treated sewage water (El-Hadi & Marchand, 2013, Ghafar, 2018). Another key element of Lower Egypt's environment is the soil quality. The delta region has several soil types, including sandy, calcareous, and clay each with different nutrient properties (Brewer, 2012; El-Hadi & Marchand, 2013). The type of soil affects both how easily the land is cultivated and how quickly crops will be affected by changes in the environment.

Lower Egypt faces three main environmental challenges. First, changes in land use have put stress on water supply. In the last decade, rapid population expansion has strained the ability of the state to provide an adequate water supply (both potable and agricultural). Because of the arid climate, water is a limited resource in Egypt. A larger population requires more water for daily activities and produces more wastewater in need of processing for irrigation. The capacity for wastewater processing has not kept pace with the rate of population expansion in Lower Egypt, and some farmers end up using unprocessed wastewater or polluted water to irrigate crops (Saleh, 2018).

This expansion has also led to urbanization of old agricultural lands and the subsequent reclaiming new areas of land for cultivation to compensate (Eladawy et al., 2015; El-Hadi & Marchand, 2013). Older agricultural lands tend to be on richer soil and on the "ancient irrigated" lands, which means that less work must be done to cultivate crops. Reclaiming land, by contrast, requires the marshland near the coast in the Port Said governorate to be drained to increase the amount of irrigable land (Wilson, 2007). These new agricultural areas may require more fertilizer and imported nutrients to sustain a crop as well as more water (e.g., if the soil is less absorbent) to produce the same yield as the now urbanized land. Both effects of population increases have affected the crop yield in Lower Egypt, particularly for crops like rice that require large amounts of water. This impacts the ability of farmers to make a living wage and strains the broader economy.

A second challenge facing Lower Egypt's environment is climate change. Over the last five years, fresh water from the Nile has stopped reaching some of the governorates in the heart of the delta, forcing those farmers to seek other water sources to compensate or risk losing their crops (Saleh, 2018). Rising sea levels are also submerging agricultural land on the coastline and affecting the salinity of water inland (Ghafar, 2018). The Delta, which sits only one meter above sea level, is sinking at a rate of four to eight millimeters per year, reducing the amount of arable land for cultivation (Ghafar, 2018). As seawater reaches further inland, both the groundwater and freshwater lakes in Egypt are slowly increasing their salinity (i.e. becoming more saltwater than freshwater), reducing the available water supply (Eladawy et al., 2015).

The third major environmental challenge is the construction of dams on the Nile. The High Aswan Dam was built in the 1960s at the first major cataract in the river in Upper Egypt to control flooding, store water for irrigation, and generate hydroelectric power (Abd-El Monsef et al., 2015). Since then, the dam has prevented the Nile Delta from receiving fresh silt during the annual floods (Elsaid, 2018). Without fresh silt, the Nile Delta cannot receive replacement nutrient and new soil, which increases the rate of erosion on the shoreline (Elsaid, 2018). Ethiopia is currently constructing its own dam, the Ethiopian Renaissance Dam, which will further limit the amount of water supplied to Egypt through the Nile river in the future (Ghafar, 2018). Though this does not have an immediate impact, it will present a serious challenge for the environment in the future. These challenges to the environment directly impact Lower Egypt's economy and landscape.

Socio-political

Egypt has long history of multiculturalism and armed conflict tied to tensions between religious groups and non-state actors, particularly between Christians and Muslim groups (TIMEP, 2018b).[12] From 2010 to 2017, Egypt has experience three changes in leadership, escalating religious violence, a steady stream of terrorist incidents, and numerous protests.

Egypt's changes in regime occurred from 2011 to 2014, resulting from the Lotus Revolution (and influenced by the Arab Spring) in Egypt of 2011. The Arab Spring began in other countries in 2010, but did not impact Egypt until 2011, when President Hosni Mubarak was ousted as a result of large-scale uprisings (involving both the Islamic groups and Coptic Christians) that demanded his resignation (Masoud, 2011). The initial impetus of the uprising involved many, sometimes contradictory, goals. While both Coptic Christians and Islamic groups called for Mubarak's resignation, Coptic Christians wanted more equality and higher wages (especially for women). Meanwhile, the Islamic groups disdained the secular government and wanted

[12] Though religion is not included in any census questions in Egypt, it is estimated that about 10 percent of the population is Christian, most of which are Coptic or Orthodox, though there are Catholics and Protestants as well (TIMEP, 2018b).

a return to an Islamic rule (Bowker, 2013; Gerbaudo, 2013; Masoud, 2011; Schwartz; 2011). The role of the military was central to this conflict as it consistently had the most power and influence (Gerbaudo, 2013). They have at times supported the uprisings and at other times suppressed them. The Supreme Council of Armed Forces (SCAF) assumed leadership of the government after Mubarak resigned until Mohammed Morsi was elected President in 2012. Morsi was then ousted in a military coup in 2013 due to his inability to find a credible alternative to an Islamic state and perceived ineptitude (Gerbaudo, 2013: 104-105). The former military chief Abdel Fattah el-Sisi has held the position of President since 2014 (Basil, 2014).

Religious violence, terrorism, and protests have all continued since President Sisi took office. Since 2014, there have been at least 400 incidents of violence, many of which coincided with incidents of property theft and looting (Amnesty International, 2017). There have been both spontaneous and organized attacks on Christian minorities as a result of attempts to build new churches, interfaith romances, and property disputes (TIMEP, 2018a). According to the Tahrir Institute for Middle East Policy (2018a), terrorism has remained relatively high from 2013 to 2017, peaking in 2015 with 1,096 incidents and averaging 618 incidents per year.[13] Although most of Egypt's terrorism occurred in the Sinai Peninsula during this time, there has been a persistent low level of terrorism in Lower Egypt targeted at the economy and security personnel (TIMEP, 2018a). Protests have also continued in Cairo and other cities in Lower Egypt, though

[13] The perpetrators of these attacks vary considerably. For example, three large categories of groups have carried out many of the attacks: (1) those dissatisfied with the results of the 2011 revolution (e.g., Popular Resistance Movement, Revolutionary Punishment, Students Against the Coup); (2) groups seeking an Islamic state (e.g., the Muslim Brotherhood, Islamic State in Egypt); and (3) new radical groups seeking an assortment of other changes through violent means (e.g., Ahrar Movement, Ultras White Knights group, etc.).

they are not always organized (TIMEP, 2018b). Discontent with economic conditions, police brutality, government inaction in response to sectarian violence, and poor representation of minorities in the political process have all led to isolated protests, but no lasting movements (TIMEP, 2018b).

Lower Egypt's Cultural Landscape

Egypt has a long, rich, history with some of the earliest examples of human civilization and has strong foundations in Ancient Egyptian religions (e.g., the cult of Theban Priests) (Brewer, 2012). Evidence of human settlement in Egypt has been found as early as the Paleolithic era (c. 8000 BCE); however, evidence of agriculture and settlements in Lower Egypt are not found until approximately 4000 BCE (Bard, 2015; Brewer, 2012). Between 8000 BCE and 3000 BCE Upper and Lower Egypt developed separately without much contact (Brewer, 2012), influencing the types of archaeological sites found in each region. Archaeology in Egypt also has a long history. Some of the earliest modern discoveries come from the Napoleonic scientific expeditions to Egypt in the early 1800s (Brewer, 2012). The plethora of cultures and sites in Upper and Lower Egypt mean that archaeologists continue to find new discoveries. For example, in 2017 a new burial ground with over 100 tombs was discovered in Upper Egypt (Parcak, 2017).

Because of the length and complexity of Egypt's history, this section provides a brief overview of the cultures present throughout in Lower Egypt's development. I then discuss the types of archaeological sites found in Lower Egypt and define key terms relevant to this dissertation.

A Brief Timeline of Ancient Egypt (8000 BCE – 1000 CE)[14]

The earliest evidence of agriculture and animal domestication in Lower Egypt dates to the Neolithic Era and is found at two archaeological sites – Merimden (4800 BCE) and Omari A/B (3750 BCE and 3650 BCE respectively) – though little is known about their cultures (Brewer, 2012). The earliest culture found in the Delta area is the Buto Ma'adi (c. 4000 – 3000 BCE), who lived in the Pre-Dynastic and Early Dynastic eras of Ancient Lower Egypt at the beginning of their political dynastic system (Brewer, 2012).[15] Generally, Ancient Egypt has 12 "eras" or time periods of history, from approximately 4000 BCE to 1000 CE. During this time, Ancient Egypt was host to over 20 cultures with hundreds of rulers (including 31 Egyptian dynasties).[16] Exact dates and boundaries for each ruler are a matter for debate since information comes from a combination of written narratives and archaeological evidence, which may contradict each other (Bard, 2015). As such, I focus here on the cultures that may be represented at archaeological sites in Lower Egypt rather than providing a geopolitical timeline of each ruler and era. Table 5 provides an art historical timeline of Ancient Egypt's eras and the cultures represented in each.

At the end of the Pre-Dynastic period (during Dynasty 0), Lower and Upper Egypt were politically unified for the first time under a single king (called "Pharaoh"). Politically, the Old Kingdom, Middle Kingdom, New Kingdom, and Late Period are

[14] Here I am using the Before Common Era (BCE) and Common Era (CE) to denote historical dates instead of Before Christ (BC) and Anno Domini (AD) because they do not have a religious connotation. BCE corresponds to BC and CE corresponds to AD.
[15] The term "culture" here (as opposed to people) refers to the fact that the Buto Ma'adi sites are the earliest with evidence of pottery and other physical remains that provide insight to the daily lives of the people in this group.
[16] A dynasty is a series of rulers sharing a common origin – they are often (but not always) from the same family (Lloyd, 2010).

generally characterized by expansion and a succession of Pharaohs who ruled over a unified kingdom. During periods of unification, a clear style or set of styles developed and so are labeled according to the era if a specific name for the style is not present. By contrast, the first, second, and third intermediate periods are characterized by invasion and external rule and the fracturing of Egypt into multiple kingdoms. The Romans brought Christianity to Egypt towards the end of their rule; however, Islam became the dominant religion in Egypt beginning in 641 CE. Though this table ends at 1000 CE, the period of Islamic rule began a process of solidifying "Egyptian" as the national identity of the current Arab Republic of Egypt.

Table 5. Lower Egypt's Art Historical Timeline 8,000 BCE – 1,000 CE

Era / Time Period	Approximate Dates	Cultures Represented at Archaeological Sites
Pre-Dynastic/Early Dynasty (Dynasty 0)	4000 – 3000 BCE	Buto Ma'adi
Old Kingdom	2686 – 2181 BCE	Old Kingdom Egypt
1st Intermediate Period	2181 – 2055 BCE	Ayyubid
Middle Kingdom	2055 – 1650 BCE	Ayyubid, Mamluk, Middle Kingdom Egyptian
2nd Intermediate Period	1650 – 1550 BCE	Theban, Hyksos
New Kingdom	1550 – 1069 BCE	Amarna period, New Kingdom Egyptian
3rd Intermediate Period	1069 – 664 BCE	Kushite, Nubian, Egyptian, Assyrian
Late Period	664 – 332 BCE	Assyrian, Achaemenid Persian, Macedonian, Kushite
Macedonian/Ptolemaic Period	332 – 30 BCE	Macedonian, Greek, Roman
Roman Period	30 BCE – 395 CE	Roman
Byzantine Period	395 – 641 CE	Byzantine
Islamic Rule	641 CE – 1000 CE	Byzantine, Sassanian, Abbasid, Fatamid

Archaeological Sites in Lower Egypt

An archaeological site is broadly defined as "any place where physical remains of past human activities exist" (SAA, 2018). Based on this definition, an archaeological site can take many shapes, from a collection of pottery fragments ("pot sherds") on a square foot of land to a mounded hill to a large city. Lower Egypt has at least 1,600 archaeological sites (see Figure 5). Many of these sites look like mounds or small hills (see Figure 6), though there are some larger cities (see Figure 7) and cemeteries (or necropolises) (see Figure 8).

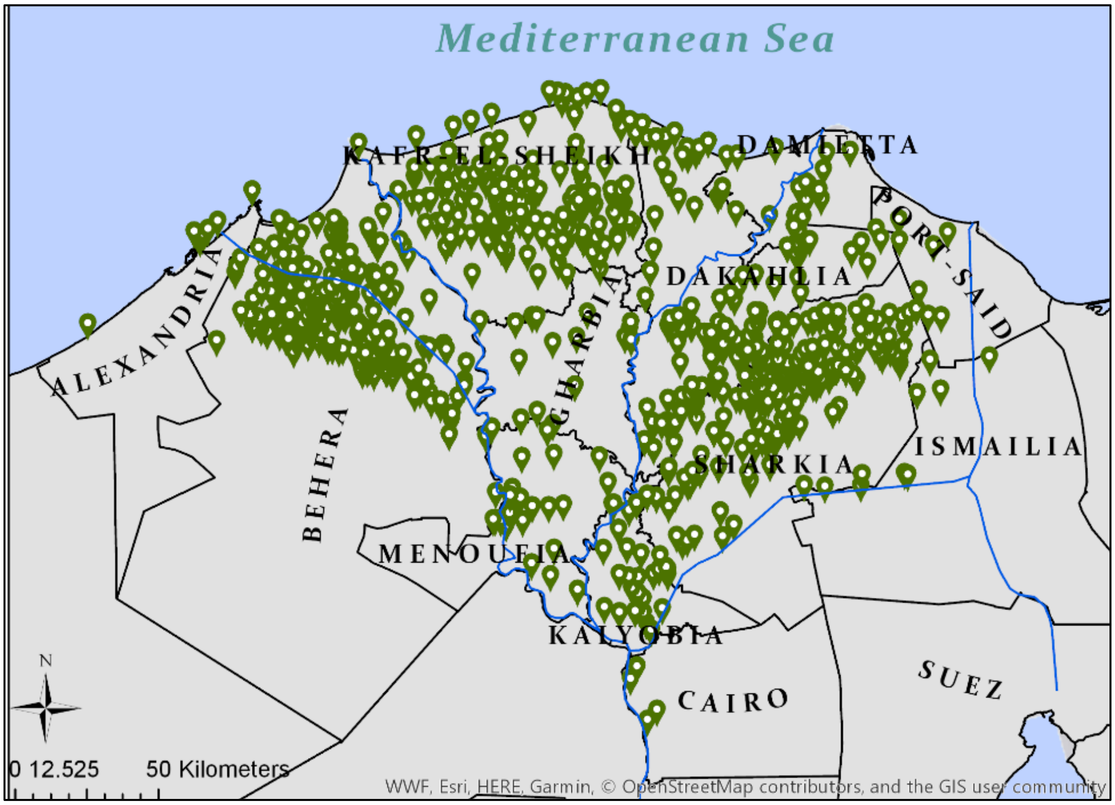

Figure 5. Archaeological Sites in Lower Egypt

Figure 6. Tell el-Gassa, an archaeological site in Lower Egypt from November 2016. "Tell" translates roughly to "mound" in English. The scale indicates this site is very large (100m is approximately the size of a football field). Image courtesy of Google Earth Pro.

Figure 7. Alexandria Amphitheater Archaeological Site in Lower Egypt from November 2016. Image courtesy of Google Earth Pro.

Figure 8. Anfushi Necropolis Archaeological Site in Lower Egypt from May 2017. Image courtesy of Google Earth Pro.

Lower Egyptian sites contain very few "cities" for two reasons. First, archaeologists traditionally defined a city based on those observed in Mesopotamia, which were clearly defined, planned, and walled settlements (Brewer, 2012). Very few sites in Egypt meet this definition and those that do tend to be the result of occupying forces influencing architectural design (e.g., Graeco-Roman architecture). Second, Egypt's geography affected the development of settlements in a different way from Mesopotamia. Settlements in Mesopotamia were under frequent threat of raids and invasion, making defensive architecture and concentrated locations of people in cities key to survival (Brewer, 2012). However, Ancient Lower Egyptian settlements were bordered by the desert and sea preventing most attacks and so did not need walls around their settlements (Brewer, 2012). As such, Ancient Lower Egypt maintained a rural character throughout much of its development, where the population was distributed among many small agricultural villages. These villages were typically located near the river and its tributaries and were built on *gezirahs*, or naturally occurring elevated mounds, to avoid flooding (Brewer, 2012). Given the cornucopia of cultures in Lower Egypt's past, archaeological sites in this area may contain a wide variety of antiquities.

Egypt's Efforts to Protect Cultural Heritage

Egypt is invested in protecting its cultural heritage and has a long history of attempting to protect and preserve its cultural heritage from being destroyed during conflict and from looters. Their strategy for reducing the looting of antiquities, especially from archaeological sites, is to pass stricter laws with harsher penalties, increase security measures, and place checkpoints at every Egyptian port (El-Aref, 2005). The Ottoman Empire (of which Egypt was nominally a part) passed the first law asserting ownership and thus protection of artifacts in 1884 (Kersel, 2010). The British also passed several laws during the early twentieth century (when Egypt was a colony) regulating the administration and ownership of Egyptian antiquities and cultural heritage.

The first law passed by Egypt as an independent country was in 1983. The 1983 Law on the Protection of Antiquities is the primary law in Egypt relating to antiquities and cultural heritage. It establishes the Supreme Council of Antiquities (SCA) as the administrative bureau tasked with registering, regulating, and monitoring archaeological sites and cultural heritage, including excavation and study, tourism, and guardianship (SCA, 2009). Under the SCA each governorate is divided into "inspectorates" that are monitored for signs of looting or other illegal activity relating to antiquities under the law.

The 1983 law also establishes that antiquities are owned by the government and must be registered. It also identifies the following activities as illegal: damaging, destroying, stealing, looting, and excavating sites without permission, as well as possessing, transporting, trafficking, and selling antiquities removed without permission (Law 117 of 1983). Punishment includes a fine of between LE 1,000 and LE 500,000 and imprisonment of up to seven years (Egypt Today, 2018).

Egypt also has a police force dedicated to the security of tourist locations, museums, and antiquities. These police are one section of the country's national police force, which also includes its military. A police chief is appointed to each governorate who is responsible for local enforcement, but who reports directly to the Minister of the Interior rather than the governor of the governorate (MOI, 2019). This combination of a national-level police force and local enforcement of the laws both makes it possible that there are regional differences in enforcing laws and makes it difficult to geographically distinguish between enforcement levels (MOI, 2019).

Beyond these measures, Egypt regularly implements new measures to improve security and prevent looted or stolen antiquities from leaving the country. In the early 2000s, Egypt placed security check-points at all ports leaving the country to screen for attempts to remove or traffic antiquities (El-Aref, 2005). This has been generally successful in capturing objects before they reach an international market but has been less successful preventing the initial looting or theft. In 2018, President Sisi approved two laws aimed at changing that. The first is a law establishing an Egyptian space agency that will launch its own satellites to monitor, among other things, archaeological sites around the country (Al-Youm, 2018). The second law is an amendment to the 1983 Protection of Antiquities Law that modified the punishments for crimes related to antiquities. Specifically, under the new amendment anyone committing a crime related to antiquities (trafficking, looting, possession, etc.) may be sentenced to: “heavy imprisonment,” life in prison, a fine of between LE 50,000 and LE 250,000, or a combination of the above.

Chapter 4: Data Collection and Coding Strategy

An integral component to any methodology for analyzing archaeological looting attempts is the collection and coding of data. The strategy employed needs to be flexible enough to accommodate different amounts of resources and access while also creating robust and reliable data appropriate for the research question. This chapter outlines how the hypotheses relate to the data collection and coding strategy and then details the process used for both collection and coding.

The theoretical framework discussed in Chapter 2 suggests multiple hypotheses relating to the spatial and temporal patterns of archaeological looting in Lower Egypt, each of which corresponds to a spatial, temporal, or spatio-temporal relationship (see Table 1). Spatial, temporal and spatio-temporal methods have different requirements for the data types, formats, and units of analysis (Table 6). As such, it was important to approach data collection and coding with an understanding of which types of data would be required for each type of relationship I evaluated.

Table 6. Data and Analytic Requirements for Spatial, Temporal, and Spatio-Temporal Data

Method	Data Types	Data Formats	Unit of Analysis
Spatial	Geo-located data (has latitude and longitude) or data that maps to standard administrative boundaries	Shapefiles of individual points or polygons	Spatial grid cell
Temporal	Event or incident data collected at regular temporal intervals	Time series data	Month
Spatio-Temporal	Data with both specific geo-locations and dates associated with each observation	Space-time cubes	Grid-cell-month

Temporal and spatial data were collected from 2015 to 2017 across 12 governorates in Lower Egypt: Alexandria, Beheira, Cairo, Damietta, Daqahliyah, Al Gharbiyah, Ismailia, Kafr es Sheikh, Al Minufiyah, Port Said, Al Qalyubiyah, and Al Sharqiyah.[17] Data were collected for the primary dependent variable, archaeological looting, and for a range of theoretically relevant socio-political, economic, and environmental independent variables.

Temporal data were collected at monthly intervals for data on archaeological looting attempts and sociopolitical stress indicators. Some of the environmental and economic stress indicators were only available at quarterly or yearly intervals, for which case data were collected using the smallest unit of time available. Spatial data were collected at the smallest spatial unit available for each variable (e.g., incident location, governorate, country) and were then geolocated and assigned to a spatial grid (10km, 50km, and 150km grid-cells)[18] – a grid of uniform cells overlaid on a study area where each cell is assigned a value for the spatial variables of interest (Strimas-Mackey, 2016). Using a grid provided a smaller unit of analysis than the governorate and captured more spatial (and spatio-temporal) variation. In this case, the grid was overlaid on top of Lower Egypt and each cell was assigned the value of any variable that intersected with that cell. The temporal and spatial data were aggregated to the month and grid-cell to create spatiotemporal data. Table 7 provides an overview of the data sources for each variable and their spatial and temporal unit.

[17] It is important to note that Lower Egypt includes 13 governorates, 4 of which are Egypt's "Metropolitan" governorates – Alexandria, Cairo, Port Said, and Suez. The last, which borders the Suez Canal, was excluded from the list of governorates I collected data for because I was unable able to identify any geo-coded archaeological site locations.

[18] See below for details on determining the optimal cell-size and shape (hexagonal vs lattice).

Table 7. Variables, Type of Data, and Data Sources

Variable Category	Variable(s) of Interest	Data Type	Data Source(s)
Archaeological Looting	Evidence of any looting attempts	Daily Satellite Imagery available for selective periods of time at resolutions of 32cm to 50cm for the archaeological sites sampled.	Digital Globe Google Earth Pro
Socio-Political Indicators of Hardship	Range of sociopolitical tensions (violent conflict, protests, and violence against civilians)	Longitudinal Geo-located Event Data	Armed Conflict Location and Event Data Project (ACLED) Uppsala Conflict Data Program (UCDP) Global Terrorism Database (GTD)
Economic Indicators of Hardship	% Unemployment (total and youths aged 15-24)	Quarterly data at the governorate level	Egypt's Central Agency for Public Mobilization and Statistics (CAPMAS) WorldBank
	Consumer price index (general and food)	Monthly data at the national level	Food and Agriculture Organization of the United Nations (FAO)
	Consumer price index-based inflation	Yearly data at the national level	WorldBank
	National Debt (as % of external debt and as % of reserves)	Yearly data at the national level	WorldBank
	Number of tourist arrivals	Yearly data at the national level	WorldBank
Environmental Indicators of Hardship	Estimated precipitation	Monthly data available at 0.25-degree spatial intervals	National Aeronautics and Space Administration (NASA)
	Soil Moisture Content	Monthly data available at 0.5-degree spatial intervals	National Aeronautics and Space Administration (NASA)
	Vegetation health index (NDVI)	Monthly data available at 0.05-degree spatial intervals	National Aeronautics and Space Administration (NASA)
	Total crop production	Yearly data at the national level	Food and Agriculture Organization of the United Nations (FAO)

To create the temporal, spatial and spatiotemporal datasets, I compiled data from multiple sources for each variable, most of which were obtained from open source databases. It was impossible to create consolidated datasets with all spatial and spatio-temporal variables of interest due to the requirements of storing large and varied quantities of such data (see Table 6). Instead, I created four groups of datasets: two spatial, one time series, and one spatio-temporal. The two spatial groups of datasets reflect the two different forms of spatial data used in geospatial analysis – vector and raster data. Tables describing the operationalization of each variable for the spatial, temporal, and spatio-temporal datasets and analyses are included at the end of each section. Some variables were operationalized in multiple ways, according to what was most appropriate for the analysis being conducted. For example, looking at the proximity of archaeological sites with evidence of looting attempts to populated areas or to conflict is most easily accomplished when the data are stored as discrete locations (point data). By contrast, when comparing the concentration of sites with evidence of looting attempts to concentrations of vegetation health, it makes more sense for the data to be stored in a combination of point data and gridded data.

Archaeological Site Satellite Image Data Collection & Coding

Because of the spatial and temporal nature of the proposed relationships, this dissertation used a combination of restricted access and open source image platforms

– Digital Globe[19] and Google Earth Pro[20] – to capture evidence of archaeological looting attempts via satellite imagery from 2015 to 2017.[21] While satellite imagery has been used to look at archaeological looting by other scholars (see e.g., Brodie & Contreras, 2012; Casana, 2015; Parcak et al., 2016), no standardized or "best" practice exists for the collection and coding of the images. Collecting and coding such data is also a time-consuming process, involving identifying the universe of archaeological sites in Lower Egypt, collecting images of archaeological sites at roughly monthly intervals across multiple sources, developing decision-rules to ensure consistency in coding, and then coding the actual imagery. Further, given the time constraints inherent in a dissertation, I designed a data collection strategy that was flexible enough to produce usable data even in the face of limited resources (e.g., if collection falls short of the census) and to allow data continuity if collection resumes at a later date. Figure 9 provides an overview of the data collection strategy – more detail is available on each step below. The data collection portion of the study took approximately one year and involved four phases of activity: (1) identification of the "universe" of archaeological sites in Lower Egypt; (2) initial image collection and recalibration and construction of sampling strategy; (3) verification of data and re-collection as necessary; and (4)

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[19] DigitalGlobe is one of the largest providers of high-resolution Earth imagery to major companies (e.g., Google Earth), defense companies, and intelligence agencies. They also maintain a 17-year time-lapse image library with resolutions ranging from 80-centimeters to 32-centimeters; however, only the last 5 or so years of images are available to view and download. For more information, see www.digitalglobe.com.
[20] Google Earth Pro is an extension of Google Maps that allows anyone to explore Earth imagery over time. Using Google Earth Pro (the desktop version), it is possible to look at all available imagery of that location over time. The imagery available through Google Earth has varying degrees of resolution, depending on an image's source. For more information, see https://www.google.com/earth/desktop/.
[21] I originally planned on using imagery from Planet, a company that uses miniature satellites to take daily pictures of the earth. While they do have imagery at 80-centimeter resolution, the imagery for Lower Egypt was between 3-meters and 5-meters, which proved insufficient for the coding strategy I employed (see below). For more information, see www.planet.com

addition of second source of satellite imagery and metadata recording in preparation for coding.

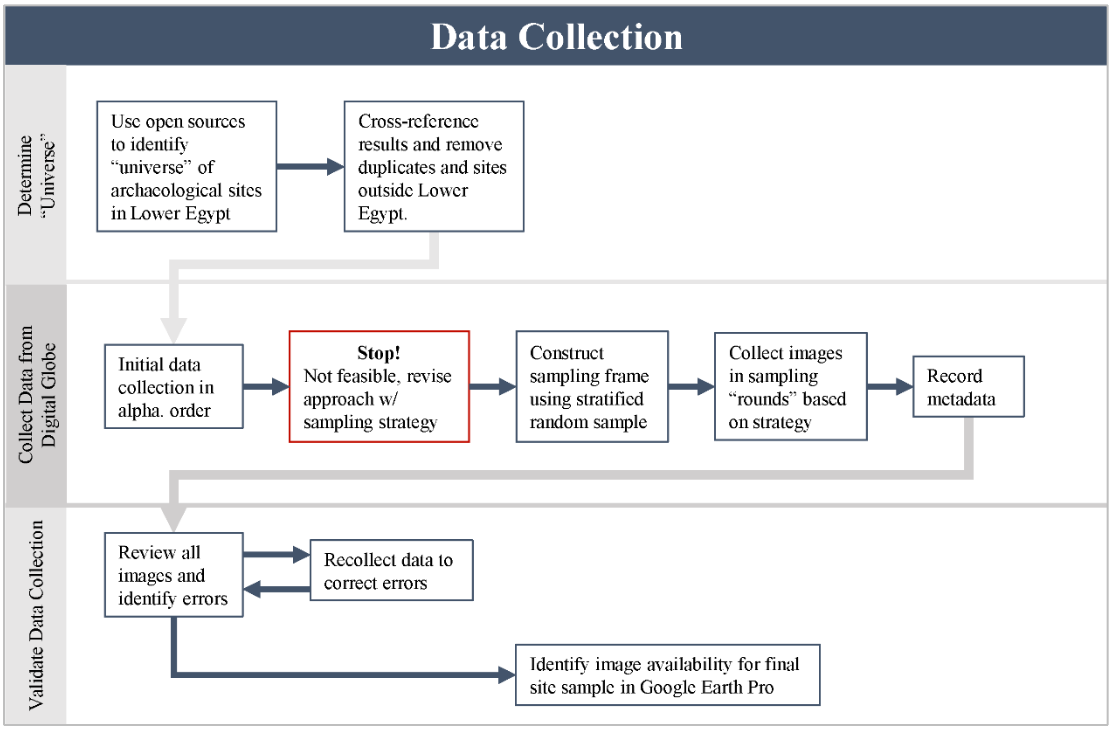

Figure 9. Satellite Imagery Data Collection Strategy

Phase 1 – Identification of the "universe" of archaeological sites in Lower Egypt

Identifying the universe of archaeological sites in Lower Egypt was a time-consuming process, as there is no "master list" of sites. New sites are routinely discovered, and it would take extensive resources to maintain and update any such list (Proulx, 2013). Instead, different individuals and organizations have compiled lists of sites that are specific to sub-regions, time periods, and type, depending on a specific need. The number of sites and the kind of information included in these lists depends on its purpose. Some lists are results from a survey[22] of a few specific sites, a specific excavation, or survey of a large geographic area, while others are a catalogue of a specific time-period (e.g., Middle Kingdom) or culture's (e.g., Graeco-Roman) sites.

The "universe" of archaeological sites in Lower Egypt for this dissertation was compiled from several of these lists, written in both English and Arabic. Table 8 describes each source, its scope, and its limitations. These sources were selected because they provided geo-locations (latitude and longitude) for the archaeological sites or enough other information about a site (e.g., an atlas image with a grid indicating latitude and longitude) to cross-reference it.

All sites from these sources were compiled and cross-referenced using their geo-locations and common spelling variants to ensure to the best of my ability that there were no duplicates. For example, most archaeological site coordinates were positioned in the center of the site. However, for particularly large or polygonal shaped sites, the exact "center" would be a judgment call and so could be listed with slightly

[22] An archaeological survey is a project designed to review a specific geographic area to identify potential new sites and review the condition of existing sites, and possibly excavate some of them.

different latitudes or longitudes. In these cases, I looked up both coordinates and deferred to the source that had more documentation for its information.

Additionally, the archaeological site names for Lower Egypt are a mixture of Arabic and Latin; however, Arabic names do not have a standardized transliteration from Arabic script to the Roman alphabet used in English. Instead, most are approximately phonetic transliterations, meaning that there are many possible variants of a name's spelling, but those variants will follow a pattern. The same site could be spelled as "Sidi Aqaba" and "Saidi Aqaba." Similarly, in Roman-alphabet Arabic, "El Tell El," "Tell El," "El Kom El," and "Kom El" all have the same meaning (mount or mound); however, the spelling changes to accommodate specific consonants used in pronunciation (Bustami, Personal Communication, 2018). I worked with a translator who speaks Arabic natively to understand how site names translate to English and identify patterns in name variants.[23]

In total, I found a universe of 1,109 archaeological sites with geolocations in Lower Egypt through this identification process.[24] Prior to the start of phase two (data collection), I excluded 450 sites that were identified as leveled, overbuilt, destroyed, or whose geolocations could not be confirmed. These sites would be indistinguishable on the ground from non-sites and so it would be difficult for a satellite image to pick up evidence of looting between buildings, among crops, or if the coordinates are wrong.[25]

[23] Arabic is a dialectic language, meaning there is no single standard form of the language. Though it would be ideal to find a translator who speaks Egyptian Arabic, someone who speaks a similar dialect will be able to provide accurate translations as well.
[24] I found 1,551 site names; however, there were only geolocations for 1,109 archaeological sites.
[25] To confirm whether the notes on site conditions were accurate, I took a sample of 26 sites marked as "destroyed," "leveled," or "overbuilt" and looked up images for them for 2010 to 2017 using Google Earth Pro's timeline feature. All of the sites tested were accurately described.

Sites that were noted as partially overbuilt or where its condition was unclear were included. After exclusions, I had identified 659 sites as my population of archaeological sites.

Table 8. Sources of Information on Archaeological Sites in Lower Egypt

Type of List	Source(s)	Scope	Features	Limitations
Surveys of Nile Delta	Egyptian Exploration Society (EES) Durham University University of Alabama at Birmingham	Academic databases of as many ancient mounds as could be identified from published sources and personal visits to the Delta. These surveys assess the current condition of lesser known sites in Lower Egypt. Online records are regularly updated (last updated March 2019).	Includes geo-location for all sites. Some have notes from the survey about its condition (e.g., changes in size, if it is destroyed, overbuilt, etc.). Some sites are linked to SCA "site numbers" while others are numbered according to the institution's specific cataloguing system.	Not all sites have the same level of detail in the information provided. Not all surveys provide the same coverage or spelling of archaeological site names in Arabic.
Online Databases of Archaeological Sites	Trismegistos[26] Ancient Locations[27] Pleiades[28]	Open source databases of archaeological sites in Lower Egypt among other places. Compiled by individuals, groups, or crowd-sourced.	Large databases of archaeological sites, most with geo-locations available. Often contain multiple spellings of site names, which helps with cross-referencing.	Not always created or maintained by academics. Archaeological site locations are not always the purpose of the database. Often the purpose of the site is to describe a specific perspective on the ancient world. Only relevant sites will be included. The selective nature of these databases means some ancient time periods may be less represented or absent.
Atlases of Egyptian Archaeology	Supreme Council of Antiquities	"Official" atlases containing lists of archaeological sites in each governorate in Lower Egypt.	Includes some geographic indicators, such as the neighborhood, city, inspectorate, and governorate in which the site is located. Images of maps are labeled with decimal degrees at 0.10 intervals. Sites are listed by their degree of ownership by the state.	Only those sites that the SCA identifies as important are included in the atlases. Geolocations are approximate, making this more useful for cross-referencing than locating. Some atlases are translated in English with the site names transliterated to Arabic in the roman alphabet, while others are entirely in Arabic script.

[26] Trismegistos is an interdisciplinary portal that links archaeological and cultural heritage site locations to ancient texts (epigraphical and papyrological) on Egypt and the Nile Valley from 800 BCE to 800 CE. For more information, see www.trismegistos.org.

[27] Ancient Locations is a database of archaeological sites of the Ancient world. Locations are included if they existed prior to 476 CE in the Old World (the end of the West-Roman Empire) and prior to 1492 CE in the New World. For more information see, http://www.ancientlocations.net/.

[28] Pleiades is a database for scholars of historical geographic information about the ancient world, covering the Greek and Roman world and is currently expanding to the Ancient Near Eastern, Byzantine, Celtic, and early medieval geography. For more information, see https://pleiades.stoa.org/home.

Phase 2 - Initial image collection and recalibration and construction of sampling strategy

I began data collection in August 2017, using access provided by a colleague to a previously compiled database of images on Lower Egypt from Digital Globe. Initially, I planned on collecting imagery on all 659 archaeological sites and so I proceeded with data collection in alphabetical order by site name. However, there was more coverage of Lower Egypt than I anticipated. In 80 hours, I was only able to collect imagery for 50 archaeological sites, indicating that I would be unable to collect images for all sites in the population given my resources.

As a result, I recalibrated my approach to data collection and decided to use a stratified random sample where data were collected in rounds. Instead of choosing a pre-determined percentage of sites from each governorate and then randomizing their order, I randomized the sites within each governorate and collected data in rounds. It was not clear how long it would take me to collect a pre-determined number of sites, so sampling sites proportionally ran the risk of having some governorates with substantially less data or no data if my data collect pace was slower than anticipated. By contrast, collecting data in rounds made sure that I was able to collect data for archaeological sites in all governorates systematically for as long as possible. Each round, one site would be randomly selected from each governorate and then all imagery would be collected, and all metadata recorded for all the sites in the sampling round before moving on to the next round. Some sites that were in my sample turned out to be overbuilt, leveled, or destroyed once I looked at the images. These sites were removed from the sample and replaced with another randomly selected site from the same governorate. With this method of data collection, I was able to collect data systematically from February 2018 to April 2018, when access to the database ended. Forty-one sites collected in the original 50 were included in the randomization for each governorate and only seven were randomly selected for collection.[29] When one of these sites was selected, I marked it as part of the round being collected but maintained the original date of collection (August 2017). Then, because my access to the previously downloaded data was in danger of being restricted, I also collected data on the next randomly selected site indicated for that governorate. Though not an ideal research practice, this did allow me to collect imagery for more sites than I would have otherwise. At the end of data collection in April 2018, I coded the other 34 sites from August as "round 0" and added them to my data, which affects the distribution of sites sampled in each governorate (see Table 9).

Images were downloaded at approximately monthly intervals for as many months as were available from 2015 to 2017, using the file format that retains the most metadata (either NITF2.1 or GeoTiff).[30] Only images with a clear picture of the archaeological site were downloaded as cloud cover or poor resolution would obscure archaeological site features (Parcak, 2009). When available, mosaics were downloaded for earlier periods of time (e.g., 2013 – 2014) to provide a comparison for the earliest images when coding evidence of looting.

[29] Nine of the sites collected in the original 50 were located in Upper Egypt and so were excluded from the universe of sites.

[30] In satellite imagery, the NITF2.1 and GeoTiff are the two most used file formats. The NITF2.1 file format is as close to the raw data as one can get. It retains all metadata, including the date and time the image was captured, the satellite that took the image, and technical information on how the image was processed. GeoTiff files do not retain as much metadata – they are essentially a capture of the image on the screen with geo-location markers for metadata. As such, GeoTiff files are much smaller and faster to download.

Mosaics are compilations of many smaller images taken over months or years and covering extremely large areas – some mosaics may cover over half of the Nile Delta. Due to their large size, mosaics are broken up into equally sized tiles, so that it is possible to separate the tiles and only keep those that contain identified archaeological sites. Each tile of the mosaic is a compilation of many smaller images of various dates, so it is impossible to tell exactly which date the image reflects. Figure 10 shows an example of 4 tiles (zoomed out) from a much larger mosaic, each of which contains at least one archaeological site that can be zoomed in on and examined for evidence of looting. In addition to downloading the file, I recorded the following information for all images:

- A unique ID for the image
- An ID for the archaeological site
- The site's name and coordinates (latitude and longitude)
- The governorate
- The earliest date the satellite started taking the image
- The latest date the satellite started taking the image[31]
- The time of day the image was taken (UTC)
- The type of image (Single or Mosaic)
- Whether the image was in Black and White (panchromatic) or Color (pan sharpened natural color)
- The resolution of the image
- Whether the image has cloud cover
- Format of the image downloaded (GEOTIFF, NITF2.1)
- Whether the image is a duplicate[32]
- The round of sampling
- The date of sampling

[31] The "start" and "end" dates are the same for single images but not for mosaics. The shortest time period for a mosaic that I have seen thus far in my data collection is four months.

[32] Duplicates are only relevant for mosaics. Their large area of coverage means that they contain many sites and have large file sizes (e.g., 50GB). As such, I only downloaded the first instance of the mosaic. This field helps to ensure that there is a record of which sites are in the mosaic.

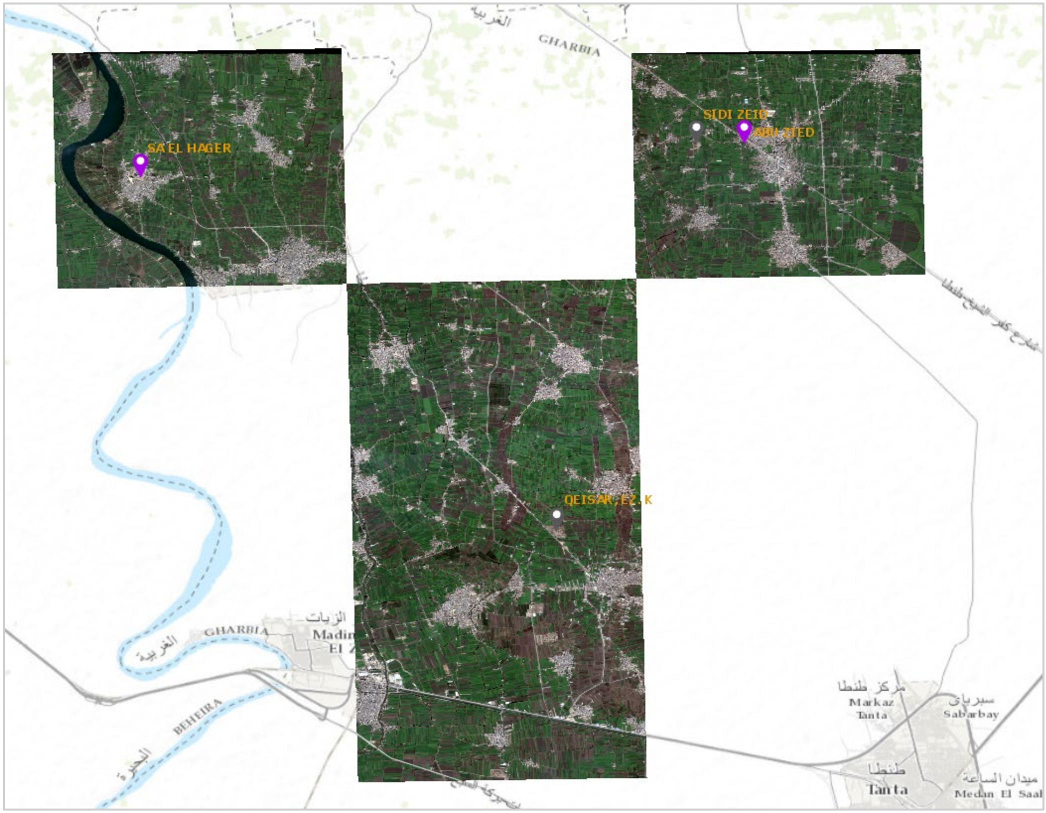

Figure 10. Example of four tiles of equal size from a much larger mosaic zoomed out. The full mosaic is made up of 84 tiles in a 7 by 12 square. Each tile is a mosaic of many smaller individual satellite images taken some time between 2010 and 2011.

From August 2017 to April 2018 I was able to collect imagery on 143 archaeological sites during the time period of interest. This strategy had several benefits. First, although I imposed disproportionality on my sampling strategy by collecting rounds of sites, doing so assured that I was able to get enough variation across all governorates and not just from the ones with the most sites. To address the disproportionality, I weighted the data by the proportion of sites sampled when analysis allowed for it.[33] Second, collecting data in rounds helped balance limited access to resources and time with the need for a representative sample. I was able to collect data within a limited time frame and know that if more resource and time became available

[33] A more detailed discussion of which analyses allowed for weights is in the methods chapter below.

later, I could add to my sample by collecting additional rounds. Table 9 lists the distribution of archaeological sites in the universe, number of sites excluded, the number of sites in the sampling frame, and the number of sites sampled, the percent sampled, and the sample weight for each governorate.

Table 9. Distribution of Archaeological Sites by Governorate in Lower Egypt

Governorate	# of Sites in Universe	# of Sites Excluded	# of Sites in Sampling Frame	# of Sites Sampled	Percent Sampled	Sample Weight
Alexandria	79	70	9	7	78%	1.286
Beheira	223	27	196	30	15%	6.5
Cairo	26	21	5	4	80%	1.25
Damietta	12	1	11	10	91%	1.1
Daqahliyah	98	27	71	16	23%	4.313
Al Gharbiyah	16	9	7	4	44%	2.25
Ismailia	146	137	9	4	44%	2.25
Kafr es Sheikh	145	24	121	22	18%	5.409
Al Minufiyah	28	8	20	7	35%	2.857
Port Said	67	63	4	2	50%	2
Al Qalyubiyah	26	4	22	10	45%	2.2
Al Sharqiyah	243	57	186	24	13%	7.792
Total	**1109**	**448**	**661**	**140**	**21%**	

Phases 3 and 4 – Review data collection from Digital Globe and additional data collection from Google Earth Pro

From August to November of 2018 I loaded all images collected in phase 2 into ArcGIS Pro to review them and note any errors that needed correcting. In total, I identified 15 sites with errors that needed to be corrected, including: correcting the coordinates used for image collection to match the site's location; removing duplicate sites identified through the image collection process; and correcting mislabeled images. Three sites were removed from the sample – two sites were incorrectly recorded as being in the Cairo governorate, when they were located in the Fayyum governorate (not included in the study region) and I could not verify the location of the third site. This brought my final sample size to 140 sites. A second round of image collection took place in early January 2019 to correct the errors.

The images collected to this point had inconsistent coverage of months from 2015 to 2017. No sites had coverage for all 36 months. Most sites had only a one or two images for 2015, a handful for 2016 and the most for 2017. This inconsistency is in part a function of DigitalGlobe's internal organizational decision-making and priorities. For example, DigitalGlobe may acquire images daily for much of the globe and they have a 17-year archive of images. Yet, only the last five years or so are available to researchers and only the most recent years have consistent image coverage. Since the amount of coverage directly affects what patterns can be observed, relying on any one source of imagery can potentially bias an analysis looking for patterns or changes over time. This also affects the data collection strategy proposed – if data collection has to be stopped, the study period of interest may no longer be available.

DigitalGlobe is considered to be the gold standard of satellite imagery; however, the inconsistency of image coverage and limited online availability can introduce error into the data coding process. To mitigate both the difficulties with image availability and bias associated with relying on only one source of data, I decided to collect data from Google Earth Pro. Though the image quality available was more varied, Google Earth Pro also had wider availability and coverage for a given location over time. As such, imagery from Google Earth Pro could be used to validate the coding of DigitalGlobe imagery (see detailed description in the next section). I experimented with exporting images of sites from Google Earth Pro and loading them into ArcGIS Pro to compare the quality to the DigitalGlobe images. It was impossible to export images from Google Earth Pro with any metadata attached to it, which would have allowed the image to be automatically geolocated in ArcGIS Pro. Images could only be exported as JPG, TIFF or PNG files. However, using the Google Earth Pro I was able to examine images in the same or nearly the same detail as those from DigitalGlobe.

As such, in lieu of formally "collecting" images, I checked that imagery was available for all 140 sites in my sample and recorded the dates of the images that I used during the coding process. Details on the number of sites coded are provided below. Table 10 below provides a breakdown of the data collected from both Digital Globe and Google Earth Pro. I collected 1,321 images from DigitalGlobe and 1,878 images from Google Earth Pro for the 140 sites in my sample across 1,191 and 1,211 site-months of the 5,040-total site-months possible, respectively. Combined, I was able to collect 3,199 images that covered 1,154 out of 5,040 site months possible (22.9%).

Table 10. Overview of Site-Months Collected from DigitalGlobe and Google Earth Pro

DigitalGlobe						
Governorate	*Avg Images*	*Total Images*	*Possible Site-Months*	*Avg Months w/ Images*	*Total Months w/ Images*	*% Collected*
Alexandria	25.00	150	252	20.57	144	57.14%
Beheira	31.50	189	1080	5.5	165	15.28%
Cairo	13.50	81	144	18.75	75	52.08%
Damietta	11.33	68	360	5.11	46	12.78%
Daqahliyeh	18.17	109	576	6.44	103	17.88%
Al Gharbiyah	8.00	48	144	11.5	46	31.94%
Ismailia	2.67	16	144	1	4	2.78%
Kafr es Sheikh	33.00	198	792	7.77	171	21.59%
Al Minufiyah	12.50	75	252	9.71	68	26.98%
Port Said	2.33	14	72	4.33	13	18.06%
Al Qalyubiyah	25.67	154	360	14.2	142	39.44%
Al Sharqiyah	36.50	219	864	8.92	214	24.77%
TOTAL	**18.35**	**1321**	**5040**	**113.81**	**1191**	**23.63%**
Google Earth Pro						
Governorate	*Avg Images*	*Total Images*	*Possible Site-Months*	*Avg Months w/ Images*	*Total Months w/ Images*	*% Collected*
Alexandria	79.71	558	252	28.14	197	78.17%
Beheira	5.03	151	1080	4.03	121	11.20%
Cairo	48.5	194	144	24	96	66.67%
Damietta	8	80	360	6.78	61	16.94%
Daqahliyeh	8.75	140	576	7.06	113	19.62%
Al Gharbiyah	15	60	144	12	48	33.33%
Ismailia	2.75	11	144	2.25	9	6.25%
Kafr es Sheikh	9.05	199	792	7.36	162	20.45%
Al Minufiyah	11.86	83	252	9.86	69	27.38%
Port Said	7	14	72	4.33	13	18.06%
Al Qalyubiyah	14.5	145	360	12.3	123	34.17%
Al Sharqiyah	10.13	243	864	8.29	199	23.03%
TOTAL	**13.41**	**1878**	**5040**	**8.65**	**1211**	**24.03%**

Combined Data						
Governorate	*Avg Images*	*Total Images*	*Possible Site-Months*	*Avg Months w/ Images*	*Total Months w/ Images*	*% Collected*
Alexandria	52.36	708	252	24.36	215	85.32%
Beheira	18.27	340	1080	4.77	87	8.06%
Cairo	31.00	275	144	21.38	96	66.67%
Damietta	9.67	148	360	5.94	61	16.94%
Daqahliyeh	13.46	249	576	6.75	103	17.88%
Al Gharbiyah	11.50	108	144	11.75	48	33.33%
Ismailia	2.71	27	144	1.63	7	4.86%
Kafr es Sheikh	21.02	397	792	7.57	162	20.45%
Al Minufiyah	12.18	158	252	9.79	69	27.38%
Port Said	4.67	28	72	4.33	13	18.06%
Al Qalyubiyah	20.08	299	360	13.25	123	34.17%
Al Sharqiyah	23.31	462	864	8.60	170	19.68%
TOTAL	**15.88**	**3199**	**5040**	**61.23**	**1154**	**22.90%**

Despite the large number of images collected from both sources, these data suffered from 77.1% missing data (Table 11). The missingness varied by governorate – Alexandria had the least missing data (14.68% missing) and Ismailia had the most (95.14% missing). The combined data had marginally more missingness overall than each source on its own, which was somewhat surprising. It appears that this reflected the amount of overlap in image coverage between Google Earth Pro and DigitalGlobe (see Table 10 above).

Table 11. Overview of Missingness

Governorate	DigitalGlobe Missingness	Google Earth Pro Missingness	Combined Missingness	Minimum Missing Months	Maximum Missing Month
Alexandria	42.86%	21.83%	14.68%	1	8
Beheira	84.72%	88.80%	91.94%	1	19
Cairo	47.92%	33.33%	33.33%	1	6
Damietta	87.22%	83.06%	83.06%	1	16
Daqahliyeh	82.12%	80.38%	82.12%	1	16
Al Gharbiyah	68.06%	66.67%	66.67%	1	12
Ismailia	97.22%	93.75%	95.14%	8	22
Kafr es Sheikh	78.41%	79.55%	79.55%	1	16
Al Minufiyah	73.02%	72.62%	72.62%	1	10
Port Said	81.94%	81.94%	81.94%	1	15
Al Qalyubiyah	60.56%	65.83%	65.83%	1	10
Al Sharqiyah	75.23%	76.97%	80.32%	1	17
TOTAL	**76.37%**	**75.97%**	**77.10%**	**1**	**22**

Using multiple sources did marginally increase coverage of the archaeological sites in my sample for some governorates; however, not all sites had equal image availability. Missing data for archaeological looting attempts are problematic. In most cases, the data had one to three missing months of data; however, some sites had as many as 22 months (almost two of the three years). With no baseline information on how quickly looting pits appear and disappear, the presence of missing months makes it difficult to know whether those months should be treated as missing or as zeros (meaning no looting). This is because evidence of looting attempts can take multiple forms, depending on the type of looting activity (new vs prior) and the history of the site. It is possible that fresh looting pits ("new" looting attempts evidence) could appear and disappear during those missing months leaving no evidence. It is also possible that "new" looting attempts could be filled in (looking like mounds on satellite imagery) and persist over several months, representing prior looting attempts. Thus, it would not be possible to reasonably impute values for all missing months. Such an approach would assume that some degree of looting occurred in all of the imputed months. Yet it is equally problematic to code the missing values as zeros as this assumes no looting occurred in those months, which is just as unreasonable an assumption as the previous case. Taking either approach would be based on strong assumptions. Instead I approached missing data with a weaker set of assumptions based on identifying patterns in changes prior looting attempts over time.[34]

In order to identify changes in prior looting, I had to be able to distinguish between fresh or "new" looting attempts and "prior" looting attempts in the satellite images from both Google Earth Pro and DigitalGlobe.[35] The clearest form of "new" evidence of looting attempts in satellite images are so-called "looting pits," which typically look like pockmarks on a satellite image, with dark or black centers surrounded by mounded earth (see Figure 11 – Parcak, 2015; Parcak et al., 2016). However, it is not always easy to distinguish between potential looting "pits," prior excavation work, and structural features of the site. Some archaeological excavations, like the excavation at El Omari in Cairo during the 1990s, have pit-like features where a tomb was opened (Figure 12).

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[34] Details on the coding of "changes in prior looting" and addressing missing data are below.

[35] Once all data were coded, I combined the imagery from both sources and coded for changes in prior looting attempts. See below for a more detailed discussion.

These holes may or may not be filled in when the excavation is done. Similarly, sites like the Alexandria Amphitheater (Figure 13), which have well excavated walls and structures, contain other physical features that may look like looting pits when they are not. Depending on the time of day the photo was taken, trees, shrubs, brush/vegetation, and walls/archaeological features can all cast shadow making them appear to be looting pits.

For this dissertation, I defined “new” evidence of looting attempts as pit-like features that did not persist for more than one or two months. This is a conservative approach to identifying evidence of “new” looting attempts – it does not capture potential looting in already opened areas (like at El Omari) or at sites where no surface evidence can be discerned (e.g., a necropolis or catacomb). While this means that my counts of new looting attempts will likely be lower than the true count of such attempts, it provides a more consistent approach to identifying looting and therefore reduces possible subjectivity bias.

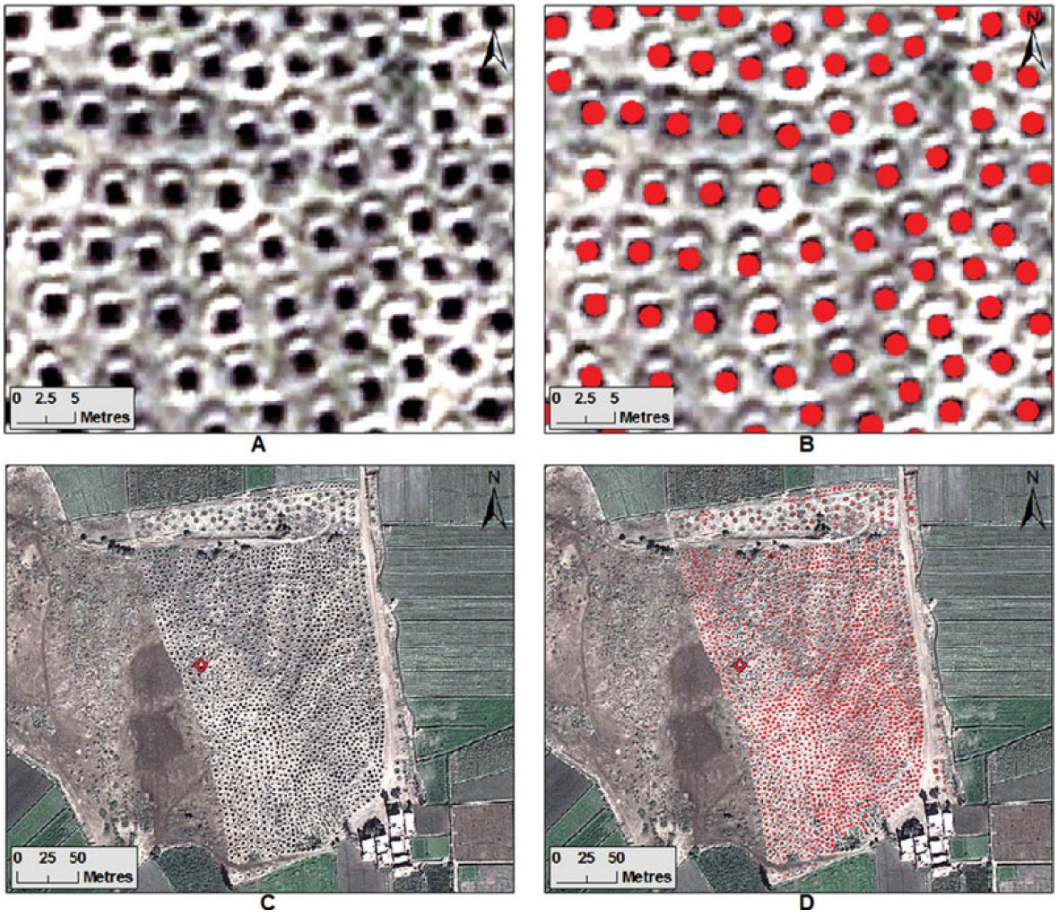

Figure 11. Example of Looting Pits from Parcak et al.'s (2016) study. Panels A and B are close ups of a small section of the larger image in panels C and D.

Figure 12. Excavation pits at El Omari from the 1990s as seen in February 2019. Image courtesy of Google Earth Pro.

Figure 13. Alexandria Amphitheater in November 2016, with examples of looting pits (red) and structural features (yellow). Image courtesy of Google Earth Pro.

Satellite images can also show evidence of prior looting attempts, which may appear in more varied forms than "new" looting attempt evidence. In some cases, they may appear as low mounds, where pits have been filled in, such that they look like remnants of activity. Prior looting may also appear as small densely clustered areas of freshly turned earth but no actual "pit-like" features. Figure 14Figure 15, & Figure 16 show Daba, T el in Kafr es Sheikh with no looting, new looting, and prior looting attempts from July to September 2015. Capturing only "new" evidence of looting attempts would have actively excluded important variation over time and across sites in looting behavior. Additionally, since satellite image availability was inconsistent, coding for the combination of prior looting evidence and changes in prior looting evidence provided some insight into possible looting attempt behaviors that occurred in between my observations.

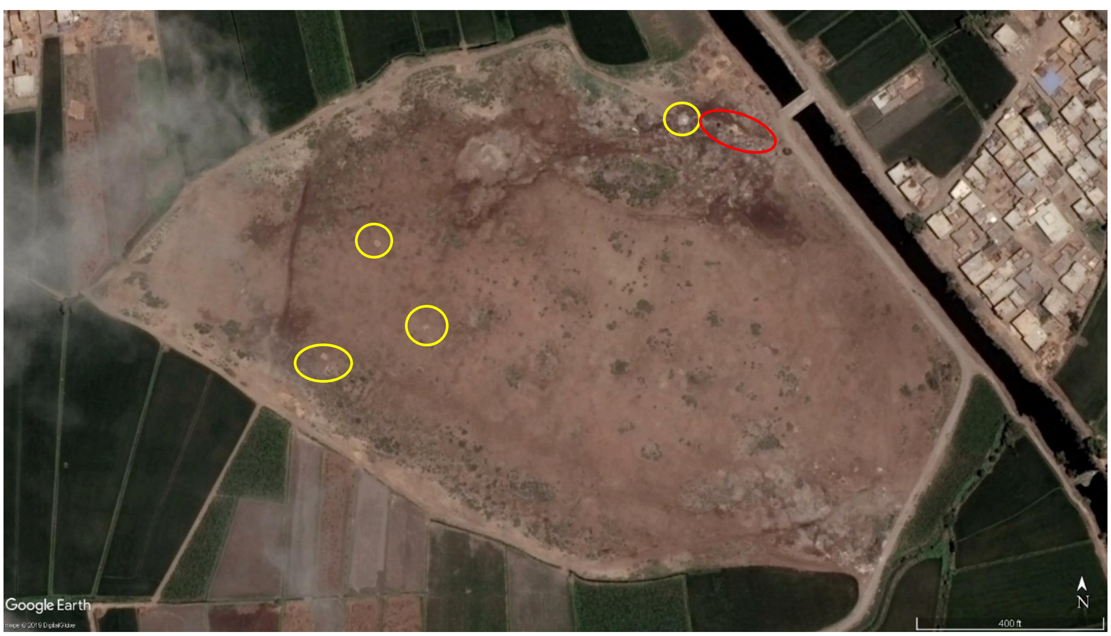

Figure 14. Daba, T el (Kafr es Sheikh) from July 2015 with evidence of new (red circles) and prior (yellow circles) looting attempts.

Figure 15. Daba, T el (Kafr es Sheikh) from August 2015 with evidence of prior (yellow circles) looting attempts.

Figure 16. Daba, T el (Kafr es Sheikh) from September 2015 with no evidence of looting attempts.

Data Coding Strategy

Similar to my sampling strategy, my strategy for coding the satellite images was designed to work with limited resources and information, yet flexible enough to still apply in situations with more data and resources. Since the temporal unit of analysis was the month, data were coded at the archaeological site-month level in the order they were sampled (i.e., by sampling round). As the only coder, I followed a set procedure for coding each site to improve the consistency of my coding. This procedure involved three general steps, each with its own detailed set of instructions (see Figure 17 on the next page – full details are located in Appendix 1): (1) create a boundary around the site; (2) determine the order in which to code each source of imagery; (3) code the data; and (4) review, validate, and aggregate the data.

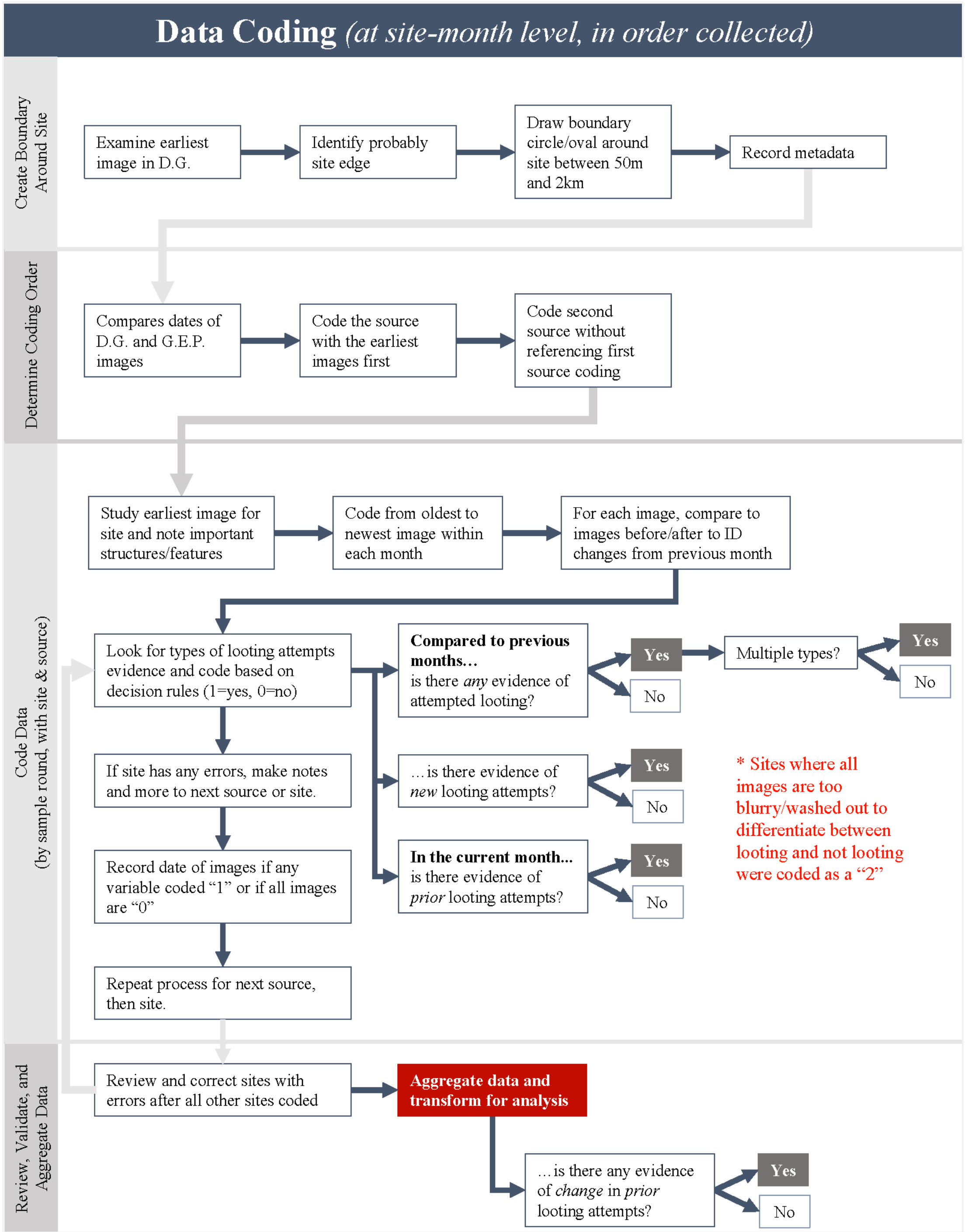

Figure 17. Overview of Data Coding Strategy

I used ArcGIS Pro to establish the boundaries around each site using the DigitalGlobe imagery because I could import the imagery with metadata attached and record attributes of the boundaries in a dataset. Establishing a boundary around the site was important for two reasons. First, it is not always clear where the edges of a site are based on imagery alone and imposing a boundary that I could be reasonably confident contained the site ensured that the entire site was coded. Second, cultural heritage management scholars suggest that the areas immediately surrounding an archaeological site may be the most vulnerable to looting because it is a gray area for management and guardianship (BC Archaeology Branch, 2017). For example, a site may be owned and managed UNESCO, but is located in a city run under different management. When establishing legal and managerial boundaries around a site, it is not always clear who is responsible for the transition zone between site and city.[36] Drawing a boundary around the site at least 50-meters from its edge allowed me to capture evidence of looting attempts that occur in these transitional areas as well as the site proper.[37]

[36] When designing a cultural heritage management plan, buffer zones of guardianship are ideally created around the site (BC Archaeology Branch, 2017). No standardized approach exists to determining how large such a buffer (or in my case, a boundary) should be. The distance should be large enough to capture the liminal space but not so large that it obscures other potentially relevant behaviors (protesting, terrorism, etc.). UNESCO's World Heritage List provides specifications for buffer zones ranging from 2-square kilometers to 500-square kilometers (large enough to include an entire city) (UNESCO, 2019). Egypt's Antiquities law as amended in 2010 defines adjacent lands in lieu of buffer zones and sets a maximum distance of 3-kilometers but leaves the minimum distance to the discretion of the Supreme Council of Antiquities (SCA, 2010). Based on these two perspectives, I decided to set the range for the distance between the site edge and the boundary to between 50-meters and 2-kilometers. I also drew the smallest possible boundary, only extending the size beyond 50-meters when I was unable to determine where the site's edge was or if the site covered a large area as the larger the site, the larger the liminal space may be.

[37] If I found an error with the site – that the image did not contain the entire site or would-be boundary or there was an error in coordinates that I did not catch during data collection – I flagged that site and moved on to coding the other source (in the case of truncation) or to the next site. After all sites without errors were coded, I went back to re-collect and code data for the sites I previously flagged. Of the 140 sites, 20 sites were flagged for errors: two sites were truncated, two had errors in coordinates, and the remaining 16 had an image that was incorrect or needed to be re-collected.

In choosing to code starting with the earliest source of imagery, I was able to consistently code images based on their earliest baseline image rather than relying on a single source to serve as the baseline. Systematically starting with either Google Earth Pro (GEP) or DigitalGlobe (DG) would have established that source as the standard to which the other source should be compared. Yet, one source of imagery is not inherently superior to the other. Determining the coding order based on the earliest image date built in variation to avoid this issue.

At the same time, I wanted to preserve the consistency of coding images within each source. The algorithms used to generate satellite imagery vary by source. Constantly switching the source of the image being coded could introduce additional unknown sources of error. To address this, once the coding order was set, all images for that source were coded before coding the images from the other source. For example, if Google Earth Pro had the earliest image date for the site being coded, I coded all images Google Earth had for the site starting with the oldest image. I would then switch to looking at the DigitalGlobe images starting with the oldest and code those images. Since I was using Google Earth Pro to validate my coding on DigitalGlobe, it was important that the images collected from each source were coded independently.

For each site, I coded a series of dummy variables assessing whether there was evidence of different types of looting attempts present. Prior research has suggested that counting the number of "pits" visible in a site is an accurate way to document looting evidence; however, such a method is difficult to replicate. Identifying and distinguishing between features in a satellite image is inherently subjective and time-consuming process[38] – especially if the coding is done manually (i.e. no algorithmic assistance).[39] Though coding any evidence of looting attempts per site-image as a binary variable rather than a count of attempts is less granular, it is much less time-consuming. Further, when combined with the detailed decision-rules and coding instructions created as part of this dissertation, this approach may be more replicable. Instead of trying to find the exact same counts, replication would only have to find similar conditions using the same of equivalent procedures.

To mitigate the limitations of conceptualizing looting as a binary activity and to address missing data, I coded a series of variables looking at different types of evidence of looting attempts:

- All Looting Evidence:
    - Whether there was any evidence of any type of looting attempt within the boundary of the site.
    - Whether there were multiple types of evidence of looting attempts at the site during the month.
- "New" Looting Evidence:
    - Whether there was any evidence of *new* looting attempts present at the site anytime during the month not present in the previous month.
- "Prior" Looting Evidence:
    - Whether there was any evidence of *prior* looting attempts present at the site anytime during the month.
    - Whether there was any *change* in evidence of prior looting attempts at the site anytime during the month compared to the previous month.

[38] I conducted a pilot test of coding looting pits in Alexandria and found that it took approximately 10 hours to code six sites.
[39] I tested the replicability of Parcak et al. (2016)'s findings on the site Region 3 Site 643 (FID 87) by looking at images available from Google Earth Pro during the same period as her study (2010 – 2013) and comparing my count of looting "pits" to hers. Parcak et al. (2016) reported 137 pits and I found around 100. Unfortunately, Parcak et al. do not provide the detailed decisions rules they used to determine whether something was a likely pit based on the imagery alone. It is possible that my results reflect a more conservative approach and so I was more likely to report fewer pits than there were. Regardless, this test highlights the subjective nature of such a method.

Because the temporal unit of analysis was the month, all images were coded by visually inspecting each one in comparison to the images immediately before and after as well as the last image from the previous month. For each image in a given month, I coded for each of the three types of looting attempts evidence (new, prior, and all) and recorded the image's date.[40] For both Google Earth Pro and DigitalGlobe, if any images showed evidence of looting attempts, I recorded only the image dates where such evidence was present. If no evidence of looting was present for any image in the month, I recorded the dates of all images reviewed. Other variables recorded for each site include the: site name, site unique identifier, latitude and longitude, and the legal ownership status of the site. A detailed set of coding instructions for all variables is included in Appendix 1.

The final stage of the coding process had several elements. First, I reviewed each source's coding for potential errors and corrected them as necessary. Second, I calculated statistics of the percent agreement in my coding for months where both sources had images. I compared the coding across both sources, flagged any months where it differed, and then reviewed each case to determine the cause of the discrepancy. It was rare for the same exact image date to be coded from both Google Earth Pro and DigitalGlobe.

Table 12 shows the validation statistics. Overall, I had over 98% agreement in the coding between sources. Of the 62 months with flags (out of 1,154), only seven of them appeared to be the result of true discrepancies. It was often the case that one

[40] If all the images for a site were too blurry or washed out to differentiate possible looting from non-looting evidence, it was coded as a "2."

source's images would reflect earlier dates than the other and that the earlier source would not yet show evidence of looting attempts (especially new evidence). In these cases, differences in coding did not reflect an actual discrepancy, but rather a more detailed picture of when in the month looting took place. The few "true" discrepancies occurred when the same period of time was covered by the images, but the coding differed. If Google Earth Pro had three images in March (March 6, March 15, & March 22) and DigitalGlobe had only one image (March 16) and the coding (especially for new looting) differed between the two sources, this would reflect a "true" discrepancy. Theoretically, the images from Google Earth Pro would have captured the looting attempts present in the singular DigitalGlobe image. If the coding does not match, it is more likely to be the result of error than anything else.

Table 12. Validation Statistics

Governorate	% Agreement (by flags)	% Agreement (true discrepancies)	Flags	True Discrepancies
Alexandria	99.21%	100.00%	2	0
Beheira	99.26%	100.00%	8	0
Cairo	96.53%	100.00%	5	0
Damietta	99.44%	100.00%	2	0
Daqahliyeh	98.09%	99.65%	11	2
Al Gharbiyah	97.92%	100.00%	3	0
Ismailia	100.00%	100.00%	0	0
Kafr es Sheikh	99.37%	100.00%	5	0
Al Minufiyah	95.63%	98.81%	11	3
Port Said	100.00%	100.00%	0	0
Al Qalyubiyah	98.89%	100.00%	4	0
Al Sharqiyah	98.73%	99.77%	11	2
Total	**98.77%**	**99.86%**	**62**	**7**

For cases that were "true" discrepancies, I deferred to the coding from the source with the most images, assuming that more images provided a more accurate and detailed view of the month. Additionally, since there were some months where only one source of imagery had data available, I decided to instead combine the data in two different ways to analytically test (where possible) how my coding decisions would impact any results. For the first set of combined data, each of the three variables (all looting attempts, new looting attempts, and prior looting attempts) for each month was counted as a "1" if that variable was coded "1" in *either* Google Earth Pro or DigitalGlobe's coding. For the second set of combined data, each variable was counted as a "1" if it was coded as "1" in *both* sources. The "either" dataset was less restrictive and allowed for months where only one source had reports of looting. The "and" dataset was more restrictive, only counting the 98.7% of cases where there was complete agreement. As Table 13 demonstrates, there were large differences in the distribution of the "all" and "new" looting variables between these two combined datasets. The differences in the "all" dataset also appear to be driven by those in the "new" variable. Because of these differences, I ran analyses on all types of looting as dependent variables, where possible (see below for details).

Table 13. Descriptives from Both of the Combined Looting Datasets ("Either" and "And")

	All Looting Attempts		**New Looting Attempts**		**Prior Looting Attempts**	
	"Either" Dataset	*"And" Dataset*	*"Either" Dataset*	*"And" Dataset*	*"Either" Dataset*	*"And" Dataset*
Observations	140	140	140	140	140	140
Mean	7.1	3.179	5.343	2.057	5.3	5.136
Standard Deviation	6.626	3.549	4.853	2.275	6.517	6.594
Minimum	0	0	0	0	0	0
Maximum	33	18	25	12	33	33

The final step of the data coding strategy was to address the missing data discussed above. To do so, I coded the variable "changes in prior looting" for each of the combined sets of data. This variable was created to identify evidence of looting attempts since the previous period, but not during the current month. Such information could help to determine whether there may have been looting attempts during any missing periods. This was particularly important for the larger missing periods (e.g., 6, 10, 22 months).

To address the problem of missing data, I examined the "changes in prior looting" variable for the month immediately before and after the period of missing data (the "bookends") and found four possible combinations present: (1) when both the month before and after the missing period were coded as zero (no change to no change); (2) when both the month before and after were coded as a one (a change to a change); (3) when the month before was coded as a one and the month after was coded as a zero (a change to no change); and (4) when the month before was coded as a zero and the month after was coded as a one (no change to a change).

How I addressed missing data depended on which of these combinations was present and how long the period of missingness lasted. Based on the number of missing months, I created two different categories for coding for missing data (four months or less vs. five months or more). Table 14 and 15 outline the decision rules used to code for missingness for all four combinations of the change in prior looting variable for the short periods of missingness and long periods of missingness, respectively. For missing periods with four or less months, I made weaker assumptions about how looting attempts could have changed over that period than periods with five or more months. When there was a change in prior looting recorded at the end of the period of missingness, I randomly selected one month to code for evidence of "new" and "prior" looting attempts. Because of the short time period, I relied more on the observed variable coding on either side of the missingness to inform how the missing month should be coded (see Table 14).

For longer periods (at least five months), I used a more complex coding system. It was unreasonable to assume that the observed values on either side of the missingness alone could inform how the missing values should be coded. Instead, I combined a set of four assumptions of looting patterns with the observed values and used both to code for missingness (see Table 15). Generally, I assumed that cases where the "changes" variable was the same on either side of the missing period reflected consistency in the looting pattern. If there was no change before or after the missing period, I assumed there was no looting attempts. If there was change both before and after, I assumed that there were multiple types of looting attempts. In the case of no change to change, I assumed that this reflected an increase in looting attempts over time. By contrast, in the case of change to no change, I assumed that this reflected a decrease in looting attempts over time. For all combinations except no change to no change, I randomly selected one month during the missing period to code for evidence of looting. For all other months in the period of missingness, I coded zero for all variables.

Once all archaeological looting attempts data were coded, I aggregated all six looting attempt variables into four datasets (two spatial, one temporal, and one spatio-temporal). Table 16 describes how the looting variables were operationalized across these four datasets.

Table 14. Treatment of Missing Data for Short Periods of Missingness (≤ 4 months)

Combinations in *change in evidence of prior looting attempts* Variable	**Assumption**	**Missing Data Approach**	**Coding Missing for "New" Looting**	**Coding Missing for "Prior" Looting**
0 to 0 (No Change to No Change)	Not likely that evidence of looting attempts occurred during the period of missing data.	Code all variables as 0 for all months of the missing data.	Code 0 for new looting attempts.	Code 0 for prior looting attempts.
1 to 1 (Change to Change)	At some point during the period of missing data, evidence of new looting likely occurred that led to the observed change in prior looting.	Randomly select one month of the missing period to code for evidence of looting attempts. Code all variables for all other missing months as 0.	Code 1 for new looting attempts.	If month at beginning of missing period is 1, code prior looting attempts as 1. If not, code prior looting attempts as 0.
1 to 0 (Change to No Change)	At some point during the period of missing data looting attempts may have occurred. However, because no change in prior looting has registered at the end of the period of missingness, there is no observed variable to suggest that "new" looting should be coded in the period of missingness.	Randomly select one month of the missing period to code for evidence of looting attempts. Code all variables as 0 for all months of the missing data.	Code 0 for new looting attempts.	If month at beginning of missing period is 1, code prior looting attempts as 1. If not, code prior looting attempts as 0.
0 to 1 (No Change to Change)	At some point during the period of missing data looting may have occurred and it increased as time passed. Because a change in prior looting registered at the end of the period of missingness, "new" looting likely occurred during the interim.	Randomly select one month of the missing period to code for evidence of looting attempts. Code all variables for all other missing months as 0.	Code 1 for new looting attempts.	If month at beginning of missing period is 1, code prior looting attempts as 1. If not, code prior looting attempts as 0

Table 15. Treatment of Missing Data for Long Periods of Missingness (≥ 5 months)

Combinations for *change in evidence of prior looting attempts* Variable	**Assumptions**	**Missing Data Approach**	**Coding Missing for "New" Looting**	**Coding Missing for "Prior" Looting**
0 to 0 (No Change to No Change)	Not likely that evidence of looting occurred during the period of missing data.	Code all variables as 0 for all months of the missing data.	Code 0 for new looting attempts.	Code 0 for prior looting attempts.
1 to 1 (Change to Change)	At some point during the period of missing data, evidence of looting likely occurred. This case assumes that there is evidence of both new and prior looting during the missing period.	Randomly select one month of the missing period to code for evidence of looting attempts. Code all variables for all other missing months as 0.	Code 1 for new looting attempts.	If month at beginning of missing period is 1, code prior looting attempts as 1. If not, code prior looting attempts as 0.
1 to 0 (Change to No Change)	At some point during the period of missing data looting may have occurred, but it decreased as time passed. This case assumes that there is a reduction in new looting but may still be evidence of prior looting.	Randomly select one month of the missing period to code for evidence of looting attempts. Code all variables for all other missing months as 0.	Code 0 for new looting attempts.	Code 1 for prior looting attempts.
0 to 1 (No Change to Change)	At some point during the period of missing data looting may have occurred and it increased as time passed. This case assumes that there is new looting, but evidence of prior looting may or may not increase.	Randomly select one month of the missing period to code for evidence of looting attempts. Code all variables for all other missing months as 0.	Code 1 for new looting attempts.	If month at beginning of missing period is 1, code prior looting attempts as 1. If not, code prior looting attempts as 0.

Table 16. Operationalizations of Archaeological Looting Attempts Variables

	Variable	Operationalization		
		Spatial (unit: grid cell)	*Temporal (unit: month)*	*Spatio-Temporal (unit: grid-cell-month)*
Evidence of Archaeological Looting Attempts†	*Looting Attempts (Total - Either & And)*	Number of months a site has any evidence of looting Average number of months a grid cell has any evidence of looting attempts from 2015 – 2017	Count of archaeological sites with any evidence of looting per month	Binary measure indicating whether a given site showed any evidence of looting attempts each month Number of archaeological sites that showed any evidence of looting attempts per month per grid-cell
	Looting Attempts (New – Either & And)	Number of months a site has new evidence of looting attempts Average number of months a grid cell has new evidence of looting attempts from 2015 – 2017	Count of archaeological sites with new evidence of looting attempts per month	Binary measure indicating whether a given site showed new evidence of looting attempts each month Number of archaeological sites that showed new evidence of looting attempts per month per grid-cell
	Looting Attempts (Prior – Either & And)	Number of months a site has evidence of prior looting attempts Average number of months a grid cell has evidence of prior looting attempts from 2015 – 2017	Count of archaeological sites with evidence of prior looting attempts per month	Binary measure indicating whether a given site showed evidence of prior looting attempts each month Number of archaeological sites that showed evidence of prior looting attempts per month per grid-cell

†All archaeological looting attempt variables were created for both types of coding – where looting evidence is present if *either* source shows evidence ("All" looting) and where looting evidence is present only if *both* sources show evidence ("And" looting).

Limitations in Archaeological Looting Attempts Data Collection and Coding Strategy

These archaeological looting attempts data have several limitations. First, because I am relying on previously published lists of archaeological site names and locations, the "universe" of archaeological sites I was able to identify is biased towards only those that are publicly well-known. Published sources can only identify known archaeological sites; my universe of sites excludes unestablished sites. Less established sites may be more attractive to looters because objects and objects of a higher quality still in the site than an established site that has been excavated and recorded. Unestablished sites also likely have the least amount of guardianship and so are the easiest targets. As such, my universe may contain sites that are less likely to experience looting attempts, which would bias any findings toward zero.

Another limitation of relying on published sources is that the distribution of sites among the governorates of Lower Egypt is not representative of the true distribution of sites in the area. For example, Cairo only had four archaeological sites in my universe, and it is very unlikely that Cairo has so few sites. Its location at the beginning of the Nile Delta – an important area geographically and historically – likely made Cairo a populous area with many sites. By relying on published sources, my universe more accurately reflects the publication bias of where archaeologists and other scholars have focused rather than the actual distribution of sites in the Delta. As a result, my findings are not be generalizable to any sites beyond those that I was able to include in my set space.

A second major limitation with these data stems from the inconsistent availability of satellite images for the sites in my sample. Not all satellites capture images at the same intervals, for the same locations, and at the same resolution. Image availability and coverage directly affect how much data researchers have access to and as a result the frequency with which a phenomenon like looting attempts can be observed. As previously discussed, there are institutional factors influencing how frequently images are taken by satellites and which images become available to researchers. This introduces measurement error into the data. Despite randomizing the coding of missingness, it is likely that the data have more zeros than there would be in the presence of full data. As such, the measurement error will bias these data towards zero.

Further, because there is no baseline of information on how quickly looting pits appear or disappear, the method for imputing missing data used here introduces another source of measurement error. For example, in assuming that no looting occurred in the case where both sides of the period of missingness report "no change in prior looting," I ignore the possibility that prior looting evidence persisted throughout the period of missingness without change. Measurement error in the dependent variable will decrease the precision of any estimates I obtain from analyses due to increased variance in the model's error term, making it less likely for any estimates to achieve statistical significance.

To mitigate the bias introduced by inconsistent coverage and availability, my approach used multiple sources of satellite imagery and an imputation strategy based on weak assumptions. This increased the number of images available for each site and reduced my reliance on a single institution's policy on which locations should have images available and for how many years. The imputation strategy I employed made the weakest assumptions possible regarding the effect of changes in prior looting across missing periods. As my data are already biased towards not finding looting when looting may be present, this imputation strategy increased the number of observations and thus the variation in the data.

A third important limitation results from my initial data collection strategy – trying to collect sites in alphabetical order. If I had had the resources to collect data on the entire universe of sites ($n = 1109$), collecting sites alphabetically would have been an odd choice, but would not have affected my data. However, I was only able to collect data on 39 sites before determining that this sampling strategy was infeasible. When redesigning the sampling strategy, I included all 39 of the "round 0" sites in the stratified random sample. Unfortunately, time and resource constraints influenced my final sample. At end of my allotted data collection period (February – April 2019), I had collected images on 107 sites, 6 of which the sampling strategy pulled from the initial 39 sites from "round 0." As I had already collected data on the remaining "round 0" sites and I needed as large a sample size as possible, I included the remaining 33 sites in the final sample count.

These 33 sites are concentrated in Beheira ($n = 16$), Daqahliyah ($n = 2$), Kafr es Sheikh ($n = 6$), and Al Sharqiyah ($n = 9$). As a result, these governorates (especially Beheira, Kafr es Sheikh, and Al Sharqiyah) have been oversampled. However, Beheira, Kafr es Sheikh, and Al Sharqiyah are also the three largest governorates in Lower Egypt with the most archaeological sites in the universe I identified. Even with oversampling, these governorates had the lowest percentage of their total sites sampled (13% in Al Sharqiyah, 15% in Beheira, and 18% in Kafr es

Sheikh). Further, I weighted the data in my analyses when possible, which fixed the disproportionality of the sample.

I also have several limitations with respect to the data coding strategy. This strategy adapts the method of counting looting "pits" proposed by Sarah Parcak to code for a series binary conceptualizations of archaeological looting attempts. Although my adaptations increase the potential for replication, the method is still grounded in the assumption that the human eye can consistently identify evidence of looting attempts. However, the human eye is easily tricked by imagery and suffers from coding fatigue over long periods of time. For example, depending on how the angle the image was taken combines with the angle of the sun and the features of the site, the final product may produce an optical illusion making it nearly impossible based on visual cues alone to understand the landscape being examined. Similarly, coding fatigue can make it more difficult to discern changes between images or months and may make errors in coding more likely. I mitigated this by using the coding protocol above, building in many layers of data review and validation, and taking frequent breaks from coding in between sources and sites. The coding decision rules I used also made it more likely that I would underreport looting attempts than over report them.

The coding strategy also cannot capture looting attempts that occurred without physically altering the terrain (e.g., without digging a "pit"). My data cannot speak to looting from structures in an archaeological site, necropolises or catacombs, storage facilities in the vicinity of a site, or museums. As a result, my findings will not apply to the spatial and temporal patterns of all looting behaviors, only those relating to looting that affects the surface of the site and that are visible on satellite imagery.

Finally, coding looting as a binary concept introduces two limitations. First, I am losing important spatial and temporal variation by equating minor looting attempts with massive looting operations. Second, by coding "all" looting attempts evidence as the primary dependent variable, I am potentially capturing the same looting attempts evidence twice – when it is fresh or "new" looting evidence and then again when it is "prior" looting evidence. I try to mitigate this by running all analyses (where possible) with each of the different types of looting evidence (all, new, & prior) as the dependent variable to test the sensitivity of my findings to possible duplication of events.

Sociopolitical Stress Data Collection & Coding

For this dissertation, I defined sociopolitical stress as any kind of conflict, including riots and protests, political violence, civil conflict, violence against civilians, and terrorist attacks.[41] To capture such a wide range of conflict types, I compiled data from three sources: the Armed Conflict Location and Event Data Project (ALCED), the Uppsala Conflict Data Program (UCDP), and the Global Terrorism Database (GTD). Each of these sources provides geo-coded event data covering the time-period of interest (2015 – 2017) on different types of conflict in Egypt.

The ACLED compiles information on a variety of political violence incidents in Egypt from 1997 – 2018. These data include information on date, location, actors in the conflict, and event type. Event type includes all battles, violence against citizens, remote violence, rioting (violent demonstrations), protesting (non-violent demonstrations), and three types of non-violent events (non-violent transfer of territory, headquarters or base established, & strategic development) (ACLED, 2015). These data also capture all political violence episodes in a given state because they do not require a fatality minimum (ACLED, 2015). The UDCP provides data on organized violence and civil war from 1989 to 2017. In addition to providing the total number of deaths and contexts of each conflict, the UCDP also distinguishes between state-based violence, non-state violence, and one-sided violence (Uppsala Universitet, 2018).

The GTD is an open-source event level database that includes terrorist events from around the world from 1970 to 2017. It was designed to be a comprehensive,

[41] Here I specifically use the term "conflict" in lieu of "armed conflict." The latter is an ambiguous term that is typically defined based on international humanitarian laws, which only applies to a specific subset of conflicts and do not include internal tensions, isolated acts of violence, riots, protests, or terrorist attacks (ICRC 2004).

robust event database of domestic and international terrorist attacks (LaFree et al., 2015). Data include variables on: incident date, region, country, state/province, city, latitude and longitude, perpetrator group name (when known), tactic used in attack, nature of the target, identity/corporation/and nationality of the target, type of weapons used, whether incident was considered a success, if and how a claim of responsibility was made, amount of damage, total number of fatalities, total number of injured, and if incident was international or domestic (LaFree et al., 2015; START, 2018). To be included, an incident must be "an intentional act of violence or threat of violence by a non-state actor" (LaFree et al., 2015: 19). Additionally, incidents are only included if they meet at least two of the following three criteria: (1) the violent act was aimed at attaining a political, economic, religious, or social goal; (2) the violent act included evidence of an intention to coerce, intimidate, or convey some other message to a larger audience(s) other than the immediate victims; and (3) the violent act was outside the precepts of international Humanitarian Law (LaFree et al., 2015: 19-20).

Each dataset contained information on the incident date, country, and location of the incident (including latitude and longitude, the governorate and the city). Rather than relying on one source's coding strategy more than the others, I developed my own coding system for conflict type and attack type (see Table 17) and then coded each incident description accordingly (see Data Coding Instructions). Each incident description was coded for: conflict type, attack type, whether unintended violence[42] occurred during the incident, whether multiple incidents were reported in the

[42] Unintended violence refers to incidents that were not intended to be violent and yet violence occurred. For example, unintended violence would be coded when a non-violent protest was the main event, but police assaulted protesters or attacked them.

description, whether the described incident was related to another incident already coded, whether the incident was domestic or international in focus, and the incident's source (ACLED, UCDP, or GTD).

Incidents were only kept if they were domestic in focus and had specific geolocations. If an incident description reported multiple incidents, each of the multiple incidents were counted. For example, if an incident reported three separate bombing locations, I coded each bombing as a separate incident according to its location. Once all data were coded, I used the *related incident* variable to cross-reference across sources and removed duplicates. In total, these data reported on 1,220 incidents of conflict from 2015 to 2017.[43]

Once all data were coded, I used the attack type and conflict type variables to create four measure of sociopolitical stress: a count of all conflict incidents, violent conflict incidents (includes terrorism, riots, religious violence, and police-militant clashes), protests (all forms of protest), and violence against civilians. These measures were then transformed as necessary, depending on the type of analysis (spatial, temporal, spatio-temporal). Table 18 describes how these measures were operationalized across the four datasets. The temporal data were merged with the looting data to create a single time series dataset. Spatial and spatio-temporal measures were kept as individual datasets.

[43] After cleaning the conflict data, there were only 3 incidents of conflict from the UCDP that were not duplicates of the incidents in the ACLED and the GTD.

Table 17. Conflict and Attack Types

Variable	Categories
Conflict Type	Riots/protests* Terrorism Religious violence Violence against civilians Police-militant clashes Other
Attack Type	Assassination Armed assault Bombing/explosion Hijacking Hostage taking (barricade incident) Hostage taking (kidnapping) Facility/infrastructure attack Unarmed assault Unknown Political protests Economic protests (famine) Economic protests (labor) Religious protests Police protests Other protests Arson Torture Riots

*Note: Incidents were coded under the conflict type "riots/protests" and then separately identified as their respective attack type. In aggregating these data, I relied on the attack type to identify appropriate incidents.

Limitations in Sociopolitical Stress Data Collection and Coding Strategy

The sociopolitical stress data have an important limitation. I had to rely on the geocoordinates provided by each data source, which are not necessarily recorded with the same degree of precision. For example, in ACLED the geocoordinates are located to the smallest possible location; however, as it reports on a variety of violent and nonviolent conflict types, not all coordinates can be equally precise. Protests occupy a larger amount of space than an isolated terrorist incident, yet both are given a single geocoordinate. The selection of the coordinate for larger incidents (like protests) or incidents that are vague in their details is unclearly established by all the datasets. As such, in relying on their coordinates, I am assuming that each location is representative of the distribution of sociopolitical stress when it may in fact be incorrect. Analytically, this also presents a challenge as some spatial methods assume that multiple incidents with the same location are duplicates instead of the independent events they reflect.

Table 18. Operationalizations of Socio-Political Stress Indicators

	Variable	Operationalization		
		Spatial (unit: grid cell)	*Temporal (unit: month)*	*Spatio-Temporal (unit: grid-cell-month)*
Socio-Political Stress Indicators	*Conflict (total)*	Geolocated incidents of all conflict from 2015 – 2017 Total number of conflict incidents from 2015 – 2017 per grid cell	Total number of conflict incidents per month	Total number of conflict incidents for each grid cell per month
	Violent Conflict	Geolocated incidents of violent conflict from 2015 – 2017 Total number of violent conflict incidents from 2015 – 2017 per grid cell	Total number of violent conflict incidents per month	Total number of violent conflict incidents for each grid cell per month
	Non-violent Conflict (protests)	Geolocated incidents of non-violent conflict from 2015 – 2017 Total number of non-violent conflict incidents from 2015 – 2017 per grid cell	Total number of non-violent conflict incidents per month	Total number of non-violent conflict incidents for each grid cell per month
	Violence against Civilians	Geolocated incidents of violence against civilians from 2015 – 2017 Total number of violence against civilians incidents from 2015 – 2017 per grid cell	Total number of violence against civilians incidents per month	Total number of violence against civilians incidents for each grid cell per month

Economic Stress Data Collection & Coding

Economic stress can occur at a local level (i.e. governorate-level) or a national level and each may influence when and where archaeological sites may be suitable targets. Additionally, national level economic data should be relevant for the temporal and spatio-temporal analyses, while local level data should be applicable to all analyses. As such, I decided to include measures of stress applicable to both levels. Local levels of stress included: total percent unemployment, percent youth unemployment, and consumer price indices (CPI) for general goods and food. The unemployment measures were collected from Egypt's Central Agency for Public Mobilization and Statistics (CAPMAS) and were reported at the governorate-level, allowing me to create rates for just Lower Egypt. The CPIs were collected from the Food and Agriculture Organization of the United Nations (FAO) and reported at national-levels. National levels of stress included: national debt as percent of reserves and as percent of external debt, inflation based on the consumer price index, and the number of tourist arrivals. All national variables were collected from the WorldBank and were reported annually at the national level.

Once all data were collected, both local and national measures were transformed as necessary, depending on the type of analysis (spatial, temporal, spatio-temporal). I created measures of both average percent change and net percent change for the spatial datasets as these changes were more relevant to my theoretical framework than a static measure. Changes in economic stress could indicate the presence of conditions that would make archaeological sites more attractive as suitable targets for looting. Table 19 describes how these measures were operationalized across the four datasets.

National-level data had no spatial variation and so no variables were created for the spatial analyses. The temporal data were merged with the looting attempts and sociopolitical stress data to create a single time series dataset. Spatial and spatio-temporal measures were kept as individual datasets.

Limitations in Economic Stress Data Collection & Coding Strategy

The economic variables have some limitations. Because they are reported at different units of analysis (monthly vs annually and by governorate vs nationally), some variables had less variation over time and space. For example, national debt is reported at a national level and annually and so did not vary spatially and had limited variation temporally. As such, some of the economic stress variables reported at higher levels of aggregation were only be useful for descriptive analyses. This is particularly true for the spatial datasets, as economic variables could not be represented as "points" on a map. Additionally, the measures used in this dissertation come from multiple sources with different methodologies. This can make it difficult to evaluate which measures are the most appropriate to use for a given analysis. For example, the WorldBank reports a measure of inflation based on consumer price index; however, it does not use either of the indices reported by the FAO. As such, the measure of inflation and the two consumer price indices may be measured very differently. To mitigate this, I tested using different combinations of variables in the analyses to determine whether the findings were sensitive to the source (see Results for more information).

Table 19. Operationalizations of Economic Stress Indicators

	Variable	Operationalization		
		Spatial (unit: grid cell)	*Temporal (unit: month)*	*Spatio-Temporal (unit: grid-cell-month)*
Economic Stress Indicators	*% Unemployment (total)*	Net percent change in unemployment from 2015 - 2017 per grid cell Average percent change in unemployment from 2015 – 2017 per grid cell	Percent unemployment in Lower Egypt per month	Percent unemployment for each grid cell per month
	% Unemployment (youths aged 15-24)	Net percent change in youth unemployment (ages 15 – 24) from 2015 – 2017 per grid cell Average percent change in youth unemployment (ages 15 – 24) from 2015 – 2017 per grid cell	Percent youth unemployment (ages 15 – 24) in Lower Egypt per month	Percent youth unemployment (ages 15 – 24) for each grid cell per month
	Consumer Price Index (general)		Change in general consumer price index relative to 2010 baseline per month	Change in general consumer price index relative to 2010 baseline per grid cell per month*
	Consumer Price Index (food)		Change in food consumer price index relative to 2010 baseline per month	Change in food consumer price index relative to 2010 baseline per grid cell per month*
	Consumer price inflation		Percent inflation based on CPI per month	Percent inflation based on CPI per grid cell per month*
	National Debt (% of external debt)		Percent national debt (% of external debt) per month	Percent national debt (% of external debt) per grid cell per month*
	National Debt (% of reserves)		Percent national debt (% of reserves) per month	Percent national debt (% of reserves) per grid cell per month*
	Tourism		Number of tourist arrivals per month	Number of tourist arrivals per grid cell per month*

*Variables that could not be used in the analyses due to insufficient variation.

Environmental Stress Data Collection & Coding

To capture the potential influence of environmental stress, I collected several indicators relating to how "healthy" the land is: the amount of precipitation; the soil moisture content; a vegetation health index (NDVI[44]); and total crop production. Precipitation data were collected from the GLDAS Noah Land Surface Model (version 2.1), which reports monthly average amounts of rainfall at 0.25-degree spatial intervals. Soil moisture content data were collected from the Modern-era Retrospective Analysis for Research and Applications (version 2 – MERRA-2) data, which reports the monthly average soil moisture content at 0.5-degree spatial intervals. The vegetation index data were collected from the NASA Visible Infrared Imaging Radiometer Suite (VIIRS) of vegetation indices, which reports monthly composite indices at 0.05-degree spatial intervals. Finally, the total crop production data were collected from the FAO, which reports annual data on aggregate crop types at a national level. For a detailed description of each data source and the construction of each variable, see Appendix 1.

Once all data were collected, these measures were transformed as necessary, depending on the type of analysis (spatial, temporal, spatio-temporal). I created measures of both average percent change and net percent change for the spatial datasets as a static measure of environmental stress would not capture as much useful information. Table 20 describes how these measures were operationalized across the four datasets. Similar to the national economic variables, total crop production had no spatial variation and so was not included in the spatial dataset. The temporal data were

[44] NDVI stands for Normalized Difference Vegetation Index

merged with the all other data to create a single time series dataset. Spatial and spatio-temporal measures were kept as individual datasets.

Limitations in Environmental Stress Data Collection & Coding

Similar to the economic data, the environmental data are measured at different spatial and temporal resolutions. Though most of the variables are reported monthly, total crop production is reported annually. Crop production is also measure nationally, whereas the other three variables range from 0.05- to 0.5-degree intervals. This impacted how values were aggregated to the grid overlays (hexagonal and lattice). All three sizes were larger than the 10km and 50km grid-cells (but not the 150km cells). This meant that multiple cells had the same value for the environmental variables. In the event that a grid-cell overlay with multiple values of soil moisture content, precipitation, or vegetation health, the grid-cell calculated the average. The lack of variation diminished the chances of finding an effect between total crop production and looting attempts.

Table 20. Operationalizations of Environmental Stress Indicators

	Variable	**Operationalization**		
		Spatial (unit: grid cell)	*Temporal (unit: month)*	*Spatio-Temporal (unit: grid-cell-month)*
Environmental Stress Indicators	*Precipitation*	Net percent change in amount of precipitation (in millimeters) from 2015 – 2017 per grid cell Average percent change in amount of precipitation (in millimeters) from 2015 – 2017 per grid cell	Amount of precipitation (in millimeters) per month	Amount of precipitation (in millimeters) per grid cell per month
	Soil Moisture Content	Net percent change in moisture content of soil (measured as millimeters per cubic inch) from 2015 – 2017 per grid cell* Average percent change in moisture content of soil (measured as millimeters per cubic inch) from 2015 – 2017 per grid cell*	Amount of moister in the soil (measured as millimeters per cubic inch) per month	Amount of moister in the soil (measured as millimeters per cubic inch) per grid cell per month*
	Vegetation Health (NDVI)	Net percent change in vegetation health (measured as a normalized differenced vegetation index – NDVI) from 2015 – 2017 per grid cell Average percent change in vegetation health (measured as a normalized differenced vegetation index – NDVI) from 2015 – 2017 per grid cell	Index value of vegetation health per month	Average index value of vegetation health per grid cell per month
	Total Crop Production		Total crop production per month	Total crop production (in tonnes) per grid-cell per month

*Variables that could not be used in the analyses due to insufficient variation.

Chapter 5: Spatial, Temporal, and Spatio-Temporal Methods

The analyses for this dissertation relied on a small number of archaeological sites ($n = 140$) and a short time frame (36 months). The limitations associated with these data (see previous chapter) preclude running any single analyses to analyze the proposed hypotheses. Instead, I use multiple approaches for each type of analysis (spatial, temporal, and spatio-temporal), evaluate the pros and cons of each, and cross-reference their results to identify common findings. Evaluating different methods is a key element of this dissertation and positions this research as a guide for others seeking to do this type of research. Further, using multiple approaches to examine each hypothesis allows me to triangulate the findings despite the limitations of the data.

Using multiple approaches necessitated storing data in multiple formats – particularly regarding the spatial analyses. This chapter discusses the process of formatting data appropriately for the range of analyses I conducted. It then outlines the approaches I used for each type of analysis. Additionally, the following sections explain both the types of analyses required for each hypothesis and how this impacts how data need to be stored and formatted. My evaluations of each method and substantive results are presented in the next chapter.

Spatial Analyses

The first three hypotheses suggest several spatial relationships. *Hypothesis 1* and *Hypothesis 1a* focus on whether site characteristics influence which sites show evidence of looting attempts. *Hypothesis 2* suggests that distance from key locations influences which sites show evidence of looting attempts. Finally, *Hypothesis 3* suggests that evidence of looting attempts may be co-located with different types of stress (sociopolitical, economic, and environmental). To test these hypotheses, I use a combination of point pattern analysis and ordinary least squares regression (see Appendix 2 for description of all spatial methods).

A point process "is a set of locations that are irregularly distributed within a designated region and presumed to have been generated by some stochastic mechanism." (Diggle, 2014: xxix). A point pattern is the spatial arrangements of points in space and is the outcome of a point process. For this dissertation, my point pattern analysis includes several descriptive methods as well as multiple tests for spatial autocorrelation, clustering, and proximity. This combination of methods allows me to evaluate the spatial distribution of my variables and select the appropriate method for testing my hypotheses.

My dependent variable is a sample that is irregularly distributed in space while my independent variables are measured across the entirety of Lower Egypt. This means that there are a lot of locations of unsampled archaeological sites or unknown sites (i.e. not in the "universe") that contain no information on archaeological looting attempts. By looking at multiple different types of clustering and proximity, I can evaluate how each variable is distributed alone and in relation to each other across different ways of formatting the spatial data. For example, clustering and proximity test may have one result when formatting the dependent variable as a series of points (site locations) or polygons (boundaries of sites) compared to grid-cells. Relatedly, though formatting variables as gridded data creates a means to compare across a variety of data, doing so also introduces the possibility of having to address more missing data (especially with archaeological sites – see below for a more on limitations with gridded data).

The spatial statistics in this study rely on vector (discrete) data formats (points, polygons, lines, grids) because my dependent variable is a series of discrete locations with attributes. Some of the methods require the variables to be in the same format (e.g., both points) while others allowed for multiple formats (e.g., point and polygon); however, all require that variables be vectors. As such, I reformatted and transformed almost all variables to create subsets of data that could be analyzed to identify spatial patterns and relationships. Table 21 describes this process for each variable. Where possible, all variables are formatted as point data, polygon data, and grids.

Point and polygon data are simple to create. Archaeological sites, sociopolitical stress, and environmental stress variables are already measured at individual locations. However, most of the environmental variables are stored as multidimensional rasters, which requires additional steps to convert it to vector data. To do so, I extract the point values for 2015 to 2017 through the process of sampling[45] and then calculate the average percent change and net percent change for each point. All independent variable point data are then spatially joined with a polygon layer outlining the governorate boundaries in Lower Egypt, creating polygon data. Archaeological site data are already formatted as both points (site locations) and polygons (the boundaries created around each site) as part of the collection and coding process and so are kept in this format. For variables without specific geolocations (e.g., the environmental variables, crop

[45] The process of sampling creates a table showing the values of cells from a set of rasters for defined locations. For more information, see https://pro.arcgis.com/en/pro-app/tool-reference/spatial-analyst/sample.htm.

production), their values are added as attributes to the Lower Egypt boundary polygon layer. The polygons are then converted into points such that there is a single point in approximately the center of each polygon.

Creating grids for all data is a more complicated process as there is no standardized guide for how large each cell of the grid should be, nor which cell shape should be used. Cell size must be specified by the user and has to balance being small enough to capture variation in the data and large enough to minimize how many observations with zeros or missing data are introduced. This is particularly relevant for my dependent variable. Grid-cells without archaeological sites in my sample could either be treated as zeros or as missing data.[46] Since the analyses used in this dissertation could be run on only the grid-cells containing data, grid-cells without any archaeological sites are considered missing.

For shape, ArcGIS Pro allows grids to be made of hexagons (flat side up), transverse hexagons (point side up), squares, diamonds, and triangles. Square grids (also called a fishnet or lattice grid) are the most common and work with the most analyses. However, hexagonal grids have some unique benefits that make them an increasingly useful option. Hexagons reduce sampling bias due to edge effects of the grid shape and suffer less distortion due to the curvature of the earth when covering larger areas. Hexagons are also often more accurate and useful for analyses focused on proximity and clustering as grid-based methods often calculate distances based on the centroid of the cell. For lattice grid-cells, the centroid is not equidistance from every

[46] I did not include unsampled archaeological sites in the gridded data. I only included the sites that were coded and for which I had data.

angle, which could affect the distances calculated. The sides of hexagons, by contrast, are all equidistant from the centroid, making distance calculations more straightforward. In this study, I create both lattice grids and hexagonal grids in three sizes (10-kilometers, 50-kilometers, and 150-kilometers). Experimentation with different cell sizes suggests that these three encompass the range of smallest and largest reasonable cell-sizes.[47]

The sample sizes of the resulting variables differ dramatically after reformatting them. Each variable has a different sample size for the point data, ranging from 12 observations (for total crop production) to 1,588 (for vegetation health index). All variables except for the archaeological looting attempt variables are joined to the same polygons and so have a sample size of 12. The archaeological looting polygons represent the size of the area coded for looting attempts and so have a sample size of 140 (the number of sites). The gridded variables have three different sample sizes according to the size of the grid-cell that ranged from 450 at 150-km to 5,040 at 10-km.[48] Variation in the sample sizes is an advantage for these spatial methods. Since all my statistical analyses (spatial statistics and OLS regression) rely on combinations of point, polygon, and gridded data, I can test each hypothesis multiple sample sizes. If I find consistent results across different data types and sample sizes, I can have more confidence in the findings.

[47] I tested creating grids at 0.05-km, 0.5-km, 2-km, 5-km, and 200-km in addition to the three sizes selected. Those less than 10-km produced too many zeros resulting in even less variation in the dependent variable than I already had. Grid-cells larger than 150-km were too aggregate and eliminated most of the variation as well.

[48] These sample sizes include cells treated as having "missing" data.

Table 21. Spatial Data Formats

	Variable	Point Data*	Polygon Data	Gridded Data*
Evidence of Archaeological Looting Attempts	*All Evidence of Looting (coded as "or" & "and")* *New Evidence of Looting (coded as "or" & "and")* *Prior Evidence of Looting (coded as "or" & "and")*	Locations of archaeological sites with number of months with evidence of looting attempts and ownership status as attributes	Boundary polygons of archaeological sites with number of months with evidence of looting attempts and ownership status as attributes	The number of months with evidence of looting per variable per grid-cell (lattice or hexagonal at 10-km, 50-km, & 150-km) with ownership status as attributes
Sociopolitical Stress	*All Incidents of Conflict* *Violent Conflict* *Non-Violent Conflict (Protests)* *Violence against Civilians*	Locations of incidents of conflict types	Number of incidents per governorate	The number of months with evidence of looting per variable per grid-cell (lattice or hexagonal at 10-km, 50-km, & 150-km)
Economic Stress	*Unemployment (Total & Youth)* *Consumer Price Indices (food & general)* *Inflation based on CPI* *National Debt (as % of external debt, as % of reserves)* *Tourism*	Average % change per governorate (measured at center of governorate) Net % change per governorate (measured at center of governorate)	Average % change per governorate Net % change per governorate	Average % change per grid-cell (lattice or hexagonal at 10-km, 50-km, & 150-km) Net % change per grid-cell (lattice or hexagonal at 10-km, 50-km, & 150-km)
Environmental Stress	*Precipitation* *Soil Moisture Content* *Vegetation Health (NDVI)* *Total Crop Production*	Locations of measurement points (at 0.05-degrees, 0.25-degrees, 0.5-degrees, and per governorate)	Average % change per governorate Net % change per governorate	Average % change per grid-cell (lattice or hexagonal at 10-km, 50-km, & 150-km) Net % change per grid-cell (lattice or hexagonal at 10-km, 50-km, & 150-km)

*Data format used in OLS analysis

The first step to a point pattern analysis is to visualize and describe the pattern in question by creating "point pattern maps" (Burt et al., 2009). These maps are created for archaeological looting attempts and each of the indicators (sociopolitical, economic, and environmental). Though, theoretically, the variables within each indicator should provide complementary perspectives on where stress is present, it is visually confusing to map all variables together for each indicator. As such, each variable is mapped on its own.

The second step is to identify patterns by determining whether autocorrelation is present among the variables. Spatial autocorrelation exists, "whenever a variable exhibits a regular pattern over space in which its values at a set of locations depend on values of the same variable at other locations," (Odland, 1988, p.7). If similar values of a variable are clustered in space, then that variable is positively spatially autocorrelated. By contrast, if dissimilar values of the variable are clustered, then that variable is negatively spatially autocorrelated (Burt et al., 2009). Most geographical methods assume that observations are independent; failing to detect and control for spatial autocorrelation affects our ability to identify patterns and statistically significant relationships. Several methods exist for detecting spatial autocorrelation, depending on how a variable is operationalized. Here, I rely on the Global Moran's I statistic, the Local Moran's I statistic, and an incremental spatial autocorrelation statistic as they test for autocorrelation in the data overall, regionally, and depending on the distance from the points, respectively. Combined they provide a detailed picture of which variables had spatial autocorrelation and under what circumstances.[49]

To test whether characteristics of sites, like ownership, influence the spatial distribution of archaeological looting attempts (*Hypothesis 1* and *1a*), I use ordinary least squares with and without clustering on the grid-cell to control for spatial autocorrelation. To see whether sample size and level of aggregation influence the results, I run this analysis with both point data and gridded data (hex and lattice) that have been exported to Stata.

Then, I use methods designed to look for clustering and proximity to test whether evidence of looting attempts is co-located with areas experiencing stress (*Hypothesis 3)* and if proximity to key locations influence evidence of looting (*Hypothesis 2)*. If two phenomena are co-located, then they are each likely clustered and are likely to be in close proximity. To look at whether individual phenomena are clustered, I calculate the Ripley K statistic, the average nearest neighbor index, and constructed Voronoi maps for each variable.

Voronoi maps take a different approach and analyze the geometric distribution underlying the spatial pattern of interest (Oyana and Margai, 2015). The map is created by constructing Thiessen polygons (also known as proximal zones) such that each polygon represents areas where any location within it closer to an associated input point than to any other input point (Mitchell, 2009). This method provides a clear visual

[49] Another useful tool for diagnosing potential misspecification of spatial analysis and models is kriging. Kriging interpolates missing values under the assumption that statistical spatial dependence exists (Burt et al., 2009). Many different types of kriging analyses exist, depending on the distribution of the data and what kind of spatial dependence trend is assumed. Though I initially tried to use kriging analyses, they are not appropriate where the phenomena are highly skewed with many zeros or count data (Oyana and Margai, 2015).

representation of clustering as well as how large the "spheres of influence" are around predefined events.

To determine proximity between areas of stress and archaeological sites, I calculate two types of "closeness": the straight-line distance ("geodesic distance") between each site and the nearest area of stress, and the nearest incident distance. Proximity measured as a geodesic distance calculates the shortest straight-line distance between two features without accounting for any potential barriers or constraints (e.g., roads or mountains).[50] The term "geodesic" refers to the fact that the straight-line accounts for the curvature of the earth. Most distance-related calculations can be set to use either geodesic or planar distance calculations. Here I use the term to distinguish this form of proximity from nearest incident proximity.

Since each indicator variable has different units of measurement and spatial resolution, I conduct this test for each one separately. This approach is useful for examining sociopolitical stress and most of the environmental stress variables. However, because the economic variables are associated with a single point in each governorate, clustering and proximity-based analyses do not provide meaningful information. To look at co-location with economic stress, I visually compare the economic variables distributed by governorate and the distribution of sites with evidence of looting attempts. Because sociopolitical stress is measured as georeferenced event data, I could test proximity by calculating the distance between

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[50] It can calculate this distance between point features, line features, and polygon features. The distance between two points is simply the shortest straight line connecting them. Distance from a point to a line is either the shortest distance perpendicular to the line or the shortest distance to the closest vertex. The distance from a point to a polygon is the shortest distance to the boundary or edge of the polygon rather than the center of the polygon. If any two features overlap (e.g., a point falls inside a polygon or two points share a coordinate) the distance is zero.

each archaeological site and its nearest incident of sociopolitical stress when constrained to using the road network in Lower Egypt.

To test proximity of archaeological sites to key locations, I use a combination of geodesic distance, nearest incident measures, and ordinary least squares regression. I operationalize key locations as three different measures of populated areas and the road network in Lower Egypt. For populated areas, I look at capital cities, urban areas (polygons), and all populated cities or towns in Lower Egypt. Euclidean distances are calculated from archaeological sites to all these operationalizations to examine how accessible sites are in my sample by distance. Proximity measured by nearest incident is calculated for all three key location measures and for sociopolitical stress. The distances acquired from the proximity analyses are compared to see whether the road network significantly affected the perception of "distance" to an archaeological site. I test regressing both the geodesic distances and nearest incident distances on the number of months with evidence of archaeological looting attempts to see if different measures affected the results. Regressions are run both with and without clustering on the hex to control for spatial autocorrelation.

Limitations

My spatial data suffer from the Modifiable Areal Unit Problem (MAUP), which is a type of ecological fallacy related to aggregating data to larger areal units. The presence of MAUP raises two general concerns – there could be a scale effect, where there is a tendency for different statistical results to be obtained from the same set of data when the information is grouped at different levels of spatial resolutions. There could also be an aggregation effect, where different areal arrangements of the same data produce different statistical findings. MAUP is more likely to be present when data are highly spatially correlated, and since archaeological sites are often relatively close to each other, my dependent variable would likely be affected by this issue. To mitigate MAUP, I constructed both traditional grids (a lattice with square cells) and hexagonal grids, which can reduce issues of spatial autocorrelation. I then ran all analyses using both hexagonal and lattice-grids and compared the results. Further, recommendations for addressing MAUP suggest reducing the scale or level of aggregation until the issue disappears. As such, I constructed each type of grid at three sizes: 10 km, 50 km, and 150 km.

Relatedly, assuming that grid-cells without any archaeological sites had missing data limited the value of using gridded data as a storage format. One benefit of using these data is the increased sample size that can result. Yet, as this dissertation demonstrates, this is only the case when most or all of the study area has values. In cases like the archaeological sites in my sample, using gridded data ran the risk of reducing the sample size. Many archaeological sites were close together, meaning grid-cells would often contain multiple sites. Since only grid-cells with values could be used in an analysis, the sample size for grid-cells could be smaller than using the point or polygon data.

Temporal Analyses

Hypotheses 4 and *5* focus on temporal patterns of archaeological looting relative to socio-political, economic, and environmental conditions. *Hypothesis 4* suggests a temporal relationship in general while *Hypothesis 5* suggests there may be a long-term or delayed effect of stress on looting attempt. To test these hypotheses, I use a series of multivariate time series methods to test different model specifications and assumptions. Specifically, I use structural equation modeling (SEM), lag augmented vector autoregression (LA-VAR), vector error correction (VEC), and autoregressive distributed lag models (ARDL).

Multiple time series models are appropriate for assessing the mutual associations between random processes as they allow for the consideration of all the possible ways that these indicators of stress and looting attempts can evolve independently and together. When conducting a multiple time series analysis, there are several decisions that have to be made that affect which model(s) are used (Pesaran & Smith, 1998):

1. The number of endogenous variables to be included
2. The number of exogenous variables to be included
3. The nature of the deterministic variables and whether there need to be any restrictions on intercepts or trend coefficients[51]
4. The order of the model
5. The order of integration of the variables
6. The number of cointegrating vectors[52]
7. The lag structure of the model or variables

The four methods in this dissertation address these decisions differently. Structural equation modeling (SEM) is a statistical modeling technique that allows researchers to estimate multiple equations at a time (Kline, 2015). An SEM has three elements: the path diagram, factor analysis, and path analysis (Kline, 2015). The path diagram models the theoretical relationship between archaeological looting attempts and conditions of stress (see Figure 18).

Each box with at least one arrow in the diagram indicates a regression equation to be modeled, where the number of arrows pointing to it depict the variables in the equation.[53] The shape identifies whether a variable is latent (oval) or observed (rectangle). Factor analysis determines how the observed variables should be best grouped into latent variables.[54] If the observed variables theoretically belong to a single construct (e.g., environmental stress), it is possible to conduct confirmatory factor

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[51] Five different trends (or cases) are often encountered in analyses: 1) no intercept of trend, 2) restricted intercepts which enter the cointegrating relations and no trend, 3) m unrestricted intercepts and no trends, 4) m unrestricted intercepts and r restricted trends, and 5) m unrestricted intercepts and m unrestricted trends (Pesaran & Smith, 1998). In these cases, r is the rank of the model and m refers to the order of integration of the variable(s).
[52] Cointegration refers to when at least two variables covary together over time such that together they are stationary, even if separately one or more of the variables are not. Engle and Granger (1987) introduced the concept of "cointegration" to allow for stochastic trends to be captured in VAR models.
[53] Note that the relationship between latent and observed variables is different in these models since latent factors are estimated rather than depicting their own regression equations.
[54] Latent variables can be used to model the relationship between theoretical constructs (e.g., economic stress) and observed variables (e.g., looting attempts).

analysis to see whether they are relevant to the construct. Prior to running SEM, factor analysis is used to correctly specify any latent variables in the structural model. The structural model (or path diagram) estimates the relationships outlined in the diagram. Because the diagram dictates the model, SEM can easily incorporate autoregressive structures, moving average processes, and variables requiring differencing to be stationary. It is also possible to add constraints to the model, such as assuming that the impact of a lagged variable on itself will always be equal. These constraints can be useful for reducing the degrees of freedom needed to estimate complex models with a limited sample size (Kline, 2015).

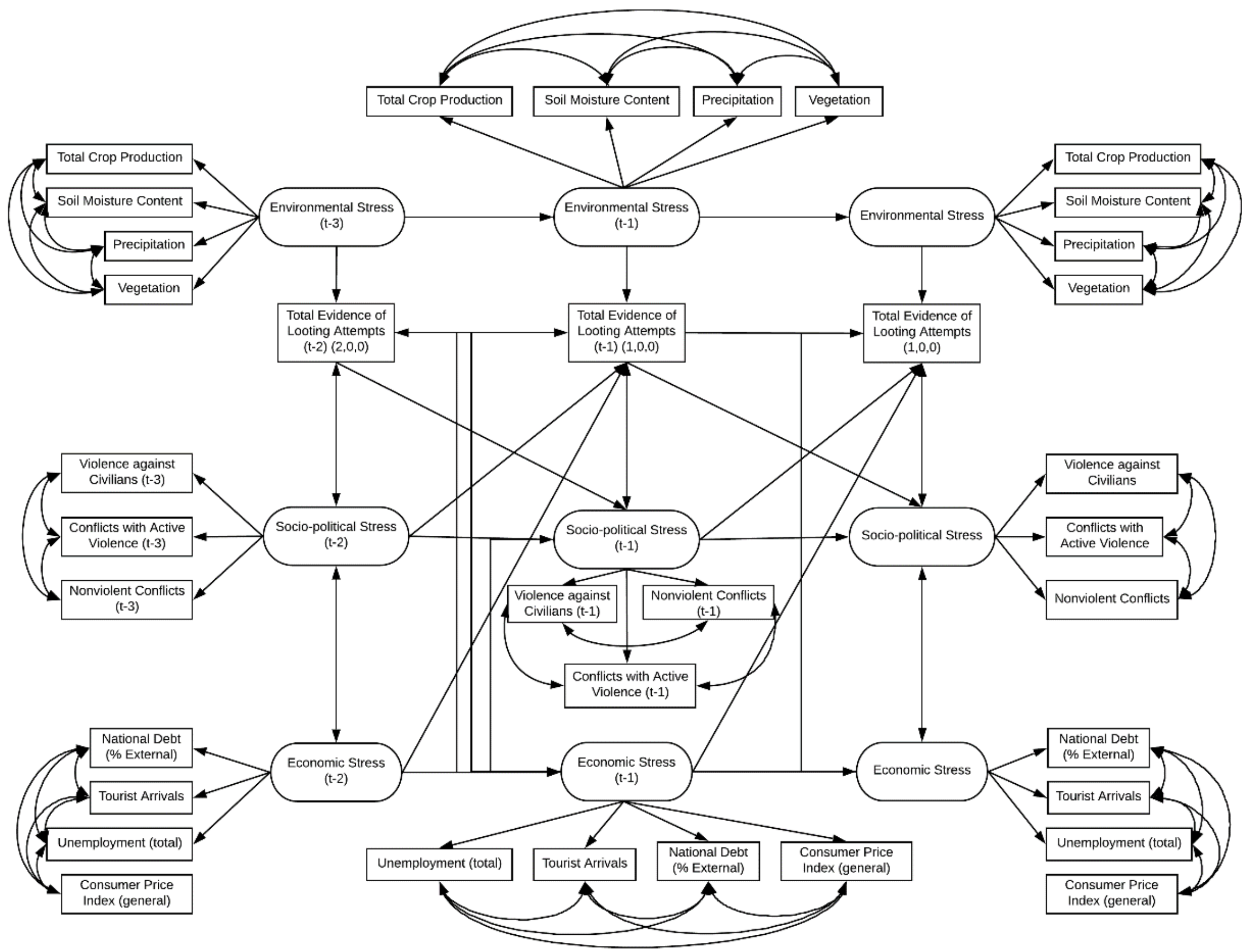


Figure 18. SEM Path Diagram

The LA-VAR, VEC, and ARDL models are extensions of the basic vector autoregression (VAR) model, which models multiple time series data so that each series is used as explanatory variables in the other (Lütkepohl, 2011: 2). All of these models also look at the short-term and long-term relationship between two or more variables over time. In this case, the model can look at the influence of prior socio-political, economic conditions and environmental conditions and prior archaeological looting attempts on current conditions and looting attempts. Typically, VAR models are employed in economics to assess the effect of changes in policy on phenomena like unemployment, inflation, and interest rates (Sola & Driffill, 1994; Stock & Watson, 2001). In criminology and political science, VAR models have been used to assess the effectiveness of antiterrorism policies and the dynamics of setting foreign policy agendas, as well as to understand the political process (Enders & Sandler, 1993).

These models are generally inductive, initially treating all variables as endogenous. VAR models and their extensions have several strengths over other time series methods. First, the inductive nature of the models makes them better at characterizing the uncertainty and underlying dynamics of the data. Second, there are multiple methods that can elucidate the relationship between the variables of interest (e.g., forecasting, Granger-causality, and structural modeling) (Lütkepohl, 2011: 2). However, basic VAR models require that all dependent variables must be the same order of integration (i.e. if one variable is differenced all of the variables have to be differenced). Another weakness of the VAR model is that they tend to have many regression parameters, reducing their parsimony and risking overparameterization (Brandt & Williams, 2007: 56).

Hiro Toda and Taku Yamamoto (1995) proposed a more reliable method for testing for cointegration and granger causality in vector autoregression models with possibly integrated processes. Their lag-augmented vector autoregression model incorporates additional lags as exogenous variables in the model. After applying a normal lag selection procedure to a potentially cointegrated VAR and determining a lag length k, a (k + $dmax$)th-order VAR is estimated, where $dmax$ represents the maximum order of integration of the variables (Toda & Yamamoto, 1995). This process has proven to be more robust for determining granger causality in small samples than alternative methods (Lütkepohl, 2006). If granger causality exists, there must be at least one cointegrating relationship in the model (Giles, 2011). As such, this method can also be useful for determining whether cointegration might exist. For any purpose other than testing for granger causality, the lag-augmented VAR has the same restrictions as the basic VAR model in that the variables must be the same order of integration (Ashley & Verbrugge, 2009; Giles, 2011).

Vector error correction (VEC) models are an extension of VAR used to estimate relationships that contain at least one cointegrating relationship and where at least the dependent variable has a unit root (Lütkepohl, 2006). These models assume that the changes in the variables depend, in part, on a form of equilibrium and require the type of trend to be explicitly identified. They also incorporate an error-correction term such that the resulting estimates are asymptotically stationary.

ARDL models are designed to look at autoregressive processes, phenomena that are explained in part by their own history and in part by the influence of other factors. The basic ARDL model is in equation (1), where $\sum \beta_i \Delta y_{t-i} + \sum \beta_j \Delta x_{1t-j} +$

$\sum \beta_k \Delta x_{2t-k}$ estimate each set of parameters in levels and $\theta_0 y_{t-1} + \theta_1 x_{1t-1} + \theta_2 x_{2t-1} + \theta_3 x_{3t-1}$ estimate the lagged (and/or differenced) parameters that combined create an unrestricted error correction term (Philips 2018). This combination of estimating the parameters in levels and lags allows for cointegrated relationships and mixed orders of integration between the parameters.

$$\Delta y_t = \beta_0 + \sum \beta_i \Delta y_{t-i} + \sum \beta_j \Delta x_{1t-j} + \sum \beta_k \Delta x_{2t-k} + \theta_0 y_{t-1} + \theta_1 x_{1t-1} + \theta_2 x_{2t-1} + \theta_3, \tag{1}$$

This combination also makes the ARDL model robust in spite of different data structures or orders of integration (i.e. some variables that are I(0) and others that are I(1)), possibly cointegrated relationships, separate lag structures for each variable, and small sample sizes (usually less than 100) (Pesaran and Shin 1997, Pesaran and Smith 1998, Pesaran et al. 2001). Further, the bounds testing methodology developed by Pesaran and Shin (1997) and Pesaran et al. (2001) was designed to work with mixed orders of integration to determine whether a long-term relationship and cointegration is present between two variables. The combination of ARDL models and a bounds testing approach to cointegration addresses potential issues that can arise from data that have different orders of integration (Philips 2018).

All four methods used in this dissertation have flexible modeling structures and can differentiate between short- and long-term relationships between two or more variables over time using systems of equations. They differ in terms of how computationally intensive they are and what requirements they make of the analyst. Structural equation modeling is the most computationally and analytically intensive, requiring the analyst to manually construct the systems of equations based on a theoretical model. Any necessary constraints or assumptions must be imposed by the analyst. As a result, it can be difficult to properly specify complex autoregressive models using SEM and doing so requires large sample sizes. By contrast, ARDL models are the most flexible and can be used on small sample sizes. However, some critique this approach as too flexible and adaptable, meaning that it can be manipulated to produce the desired result. Lag augmented vector autoregression and VEC fall somewhere in between these two approaches with respect to their flexibility and data requirements. For this dissertation, I tested all four approaches with multiple specifications because my theoretical model is analytically complex while my sample size is very small ($n = 36$ months).

Spatio-Temporal Analyses

Only *Hypothesis 7* asks a question for which spatio-temporal analysis is appropriate – are archaeological looting attempts clustered in time and space with economic, environmental, and socio-political factors? Spatio-temporal analyses are conceptually and computationally challenging, requiring extremely large samples and simulations to analyze the data (Diggle, 2014).[55] Even with setting the unit of analysis to the month-grid-cell, I do not have enough data to use such methods. Instead, I transform my data to space-time cubes and use a combination of visualizing relationships in 2D and 3D and calculating two spatio-temporal statistics: spatio-temporal clustering and outliers and spatio-temporal hot spots.

A space-time cube is a multidimensional raster data format and a way of visually representing three-dimensional data. Figure 19 is an example of what a space-time cube looks like. Each bin represents a grid-cell for a specific time period, each row represents a time period for all locations, and each column represents a single location's time series.

[55] Typically, three approaches exist for computationally intensive analyses: (1) where time is considered discrete and space is continuous (temporally discrete); (2) where space is considered discrete and time continuous (spatially discrete); and (3) where both time and space are continuous (Diggle, 2014). A spatially discrete analysis could involve looking at all incidents of armed conflict at once (as a "fixed" image) and then seeing how their locations affect the spread of archaeological looting over time. A temporally discrete analysis would look at how locations changed over larger intervals of time (e.g., over years). A continuous analysis would look at how location and time change at granular units. Allowing both space and time to vary requires very large samples and is computationally intensive, involving extensive simulations to run the analyses to accommodate the exponential rate with which spatial and temporal lags grow (Diggle, 2014).

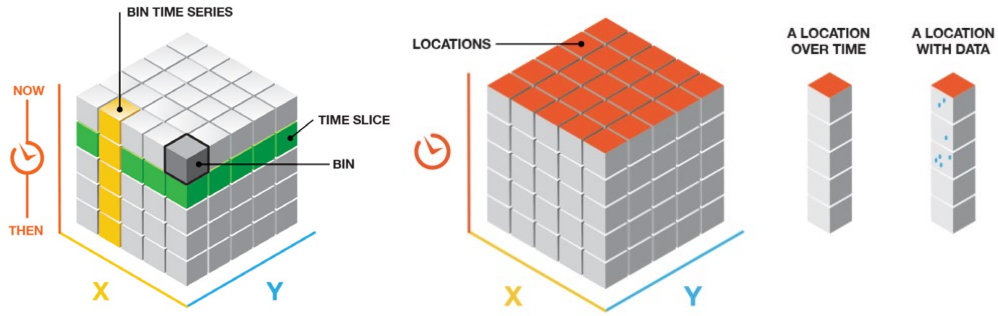


Figure 19. Two visual representations of a space-time cube: aggregating from defined locations (left) and aggregating from individual points (right). Images courtesy of Esri (2019).

Space-time cubes can be created two ways from spatial data, both of which require the data to have variation of time and space. If the spatial data are a series of fixed locations for which you have different values over time, you can aggregate by location. For example, many of the environmental data and the looting attempts data are measured at fixed locations. Similar to how spatial data are stored, you can aggregate multiple attributes of a location at the same time (e.g., multiple measures of looting) as long as they are associated with the same location and units. If the spatial data are event or incident data and so are not measured at fixed locations, you can create a cube by aggregating the points into a grid (the same concept as creating gridded data described above). For either method, you can select how the values should be aggregated (sum, mean, min, max, etc.). You can aggregate data at defined locations by treating them as individual incidents, but you cannot aggregate individual incidents by treating them as defined locations (there must be repeated measures at the same locations). An advantage of treating defined locations as individual timestamped points is that you can choose to either create a lattice-grid cube or a hexagonal-grid cube.

In this dissertation, space-time cubes are created for archaeological looting attempts, the vegetation health index, precipitation, soil moisture content, and sociopolitical stress (with conflict types as attributes). There is insufficient variation spatially or temporally to create space-time cubes from the economic data and the total crop production variable. To capture economic stress in the spatio-temporal analysis, I visualize a combined 2D and 3D maps with the economic variables in 2D and the spacetime cubes in 3D. To test whether the method of aggregation and grid-shape affected the results, space-time cubes for all variables that could be transformed are created using both methods of aggregation and both as lattice and hexagonal grids. To be consistent with my spatial analyses, I experiment with cube bin-sizes at 10-km, 50-km, and 150-km. However, because a space-time bin occupies 3-dimensional space, the size of the 50-km and 150-km bins are too large to be useful or capture spatio-temporal variation. As such, I only create bins at 10-km.[56] Similar to the spatial grid data, space-time bins without any values are treated as missing values.

Because each variable is aggregated into its own cube, I run all three space-time measures on each variable. The spatio-temporal clustering and outlier statistic uses the aggregated space-time values to calculate a spatio-temporal version of Anselin's Local Moran's I statistic for each bin in a cube (Anselin, 1995; Mitchell, 2009). The results of this analysis indicate whether a given bin experienced any statistically significant clusters, outliers, or multiple types of clustering and outliers. Each bin has six possible outcomes:

[56] When aggregating by point you can set the size of the cube by defining a "distance interval," which refers to the height of the bin. For lattice-grids, this did not affect comparison to the 2-dimensional grids as all dimensions are equal in a cube. However, for hexagonal shaped grids, the height of the hexagon is not the same as the width and so the actual size of each bin was slightly larger than the distance ($Distance(height) = \frac{Width*\sqrt{3}}{2}$. A hexagon height of 10-km had a width of 11.5-km, I tested setting the height such that the width was 10-km (required a height of 8.66-km); however, the difference did not affect results. As such, I prioritized comparability between the different cube-shapes and kept the distance at 10-km.

- **Never Significant:** A location that never had any statistically significant clusters or outliers
- **Only High-High Cluster:** A location where only statistically significant clusters of high values occurred.
- **Only High-Low Outlier:** A location where only statistically significant high value outliers were surrounded by primarily low values
- **Only Low-Low cluster:** A location where only statistically significant clusters of low values occurred.
- **Only Low-High Outlier:** A location where only statistically significant low value outliers were surrounded by primarily high values
- **Multiple Types:** A location where multiples types of statistically significant clusters or outliers occurred at different times.

The spatio-temporal hot spots analysis calculates the Getis-Ord Gi* statistic[57] for each bin in a cube using the aggregated spatial values and tests for statistical significance (Mitchell, 2009). The identified trends for each bin are then evaluated using the Mann-Kendall trend test[58] to determine the specific type of trend occurring at each location over time. Each bin is categorized as one of nine patterns, which can apply to either hot spots (clustered high values) or cold spots (clustered low values) (Mitchell, 2009):

[57] The Getis-Ord Gi* statistic identifies local departures from the average value of a variable's neighbors over a broader region and then calculates a z-score to determine whether the departure is statistically significant (Burt et al., 2009; Getis & Ord, 1992, 1995)

[58] The Mann-Kendall trend test calculates a rank correlation analysis for the time series of values within each bin (the Mann-Kendall statistic). Each bin value is compared to the one after it in the series and assigned a value depending on whether it is larger (+1), smaller (-1), or the same (0). These values are then summed and compared to the expected sum (zero), under the assumption of no trend to determine if the difference is statistically significant (Kendall & Gibbons, 1990; Hamed, 2009).

- **No Pattern Detected:** No statistically significant hot or cold patterns identified.
- **New Hot/Cold Spot:** A location that is a statistically significant hot or cold spot in the last time period and has never been a statistically significant hot or cold spot before.
- **Consecutive Hot/Cold Spot:** A location with a one-time uninterrupted series of statistically significant hot or cold spots in the last time periods, has never been a statistically hot or cold spot before, and less than 90% of all bins are statistically significant hot or cold spots.
- **Intensifying Hot/Cold Spot:** A location that has been a statistically significant hot or cold spot for 90% of the time periods (including the final period) and where the intensity of clustering has seen a statistically significant increase over time for high values (hot spots) or low values (cold spots) over time.
- **Persistent Hot/Cold Spot:** A location that has been a statistically significant hot or cold spot for 90% of time periods with no clear trend indicating an increase or decrease in intensity over time.
- **Diminishing Hot/Cold Spot:** A location that has been a statistically significant hot or cold spot for 90% of the time periods (including the final period) and where the intensity of clustering has seen a statistically significant decrease over time for high values (hot spots) or low values (cold spots) over time.
- **Sporadic Hot/Cold Spot:** A location that has been a statistically significant hot spot occasionally (for no consecutive time periods) for less than 90% of time periods and that has never been a statistically significant cold spot (the inverse description applies for cold spots).
- **Oscillating Hot/Cold Spot:** A location that is a statistically significant hot or cold spot for the last time period, less than 90% of time periods have been statistically significant hot spots, and that has a history of being both hot and cold spots (the inverse description applies for cold spots).
- **Historical Hot/Cold Spot:** A location for which the most recent time period is not a statistically significant hot or cold spot, but that has had statistically significant hot or cold spots for at least 90% of time periods.

Chapter 6: Results

Descriptives

This section reports the descriptive statistics and temporal, spatial, and spatio-temporal analyses run in this dissertation. Descriptives provide an overview of the phenomena of interest – how they are distributed across space and time – and how they may relate to each other. Looking descriptively is an essential step to these analyses because they provide important contextual information that can help to guide the direction of the analysis. In general, only those descriptives that are relevant to the hypotheses tested in the next three sections are presented here, the rest are reported in Appendix 3. Table 22 – Table 24 provide an overview of the main variables of interest across spatial, temporal, and spatio-temporal datasets.

Table 22. Spatial Summary Statistics

	Obs	**Mean**	**Std. Dev.**	**Min**	**Max**
Evidence of Archaeological Looting Attempts					
All looting attempts (either)	140	7.1	6.626	0	33
All looting attempts (both)	140	3.179	3.549	0	18
New looting attempts (either)	140	5.343	4.853	0	25
New looting attempts (both)	140	2.057	2.275	0	12
Prior looting attempts (either)	140	5.3	6.517	0	33
Prior looting attempts (both)	140	5.136	6.594	0	33
Sociopolitical Stress					
All sociopolitical stress	251	4.849	15.865	1	219
Violent conflict	251	2.044	9.465	0	128
Non-violent conflict	251	1.940	3.862	0	46
Violence against civilians	251	0.757	5.485	0	80
Economic Stress					
Average change in unemployment in Lower Egypt (total)	12	-7.859	8.834	-19.386	10.920
Average change in unemployment in Lower Egypt (youth)	12	6.318	13.459	-10.870	26.571
Environmental Stress					
Average change in vegetation health index (NDVI)	1588	38.121	20.982	-20.741	68.385
Average change in precipitation	1206	166.151	252.167	11.364	2892.735

Table 23. Temporal Summary Statistics

	Obs	Mean	Std. Dev.	Min	Max
Evidence of Archaeological Looting Attempts					
All looting attempts (either)	36	27.611	16.213	4	71
All looting attempts (both)	36	12.361	10.694	0	39
New looting attempts (either)	36	20.778	13.920	2	62
New looting attempts (both)	36	8	8.029	0	29
Prior looting attempts (either)	36	20.611	11.352	3	52
Prior looting attempts (both)	36	19.972	11.049	3	50
Sociopolitical Stress					
All sociopolitical stress	36	33.889	31.96139	4	157
Violent conflict	36	13.611	19.932	1	102
Non-violent conflict	36	14.25	10.007	3	45
Violence against civilians	36	5.278	12.293	0	56
Economic Stress					
Consumer price index (general)	36	188.7885	33.189	148.620	246.051
Consumer price index (food)	36	222.824	48.521	162.858	299.681
Inflation based on consumer price index	36	17.891	8.448	10.362	29.502
Total unemployment in Lower Egypt	36	8.174	0.205	8.014	8.460
Youth unemployment in Lower Egypt	36	28.648	1.205	26.984	29.678
National debt (as % external debt)	36	23.454	0.643	22.684	24.238
National debt (as % reserves)	36	13.413	3.523	9.152	17.660
Tourist arrivals (in millions)	36	751.8	167.095	525.8	913.9
Environmental Stress					
Vegetation health index (NDVI)	36	0.388	0.050	0.290	0.470
Soil moisture content	36	0.428	0.021	0.409	0.492
Precipitation	36	1.443	1.987	0	10.841
Total crop production (in millions)	36	93.839	1.296	92.579	9.590

Table 24. Spatio-temporal Summary Statistics

	Obs	Mean	Std. Dev.	Min	Max
Evidence of Archaeological Looting Attempts					
All looting attempts (either)	5040	0.197	0.398	0	1
All looting attempts (both)	5040	0.088	0.284	0	1
New looting attempts (either)	5040	0.148	0.356	0	1
New looting attempts (both)	5040	0.057	0.232	0	1
Prior looting attempts (either)	5040	0.147	0.354	0	1
Prior looting attempts (both)	5040	0.143	0.350	0	1
Sociopolitical Stress					
All sociopolitical stress	1217	1	0	1	1
Violent conflict	1217	0.156	0.363	0	1
Non-violent conflict	1217	0.422	0.494	0	1
Violence against civilians	1217	0.420	0.494	0	1
Environmental Stress					
Vegetation health index (NDVI)	57168	0.381	0.224	-0.335	0.861
Precipitation	43416	1.662	8.139	0	362.389

The sample sizes vary greatly across the three types of methods. The temporal data have the most consistent sample size, by design; the spatio-temporal have the largest number of observations. The temporal analyses include the greatest number of variables for each indicator initially, though as discussed below not all of them are included in the final models. By contrast, the spatio-temporal analyses include the fewest variables. These analyses have the most requirements of the data, in that there must be enough spatial and temporal granularity and variation for an analysis to be meaningful. Additionally, most of the spatio-temporal variables are coded as binary, which affect how they were processed by the analyses conducted (see below).

Looking at the dependent variable, both sets of archaeological looting attempts variables (from “either” source or “both” sources) vary across the 36-month time period and are not as skewed as previous attempts at measuring looting (see Fabiani, 2018). Figure 22 – Figure 23 show the spatial, temporal, and spatio-temporal distributions for the looting attempt variable (*All Looting – either source*) used for the analyses (see Appendix 3 for distributions of the other looting attempt operationalizations). Looting attempts evidence varies across all three dimensions. Both spatial and spatio-temporal distributions show similar concentrations of areas with more evidence of looting attempts. Interestingly, there are very few locations that alternate between being a hot spot and a cold spot. It is more common for a hex-grid to be one or the other. Temporally, the hot spots appear to start about half-way up most columns, which would correspond roughly to 2016 (the highest peaks in Figure 22). Yet the hot spots do not diminish as they approach the end of 2017 in the spatio-temporal distribution compared to the temporal distribution. This could suggest that the purely spatial and purely temporal analyses will be missing important context provided by the spatio-temporal analysis.

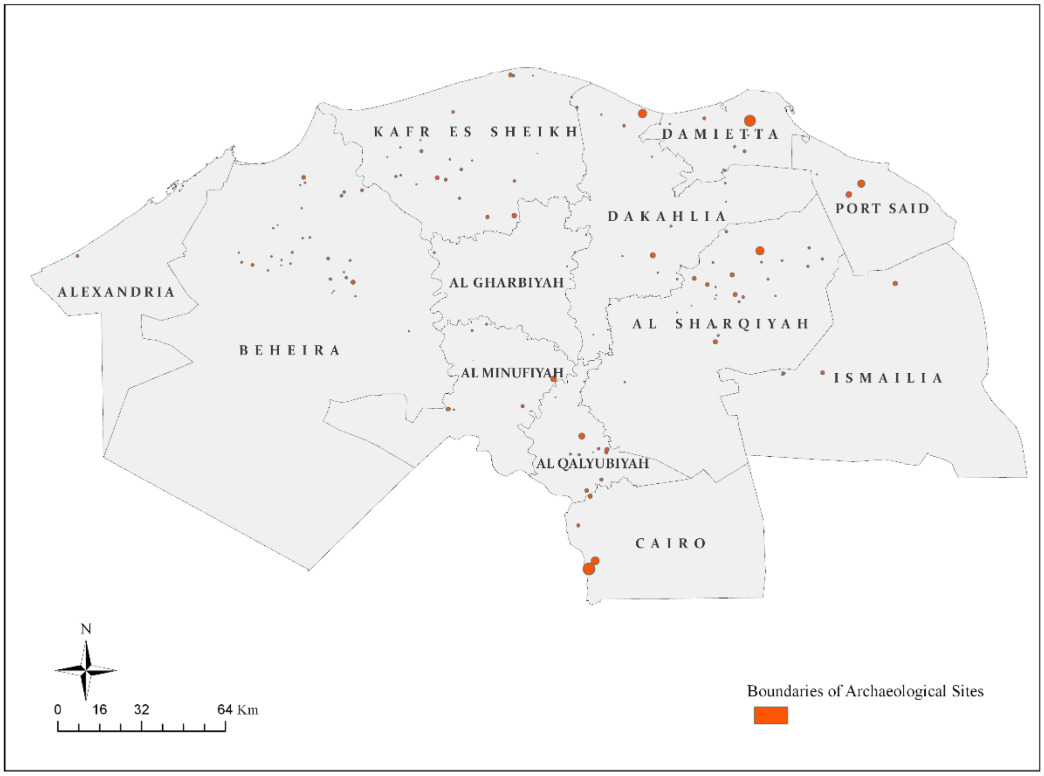


Figure 20. Spatial distribution of archaeological site boundaries.

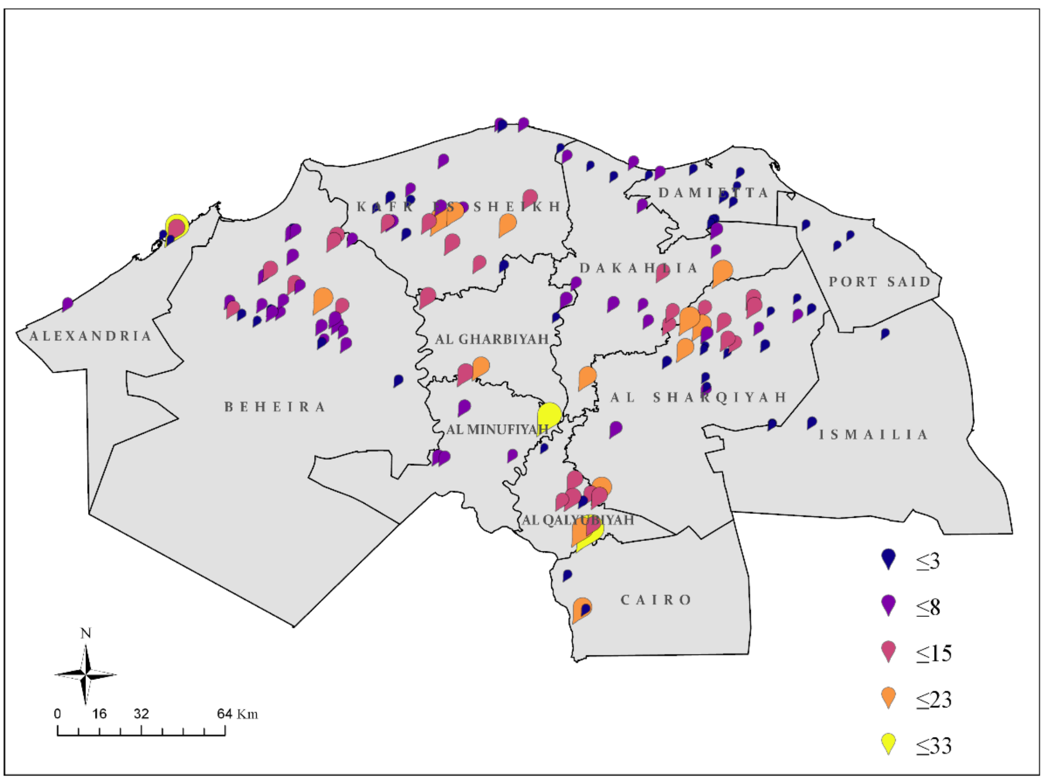


Figure 21. Spatial distribution of archaeological sites with evidence of looting in space. Sites with larger and lighter colors indicate more months with evidence of looting attempts from 2015 to 2017.

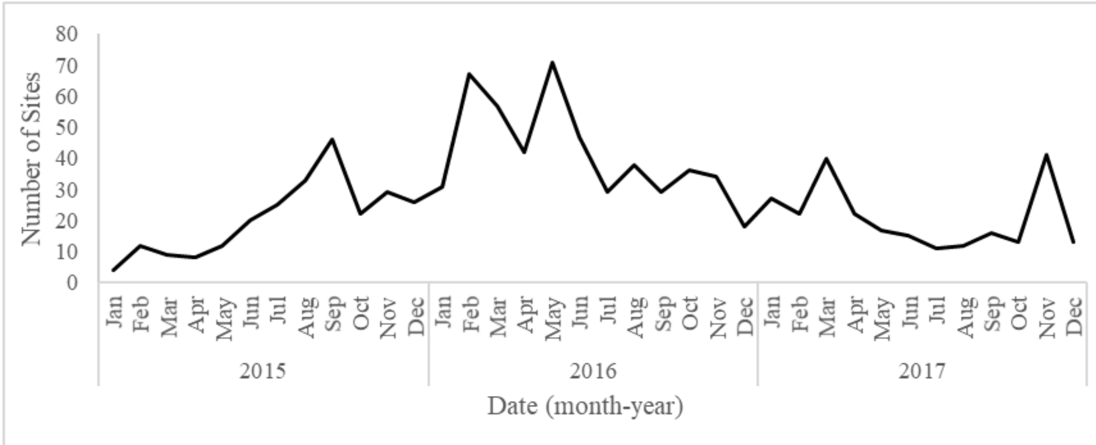


Figure 22. Temporal distribution of all looting attempts evidence from 2015 to 2017.

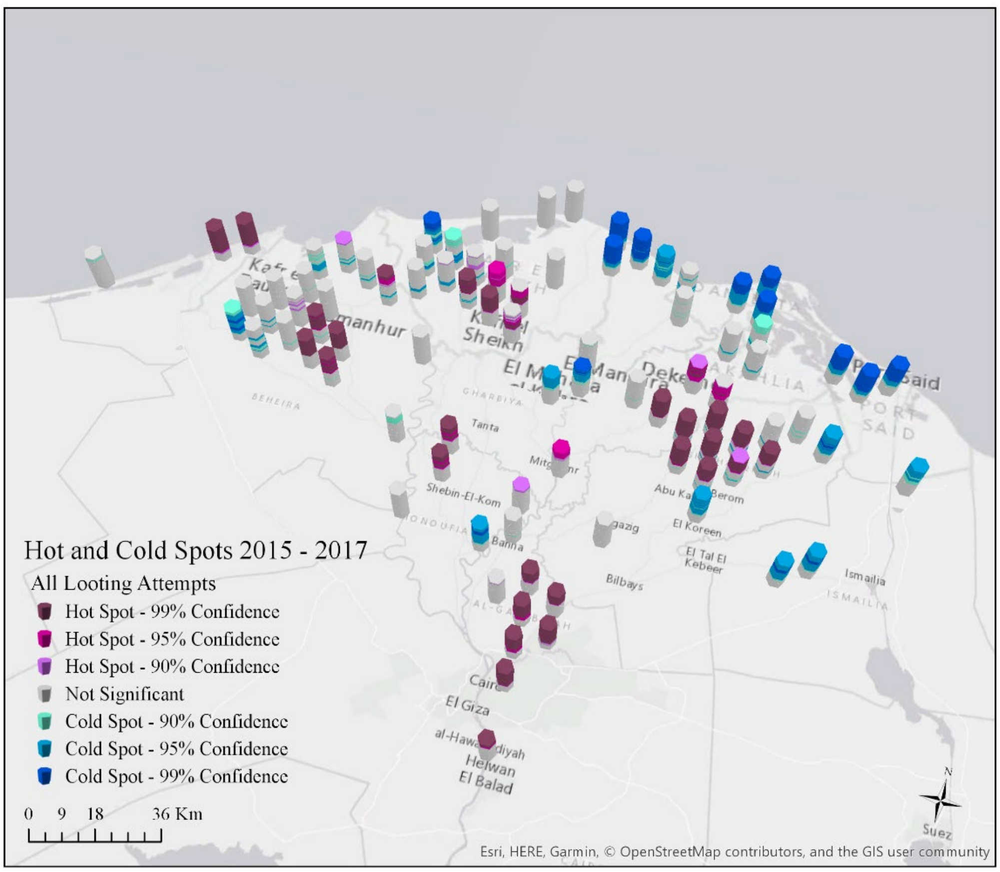


Figure 23. Spatio-temporal distribution of archaeological sites with looting attempts from 2015 to 2017 with 10-km space-time hexagons. Earlier time periods are lower each in each stack. Hot spots indicate concentrations of high values over time in that location (more months with looting attempts) and cold spots indicate concentrations of low values over time in that location.

When comparing archaeological looting attempts to sociopolitical, economic, and environmental stress, it is important to keep in mind that most of the variables in the summary statistics tables (Table 22 - Table 24) are measured in different units and at different levels of aggregation. As such, it is useful to identify the expected direction of each variable based on their hypothesized relationships. Table 25 outlines both the individual variable direction and the expected direction of the broader latent construct.

Table 25. Hypothesized Relationships between Archaeological Looting Attempts & Indicators of Stress

Indicator/Variable	Relationship
Sociopolitical Stress	*Positive*
All sociopolitical stress	Positive
Violent conflict	Positive
Non-violent conflict	Positive
Violence against civilians	Positive
Economic Stress	*Positive*
Consumer price index (general)	Positive
Consumer price index (food)	Positive
Inflation based on consumer price index	Positive
Total unemployment in Lower Egypt	Positive
Youth unemployment in Lower Egypt	Positive
National debt (as % external debt)	Positive
National debt (as % reserves)	Positive
Tourist arrivals (in millions)	Negative
Environmental Stress	*Positive*
Vegetation health index (NDVI)	Negative
Soil moisture content	Negative
Precipitation	Negative
Total crop production (in millions)	Negative

When examined in aggregate, it appears that archaeological looting attempts have an inverse temporal relationship with sociopolitical stress – as sociopolitical stress decreased, the number of sites with looting attempts would increase (Figure 24). This pattern roughly held for both violent conflict and violence against civilians (see Appendix 3). Looking at the correlations between looting and sociopolitical stress finds similar results. All sociopolitical stress, violent conflict, and violence against civilians all have negative correlations with looting attempts (see Table 26). Though looting attempts and non-violent conflict show a positive correlation (0.0615), it is very small despite their more similar temporal patterns (see Figure 25). This suggested that there may ether be a temporal relationship between them or that they were both explained by a third factor.

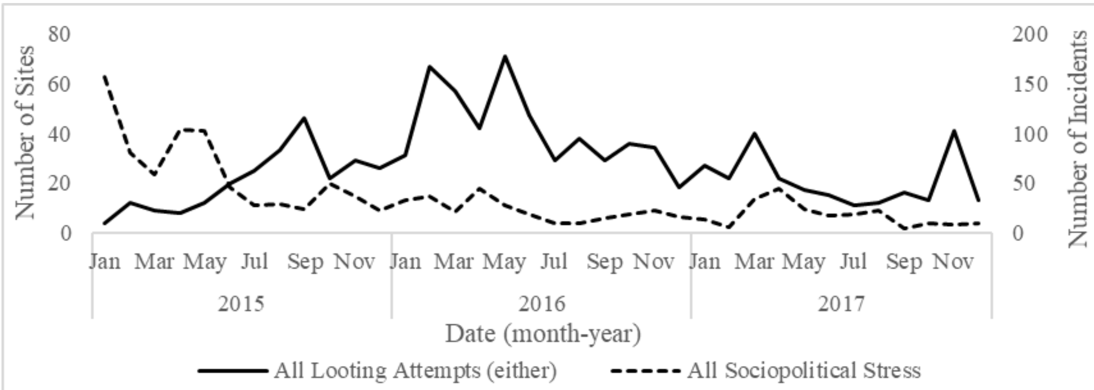


Figure 24. Archaeological looting attempts compared to all sociopolitical stress from 2015 to 2017.

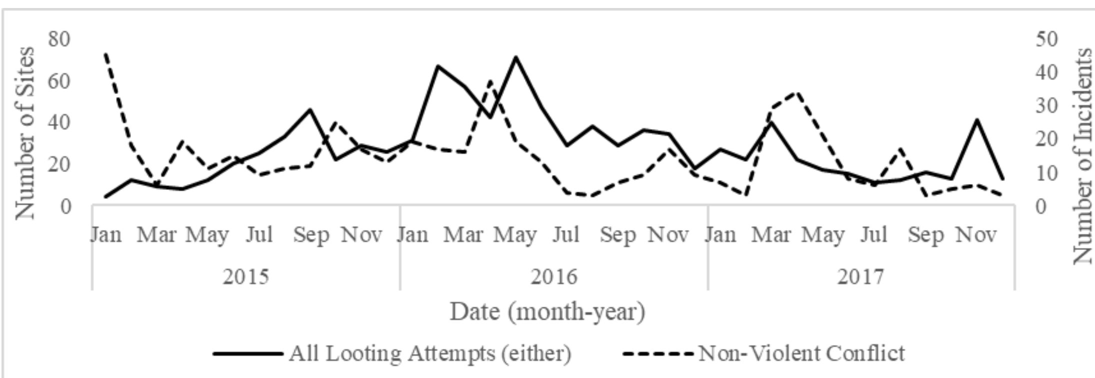


Figure 25. Archaeological looting attempts compared to non-violent conflict from 2015 to 2017.

Table 26. Correlations between Sociopolitical Stress Indicators and Looting Attempts

Indicator/Variable	Correlation
All sociopolitical stress	-0.3487
Violent conflict	-0.4753
Non-violent conflict	0.0615
Violence against civilians	-0.1771

Spatially, incidents of sociopolitical stress appeared to be more proximate to archaeological sites with evidence of looting attempts (Figure 26). The two areas with the highest concentrations of sociopolitical stress (Cairo and Alexandria) also had the most months with looting attempts (see Figure 21). Other mid-density areas of sociopolitical stress, such as in Al Sharqiyah align with sites that were also in the middle of their distribution (i.e. had between 15 and 23 months with evidence). This suggests that there may be a spatial relationship between these two phenomena.

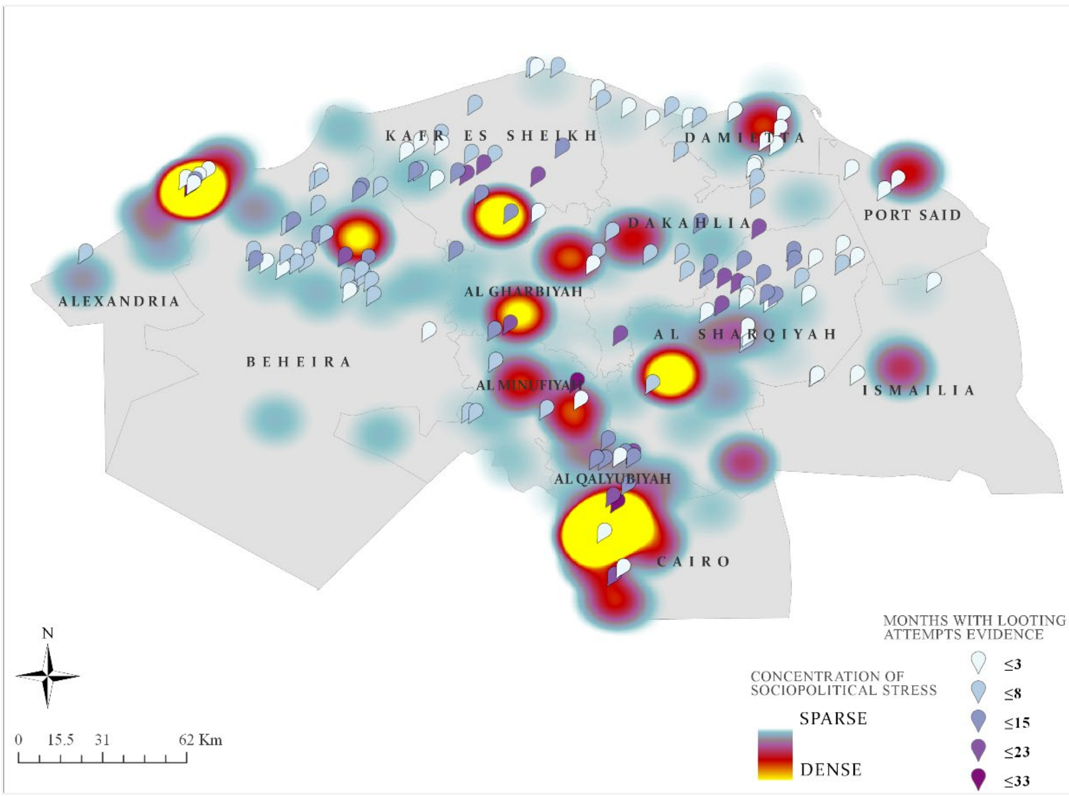


Figure 26. Archaeological site locations with evidence of looting attempts compared to concentrations of sociopolitical stress

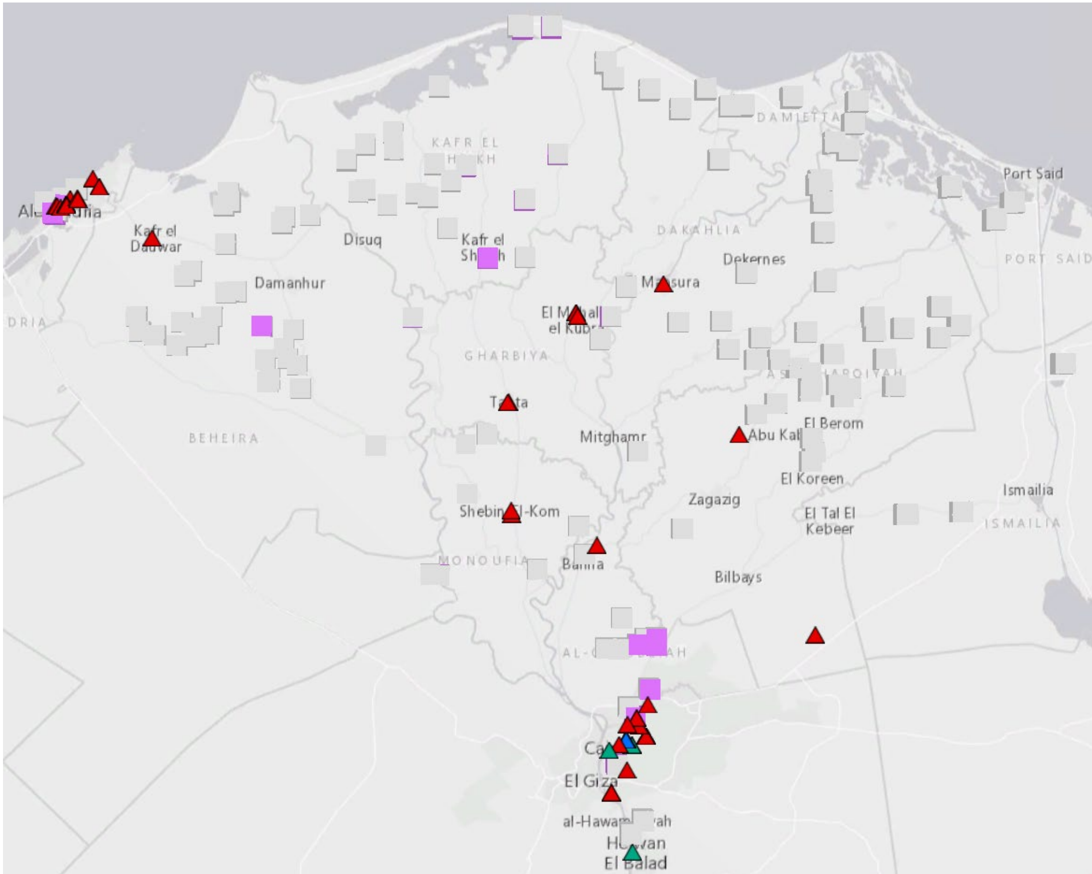


Figure 27. Archaeological site locations with evidence of looting attempts compared to sociopolitical stress in February 2015. Purple squares indicate evidence of looting attempts. Red triangles indicate violent conflict, green triangles indicate non-violent conflict, and blue triangles indicate violence against civilians.

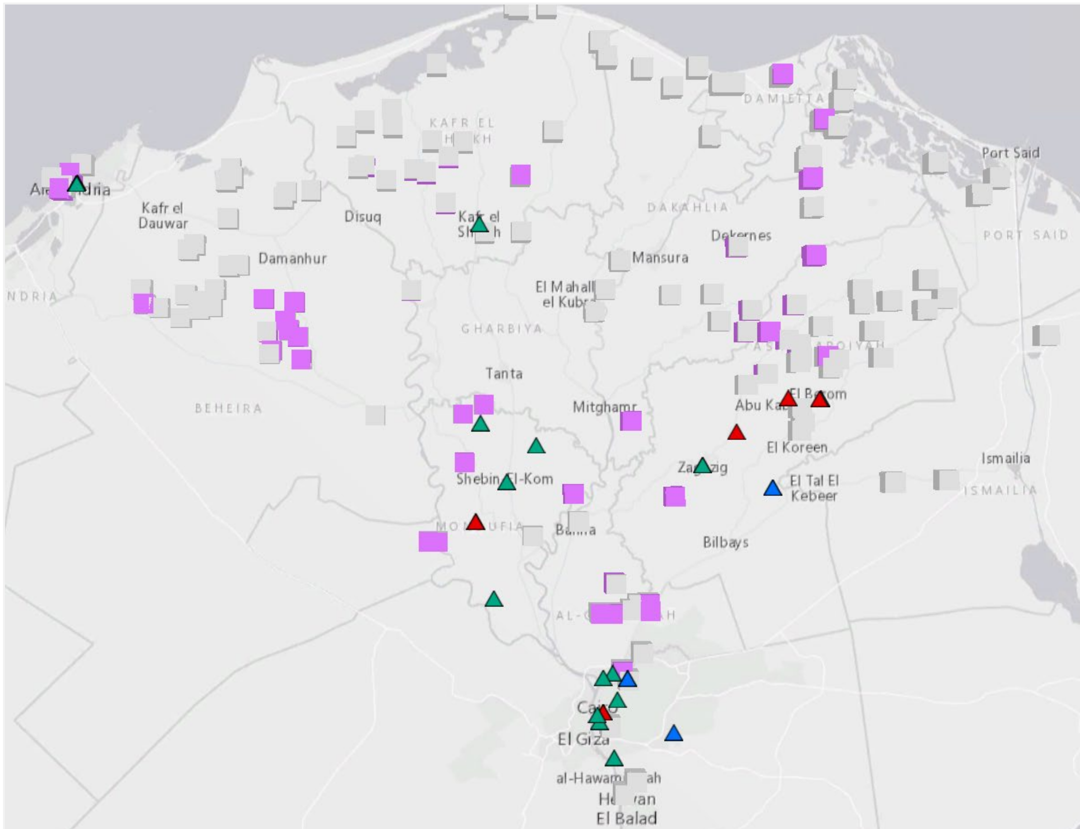


Figure 28. Archaeological site locations with evidence of looting attempts compared to sociopolitical stress in December 2015. Purple squares indicate evidence of looting attempts. Red triangles indicate violent conflict, green triangles indicate non-violent conflict, and blue triangles indicate violence against civilians.

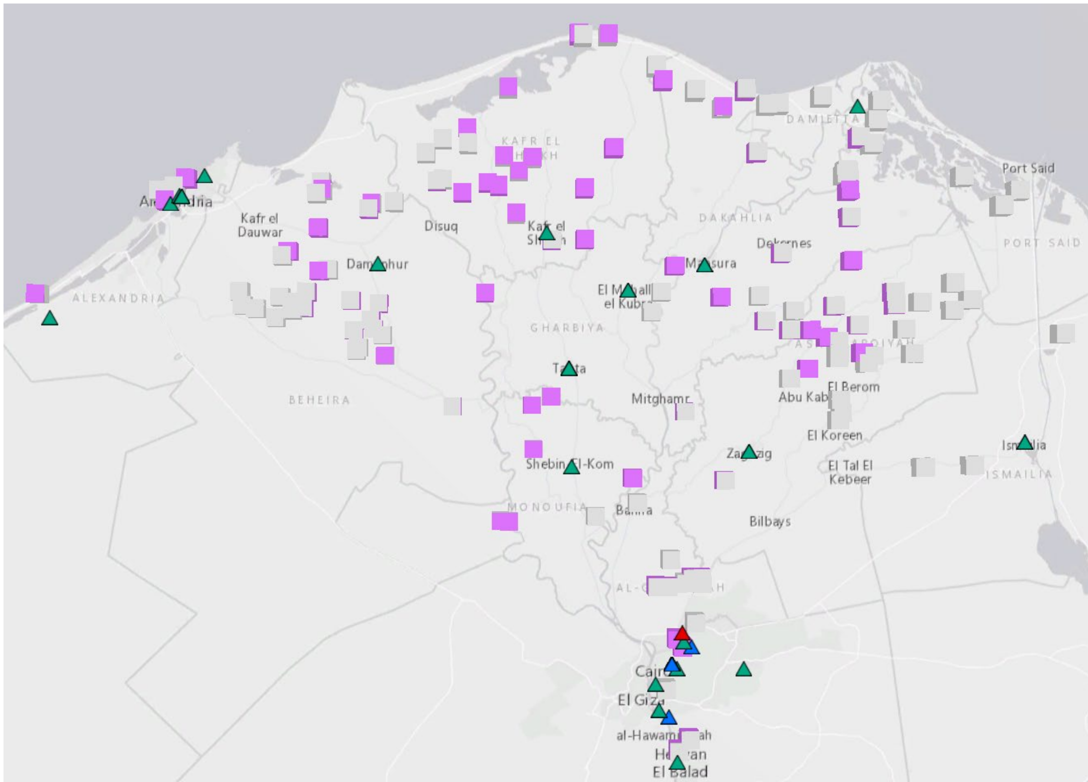


Figure 29. Archaeological site locations with evidence of looting attempts compared to sociopolitical stress in March 2016. Purple squares indicate evidence of looting attempts. Red triangles indicate violent conflict, green triangles indicate non-violent conflict, and blue triangles indicate violence against civilians.

Spatio-temporally, incidents of looting and sociopolitical stress were often in proximity to each other (Figure 29 – Figure 29). However, there were also many sites with evidence of looting not near any type of sociopolitical stress. As such, based purely on visualization alone it is difficult to discern a clear pattern.

With respect to economic stress, most of the economic indicators appear to have an inverse temporal relationship with archaeological looting attempts based on a visual analysis (see Appendix 3). This is counter what would be expected based on my hypotheses. The exception was for the number of tourist arrivals (Figure 30). The peak in number of sites with evidence of archaeological looting attempts corresponds to when tourist arrivals were at their lowest, in 2015. Looking at the correlations, all of the economic variables except for national debt (as % of external debt) are highly correlated with looting attempts (see Table 27). Many of them also suggest a negative correlation (except for national debt as a percent of reserves).

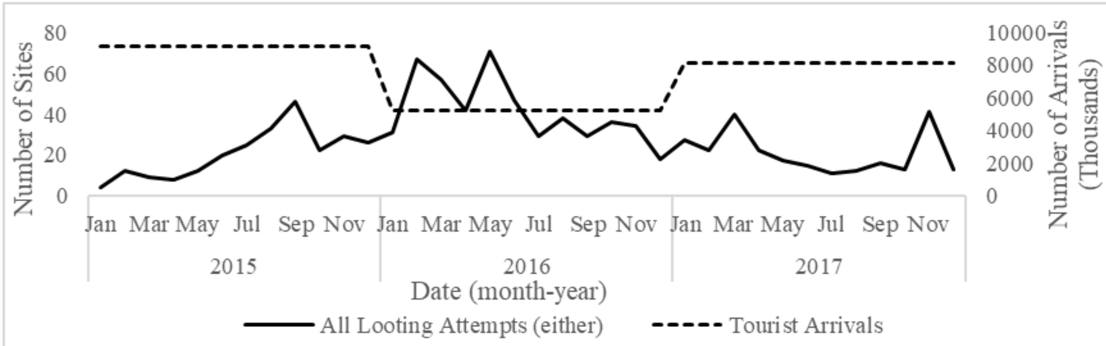


Figure 30. Archaeological looting attempts compared to total tourist arrivals from 2015 to 2017.

Table 27. Correlations between Economic Indicators and Looting Attempts

Indicator/Variable	**Correlation**
Consumer price index (general)	-0.1963
Consumer price index (food)	-0.2043
Inflation based on consumer price index	-0.2081
Total unemployment in Lower Egypt	-0.3511
Youth unemployment in Lower Egypt	-0.6114
National debt (as % external debt)	-0.0164
National debt (as % reserves)	0.5378
Tourist arrivals (in millions)	-0.6010

Spatially, only the unemployment rates were available at the governorate level. However, no clear pattern emerges by visualizing looting attempts and unemployment rates (total or youth – see Figure 31 and Figure 32), regardless of which operationalization is used (average percent change or net percent change). Between the two operationalizations of the unemployment variables, average percent change had more variation than net percent change. As such, I use average percent change in the remainder of the analyses. Further it is impossible to analyze the economic indicators spatiotemporally given the aggregate nature of the data.

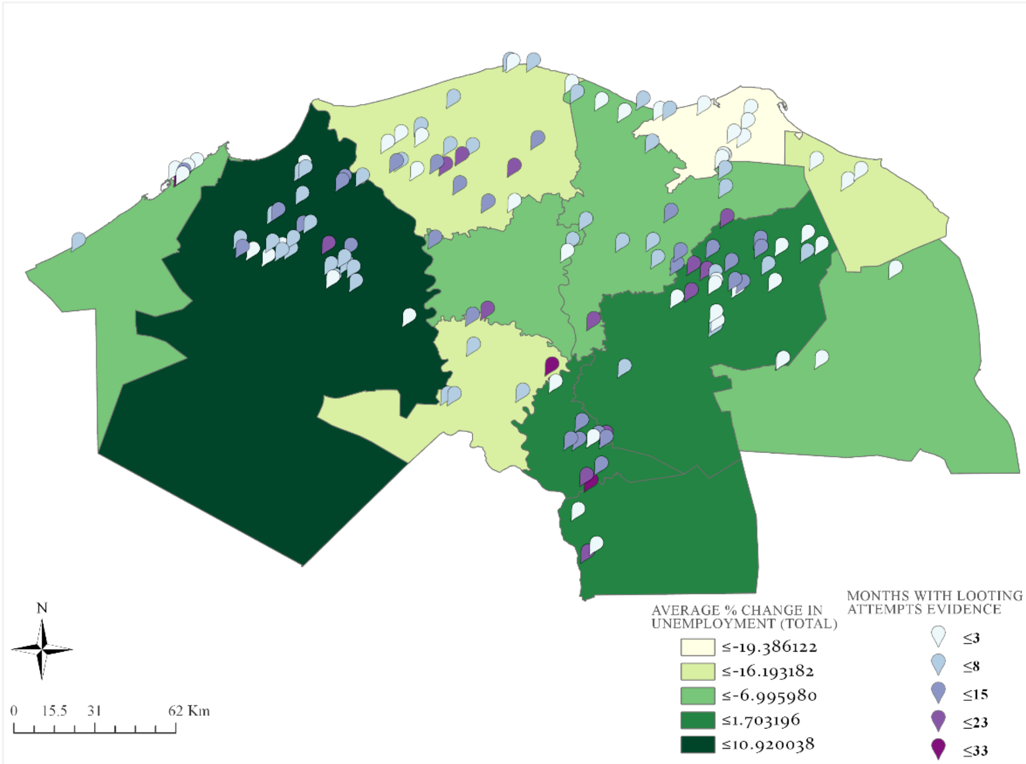


Figure 31. Spatial distribution of archaeological looting attempts and total unemployment in Lower Egypt.

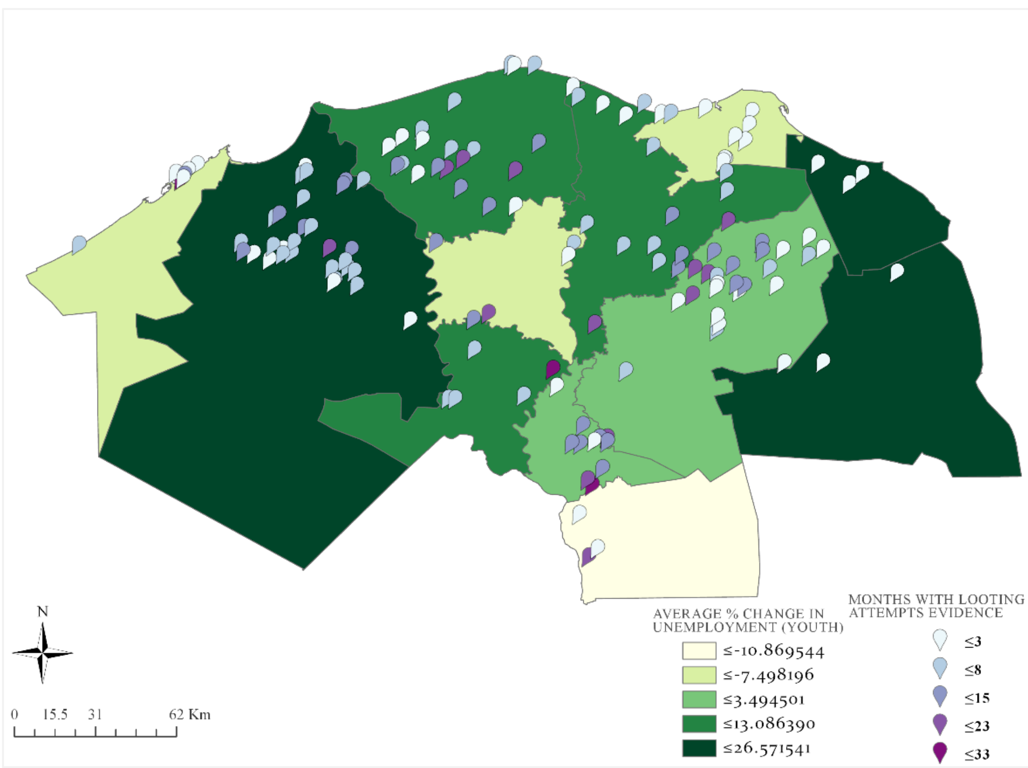


Figure 32. Spatial distribution of archaeological looting attempts and youth unemployment in Lower Egypt.

Environmental stress varies considerably from 2015 to 2017.[59] Total crop production and precipitation both descriptively suggest a relationship. For both variables, periods where they are at their lowest correspond to periods with peaks in looting attempts (see Figure 33 and Figure 34). Total crop production also has the highest correlation with looting attempts (see Table 28). Precipitation is a seasonal phenomenon, so a temporal relationship may suggest that there is a seasonal element to looting attempts as well (Figure 35). Soil moisture content and vegetation health does not visually correspond to any peaks or trough in the dependent variable (see Appendix 3). Spatially, it is difficult to determine whether there is a relationship because each grid-cell represents the average amount of precipitation across three years and so a lot of variation is lost (Figure 36).

Table 28. Correlations between Environmental Indicators and Looting Attempts

Indicator/Variable	Correlation
Vegetation health index (NDVI)	-0.0462
Soil moisture content	-0.1007
Precipitation	-0.0437
Total crop production (in millions)	-0.1735

[59] I compared the average percent change and net percent change variables for all the environmental variables. The net percent change consistently showed less variation than the average and was theoretically less useful compared to the average percent change. This was especially true for the grid based analyses, where each cell was an average of all the values. An average of a net percent change was not a meaningful variable. To maintain consistency, I used the average percent change variables across all spatial analyses.

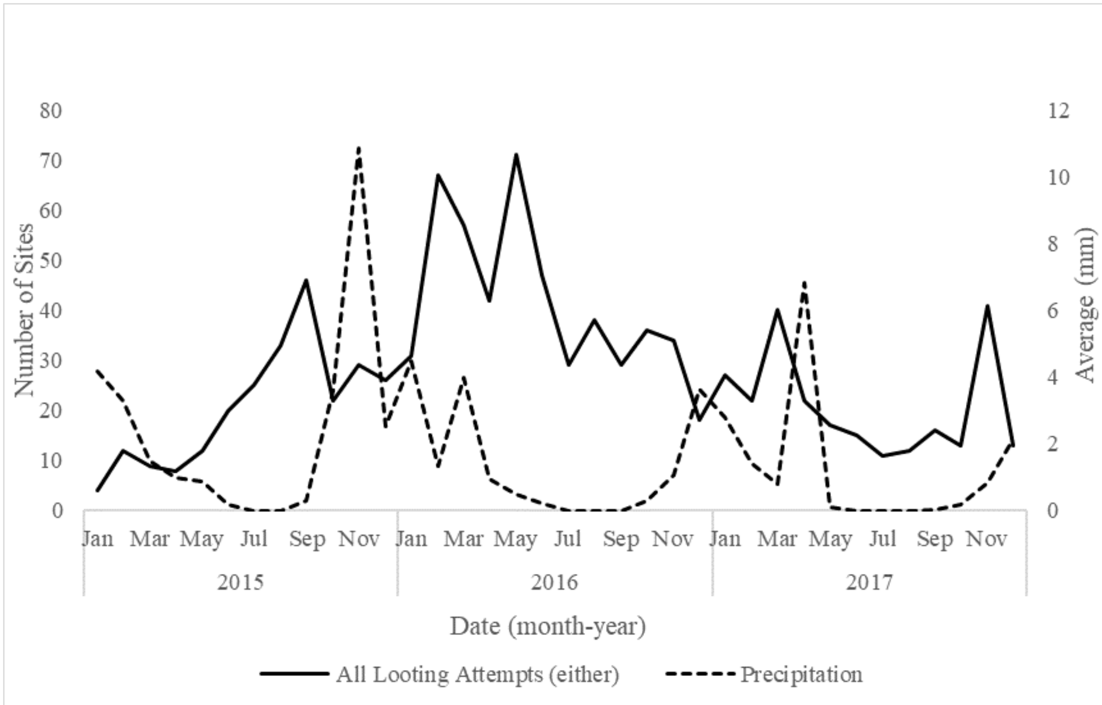


Figure 33. Temporal distribution comparing archaeological sites with any evidence of looting attempts to the 3-hour average precipitation of all 3-hour periods in a given month (in mm) for a given 0.25-degree grid-cell from 2015 to 2017.

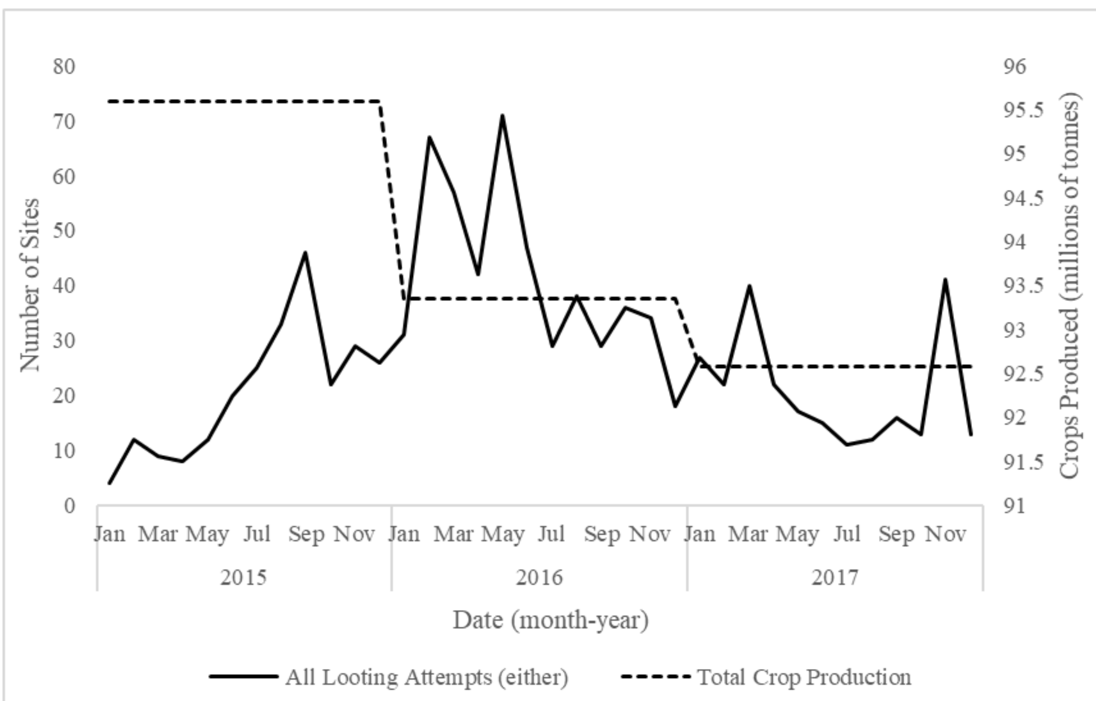


Figure 34. Temporal distribution comparing archaeological sites with any evidence of looting attempts to the total crop production (in millions of tonnes) from 2015 to 2017.

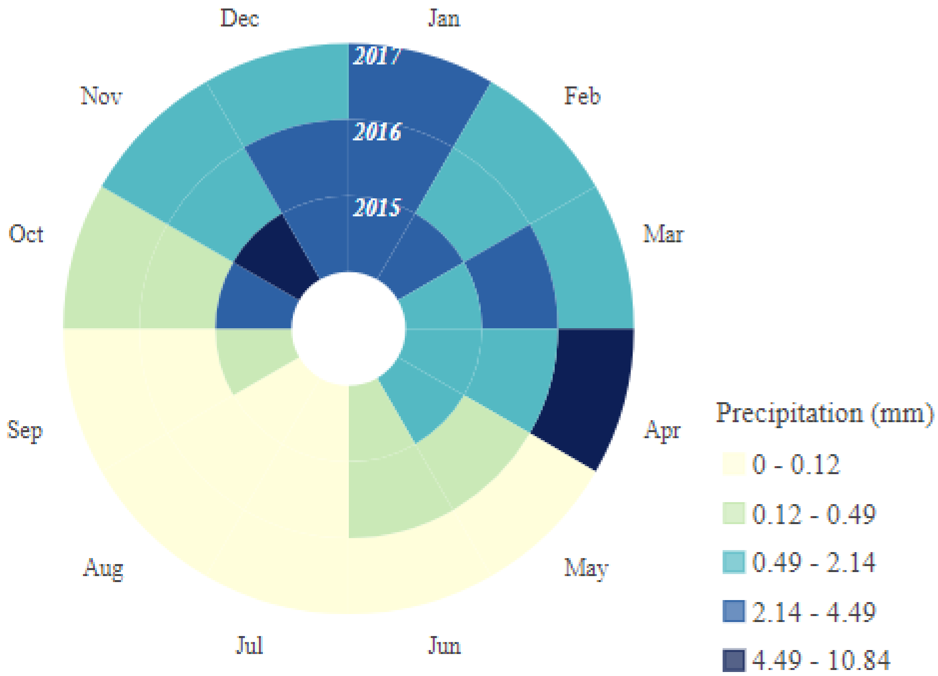


Figure 35. Changes in precipitation amounts from 2015 to 2017 by month over year.

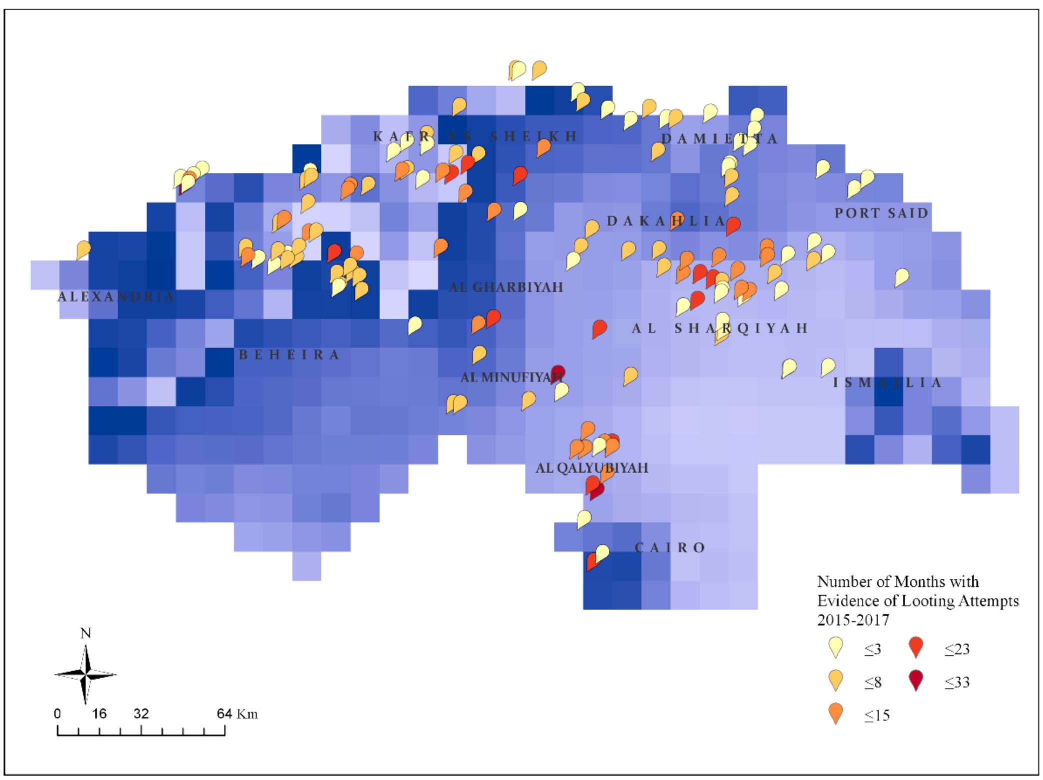


Figure 36. Average change in precipitation amounts from 2015 to 2017. Darker blue indicates more precipitation (in millimeters).

The spatio-temporal data provide the greatest detail for the relationship between environmental stress and looting attempts (see Figure 37 and Figure 38). For example, during months where there is little to no precipitation, more sites appear to have evidence of looting attempts. At the same time, the presence of precipitation does not reduce the number of sites with evidence. Interestingly, the same does not hold for vegetation health. Spatio-temporally, a visual inspection suggests that looting is not dependent on the vegetation nearby. Some of the months with the most sites evidencing looting attempts also have healthier vegetation (in the context of an arid climate). Neither the soil moisture content nor total crop production variables are available at a granular enough level to be able to visualize them spatio-temporally and obtain any useful descriptives.

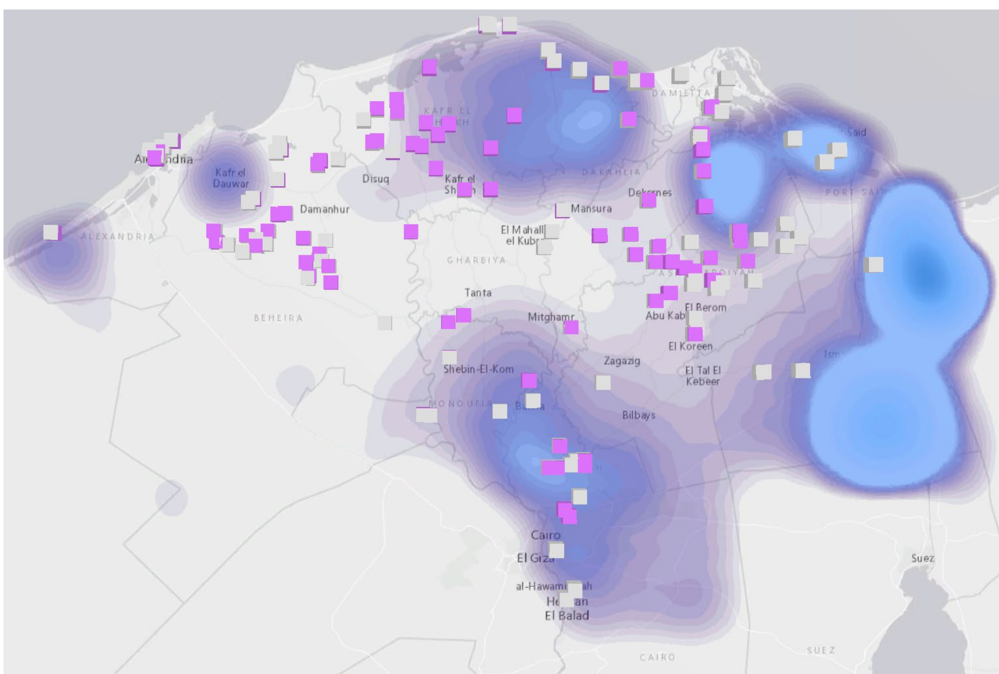


Figure 37. Archaeological looting attempts and precipitation in May 2016. The darker the blue the more precipitation. Purple indicates the presence of looting attempts.

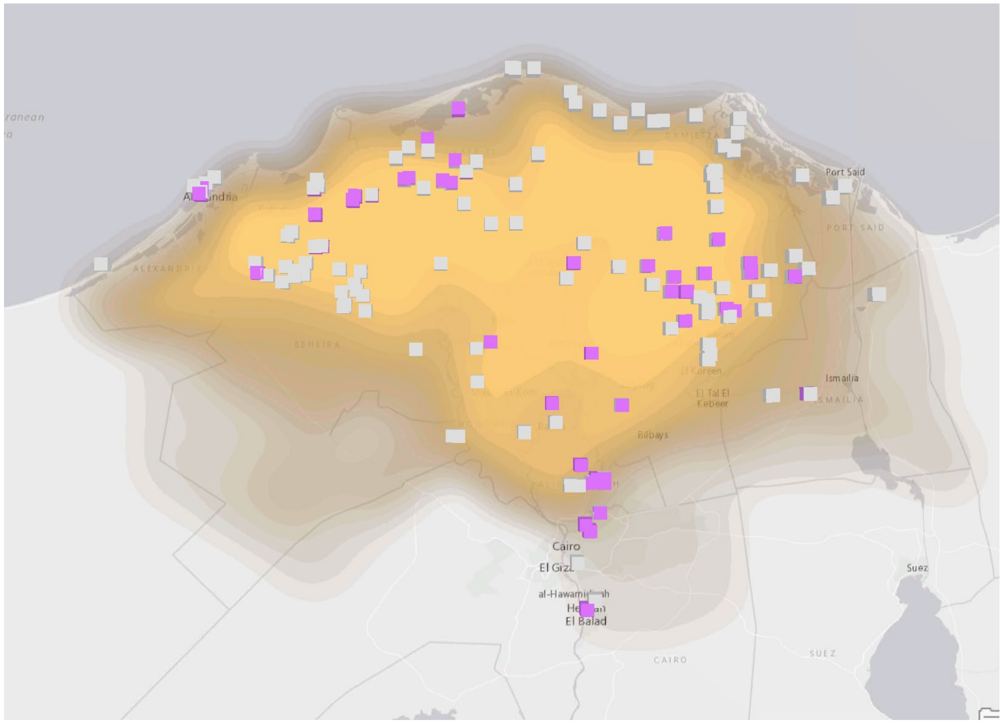


Figure 38. Archaeological looting attempts and vegetation health in February 2017. The more saturated the color for vegetation (from pale brown to opaque bright yellow and then to green) the healthier the vegetation. Purple indicates the presence of looting attempts.

Overall, this dissertation finds some evidence for a spatial relationship, temporal relationship, and spatio-temporal relationship between archaeological looting attempts and stressful conditions in the around the site. Sociopolitical stress and looting attempts are the most consistently related across space and time, though there are still inconsistencies. For example, the aggregate descriptives suggest an inverse relationship between sociopolitical stress and looting attempts, while the temporal and spatio-temporal suggest a more nuanced positive relationship. The effects of economic stress are most visible temporally while those of environmental stress are most visible spatio-temporally. These findings should be interpreted with caution as they may be artifacts of the measurement strategy used and a small sample size.

Spatial Analyses (Hypotheses 1 – 3)

The spatial hypotheses suggest three types of spatial relationships with respect to looting attempts. First, it is possible that site characteristics will influence which sites are looted (*Hypotheses 1* and *1a*). Or, proximity to key locations like cities will influence looting attempts (*Hypothesis 2*). Finally, that stressful conditions will be co-located with sites that have evidence of looting attempts (*Hypothesis 3*). Each of these hypotheses required a different set of approaches, as outlined in the previous chapter. In this section, I discuss the effectiveness of the analytic strategy proposed, followed by what, if any, substantive results I find for each of the three spatial hypotheses.

The analytical approach for the spatial analysis generally follows a point pattern analysis, supplemented with OLS. As such, some analyses are run at the site level and others at the grid-cell level (hexagonal or lattice). A point pattern analysis typically begins with describing the phenomena of interest, identifying the spatial distribution, and determining whether there is any spatial autocorrelation that needs to be addressed. Then, depending on the research question and descriptive results, the analyst can employ a range statistical approaches to test hypotheses and evaluate spatial relationships.

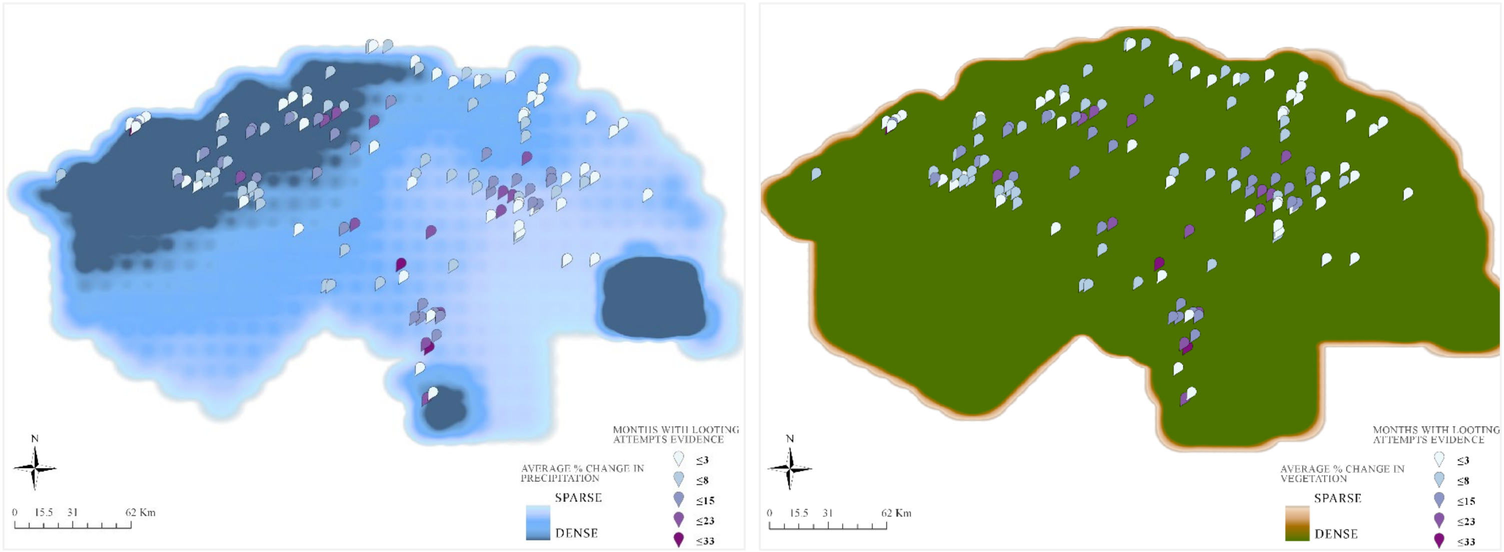
Overall, this approach works reasonably well; however, there are two challenges that required an adjustment to my analytic plan. First, due to the structure of my data I am unable to use more sophisticated geospatial methods like Kriging. The more sophisticated statistical analyses rely on spatial data interpolation to create sufficient sample sizes for testing hypotheses. Specifically, looting attempts and sociopolitical stress are coded as incident data that contained sudden spikes, which make such interpolation-based methods inappropriate (Oyana & Margai, 2015). Another challenge is that although using grid-cells increase the number of potential observations in the data, only cells with values can be used in an analysis. This avoids assuming missing data represent zeros for a given variable, but it also means that changing the format of the data does not significantly increase the sample size, as hoped. In some cases, it decreases the sample size. For example, when running OLS clustered on the grid-cell, only those grids that contained values for all the parameters are used. The most observations I can have clustering on the grid-cell was 190 and the least was 57. For an area as large as Lower Egypt, these are small sample sizes.

With these two challenges in mind, I approached the spatial analyses by trying to maximize the variation I could within each type of stress and only used methods that I know to be appropriate for my data. For sociopolitical stress, I use both the overall measure and the three types of conflict. From the environmental data, I rely on the vegetation health index and the precipitation data because they were measured every 0.05 and 0.25 spatial degrees, respectively. Each variable is calculated as an average percent change, net percent change, and straight average from 2015 to 2017. Neither total crop production nor soil moisture content are useful for these analyses. From the economic data, I use the average percent change in the rate of unemployment (total and youth) since they are available at the governorate level. However, because of the aggregate nature of the data, economic stress can only be evaluated descriptively. Below are the results of the point pattern analysis, starting with the descriptive results.

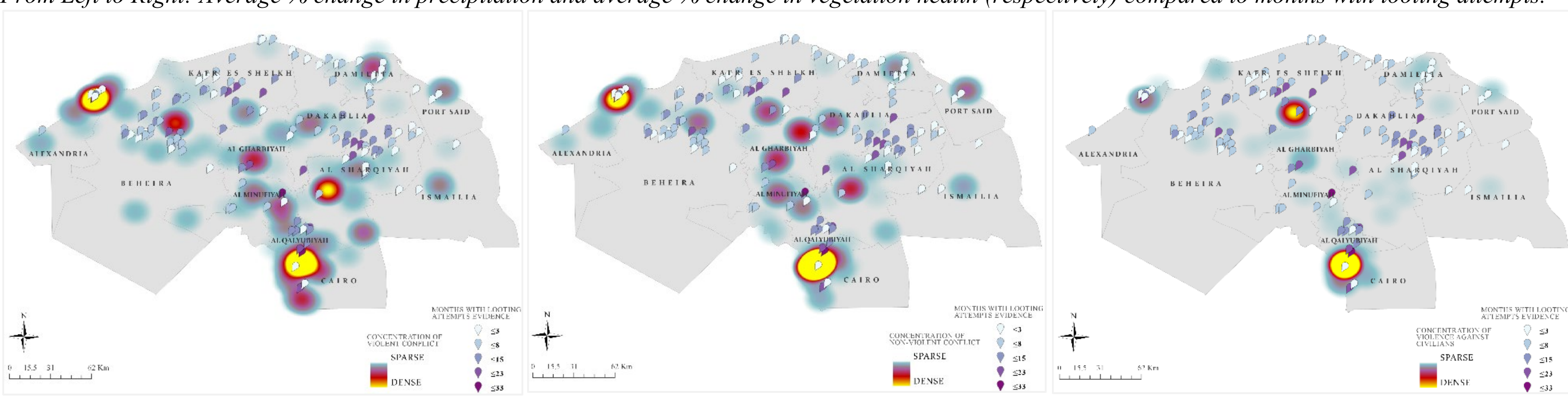
Point Pattern Analysis Results

To describe the spatial data, each variable of interest is visualized using either a point pattern map (point data) or a heat map (for raster data) and then layered each independent variable on top of the looting attempts distribution (see Figure 31, Figure 32, and Figure 39, see Appendix 3 for individual distributions). For sociopolitical stress and looting attempts, I also visualize their distributions with capital cities and urban areas. Sociopolitical stress maps very closely to Lower Egypt's urban areas and many of the archaeological sites are in or near an urban area (see Figure 40). Sociopolitical stress is also the only type of stress to be clearly concentrated near archaeological sites in general and more specifically near sites with evidence of looting attempts. However, as both phenomena appeared to be near populated areas, their proximity does not indicate a relationship without further support.

After evaluating the spatial distributions, I test each variable for spatial autocorrelation at multiple levels: overall (Global Moran's I), at a local level (Local Moran's I), and at varying distances (incremental spatial autocorrelation). These tests calculate a z-score between -2.58 and 2.58. A score that is statistically significant and positive indicates that variable is positively spatially correlated (clustered). A negative statistically significant score indicates that variable is negatively spatially correlated (dispersed). Non-statistically significant results indicate that the spatial distribution for that variable is not significantly different from random.



From Left to Right: Average % change in precipitation and average % change in vegetation health (respectively) compared to months with looting attempts.



Sociopolitical stress compared to months with looting attempts. From Left to Right: Violent conflict, non-violent conflict, and violence against civilians
Figure 39. Spatial distribution of indicators of stress and looting attempts.

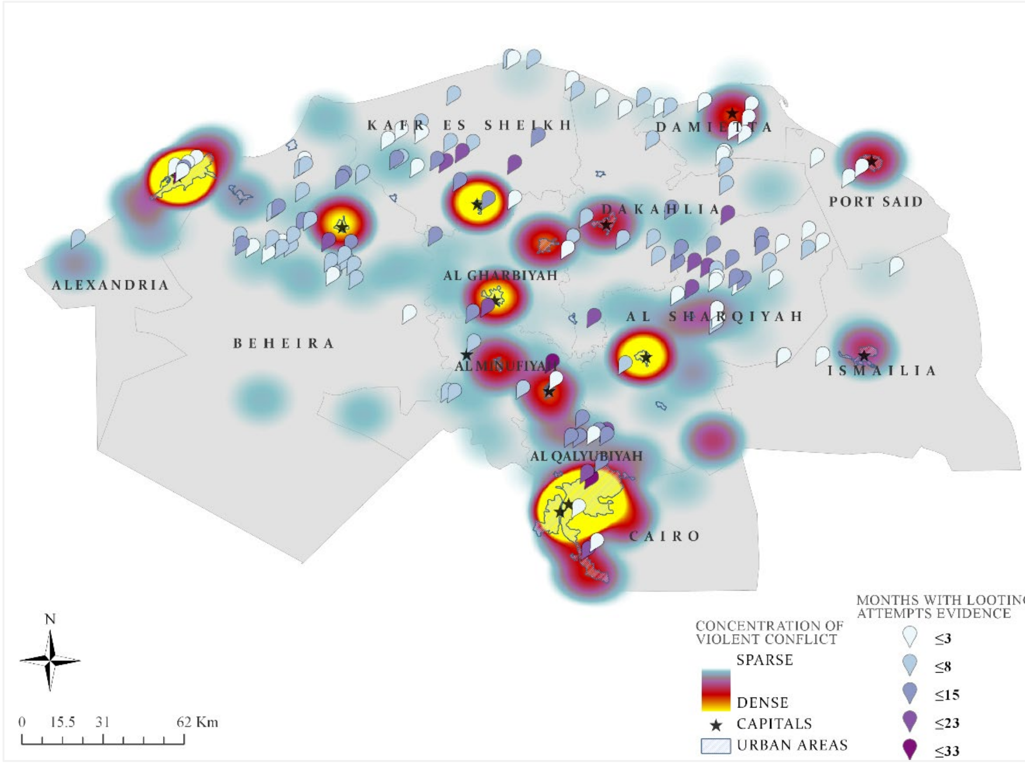


Figure 40. Sociopolitical stress and looting attempts relative to urban areas and capital cities in Lower Egypt.

Table 29 reports the results of the global tests for spatial autocorrelation. Positive spatial autocorrelation is present for almost all versions of looting attempts variables. The polygon formatted data – the site boundaries – are more highly correlated than the point data. Across both types of data, *new looting attempts (both)* is the only variable to show no signs of spatial autocorrelation; however, it also has the least amount of variation. As I use the boundary data for most of the spatial analyses, I report their numbers below. Based on these results, it appears that looting attempts are clustered.

By contrast, none of the tests find sociopolitical stress (as a total measure of conflict or by type of conflict) to be significantly different from random. This was surprising, considering how closely the incidents of sociopolitical stress map to urban areas. Both the vegetation health index and precipitation are positively correlated, which makes sense given the systematically sampled observations that are close to each other. Nearby locations are likely to be affected by the same weather patterns and environmental influences, influencing the likelihood of spatial autocorrelation among these variables. Neither total nor youth unemployment's distribution show any evidence of clustering. The Global Moran's I index (the only one that could be calculated for these variables) suggests they are not different from complete spatial randomness.

Table 29. Global Spatial Autocorrelation

	Global Moran's Index	**Variance**
Evidence of Archaeological Looting Attempts		
All looting attempts (either)	0.178811***	0.001471
All looting attempts (both)	0.123967***	0.001454
New looting attempts (either)	0.115054***	0.001458
New looting attempts (both)	0.051270	0.001458
Prior looting attempts (either)	0.119970***	0.001460
Prior looting attempts (both)	0.109590***	0.001458
Sociopolitical Stress		
All sociopolitical stress	0.016501	0.008518
Violent conflict	0.099594	0.012937
Non-violent conflict	0.030084	0.008607
Violence against civilians	0.011046	0.005388
Economic Stress		
Average change in unemployment in Lower Egypt (total)	0.134117	0.068796
Average change in unemployment in Lower Egypt (youth)	-0.418627	0.077761
Environmental Stress		
Average change in vegetation health index (NDVI)	0.926150***	0.000336
Average change in Precipitation	0.688819***	0.000813

* $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$

The results from the local Moran's I analyses also suggest that there is clustering and spatial dependence among looting attempts, sociopolitical stress, and environmental stress (Table 30). For both looting attempts and sociopolitical stress, the high-high clusters (high values surrounded by other high values) indicate the presence of clustering of increasing activity. By contrast, for environmental stress, it is the low-

low clusters that indicate stress as they are low values (less precipitation and less healthy vegetation) surrounded by other low values. The only variable to no show evidence of clustering is new looting attempts from either source. The presence of clustering among these variables makes it more likely that they could be spatially co-located.

Table 30. Local Moran's I Spatial Autocorrelation and Clustering

	High-High Clusters	Low-Low Clusters	Low-High Outliers	High-Low Outliers	Not Significant
Evidence of Archaeological Looting Attempts					
All looting attempts (either)	11	19	8	1	101
All looting attempts (both)	10	18	9	1	102
New looting attempts (either)	0	19	8	2	101
New looting attempts (both)	9	10	11	1	109
Prior looting attempts (either)	8	19	7	2	104
Prior looting attempts (both)	7	17	9	2	105
Sociopolitical Stress					
All sociopolitical stress	9	3	30	1	208
Violent conflict	9	2	9	0	231
Non-violent conflict	9	2	32	4	204
Violence against civilians	7	0	13	7	224
Environmental Stress					
Vegetation health index (NDVI)	506	437	2	0	643
Precipitation	1280	11428	2422	1363	26923

The incremental measure of spatial autocorrelation identifies both the presence of spatial autocorrelation and whether there are distances at which it peaked. All graphs for incremental spatial autocorrelation results are in Appendix 4. For looting attempts, the highest spatial autocorrelation is between observations 50km – 65km away from each other. These distances are used to help identify the grid sizes used in the later analyses. Similar to previous analyses, none of the measures for sociopolitical stress show signs of correlation at any distance. Both indicators of environmental stress report positive spatial autocorrelation across all distances, but there are no statistically significant peaks.

As mentioned above, I also tried initially to conduct a descriptive kriging analysis as a means of identifying clustering within variables and between variables. The kriging method has many specification options, depending on the structure of your data and whether autocorrelation is present. I tried all specifications that were reasonable for my data using the universal kriging, which is designed to account for the presence of autocorrelation. Unfortunately, because the looting data have spikes and are based on incident data, I could not specify a model that was stable and had results I could be confident in. Instead, my analytic strategy has been adjusted to focus on statistics and tests that will be accurate based on the structure of my looting data.

After conducting all tests for autocorrelation and eliminating kriging as a viable option, three sizes of grids (both hexagonal and lattice) are created. Using the distances identified in the incremental spatial autocorrelation test as a guide, I select 50-km to be the mid-sized grid, 10-km to be the smallest, and 150-km to be the largest. Ten kilometers is large enough to include environmental observations at least every other cell and small enough to have most sites be in their own cell (to maximize the number of observations). Fifty kilometers is the low end of the peak spatial autocorrelation distance between archaeological sites while still being small enough to capture a decent amount of variation in the environmental variables. One hundred and fifty kilometers is the largest grid that provided variation in all variables that was still smaller than the governorate. These grids are then used in the analyses below.

Characteristics of Archaeological Sites & Looting Attempts (Hypotheses 1 and 1a)

Based on a visual inspection (Figure 41) and the OLS regression results, there is no support for site characteristics influencing which sites were looted. No clear pattern emerges from these analyses nor concentration of specific ownership statuses or sites are owned compared to not owned by the Supreme Council of Antiquities. Similarly, OLS results clustered on the hex, grid, and not clustered on the site show no statistically significant results (Table 31 below). I tested using all three sizes of grid-cells, however, only the 10-km cells provide sufficiently detailed data to capture any amount of variation in the dependent variable. As such only the results for 10-km hexagon- and lattice-cells are provided. Additional specifications controlling for indicators of stress do not affect the results. These results also do not change using different measures of looting attempts, including weighting the data. For results of the weighted analyses see Appendix 4.

Table 31. Archaeological Site Characteristics and Evidence of Looting Attempts

DV: All looting attempts (either)	**Clustered on Hex-cell ($n = 190$)**	**Clustered on Grid-cell ($n = 231$)**	**Site-level ($n = 140$)**
Owned by SCA (compared to not)	-0.09413 (1.18255)	-0.98560 (1.2097)	0.18257 (1.19002)
Owned by SCA	-1.10179 (1.17747)	-1.63810 (1.21031)	-0.32292 (1.27751)
Protected under Law	0.75879 (1.17855)	-0.29825 (1.74259)	0.25 (1.67265)
Submitted for Protection	1.63874 (2.05053)	1.90476 (1.96810)	1.33333 (3.48190)

* p ≤ 0.10, ** p ≤ 0.05, *** p ≤ 0.01

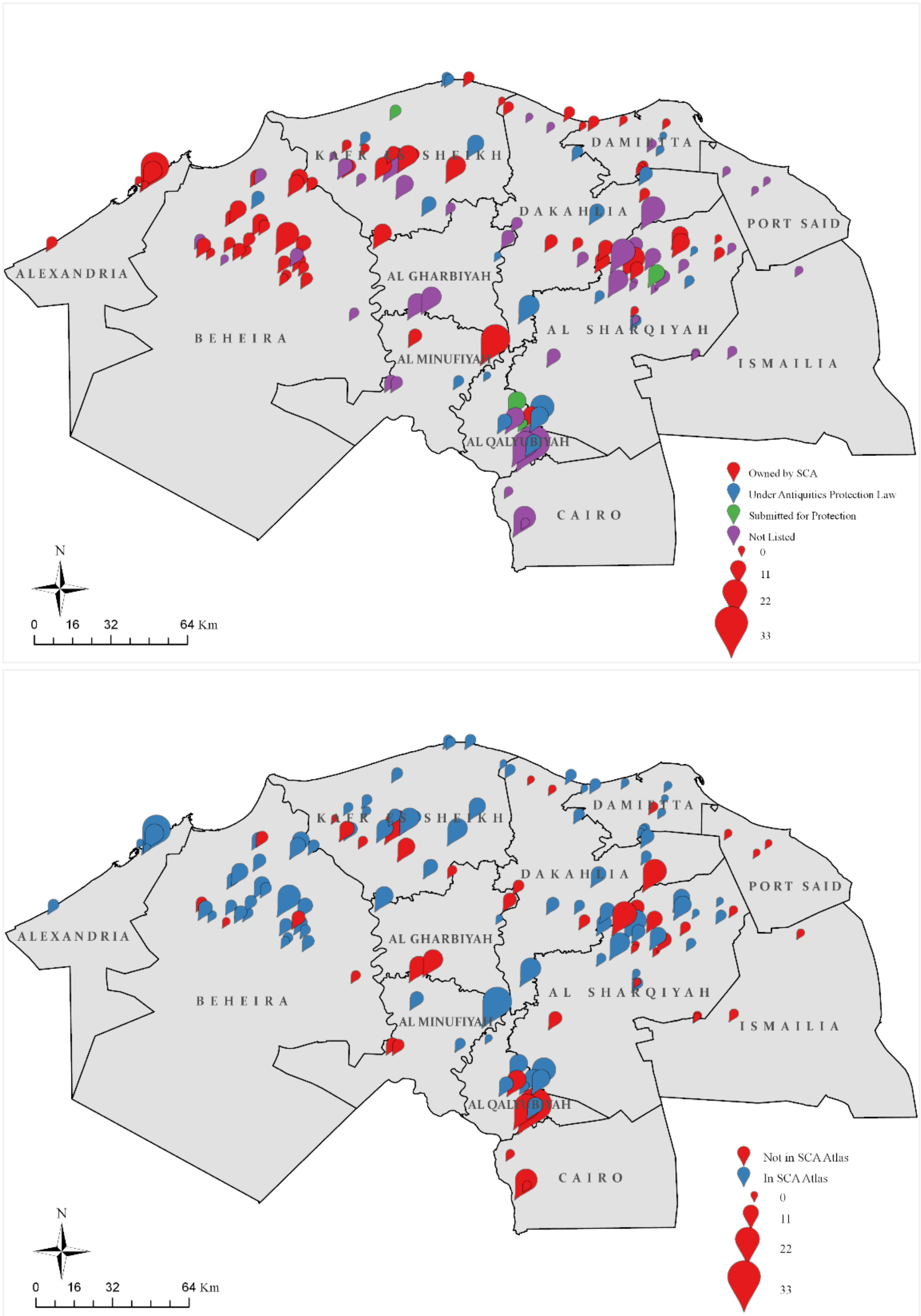


Figure 41. Distribution of archaeological sites with evidence of looting by degree of ownership (top) ownership status (bottom).

Proximity and Evidence of Looting Attempts (Hypothesis 2)

Some support exists for the hypothesis that an archaeological site's proximity to key locations influences whether a site has evidence of looting attempts. To evaluate this hypothesis, I calculate the distance from each site to the nearest road, city, urban area, and capital using two methods. The first method calculates straight line distances and the second constrains the distance based on the route via road to the nearest city, urban area, and capital. Archaeological sites are typically in very close proximity to a road and to a city (Table 32). Based on these results, the farthest someone would have to travel to get to a site going in a straight line is just over 90 km, though on average they would only need to travel just under 20km. The nearest incident distances are often longer than the geodesic as a result of the road network constraints. Specifying different types of travel modes (rural driving vs not rural driving) does not significantly affect the results. On average, an archaeological site is 31.46 km from a capital and 11.62 km from a city and 55.4 minutes and 20.84 minutes away, respectively.

To test whether proximity affects the number of months a site had evidence of looting, both straight line and road-based distances are exported to Stata and included in a regression. The straight-line distances could be calculated for point data, hex-cells, and grid-cells, but road-based distance could only be calculated with point data. However, the distances calculated based on gridded data are consistently smaller than point data. Since each grid-cell can contain multiple attributes (e.g., both sites with looting attempts and a city), distance-based calculations often returned a result of zero. This did not provide any useful information for evaluating the proximity hypothesis.

As such, I only present regressions on the straight-line and road-network distances using the point-based data.

Table 32. Distances to Nearest Key Locations

Key Location	**Geodesic Distance (km)**			
	Mean	*Std. Dev*	*Min*	*Max*
Capital	23.469	12.474	0.308	54.084
City	7.995	4.954	0.301	24.793
Urban Area	16.050	10.970	0	49.569
Road	0.663	0.901	0.007	5.147
Key Location	**Driving Distance in km (Travel time in minutes)**			
	Mean	*Std. Dev*	*Min*	*Max*
Capital	31.549 (55.414)	17.159 (24.258)	0.572 (2.812)	90.481 (122.535)
City	12.140 (21.536)	7.336 (11.232)	0.329 (1.352)	45.177 (53.583)
Key Location	**Rural Driving Distance in km (Travel time in minutes)**			
	Mean	*Std. Dev*	*Min*	*Max*
Capital	31.376 (55.339)	17.567 (24.377)	0.572 (2.812)	99.538 (119.441)
City	11.106 (20.143)	8.835 (11.931)	0.330 (1.352)	77.774 (89.045)

*Note: travel time could only be calculated between points, so only applies to nearest incident distances.

For the straight-line distances, I compare the results using the site locations (as points) and the boundaries of the sites (polygons) to see how sensitive the results are to the area of a site. From the first set of models (looking at straight line distance), distance to urban areas, roads, and cities (in 3 versions) are statistically significant. The results for distance to the road appear to be the most consistent – where sites further from the road are more likely to have between 0.1 and 1.18 more months with evidence of looting attempts. For urban areas, the model using distance from site location find consistently significant relationships; however, the direction of the coefficient changes from negative to positive depending on the definition of looting. These models also have R^2 values between 0.01 and 0.08, suggesting that a maximum of 8% of the variation in archaeological looting attempts can be explained through distances to key locations.

The second set of models looking at distance via roads could only look at the relationship between looting attempts and capitals and cities. However, I test two assumptions about driving distance and time to key locations across all definitions of looting attempts (see Table 34). The top half of Table 34 assumes that there are barriers to access to the archaeological sites in the form of gates, stop-lights, and an aversion to driving on unpaved roads. Consistent with the first set of models, these results suggest no relationship between proximity to cities and capitals and looting attempts. The few exceptions are only found in the more restricted definitions of looting attempts.

Table 33. Straight Line Proximity versus Evidence of Looting Attempts

Sample Size: 140	**All Looting Attempts**		**New Looting Attempts**		**Prior Looting Attempts**	
	Either Source	*Both Sources*	*Either Source*	*Both Sources*	*Either Source*	*Both Sources*
Distance from Site Location						
Capitals	-0.059 (0.056)	-0.018 (-.030)	-0.056 (0.042)	-0.013 (0.019)	-0.045 (0.056)	-0.028 (0.057)
Cities	-0.182 (0.125)	-0.135* (0.069)	-0.094 (0.099)	-0.083* (0.047)	-0.166 (0.130)	-0.197 (0.132)
Urban Area	0.0002** (0.000)	-0.009* (0.000)	0.0002*** (0.000)	0.00007** (0.000)	0.0004*** (0.000)	0.0004*** (0.000)
Road	-0.819** (0.460)	-0.407* (0.239)	-0.538 (0.361)	-0.189 (0.159)	-0.799** (0.398)	-0.603 (0.418)
Distance from Site Boundary Polygons						
Capitals	0.002 (0.076)	0.018 (0.044)	-0.043 (0.056)	-0.021 (0.030)	0.076 (0.066)	0.064 (0.067)
Cities	-0.393 (0.285)	-0.209 (0.171)	-0.160 (0.197)	-0.064 (0.099)	-0.480* (0.282)	-0.436 (0.291)
Urban Area	-0.064 (0.085)	-0.016 (0.050)	0.002 (0.063)	0.027 (0.035)	-0.134* (0.070)	-0.141** (0.070)
Road	-0.968 (0.664)	-0.512* (0.287)	-0.423 (0.582)	-0.150 (0.225)	-1.069** (0.523)	-1.185** (0.519)

* p ≤ 0.10, ** p ≤ 0.05, *** p ≤ 0.01

Yet as large portions of Egypt are desert-based, it may not be a reasonable to assume that people will avoid driving on dirt roads. As such, the bottom half of the table presents results where the models allow for unpaved roads. The results of these less restricted models consistently find a negative relationship between the distance to capitals and the time it takes to reach cities. This suggests that the findings of these proximity analyses are highly sensitive to assumptions about how individuals would travel between a key location and an archaeological site.

Looking across all the proximity analyses, there are few consistent findings. There appears to be marginally more support for the idea that proximity to key locations could act as a protective effect on evidence of looting attempts. However, this relationship is not present consistently for any of the types of key locations. The straight-distance analyses find urban areas and roads to be the most consistently related to looting attempts. By contrast, the road-network distances find cities and time to capitals most consistently. All these results are (primarily) negative and very closer to zero. Additionally, the fact that the road-network results changes dramatically depending on the restrictions imposed on the route implies that the results are highly sensitive to underlying assumptions.

Table 34. Road Network Proximity versus Evidence of Looting Attempts

Sample Size: 140	**All Looting Attempts**		**New Looting Attempts**		**Prior Looting Attempts**	
	Either Source	*Both Sources*	*Either Source*	*Both Sources*	*Either Source*	*Both Sources*
Driving Distance & Time						
Km to Capital	-0.050 (0.043)	-0.013 (0.022)	-0.049 (0.031)	-0.012 (0.013)	-0.033 (0.043)	-0.025 (0.044)
Km to Cities	-0.128 (0.092)	-0.106** (0.050)	-0.059 (0.068)	-0.059* (0.031)	-0.132 (0.097)	-0.136 (0.097)
Min to Capital	-0.017 (0.029)	-0.003 (0.015)	-0.019 (0.021)	-0.003 (0.009)	-0.012 (0.029)	-0.007 (0.030)
Min to Cities	-0.073 (0.063)	-0.059* (0.034)	-0.036 (0.049)	-0.040* (0.021)	-0.066 (0.064)	-0.066 (0.065)
Rural Driving Distance & Time						
Km to Capital	-0.078** (0.036)	-0.033* (0.019)	-0.063** (0.027)	-0.022* (0.012)	-0.061* (0.036)	-0.055 (0.037)
Km to Cities	-0.044 (-0.047)	-0.037 (0.025)	-0.022 (0.037)	-0.022 (0.017)	-0.044 (0.050)	-0.039 (0.050)
Min to Capital	-0.011 (0.027)	-0.002 (0.014)	-0.012 (0.020)	-0.002 (0.009)	-0.008 (0.027)	-.003 (0.023)
Min to Cities	-0.157*** (0.056)	-0.091** (0.035)	-0.106*** (0.034)	-0.055** (0.021)	-0.131** (0.059)	-0.129** (0.058)

* $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$

Co-location of Archaeological Looting Attempts and Indicators of Stress (Hypothesis 3)

To evaluate whether looting attempts are co-located with indicators of stress, I use a combination of clustering descriptive methods and proximity analyses. I examine the degree to which each type of stress (measured by their individual indicators) is clustered within itself and then plot this relative to the distribution of looting attempts. For the economic and environmental indicators, I could only conduct a descriptive test of this hypothesis because of the format of the data. Any proximity analysis would by definition find archaeological sites to be proximate to the locations at which vegetation health and precipitation were measured. Similarly, the economic data apply to an entire governorate and so any site within the governorate would be found to be "proximate" to that indicator.

Archaeological looting attempts, sociopolitical stress and environmental stress are all clustered to some degree. I ran both baseline and weighted Ripley K analyses for these three sets of variables, where the weights were the values associated with different variables (e.g., the operationalizations of looting attempts). For all but one variable, both the baseline and weighted tests find the variables to be clustered across all ten distance bands (with an alpha level of 0.01). The exception is the average percent change in precipitation measure of environmental stress – the first distance band and last two distance bands are not distinguishable from complete spatial randomness.

It is not surprising that a weighted result is more clustered than the baseline; however, it was interesting to see the degree of clustering of the weighted analyses relative to the baseline. The difference between the weighted observed K-value and the upper limit of the baseline 99% confidence interval determine how much more clustered the variable was as a result of the weights used. For example, with sociopolitical stress, violent conflict most closely matches the clustering pattern of the baseline, while non-violent conflict and violence against civilians were both more highly clustered (Figure 42). By contrast, all of the looting variable operationalizations are more highly clustered than the baseline and all followed a similar pattern. The first distance band and last two distance bands K-values are very close to the observed (though still marginally larger) while the middle periods have a greater difference in clustering (Figure 43).

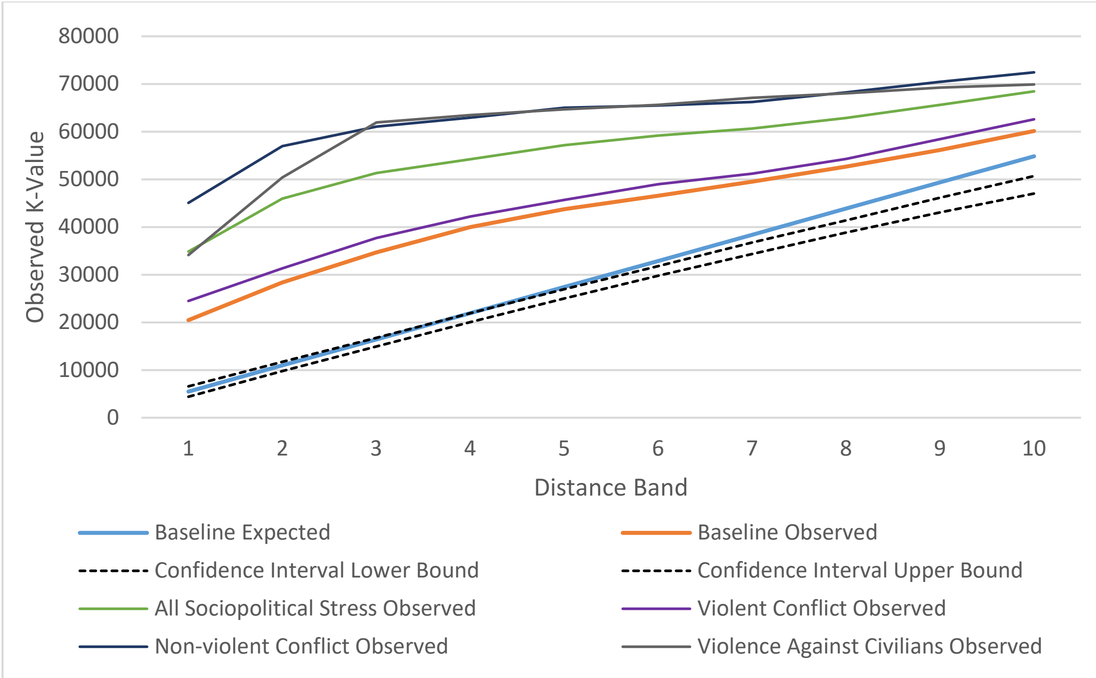


Figure 42. Sociopolitical stress baseline vs weighted Ripley's K Function results

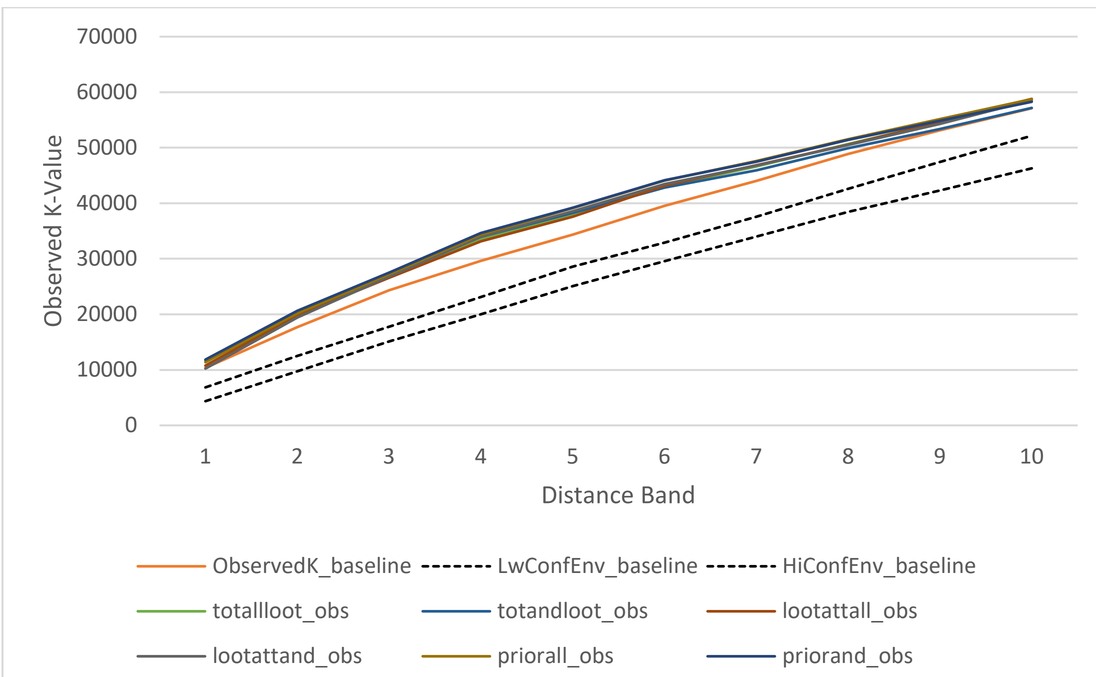
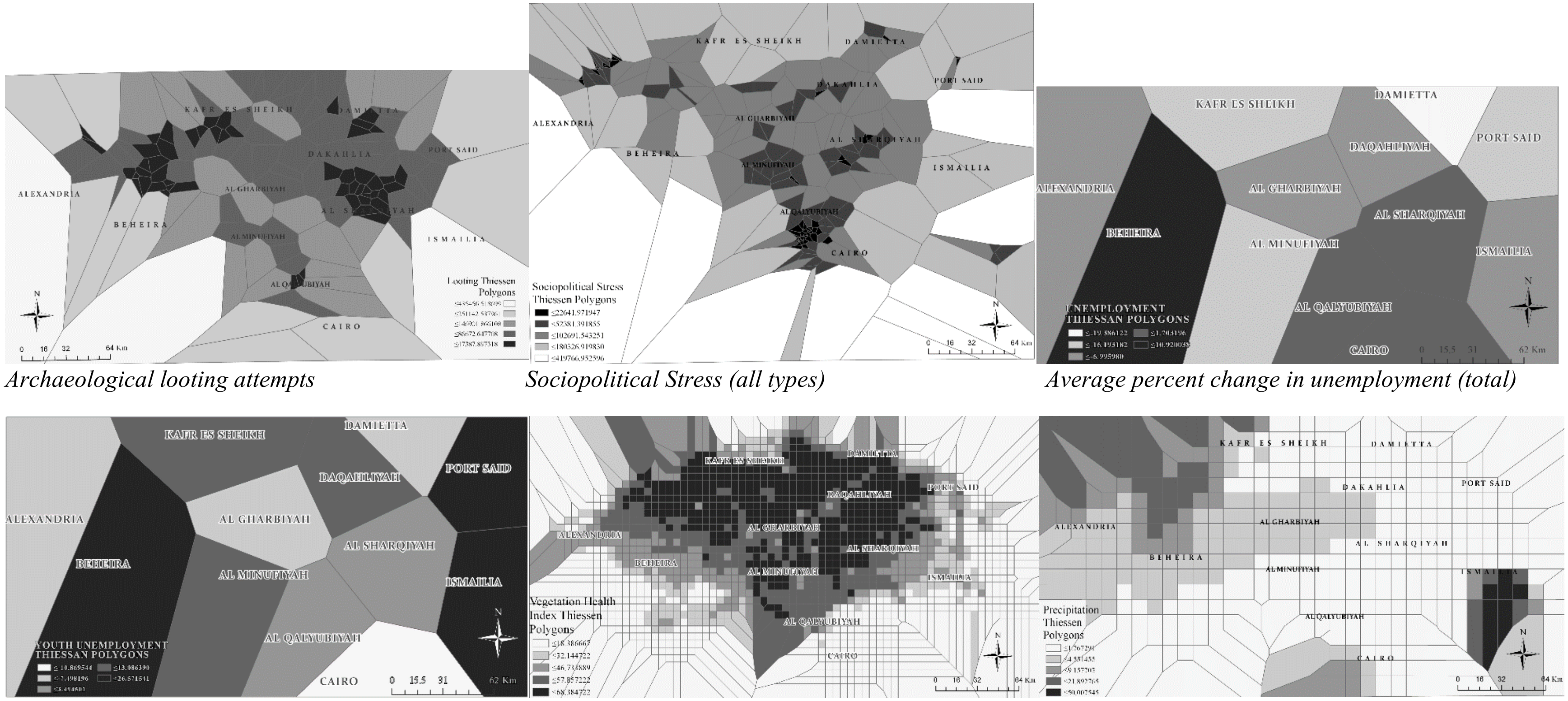


Figure 43. Archaeological looting attempts baseline vs weighted Ripley's K Function results

The Voronoi maps (Figure 44) provide a visual representation of the clustering according to how the Thiessen polygons created. Based on the Voronoi maps, it appears that looting attempts and sociopolitical stress are generally concentrated in the same areas. There is no clear pattern with respect to either the environmental stress variables or the economic stress variables. Visualizing the distribution of looting attempts with the environmental and economic stress variables similarly shows no clear pattern. My data and available methods are insufficient to truly test whether environmental stress and economic stress were co-located.



Archaeological looting attempts *Sociopolitical Stress (all types)* *Average percent change in unemployment (total)*

Average percent change in unemployment (youth) *Average percent change in vegetation health (NDVI)* *Average percent change in precipitation*

Figure 44. Voronoi maps of clustering for key variables. Darker colors indicate higher concentrations and therefore more clustering.

With respect to sociopolitical stress, I follow a procedure similar to the analyses involving key locations. I calculate the average distance to different types of sociopolitical stress and then regress the distances on evidence of looting attempts. Because both sociopolitical stress and looting attempts are discrete points irregularly distributed in space, it is more informative to calculate the distances based on their respective geolocations instead of the distance between their grid-cells. I also calculate a road-network distance to use in the regression analysis. The results for rural and non-rural driving distances are equivalent and so I report only one set of the output (see Table 35). Similarly, weighting the looting has no impact (see Appendix 4).

Table 35. Distance to Sociopolitical Stress versus Evidence of Archaeological Looting Attempts

Sample Size: 140	**All Looting Attempts**		**New Looting Attempts**		**Prior Looting Attempts**	
	Either Source	*Both Sources*	*Either Source*	*Both Sources*	*Either Source*	*Both Sources*
Distance from Site Location						
All Sociopolitical Stress (SPS)	-0.075 (0.107)	-0.030 (0.061)	-0.010 (0.078)	0.005 (0.039)	-0.021 (0.107)	-0.027 (0.106)
Violent Conflict	-0.055 (0.095)	0.029 (0.052)	0.078 (0.071)	0.020 (0.035)	0.083 (0.096)	0.078 (0.098)
Non-violent Conflict	-0.084 (0.067)	-0.006 (0.036)	-0.065 (0.052)	-0.006 (0.022)	-0.076 (0.063)	-0.088 (0.064)
Violence Against Civilians	-0.142 (0.042)	-0.068 (0.023)	-0.110 (0.029)	-0.035 (0.014)	-0.127 (0.425)	-0.123 (0.044)
Distance from Site Boundary Polygons						
All Sociopolitical Stress (SPS)	-0.402 (0.236)	0.154 (0.113)	-0.237 (0.197)	-0.031 (0.084)	-0.326 (0.232)	-0.281 (0.239)
Violent Conflict	0.056 (0.105)	0.022 (0.064)	0.026 (0.074)	0.010 (0.038)	-0.006 (0.010)	0.030 (0.100)
Non-violent Conflict	-0.097 (0.091)	-0.008 (0.056)	-0.085 (0.064)	-0.014 (0.034)	-0.076 (0.089)	-0.089 (0.088)
Violence Against Civilians	-0.030 (0.048)	-0.021 (0.027)	-0.003 (0.038)	0.003 (0.019)	-0.015 (0.048)	-0.033 (0.046)
Driving Distance & Time						
Km to SPS	-0.061 (0.063)	-0.027 (0.035)	-0.017 (0.047)	-0.006 (0.022)	-0.024 (0.063)	-0.026 (0.062)
Min to SPS	-0.007 (0.048)	-0.003 (0.026)	0.014 (0.0360)	0.004 (0.017)	0.017 (0.046)	0.015 (0.046)

* p ≤ 0.10, ** p ≤ 0.05, *** p ≤ 0.01

Interestingly, none of these analyses find statistical evidence of a relationship between archaeological looting attempts and distance to sociopolitical stress. This is a surprising finding considering that the descriptive results suggest that both events occur in the same locations. It is possible that though they occur in the same areas spatially, the events occur in different times such that these two phenomena are unrelated.

Overall, the spatial analysis finds moderate support for the influence of proximity and co-location. Proximity to urban areas and to roads show a slight negative relationship with looting attempts, though this relationship does not hold when looking at capital cities or all cities. Proximity to sociopolitical stress is also related to looting attempts, which combined with the visual evidence of similar clustering patterns suggests that these two phenomena are co-located. With these data and methods, I am unable to adequately test whether environmental and economic stress were co-located with looting attempts. Finally, there is no support for a site's ownership status influencing looting attempts.

Temporal Analyses (Hypotheses 4 & 5)

The temporal hypotheses suggest that archaeological looting attempts would have a non-recursive relationship with three theoretical constructs or latent variables – sociopolitical stress, economic stress, and environmental stress. Further, they suggest that there may be both a short and long-term relationship between these latent variables and looting attempts. Given the theoretical complexity of the models proposed and my small sample size ($n = 36$), accurately specifying a multivariate time series model is a challenge. Therefore, I start with the most complex model and simplified with each subsequent variation to see if any of the approaches would work. Ultimately, the only models that converge and produce substantive results are the autoregressive distributed lag models. This section first presents the results of my tests of all four modeling strategies and then discusses whether there was any support for *Hypotheses 4* and *5*.

Structural Equation Modeling Results

In total, I ran 29 variations of five structural equation models. None of the SEM models would converge, regardless of the combination of exogenous or endogenous variables, the number of lagged variables, or how many constraints I place on lagged relationships. Below I describe the decision process for each set of models and their advantages and disadvantages. To create the latent variables, I conduct factor analysis to confirm that each type of variable is relevant to its theoretical construct; however, the factor analysis would only converge when subsets of the variables for each construct were included. Table 36 presents the final factors I use for the temporal analyses.[60]

Table 36. Latent Variable Compositions

Sociopolitical Stress	Economic Stress	Environmental Stress
Violent Conflict Non-violent Conflict Violence Against Civilians	Unemployment (total) National Debt (% external debt) Tourist Arrivals	Vegetation Health Index Soil Moisture Content Precipitation

The first model I ran was the full theoretical model based on the hypotheses (Figure 18). Including all indicators as part of latent variables allows me to capture the full complexity of each type of stress. I test having all three latent variables be endogenous to the model and included lags of each variable; however, with my small sample size the full model is highly unstable. Table 37 outlines both variations and their advantages and disadvantages.

Table 37. Advantages and Disadvantages of SEM Model 1

Model #1: Three latent variables regressed on all evidence of looting attempts		
Variation	*Advantages*	*Disadvantages*
Two-stage model (confirmatory factor analysis and path analysis) with all three latent variables endogenous to the model	Using latent variables most accurately represented the theoretical relationship while accounting for the highly correlated nature of individual indicators in each latent variable.	Modeling an SEM with latent variables and non-recursive relationships requires a large sample size. For a small sample size, these models are very unstable and are not likely to converge.
Two-stage model with only sociopolitical stress endogenous to the model	Reducing the number of endogenous variables reduces the complexity of the model; however, not enough to allow the model to converge.	Assuming that a latent variable is exogenous when in fact it may not be ignores the proposed theoretical relationship and may affect findings.

[60] The following variables were dropped because they did not add anything to the factor analysis: inflation based on consumer price index, consumer price index for food, and national debt based on percent reserves.

Some literature suggests that with smaller sample sizes, models are more likely to converge with fewer latent variables that have a higher factor loading score (at least 0.8) and at least four indicators (Wolf et al., 2013). To test this, I decide to try using only one latent variable in the second, third, and fourth models. Since the observed variables in each latent variable are highly correlated, including them all would introduce multicollinearity into the model. Instead, I select a single variable indicator for each latent variable to serve as a proxy (see Table 38). Each model is tested with one, two, and three lags of the variables to account for the possibilities of delayed effects.

For sociopolitical stress, I select the variable measuring all types of conflict (*total conflict*). For economic stress, both the consumer price index (*cpi*) and unemployment (*total unemployment*) directly measure the amount of strain the economy could place on individuals. They are also measured at the most granular levels. I ultimately choose the consumer price index for general goods as the proxy as it had the highest factor loading score (0.9082), suggesting that it would be the most representative of economic stress.[61] With regards to environmental stress, the vegetation health index (*ndvi*) could theoretically encompass elements of the other variables. If an area has a high index, then it will likely have had more precipitation, higher soil moisture content, and would likely have had a larger crop production.

[61] Just to be sure, I also tried running a few test models with unemployment and it did not affect the findings.

Table 38. Advantages and Disadvantages of SEM Models 2 – Models 4

Models #2 – Model #4: One latent variable and two individual observed variables as indicators of the other two forms of stress. All independent variables regressed on all evidence of looting attempts.		
Variation	*Advantages*	*Disadvantages*
Two-stage model where the latent variable was assumed to be exogenous. Model tested with 1, 2, & 3 lags.	Reducing the number of latent variables and assuming it is exogenous simplifies the model (reduces the parameters) and makes it more likely to converge.	Assuming the latent variable to be exogenous actively ignores the theoretically nonrecursive relationship between different types of stress. Using only one variable as a proxy each type of stress oversimplifies each concept and raises issues of construct validity.
Two-stage model where the latent variable was assumed to be endogenous. Model tested with 1, 2, & 3 lags.	Reducing the number of latent variables and assuming it is endogenous simplifies the model (reduces the parameters) while accounting for the nonrecursive relationship between types of stress.	Assuming the latent variable to be endogenous introduces more complexity to the model and makes it difficult for it to converge. Using only one variable as a proxy each type of stress oversimplifies each concept and raises issues of construct validity.

Despite the simplification, none of these models converge. Including only one latent variable makes the model more unstable rather than less unstable. I decide to try estimating the simplest version of the models and then slowly add elements back in. This model had no latent variables, only proxies for each indicator (Table 39). I start with all indicators exogenous to the model and slowly make the economic stress and sociopolitical stress variables endogenous.

Table 39. Advantages and Disadvantages of SEM Model 5

Model #5: No latent variables, just three individual observed variables as indicators of economic stress (monthly average consumer price index – general goods), environmental stress (monthly average vegetation health index), and sociopolitical stress (total conflict). All three regressed on all evidence of looting attempts.		
Variation	*Advantages*	*Disadvantages*
Two-stage model where all variables are assumed to be exogenous. Model tested with 1, 2, & 3 lags.	Using single indicator proxies estimates the simplest version of the model, reducing the number of parameters, while still trying to maintain theoretically relevant relationships.	Using single indicators as proxies assumes that it is possible to capture complex macro-level dynamics with a single measure. Keeping variables exogenous ignores their proposed theoretical relationships.
Two-stage model where both economic and environmental variables are assumed to be exogenous. Model tested with 1, 2, & 3 lags.	Including sociopolitical stress as an endogenous variable maintains nonrecursive relationship between types of conflict and looting attempts while keeping the model as simple as possible.	Using single indicators as proxies assumes that it is possible to capture complex macro-level dynamics with a single measure. Keeping economic stress exogenous ignores the theoretically endogenous relationships between sociopolitical stress, economic stress, and looting attempts.
Two-stage model where only the environmental variable is assumed to be exogenous. Model tested with 1, 2, & 3 lags.	Including both sociopolitical stress and economic stress as endogenous variables maintains their nonrecursive relationships between while keeping the model as simple as possible.	Using single indicators as proxies assumes that it is possible to capture complex macro-level dynamics with a single measure.

Structural equation modeling is not a useful approach for modeling the proposed relationships. The small sample size makes any model unstable with this approach. It is possible that this approach would prove more useful given a larger sample size. Prior research has found that armed conflict and archaeological looting attempts are cointegrated (Fabiani, 2018). Ultimately, it is difficult to model cointegration accurately using structural equation modeling. As such, I try variations on Vector Autoregression, an approach used in econometrics to model dynamic cointegrating relationships.

Lag-Augmented Vector Autoregression & Vector Error Correction Results

I ran two models with different specifications using lag-augmented vector autoregression and vector error correction models. Similar to my approach to the structural equation models, I start with the most all-inclusive and theoretically relevant model and adjusted each version as necessary. Table 40 outlines the LA-VAR model variations and their advantages and disadvantages. One of the benefits of using LA-VAR and VEC is that these methods can distinguish between short- and long-term effects. They are also able to explicitly model non-recursive relationships by treating all endogenous variables as both a dependent variable in their own equation and independent variables in all other equations.

I start with an LA-VAR model specification as it does not make any a priori assumptions about model structure. As such, I use the model specification process for a VAR to determine which variables were theoretically relevant within each latent construct. The first model variation includes all of my variables as endogenous to the model; however, the sample size is too small, and the independent variables are too collinear for the model converge. For subsequent variations, I use the factor loadings as a starting point for which combinations of observed variables to include for each latent construct. The variables total crop production, youth unemployment, total unemployment, national debt (as % reserves), consumer price index (food), and inflation based on consumer price index are consistently excluded from model combinations by Stata due to collinearity.[62]

The model performed best when sociopolitical indicators (*violent conflict, non-violent conflict,* and *violence against civilians*) were endogenous while both the environmental indicators (*ndvi*, *precipitation*, and *soil moisture content*) and economic indicators (*cpi for general goods*, *national debt – external*, and *tourist arrivals*) are treated as exogenous. Yet even with this specification, the model is unstable and problematic. This is contrary to the theoretical model proposed in this dissertation, suggesting that the model was misspecified, the method was inappropriate, or both.

Though VAR models (and LA-VAR models in particular) are very good at identifying the presence of granger causality and for looking at relationships inductively, they are not designed to explicitly model cointegrating relationships. By contrast, VEC models are designed to model such relationships and are more appropriate when there are unit roots present in the data (Brandt & Williams, 2007). As such, I also ran a VEC model. Unfortunately, this model excludes or fails to estimate most if not all of the variables, regardless of the specification. Since VEC models do

[62] National debt (as % external debt) and total unemployment were identified as collinear in almost every model. Though also measured annually at the national level, this measure of national debt was more often included in the model by Stata than the other variables above. Sensitivity tests including and excluding different combinations of economic variables did not affect the results of any of the models. As such, I kept the default three variables Stata recommended for the economic stress construct: Consumer price index (general), tourist arrivals, and national debt (as % external debt).

not allow for different orders of integration between variables, this suggests that one or more of my variables might have a higher order of integration than the others.

Table 40. Advantages and Disadvantages of Model 6 - LA-VAR Model Variations

<table>
<tr><th colspan="3">Model #6: LA-VAR with all (or combinations of) observed variables as endogenous regressors in the model.</th></tr>
<tr><td>Variation</td><td>Advantages</td><td>Disadvantages</td></tr>
<tr><td>All variables included and considered as endogenous</td><td rowspan="3">Including multiple indicators as measures of their latent construct allows for a more nuanced understanding of how those dimensions affect looting attempts over time.</td><td rowspan="5">LA-VAR assumes that all variables have the same order of integration, regardless and imposes the same lag structure on all equations. This can lead to overparamaterization.

Using single indicators as proxies assumes that it is possible to capture complex macro-level dynamics with a single measure.

Treating some variables as exogenous (particularly those related to economic stress) ignores their theoretically non-recursive relationship with both looting attempts and sociopolitical stress.</td></tr>
<tr><td>Endogenous – violent conflict, nonviolent conflict, violence against civilians, consumer price index (general)
Exogenous – national debt, tourist arrivals, ndvi, precipitation, soil moisture content</td></tr>
<tr><td>Endogenous – all conflict, consumer price index (general)
Exogenous – national debt, tourist arrivals, ndvi, precipitation, soil moisture content</td></tr>
<tr><td>One indicator per type of stress
Endogenous – all conflict, ndvi, consumer price index (general)</td><td rowspan="2">Including a single indicator as a proxy simplifies the model and reduces the number of parameters being estimated for the small sample size.</td></tr>
<tr><td>One indicator per type of stress
Endogenous – all conflict
Exogenous – ndvi, and consumer price index (general)</td></tr>
</table>

Autoregressive Distributed Lag Model (ARDL) Results

ARDL models are the most flexible of the VAR model extensions. They estimate short- and long-run relationships, can account for mixed orders of integration, and allow each variable to have its own lag structure. VAR and VEC models avoid addressing moving average or autoregressive processes until after the initial model has been specified. By contrast, ARDL models are considered a special case of autoregressive integrated moving average (ARIMA) models and so incorporate these elements into the model. As a VAR extension, ARDL models can account for non-recursive relationships; however, they must be modeled separately. That is, the output for ARDL looks only at one dependent variable at a time because each equation requires a different lag structure. As such, I ran a single set of ARDL models where the specification remained consistent, but the dependent variable and lag structure changed.

Based on the previous model variations, I decide to run the ARDL models with one type of stress as endogenous (sociopolitical) and two exogenous (economic and environmental).[63] I test multiple variable combinations for each type of stress and find that the most stable model was considered "identified" with the following combinations: sociopolitical stress broken into violent conflict, nonviolent conflict, and violence against civilians; economic stress measured by consumer price index (general), national debt (as % external), and tourist arrivals; and environmental stress measured by vegetation health (ndvi), precipitation, and soil moisture content. The other variables are either collinear or nonsignificant and so are not included.

[63] Attempts to include either economic or environmental variables as endogenous regressors failed as they were too collinear for the model to estimate in levels, lags, and differences.

The ARDL models both converge and pass all model specification tests and so may be considered "identified,"[64] (see Appendix 5 for results of model specification tests and models with sociopolitical stress dependent variables). The results of the primary model of interest (looting attempts dependent variable) are presented in Table 41 below. The lag structure for each of the models is based on the AIC criteria recommendation in Stata. I experimented with alternate lag structures as well; however, none provided better results. For all models except violence against civilians as the dependent variable I include a trend variable based on the results of their tests for stationarity. Including a trend variable for violence against civilians is unnecessary and if included makes the model unstable. Due to the small sample size, the substantive results of these models should be interpreted with extreme caution.

The error correction term, which measures the speed with which the system returns to equilibrium after a shock, should normally be between 0 and -1. An error correction term in this range indicates that the return to equilibrium follows a monotonic pattern. When an error term falls between -1 and -2, it indicates that the return to equilibrium oscillates – the closer to -2, the longer it takes for the system to reach equilibrium (Narayan & Smyth, 2006: 339). Anything below -2 indicates that equilibrium would not be reached in the long-run and that the model may not be properly specified. Models with small sample sizes are particularly vulnerable to error correction terms below -2. As Table 41 indicates, the error correction terms for these data range from -1.9038 (for looting attempts) to -3.1264 (for violent conflict),

[64] The flexibility of this modeling strategy combined with the small sample size makes me less confident that the model is truly fully identified and so the results should be interpreted with caution.

suggesting that only the model with archaeological looting attempts as the dependent variable would reach equilibrium after a shock. I test running ARDL with the combined sociopolitical variable (*total conflict*) and the error correction term for all specifications was within the normal range. This supports the idea that the small sample size and number of parameters are influencing the error correction term in the above results.

Table 41. Results of ARDL Models

DV: Looting Attempts	Variable	Coefficient	Std. Error
Error Correction Term	Looting Attempts (-1)	**-1.9038*** **	0.2564
Short-term Relationships	D(Violent Conflict)	**9.1146*** **	2.4128
	D(Violent Conflict (-1))	**5.8033** **	1.9034
	D(Violent Conflict (-2))	3.2715	1.7700
	D(Violent Conflict (-3))	0.1984	0.8488
	D(Violence Against Civilians)	-5.0742	1.9251
	D(Violence Against Civilians (-1))	-2.5826	1.2827
	D(Violence Against Civilians (-2))	-1.2637	0.6187
	D(Violence Against Civilians (-3))	-0.7739	0.4617
	D(Non-Violent Conflict)	1.1976	0.7117
	D(Non-Violent Conflict (-1))	**1.1957***	0.6048
	D(Non-Violent Conflict (-2))	**1.2076***	0.5284
	D(Non-Violent Conflict (-3))	0.5518	0.3253
	Vegetation Health Index	170.7923	67.9757
	Precipitation	0.8246	1.4541
	Soil Moisture Content	**-358.2247** **	154.6613
	National Debt (% external)	-11.9904	10.1051
	Tourist Arrivals	**-0.0714***	0.0314
	Consumer Price Index (general)	**3.1409***	5.2367
Long-term Relationships	Violent Conflict	-5.2351	0.9201
	Violence Against Civilians	**4.3949** **	1.5777
	Non-Violent Conflict	-0.6513	0.4147

* p ≤ 0.10, ** p ≤ 0.05, *** p ≤ 0.01

Sensitivity Analyses

All of the above modeling approaches were initially tested with the looting attempt variable measuring all looting attempts recorded by either source (*All looting*) since it was the broadest definition of "looting attempts." If a model converged, was stable, and produced results, I then ran it with all of the other measures of looting attempts in both sets of measures (recorded by either source of satellite imagery vs. recorded by both sources). Since only the ARDL models both converged and could be considered identified, I only compared results for looting variables with this method. None the temporal analyses were run with weighted data since the weights are based on the proportion of sites in each governorate and these temporal analyses do not account for a spatial dimension.

The substantive results did not change between definitions of a variable – results for all looting recorded by either source were similar to all looting recorded by both sources (see Table 42). However, results did change between the types of looting measured. Coefficients were smaller and less likely to achieve significance for new looting attempts compared to all looting attempts and for prior looting attempts compared to new looting attempts. This pattern may reflect a decrease in the variation captured by each type of looting rather than a substantive difference as all looting captures the most variation followed by new looting and then prior looting. As such, all results discussed below are in reference to the broadest definition of looting attempts.

Table 42. Sensitivity Analyses for ARDL Models

	Variable	**All Looting Attempts**		**New Looting Attempts**		**Prior Looting Attempts**	
		Either Source	*Both Sources*	*Either Source*	*Both Sources*	*Either Source*	*Both Sources*
Long-term	Error Correction Term	-1.90***	-1.32***	-1.64***	-1.19***	-1.88***	-1.88***
	Violent Conflict	-5.24***	-3.27**	-4.66**	-2.65*	-3.37**	-3.13**
	Violence Against Civilians	4.39**					
	Non-Violent Conflict						
Short-term	D(Violent Conflict)	9.11***	3.22*	6.57*		5.79**	5.66**
	D(Violent Conflict (-1))	5.80**				3.57**	3.60*
	D(Violent Conflict (-2))						
	D(Violent Conflict (-3))						
	D(Violence Against Civilians)	-5.07**				-2.98*	-2.96*
	D(Violence Against Civilians (-1))	-2.58*					
	D(Violence Against Civilians (-2))	-1.36**					
	D(Violence Against Civilians (-3))						
	D(Non-Violent Conflict)						
	D(Non-Violent Conflict (-1))	1.20*					
	D(Non-Violent Conflict (-2))	1.21*					
	D(Non-Violent Conflict (-3))						
Exogenous	Vegetation Health Index	170.79**				114.41*	129.33*
	Precipitation						
	Soil Moisture Content	-358.22**					
	National Debt		-16.42*				
	Tourist Arrivals	-0.07*	-0.58**				
	Consumer Price Index (general)	3.14*	1.89*				

* p ≤ 0.10, ** p ≤ 0.05, *** p ≤ 0.01

Results by Hypothesis

Based on the above analyses, there is some evidence to support both temporal hypotheses. *Hypothesis 4* focuses on a more immediate or short-term relationship between stress and looting attempts while *Hypothesis 5* suggests a long-term or delayed effect. There is more evidence to support a short-term effect than a long-term effect and it varies by individual variables and theoretical constructs (Table 41).

With respect to short-term relationships, all three types of stress have at least one variable that increases the number of archaeological sites with evidence of looting attempts. For sociopolitical stress, both violent conflict and non-violent conflict are related to increases in looting attempts in the short-term but not the long-term. Changes in violent conflict in the current or previous month or month are associated with increases in the number of archaeological sites with looting attempts (9.11 and 5.80, respectively). Changes in non-violent protests show an effect one to two months prior (1.20 and 1.21, respectively) but not for the current month.

For long-term relationships, only sociopolitical stress could be evaluated and only one variable is statistically significant. Violence against civilians is related to looting attempts in the long-run but has no relationship in the short-term. These results suggest that over the period of 36 months, each additional incident of violence against civilians is associated with an approximately four more sites (4.39) with evidence of looting attempts.

Due to the ARDL model specifications, I can only speak to the effect of environmental and economic indicators on looting attempts in general – it is impossible to distinguish between short- and long-term effects. Only soil moisture content shows a relationship – in months where there is less moisture (drier soil), there will be more sites with evidence of looting attempts and vice versa. Economically, both tourist arrivals and the consumer price index are related to looting attempts. Fewer tourists leads to a slight increase in the number of sites (less than 1) while consumer prices have a stronger effect. A 1% change in the index from the 2010 baseline leads to an average of 3 additional sites (3.14) with evidence of looting attempts. It is possible that these relationships could hold across the short- and long-term; however, it is impossible to say for certain. As such, this can only provide suggestive evidence for the temporal hypotheses.

Spatio-Temporal Analyses (Hypothesis 6)

The spatio-temporal hypothesis suggests that archaeological looting attempts are clustered in both space and time with conditions of stress. To evaluate this hypothesis, I use primarily descriptive methods. As discussed in the methods chapter, I do not have sufficient data in this study to conduct any computationally intensive spatio-temporal analyses. Instead, I approach this hypothesis more qualitatively. First, I aggregate each key variable to its own space-time cube and calculate clustering and hot spot statistics for each.[65] I then visualize them in 2D and 3D to observe whether the identified patterns in the data change over time and space with each other. These analyses suggest limited support for the idea that archaeological looting attempts are co-located in space and time with conditions of stress. However, no clear patterns can be identified for any indicators of stress. This section first describes the results of creating the space-time cubes and then presents findings for the final hypothesis in more detail.

It is possible to create a space-time cube for a given variable either by aggregating based on defined locations (akin to space-time panel data) or based on individual points. Aggregating based on defined location only allows for a lattice-grid-shaped cube and does not allow for specific bin size specifications. Aggregating by point, on the other hand, allows for either lattice or hex shapes and has more flexibility with bin size options. With the exception of the data on sociopolitical stress, all of my key variables are space-time panel data and so I could aggregate them using the defined location tool. Following the same approach as my spatial analysis, I create space-time

[65] ArcGIS Pro only has three analyses you can run for spatio-temporal data: clustering, hot spots, and time series clustering. I initially ran all three analyses; however, because most of my data were binary rather than counts or continuous, the time series clustering did not produce any meaningful results. As such, only the results of the clustering and hot spots analyses are presented here.

cubes in multiple levels of aggregation and via multiple formats. Sociopolitical stress data are aggregated by point into hexagonal and lattice cubes with 10km and 50km bins. All other variables are aggregated by defined location into a lattice cube and by point into hexagonal and lattice cubes with 10km and 50km bins. I experiment with bins that were 150km; however, as a cube, this was too large of a size to capture any variation in the data.

These two methods of aggregation produce drastically different results. Aggregating by defined location maintained the location of each individual observation and so perfectly mirrors the underlying spatial distribution. Aggregating by point altered the spatial distribution by averaging where the bins location would be based on the locations of the individual points being aggregated. Figure 45 below demonstrates the differences in spatial distribution resulting from these two methods of aggregation for irregularly distributed data (e.g., looting). The differences for the environmental data which are collected in a uniform grid are not significant.

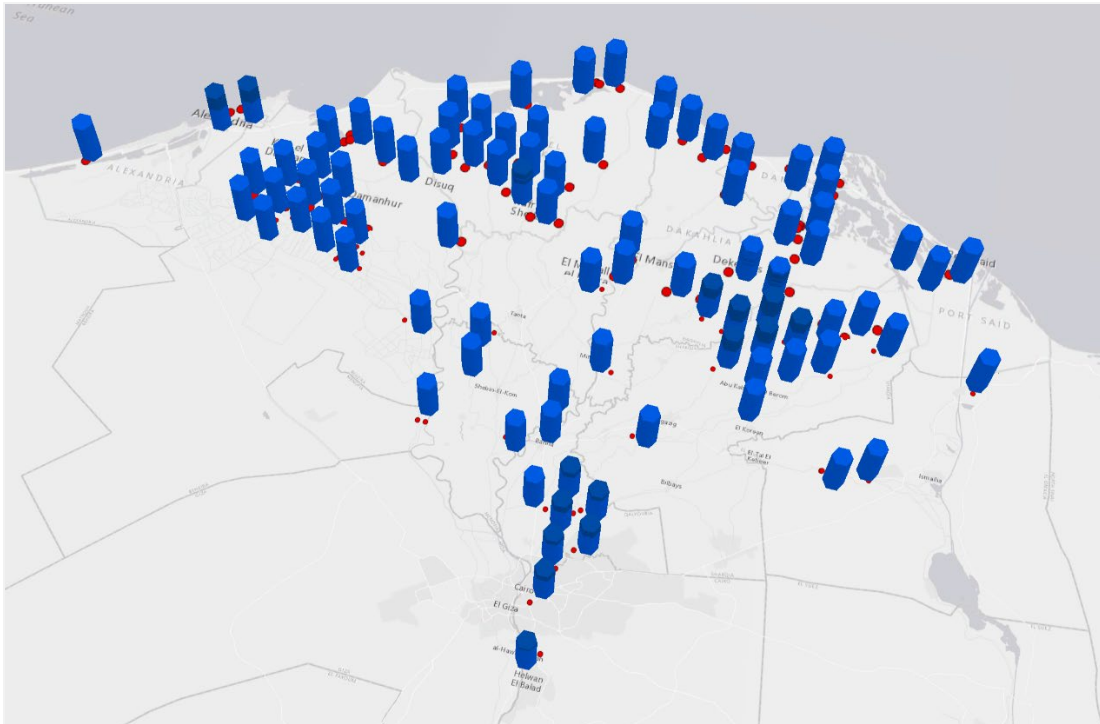


Figure 45. Aggregating archaeological looting attempts by point versus by defined location. Blue hexes indicate the locations for the aggregation by point bins. Red dots are the actual locations of archaeological sites.

Further, upon comparing the hexagonal and lattice-cubes, I find that the hexagonal "bins" do not perform as well in a spatio-temporal context as a result of their bin shapes. Lattice bins are the same size on all sides, whereas hexagonal bins are not. As such, the lattice provides a better comparison to the defined location cube, which also used a lattice shape. Similarly, I experiment to see how the 10-km and 50-km bin sizes compare in the spatio-temporal analyses below. The 50-km bins do not map as well to the spatial distribution as the 10-km bins and prove to be too aggregate to provide useful results for these data. Ultimately, I decide to test the spatiotemporal hypothesis using only the 10-km lattice grid cubes for the independent variables and the defined location cube for archaeological looting attempts. This preserves the original spatial distributions more accurately while allowing me to compare patterns in space and time.

Spatio-temporal Clustering of Looting Attempts with Indicators of Stress (Hypothesis 6)

To descriptively evaluate whether looting attempts is co-located with conditions of stress in space and time, I ran spatio-temporal versions of clustering and hot spots analyses. The results of these suggest that looting attempts are somewhat co-located with changes in sociopolitical stress and vegetation health. There are no clear patterns relative to precipitation amounts. It is also impossible to analyze any of the economic indicators spatio-temporally. The economic indicators have either temporal or spatial variation, but not both with enough granularity to be useful for a descriptive analysis. It is possible to create a space-time cube with annual time steps; however, since all other variables were measured at monthly intervals, an annual cube is not an appropriate comparison in this case. Similarly, the most granular spatial unit is the governorate, and an annual governorate cube is not appropriate for this set of analyses. As such, I could not evaluate whether looting attempts clustered in time and space with economic stress.

The spatio-temporal statistics provide a more detailed view of the type of clustering or hot spot activity than their spatial versions. Appendix 6 presents the detailed results for each analysis. Looting attempts have the most variation in their patterns, including consecutive, sporadic, and oscillating hot spots (30.7% of locations) as well as new, consecutive, intensifying, persistent and sporadic cold spots (26.4% of locations). Sociopolitical stress has very few statistically significant patterns – only 8% of locations had any evidence of hot or cold spots. Environmental stress locations are evenly split between hot and cold spot patterns for both vegetation health and precipitation.

From the clustering and outlier analyses, it appears that high value clusters (more locations with looting attempts) increase primarily during 2016 and the first part of 2017. Between 20% and 30% of locations exhibit some form of clustering or outliers across all time periods (see Appendix 6). Sociopolitical stress show increases in high-value clusters (locations with more incidents of conflict types) primarily in the end of 2015 and 2016. This suggests that there may be some temporal overlap with the clustering of looting attempts. For the environmental stress variables, I looked for low-value clusters, which corresponded to lower amounts of precipitation and values on the vegetation health index. Precipitation shows sharp increases in the end of 2015, 2016, and 2017. Vegetation health does not show any variation in the types of clustering present – there are large groups of low- and high-value clusters across all time periods. This suggests that if archaeological looting attempts are co-located with environmental stress, it is more likely to be with vegetation health than precipitation.

The results from these analyses indicate that there were several time periods in which increases in looting attempts might be co-located with sociopolitical and environmental stress. Using these findings as a guide, I visually inspected the end of 2015 to the beginning of 2016, end of 2016 to early 2017, and mid-2017 in more detail for evidence of co-located trends. The visual comparison finds some evidence to suggest that looting attempts are co-located in both space and time with conditions of stress; however, no consistent pattern can be identified (see Figure 46 – Figure 48). Similar to previous findings, sociopolitical stress and looting attempts are more likely to have spatial and temporal clustering or hot spots coincide. Though some precipitation and vegetation health concentrations share similar patterns to looting attempts, there is no clear visual relationship between these phenomena. Therefore, I can only find moderate support for this hypothesis.

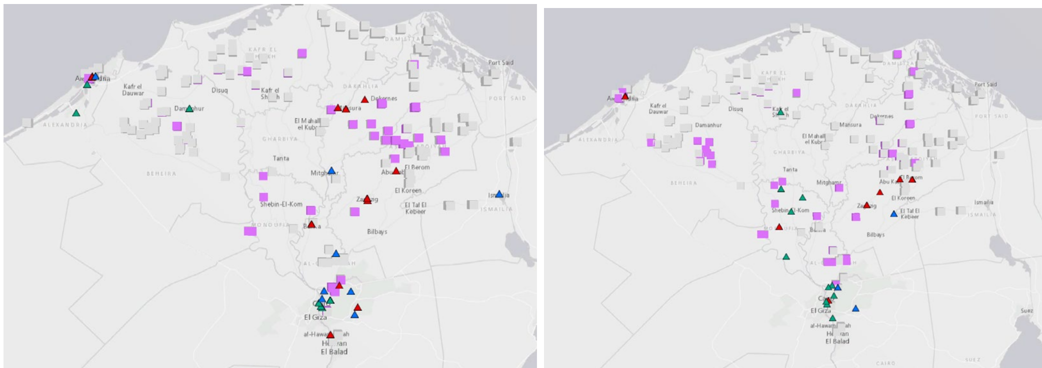


Figure 46. Sociopolitical stress by type and looting attempts in October 2015 (left) and December 2016 (right). Blue triangles indicate violence against civilians, green triangles indicate non-violent conflict, and red triangles indicate violent conflict. Purple indicates the presence of looting attempts.

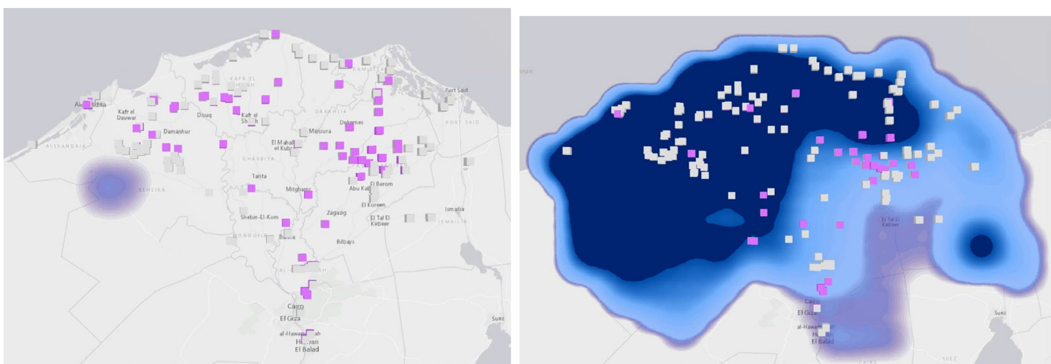


Figure 47. Precipitation and archaeological looting attempts in August 2015 (left) and October 2015 (right). Darker blue indicates more precipitation. Purple indicates the presence of looting attempts.

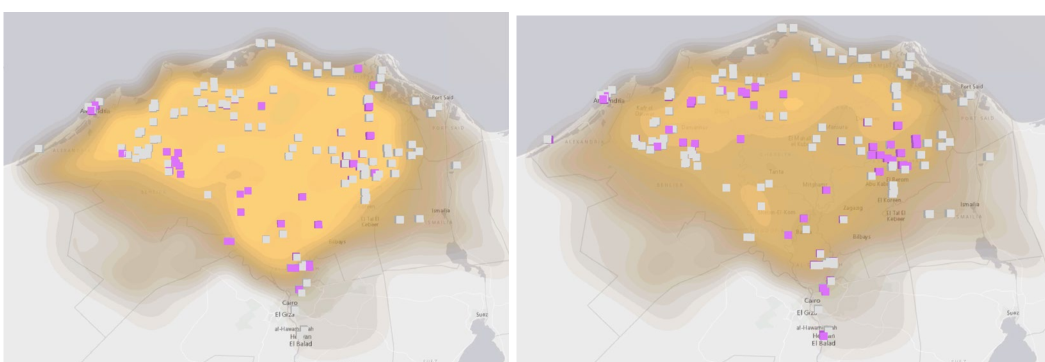


Figure 48. Vegetation health and archaeological looting attempts in December 2015 (left) and October 2016 (right). The darker the green, the healthier the vegetation. Purple indicates the presence of looting attempts.

Summary of Results

Overall, the above results indicate a mixed set of results for the six hypotheses tested in this study. Table 43 provides a summary of the results for each hypothesis. None of the analyses find strong or conclusive support for the hypothesized spatial, temporal, and spatio-temporal relationships. Further, in many cases, it is impossible to consistently use the same indicators of stress across types of analysis, which limits comparisons between findings. The spatial results are generally consistent across data format (gridded data vs point or polygon data), while both spatial and spatio-temporal results are highly dependent on the specifications used. These results should be interpreted as a reflection on the applicability of spatial, temporal, and spatio-temporal methods rather than substantively. Indeed, these results suggest that additional data and different types of data are necessary to evaluate the hypotheses presented in this dissertation substantively.

Table 43. Summary of Results

Hypothesis		Findings
1, 1a	Site characteristics (ownership, degree of ownership)	No support
2	Proximity to key locations (e.g., to populated centers, farms, etc.)	Limited Support
3	Co-location with areas experiencing sociopolitical, economic, or environmental stress	Moderate Support
4	Short-term relationship with conditions of stress	Moderate Support
5	Long-term relationship with conditions of stress	Limited Support
6	Co-location in space and time with conditions of stress	Limited Support

Chapter 7: Spatial and Temporal Patterns of Archaeological Looting Attempts

The results presented above provide an initial step towards understanding the spatial and temporal patterns of archaeological looting and a means of evaluating the utility of the methodological approach taken in this dissertation. Most importantly, they emphasize the importance of looking at multiple dimensions of archaeological looting. This chapter begins with a discussion of the importance of multidimensional analyses and the utility of satellite imagery for identifying looting attempts. It then discusses what, if anything, this study can say about spatial and temporal patterns of archaeological looting in Lower Egypt from 2015 to 2017. The chapter ends with a discussion of the limitations of this study and future directions for research.

The utility of spatial and temporal methods for identifying patterns in archaeological looting attempts

Using the combination of spatial, temporal, and spatio-temporal methods to investigate archaeological looting instead of just spatial or just temporal proved to be an important strategy for identifying possible patterns in archaeological looting attempts. Looking at a phenomenon like archaeological looting through only one dimension or using descriptives provides an incomplete picture. Such an aggregate view presents a misleading picture, especially when it relies of purely descriptive analyses. For example, looking descriptively at the overall temporal trends in sociopolitical stress and looting attempts suggests that there is an inverse relationship between the two (see Figure 24). Yet, the statistical temporal and spatial analyses suggested a more complex and nuanced relationship between the two phenomena. In particular, sociopolitical stress appeared to be largely driven by violent conflict, which could have either an immediate (short-term) or delayed (long-term) impact on archaeological looting attempts. The value of using spatial, temporal, and spatio-temporal methods in a unified methodological approach is that they can help to get closer to understanding the "true" underlying dynamics of these complex relationships. Even with limitations in data (small sample sizes, limited access to resources, measurement error, etc.) these methods help to uncover important dynamics that could otherwise by obscured by a unidimensional or purely descriptive analysis.

Beyond their ability capture dynamic relationships, the combination of these three types of methods is a particularly appropriate approach for analyzing data of varying qualities. Across all three dimensions, there are a range of possible analyses from descriptive to regression- and simulation-based. Though not all analyses will provide equal information or certainty about any underlying causal relationships, they can still provide useful insight into underlying patterns. This is particularly important for research that is seeking to investigate new areas where there is a lack of data or limited data. The range of analytical options allows researchers to examine questions with data of lower quality and to then expand their analyses later on when (or if) better data become available.

For example, in this dissertation there were several challenges with the data. The data on archaeological looting attempts had a very small sample size both spatially and temporally, which limited which kinds of analytical approaches were appropriate. Several of the independent variables were also only available at aggregate levels that provided insufficient variation for some of the analyses. Yet, I was able to conduct descriptive analyses for almost all of the conditions of stress of interest and identified possible patterns between archaeological looting and areas and times of stress. If, in the future, additional data were to become available, I could re-run the analyses used here and expand on them by incorporating the more sophisticated options available in each type of method, as appropriate. This flexibility makes using the combination of spatial, temporal, and spatio-temporal methods particularly suitable for investigating phenomena like archaeological looting. Further, even with the limitations in the archaeological looting data, satellite imagery proved to be a valuable source of data for the future.

The utility of satellite imagery for identifying looting attempts

This study found that there was significantly more satellite image coverage and availability of archaeological sites in Lower Egypt than expected. Some sites had almost complete coverage for every month of the three-year study period, and I was able to collect data from multiple different sources of imagery. Satellite imagery is currently one of the best sources of data on archaeological looting. Further, as it becomes easier to launch satellites, it is likely that coverage and availability of imagery will only increase. Already, companies like Planet have committed to trying to have 100% coverage of the earth every day. This increase in access and coverage will also likely continue to make satellite imagery a popular source of data in the future.

At the same time, the results of this study emphasize the importance of transparency in the data collection and coding process. Satellite sources can vary in the quality of imagery produced, depending on their algorithms, which can affect how clearly features are visible. Coding satellite images is an inherently subjective process

– what features are visible or not varies from person to person and their definition of "looting attempts." For example, I tried to replicate Parcak et al.'s count of looting "pits" for Region 3 Site 643 but was unable to do so, in part due to the differences in our approaches. Thus, being transparent and consistent about the methodology used to collect and code data is important for developing a robust and reliable database on archaeological looting for researchers and policymakers.

What does this tell us about spatial and temporal patterns of archaeological looting evidence?

Although it was impossible to identify any concrete underlying patterns in archaeological looting in space and time, the results presented above represent a baseline of information that future research can rely on. Additionally, though not conclusive some interesting findings emerged across the three sets of methods that enrich our understanding of looting attempts and suggest possible patterns. First, this study found no relationship between archaeological site ownership and whether that site had evidence of looting attempts. This runs counter to the theoretical framework of routine activity theory as ownership is often a clear sign of guardianship. It may be that there is no difference in guardianship between levels of ownership (e.g., all sites under any status receive active guards). Or, it is possible that the supreme council of antiquities does not supply any protection afforded by ownership status and so merely recording whether they are owned would not get at guardianship of a site.

Second, whether individual indicators of stress were related to looting attempts varied across method. For example, both spatial and spatio-temporal analyses suggested that precipitation and vegetation health were co-located with archaeological looting attempts. Yet, neither were significant in the temporal analyses. Soil moisture content exhibited the opposite pattern – it was statistically significant in the temporal analysis but had no impact on spatial or spatio-temporal analyses. Similarly, all types of sociopolitical stress had either statistically significant short- or long-term relationships with archaeological looting attempts. However, only violent conflict and non-violent conflict had any evidence of spatial or spatio-temporal co-location.

In part, this can be explained through the differences in measurement between the variables. Soil moisture content was measured as the largest spatial interval of the environmental variables and violence against civilians had the fewest incidents. As such they were less likely to have a spatial relationship. It is interesting to note though that neither of these variables showed a relationship in the spatio-temporal analysis either. This could suggest that the temporal relationship is in fact not correct, that the spatial relationship is inaccurate, or a combination of both. More generally, the fact that none of the conditions of stress examined in this dissertation had consistent findings across indicators and methods implies that they may need to be operationalized differently. For example, it may be that focusing largely on environmental variables like precipitation and vegetation health have an indirect relationship to looting attempts via economic stress. Even sociopolitical stress, which was ostensibly measured in consistent units had inconsistent results across methods. It is also possible that the time period used in this study was not long enough to capture delayed effects of environmental and economic changes, particularly at a national level.

A third interesting finding is that proximity was not consistently statistically significant and was only a possible protective factor. The theoretical framework presents two competing hypotheses with regards to proximity. Close proximity could on the one hand facilitate more looting attempts through ease of access and opportunity. Or, it could make looting attempts less likely through increased guardianship both officially (designated guards) and unofficially (more possible witnesses).

The results here suggest that there may be a very slight protective effect of being near an urban area or road, but not necessarily to a city or a capital. Though most capitals are in urban areas, it appeared that urban areas had an effect above and beyond any effect from capitals. The limitations of my data mean that any analyses are biased towards zero – towards not finding an effect when in fact there is one. Thus, though the magnitude of the effect is very small, the fact that the relationship is significant at a high level (0.001) lends support to its presence. The negative relationship between proximity to roads is also interesting as it suggests that when more effort is required to get to a site, it is more likely to experience looting attempts. Whether this is an artifact of the sample used in this study or a more general finding is an important question for further investigation.

In addition to these individual findings, two more general themes emerged from the results presented above. Of the types of stress analyzed in this dissertation, sociopolitical stress was most consistently related to looting attempts both descriptively and analytically. This held both at an aggregate level (all sociopolitical stress) and for violent and non-violent conflict. The relationship between violent conflict and looting has been proposed and discussed in previous studies (see e.g., De la Torre, 2006; Fabiani, 2018). However, a possible relationship with non-violent conflict, such as protests has received less attention. It is possible that this measure captures an element of economic stress as well as some of the protests were related to poor working conditions and access to food. If, indeed, looting attempts are co-located with non-violent forms of conflict in space and time, this is an important finding to investigate further. The consistency with which looting attempts appeared to be co-located with sociopolitical stress suggests that there may be something to this relationship; however, without more conclusive results it remains informed speculation.

A second theme of the results was that the methods used did not align as was theoretically expected. The results of the spatial and spatio-temporal analyses aligned more closely with each other than with the temporal results. It is true that ArcGIS Pro was used for both of sets of methods and this may impact the similarity of findings. Yet, theoretically, there should be some overlap between all three methods if looting attempts and conditions of stress are co-located in both space and time. The discrepancies with the temporal results center primarily on the role of environmental and economic stress, which could not be modeled as originally intended.

All three types of methods found some potential evidence of co-location with conditions of stress, implying that there may be important spatial and temporal patterns to uncover with better data in the future. At the same time, the discrepancies with the temporal results suggest that they may be inaccurate, that the spatio-temporal results are inaccurate, or some combination of the three are inaccurate. Though problematic for identifying substantive results from this particular dataset, this confirms that these methods can be used to validate each other's findings – particularly when spatio-temporal methods are used. Independently, spatial and temporal analyses may present conflicting accounts that cannot be easily reconciled. By including spatio-temporal analyses, it is possible to present a more complete picture and to identify possible model misspecifications to correct. If the results of all three methods align, then there is a stronger foundation for interpreting them substantively.

Theoretical Implications

Finally, the results presented above have implications for our understanding of archaeological looting as a routine activity. Each of the six hypotheses tested in this dissertation speak to the role of guardianship (via site ownership and proximity) and target suitability (via proximity and clustering in space and time with stressors) in this phenomenon. For example, none of the tests looking at guardianship found strong support for its role in decreasing looting attempts. Archaeological site ownership was not related to evidence of looting attempts and whether proximity to key locations was associated with fewer attempts depended on the individual model being tested. These findings raise questions about the best way to measure guardianship. Ownership and proximity are two of the simplest forms of protection. Ownership asserts that a single party is responsible for the area and is invested in its maintenance while being close to a key location like a city implies that there will be more people watching and thus there may be less opportunity.

Yet, a site can be both owned by the Supreme Council of Antiquities and included on the UNESCO world heritage site list. Theoretically, each designation provides protection for the archaeological site. In practice, establishing clear boundaries between different group's responsibilities (i.e. providing guards, maintaining the area, etc.) may make it more difficult to provide adequate protection. There may also be multiple levels of government (local, regional, and national) involved in the oversight of an archaeological site. Similarly, proximity to a city may increase opportunity because more individual routine activities may intersect with the site (e.g., utility workers). Both of these cases introduce additional complexity to the concept of guardianship and suggests that a clearer picture of the full scope of protections currently in place is needed before guardianship can be accurately evaluated. Further, only by evaluating the effectiveness of current practices can we better understand how to measure the concept of guardianship and thus improve the protection of archaeological sites.

The above findings also inform our understanding of what distinguishes sites that are suitable for looting attempts from those that are not. Some of the contextual factors – sociopolitical stress and precipitation – showed evidence of co-location with looting attempts spatially, temporally, or spatio-temporally. Others, such as vegetation health and unemployment showed no clear relationship. For example, precipitation showed significant relationships spatially and spatio-temporally, but not temporally. Similarly, sociopolitical stress showed the most evidence of a relationship to archaeological looting attempts across dimensions; however, even then there were no patterns evident in the relationships.

This inconsistency of the findings across dimensions suggests that there may be other factors not considered here that could be influencing which sites are considered suitable targets. It may be that characteristics of the archaeological sites themselves (e.g., site area, history of excavation, the types of antiquities represented at the site) or of the art market (e.g., prices for different types of objects) are more predictive of target suitability. This aligns with Clarke's (1999) object-focused CRAVED principles, which expands Cohen and Felson's definition of target suitability to focus on attributes that make objects more likely to be taken.

Contextual factors may still influence target suitability; however, they may also reflect offender motivation. For example, vegetation health and environmental conditions may dictate which sites experience looting attempts and who is able to attempt looting. Archaeologists often have to remove the top soil (can be several feet) to get to the archaeological remains using hydraulic equipment or dynamite, depending on the type of soil. If the soil is very difficult to dig through, then offenders may be less motivated to attempt looting at that site because they lack access to the necessary tools, or it would take too long to dig.

Though not explicitly examined, the results of this study allow for speculation about possible offender motivations. The temporal dynamics of different types of sociopolitical and looting attempts suggest that looting attempts may be viewed as a rationalized behavior resulting from multiple motivations. For example, the long-term relationship between archaeological looting attempts and violence against civilians implies that there is a delayed response between the incident of violence and the looting attempt. With the frequent protests and incidents of violence against civilians, discontent with the government is likely. In the aftermath of incidents of violence, it may be easier to rationalize looting an archaeological site. Since the Egyptian government is invested in its cultural heritage, looting a site could be seen as a justifiable way to act out against the government while also being a justifiable way of earning extra income.

At the same time, looting could be a routinized criminal activity that depends more on ease of accessibility among network actors than specific offender motivation. The proximity analyses suggested that sites closer to key locations are less likely to be looted, yet descriptively many sites were near a road (the maximum distance was 5 km). It may be that this road proximity is more important than proximity to a city as it provides a means of transporting artifacts to the next actor.

Limitations

The analyses and results of this study have some limitations that can be divided into those that will persist regardless of how much data is available and those that are the result of the limited data collection in this dissertation. Most of the limitations of this study could persist even with perfect data. Differences in the units of analysis across the individual indicators of stress made it difficult to include all variables in all analyses. For example, because most of the economic stress indicators (e.g., consumer price indices, unemployment, etc.) were measured annually and either at the governorate or national-level, they had very little variation temporally or spatially. In particular, the lack of spatial variation prevented their inclusion in any spatial or spatiotemporal analyses. As a result, economic and environmental stress, as theoretical constructs, were defined and operationalized differently across spatial, temporal, and spatio-temporal analyses. Relatedly, these differences in operationalization made it difficult to compare findings across these different types of methods. Soil moisture content, precipitation, and vegetation health all represent different dimensions of environmental stress and may not be directly comparable.

Another important limitation regardless of data concerns the operationalization of the dependent variable. Conceptualizing looting attempts as a binary variable impacted the types of methods that could be used in the spatio-temporal analyses. Temporally and spatially, these data were aggregated and so became a count variable representing either the number of sites or number of months with evidence of looting attempts, respectively. However, spatio-temporally, each site for each month was coded either as having evidence of looting attempts or not. Having a binary variable (as opposed to a count or continuous) interfered with some of the calculations used to identify spatio-temporal clustering. In particular, the time series clustering analysis relied on the attribute values of the looting attempts variable to identify patterns over time. With only two possible values, the results from this analysis proved uninterpretable, reducing the number of possible avenues of investigation.

Relatedly, despite all attempts to be transparent and document the methodology employed in this study, it may still be difficult to replicate these results. The analytical choices made in the modeling process for each method are inherently subjective. They represent what I thought was the most appropriate choice based on the limitations of the data. However, there is no guarantee that others would make the same choices and as such may come to different conclusions.

An important limitation related to the data collection used here relates to what methods were appropriate for analyzing the proposed hypotheses. The small sample size and presence of spatial and temporal autocorrelation affected which models were appropriate for testing the six hypotheses suggested by my theoretical framework. As a result, the findings from this dissertation are largely the product of descriptive analyses, which rest on individual interpretation. It is impossible to say anything concretely about the spatial and temporal patterns of archaeological looting attempts in Lower Egypt. Additionally, because the data could only capture surface-level attempts at looting, the results cannot be applied to other forms of theft or looting that may or may not occur at archaeological sites. For example, this dissertation cannot speak to looting attempts from within a necropolis or pre-existing archaeological excavations that were never filled in. It can only speak to such sites where there was evidence of someone trying to tunnel into the underground structure (e.g., a “pit” attempt). Though this was not a causal dissertation, the results should still be interpreted with caution and cannot be generalized beyond the sample used here.

Relatedly, I ran a lot of tests for significance across all of the methods employed in this dissertation. As such, it is possible that some of the findings presented above could be significant by chance. At the same time, the fact that the sensitivity analyses largely support the conclusions lends them some additional credibility.

Finally, using satellite images required a lot of storage space due to their large file sizes. The 1,321 images collected from DigitalGlobe combined used over a terabyte of space. As such, I stored all images collected and the ArcGIS Pro project they were loaded into on an external hard drive. Unfortunately, the hard drive containing all these images corrupted before I could finish coding the images that were re-collected during the coding validation process. It is important for future researchers to consider a data storage plan that incorporates multiple backups or a server to avoid these issues.

Future Directions

This dissertation suggests several avenues for future research that can be divided into data collection and coding and analysis. With respect to data collection and coding, this study identifies areas for improvement in both the dependent and independent variable. Future research should look to expand the number of archaeological sites in the "universe" as well as those sampled. The current sample and universe suffered from probable publication bias, which may have impacted the results in unknown ways. Using satellite remote sensing with on-the-ground verification ("ground-truthing") to identify both known and unknown archaeological sites would help to increase the sample size while avoiding possible publication bias.

Similarly, expanding the universe beyond Lower Egypt, to the entirety of Egypt and other countries would dramatically increase the sample size and variation among archaeological sites. Future research should also seek to sample more archaeological sites for analysis following the model of a stratified random sample. The governorates in Egypt are not equal in size, population, or concentration of archaeological sites. It is important that any stratification account for this imbalance and proportionally collect or weight the sample prior to analysis.

In addition to a wider geographic scope, data on archaeological looting should be collected over a longer period of time. Both environmental and economic stress may feasibly have delayed effects on increases in looting attempts. The temporal analyses here suggest that a three-year window (or at least this three-year window) was not long enough to identify any such long-term relationships. The longer the study period, the more nuanced any analysis of spatial and temporal patterns will be. Future research should also continue to use multiple sources of satellite imagery to collect data as this increases the temporal coverage of a given site and minimizes any stochastic processes determine image availability. Relatedly, future research should endeavor to collect archaeological information on the types of sites in the sample and their richness of content. This would provide important contextual information and facilitate analyses on whether patterns vary by type of site.

Further, future research should consider using both machine learning and ground-truthing in the process of coding archaeological looting attempts. The current study identified how challenging it is for the human eye to reliably and with reasonable confidence capture visual evidence of looting attempts consistently over an extended period of time. Using a set of training data, researchers could train an algorithm to do an initial pass through a set of images and identify "probable" looting evidence, "possible" looting evidence, and "not" looting evidence. Then, using ground-truthing to verify the results of the computer algorithm, researchers could improve the reliability of the initial results. Human coding would still be required; however, it would be to review and correct the initial coding decision. Such a process would introduce multiple layers of validation and inter-rater reliability, improving the quality of the resultant data.

Independent variables should be collected at more consistent spatial and temporal units. For example, using regional or governorate-level spatial data for all economic variables and environmental variables measured at closer spatial-intervals. Alternative measures for environmental and economic stress may be important for future research as well. For example, it may be that environmental stress only has an indirect relationship to looting attempts via poor harvests and economic stress. In this case, the focus should be on more detailed data on harvests and the economy. Other possible measures could include the number of tourists specific to cultural heritage sites and the presence of irrigation channels in a given area. Egypt collects data on the number of tourists who visit a variety of heritage sites; however, there is approximately a two-year delay in publication of these numbers. As such, any attempt to include these variables should also be looking at least two years in the past for the most recent data collection.

Or, it may be that some of the environmental measures, such as vegetation health, need to be measured in more detail. The current study used an aggregate index of vegetation health that did not distinguish between the different types of vegetation or the varied landscape in Lower Egypt. It may be more appropriate to look at the variation in vegetation in the region and to code for the presence of different types of vegetation in and around the archaeological sites in question. This may provide important contextual information that can speak to both the site's target suitability as well as offender motivation. The type of soil will dictate what kinds of vegetation are present and how difficult it is to dig there. Since agriculture plays a large role in Egypt's economy, it is likely that offenders could use the type of vegetation present as an indicator of how much effort they would need to loot in that area.

It may also be important for future research to look more at a wider variety of sociopolitical stress independently. This study identified three-types of stress that were theoretically relevant – violent conflict, non-violent conflict, and violence against civilians. Yet both violent and non-violent conflict contained a variety of types of stress that could be important to include on their own. For example, non-violent conflict included multiple types of economic protests (labor and famine-related), police protests, and religious protests. Economic protests may be a better indicator of economic stress than sociopolitical stress and could be included on its own in the future. Similarly, violent conflict contained both terrorism and police-militant clashes, which may theoretically have different relationships with looting attempts.

By incorporating a larger sample temporally and spatially as well as a more consistently measured set of indicators of stress, future research should be able to employ a wider variety of spatial, temporal, and spatio-temporal analyses. In particular, if the sample is large enough, the use of more computationally intensive simulation-based spatial and spatio-temporal analyses should be considered. These methods would allow for a more causal investigation of the spatio-temporal relationships between looting attempts and conditions of stress. Future research should also consider using alternative programs for conducting spatial and temporal analyses. Though very powerful, ArcGIS Pro is limited in the variety of spatio-temporal methods available and cannot handle temporal analysis at all. By contrast, the open-source statistical software R has a number of packages developed for spatial, temporal, and spatio-temporal analysis of complex systems that may be applicable to the study of archaeological looting attempts with a larger sample. Finally, researchers should also investigate the applicability of agent-based modeling for investigating these relationships due to its ability to accommodate small sample sizes and simulate behaviors.

Chapter 8: Conclusion

This dissertation sought to better understand archaeological looting in Lower Egypt and address the need for an empirical baseline of information in two ways. First, it sought to develop a transparent methodology for collecting and analyzing quantitative data on looting attempts. Second, it attempted to empirically identify possible spatial and temporal patterns of archaeological looting in Lower Egypt to establish a baseline of information from which future research can expand. Using a framework of routine activity theory from criminology, I identified six hypotheses suggesting spatial, temporal, and spatio-temporal relationships between archaeological looting and conditions of stress. Then, I collected images on 140 archaeological sites from multiple sources of satellite imagery and employed a systematic protocol for coding evidence of looting attempts. Finally, I systematically tested multiple specifications and methods for spatially, temporally, and spatio-temporally analyzing this new dataset.

Several findings are worth highlighting from this two-fold process. First, this research demonstrates the importance of looking at a complex phenomenon like archaeological looting across multiple dimensions. Looking solely at the temporal or spatial elements of this study would misrepresent the underlying relationship between looting and surrounding conditions of stress. Instead, the methodology presented in this dissertation focuses on looking dynamically across space and time to more accurately model relationships. In doing so, it facilitates a more nuanced means of modeling the possible interactions between the environment and situational opportunity that can result in crimes like archaeological looting. Further, the methodology employed is universal enough to be applied to other nascent areas of research.

Second, the data collection and coding strategy proved to be both practical and flexible as an approach to quantitative data collection. I was able to collect a large number of images on a small sample with limited resources and, had additional resources become available, would have been able to add to my data collection without difficulty. Satellite imagery also provided the most detailed data on archaeological looting attempts available via open source (especially compared to traditional and social media).

Third, even with the small sample size and challenges involved in using a binary measure of looting attempts, the analytic approach was able to identify possible patterns that could serve as a baseline for future research. Sociopolitical stress and looting attempts were the most consistently related across space and time, including both violent and non-violent conflict. There was also some evidence that environmental stress was co-located with archaeological looting attempts in space and time. Economic stress was only related temporally and in the short-term. Additionally, the proximity of archaeological sites to urban areas and roads appeared to have a protective effect, suggesting that more remote sites in this sample may have been more likely to be targeted.

Though the substantive findings of this study should be interpreted with caution, they provide a baseline of information and the proposed methodology suggests several directions for future research. First, future research should increase the representativeness of archaeological sites (known and unknown) in the "universe" for sampling. The sample size should also include more sites over more of Egypt and for a longer time period. Similarly, the theoretical constructs of sociopolitical, economic, and environmental stress should be refined through the use of new or different measures. More specific indicators of each type of stress (e.g., specific forms of protests as opposed to broad categories of conflict) should be included and every effort should be made to collect indicators with consistent temporal and spatial units of analysis. Second, the methodology proposed here should be applied in other contexts – Egypt as a whole, other countries, and other time periods – to see if the strategies described are applicable. Third, a combination of machine learning, ground-truthing, and additional layers of review should be incorporated into the satellite image coding strategy. This will provide increased validity and reliability to the resulting data.

Finally, future research should investigate a broader range of spatial, temporal, and spatio-temporal methods for analyzing this phenomenon. With more and more consistent data, methods like Bayesian modeling, spatio-temporal point pattern analysis, risk analysis, and agent-based modeling could more dynamically model the proposed relationships. Using methods designed for causal inference will also help to distinguish between statistically significant and irrelevant spatial and temporal patterns.

Ultimately, this dissertation presents a solid methodological foundation from which future research into the spatial and temporal patterns of archaeological looting attempts can build. The theoretical framework of routine activity theory facilitated the development spatial, temporal, and spatio-temporal hypotheses and could easily be expanded upon to include potential offender motivations. Satellite imagery provided a plentiful supply of data and given additional resources in the future could prove to be a valuable source of information globally. Such information will be especially valuable when used in concert with the transparent collection and coding strategy presented here, which increases the replicability of future studies. In particular, the results of this dissertation could be useful for Egypt's Ministry of Antiquities in the future. Egypt's recent law establishing a space archaeology program highlights the value they see in using satellite imagery to monitor their cultural heritage. The methodology proposed in this study could serve as a baseline from which Egypt's new space archaeology program could build and develop a robust and reliable approach to monitoring their heritage.

Appendix 1: Data Coding Instructions

Archaeological Looting Attempts Data Coding

The data take the form of raw satellite images from multiple sources (e.g. DigitalGlobe, Google Earth Pro). There are three steps to coding every archaeological site: (1) create the boundary of the site and record the attributes; (2) code images from the first source; and, (3) code images from the second source. Even though images are taken at daily intervals, these data are coded according to the month-year. There may be multiple images for a given month that will be coded at the month-year level. All images for a given month are reviewed in detail and coded into a single row. See **dates of satellite images coded** below for more detail on how to reconcile images with looting and without looting during the same month.

Step 1: Creating the Boundary for Each Site

Not all sites have distinct boundaries that are visible on satellite imagery and there is evidence that the boundaries and areas immediately next to the boundaries of a site may be the most vulnerable to looting attempts (BC Archaeology Branch, 2017). As such, prior to coding any information on looting evidence, draw a circle or oval around the earliest image for the site to set the "boundary" of the site. In ArcMap or ArcGIS Pro, use the *create feature layer* tool to create a layer dedicated to site boundaries. Using the *create feature* tool, select the circle or oval shape (depending on the shape of the site) and draw the boundary from approximately the center of the site such that there is a minimum of 50 meters from the "edge" of the site to the boundary. Use the measure tool to be sure. Record the site information in the attributes tab (**site name, FID, governorate,** and **buffer distance**). Once all boundaries for all sites have been created, use the *calculate geometry* tool to calculate the **boundary area** and export the layer to an excel table. Each of these variables is described in more depth below.

Site Name *(site name)*: The name of the archaeological site. Record the site name in the attribute field of the boundary layer.

FID (*FID)*: The unique identifier for each archaeological site created during the data collection process. Record the FID in the attribute field of the boundary layer.

Governorate (*governorate)*: The governorate – the first administrative boundary in Egypt – in which the site is located. Record the governorate in the attribute field of the boundary layer.

Boundary Distance *(distance)*: The distance from the "edge" of the site to the imposed boundary. This distance should be between 50 meters and 2 kilometers, depending on the size of the site and the surrounding area. Draw the smallest reasonable boundary possible. Record distances in meters in the attribute field of the boundary layer. It can be difficult to identify the "edge" of the site. When in doubt, try to find information from prior archaeological excavations or studies online. If no information is available, use the farthest site features you can find to establish an "edge" and draw a slightly larger boundary to ensure that to the best of your ability, the entirety of the archaeological site falls within the boundary.

Boundary Area *(area)*: The area of the boundary polygon in hectares. Calculate this field once all boundaries have been created and recorded.

<u>Steps 2 & 3: Code Each Source of Satellite Imagery Separately</u>

Code images by sampling round and then by source of imagery. In this case images were collected using a random sample stratified by governorate. As such, each sampling round includes approximately one site from each governorate. To code these data, start with the first site (identified by FID = 1) and code all images in the first source (e.g., DigitalGlobe) and then code all images in the second source (e.g., Google Earth Pro). Once all images from both sources are coded, move onto the next site in the sampling round and follow the same procedure. This ensures that each source of imagery is coded separately without the influence of the other source and relies on the assumption that coding images for a single site in one sitting will produce more consistent results.

If you have collected or have access to images taken prior to the study period of interest, briefly examine a few to note whether there is any evidence of looting prior to the start of the study period. This will help in coding the **evidence of prior looting** and **changes in prior looting** variables below. The earliest image for each site during the period of interest (here January 2015) should be examined in detail and carefully to identify key features (e.g., hills, buildings, natural features, lakes) that can cause shadows that can look like looting pits. By making note of these features, you can use them to identify what has changed or not changed from one image to the next. When in doubt about whether something is a hill or a hole (i.e. convex or concave), use the metadata from the image (time of day and date the image was acquired by the satellite) to calculate the sun's angle/position. This will identify where the shadows *should* occur for a concave or convex feature. Record the following information for each image – variables that are coded for multiple sources are described once with the variable's name for each source in parentheses.

Site Name *(site name)*: The name of the archaeological site.

Latitude (*latitude)*: The latitude coordinate in decimal degrees.

Longitude (*longitude)*: The longitude coordinate in decimal degrees.

Governorate (*governorate)*: The governorate – the first administrative boundary in Egypt – in which the site is located.

Month (*month)*: month

Year (*year*): year

Date (*date*): the date in the format YYYYMM.

Sampling Round *(sampling round)*: The round in which the site was sampled.

Coding Date (*coding date*): The date each image was coded. When possible, try to code an entire site's set of images on the same day during the same session. This will limit the potential for inconsistent coding.

Evidence of Looting Attempts *(DG_Evidence, GEP_Evidence)*: Records whether there is any evidence of looting attempts present in the current image. This can include both "fresh" instances of looting attempts (i.e., pits, trenches, etc.) and new evidence of prior looting attempts (i.e., mounding or filled in holes). This is coded as a binary variable – evidence of looting attempts is either present or it is not. When there are multiple images coded for a given month, mark a 1 if any of the images show evidence of looting attempts. If no images for a given month show evidence of looting attempts, mark a 0.

1 = There is evidence of looting attempts
0 = There is no evidence of looting attempts

Multiple Types of Evidence *(DG_MultType, GEP_MultType)*: Indicates whether there is evidence of both "fresh" looting attempts and prior looting attempts. This is coded as a binary variable. When there are multiple images for a given month, mark 1 if across all the images there are multiple types of looting. For example, if an image 2/5/2015 shows evidence of prior looting attempts and an image for 2/16/2015 shows evidence of "fresh" looting attempts, then mark 1. If only one type of evidence is present across all images, mark 0.

1 = There are multiple types of looting attempts present
0 = There are not multiple types of looting attempts present

Fresh Looting Attempts Evidence *(DG_LootAtt, GEP_LootAtt)*: Indicates whether there is any *new* evidence of fresh looting attempts compared to the previous month. Evidence includes potential looting pits that were not present in previous images, signs of active digging (fresh mounding of earth in close proximity to potential looting pits). Freshly turned earth is darker in color than the surrounding soil. This is coded as a binary variable. When there are multiple images for a given month, mark 1 if any of the images show new evidence of fresh looting attempts since the previous month. If none of the images do, mark 0.

1 = There is new evidence of fresh looting attempts since the last image/month coded
0 = There is not new evidence of fresh looting attempts since the last image/month coded

Prior Looting Attempts Evidence *(DG_Prior, GEP_Prior)*: Indicates whether there is any *new* evidence of prior looting attempts compared to the previous month. Prior looting attempts usually refers to mounded earth that does not appear to have been disturbed recently. There are no potential holes present in the mounding but there is also usually no vegetation covering the mounds yet. Evidence of prior looting attempts is more likely to be present when there is a gap in monthly coverage of a site (i.e., if there are four months in between the previous month and the current month and image). This is coded as a binary variable. When there are multiple images for a given month, mark 1 if any of the images show new evidence of prior looting since the previous month. If none of the images do, mark 0.

1 = There is new evidence of prior looting attempts since the last image/month coded
0 = There is not new evidence of prior looting attempts since the last image/month coded

Change in Prior Looting Attempts Evidence *(DG_ChgPrior, GEP_ChgPrior)*: Indicates whether since the previous month there has been a change in the evidence of prior looting. This can take several forms: (1) going from no evidence of prior looting to evidence of prior looting; (2) going from evidence of prior looting to no evidence of prior looting; (3) increased area / amount of evidence of prior looting; or (4) decreased area / amount of evidence of prior looting. When there are multiple images for a given month, mark 1 if the *earliest* image for the month shows changes in prior looting compared to the previous month coded, otherwise code 0.

1 = There is evidence of changes in prior looting attempts since the last image/month coded
0 = There is no evidence of changes in prior looting attempts since the last image/month coded

Dates of Satellite Images Coded *(DG_ImageDate, GEP_ImageDate)*: The date of the satellite image coded. This is also the date that the image was acquired by the satellite. Because the study period is the month-year, there may be multiple images for the same month. If no looting evidence is present across any of the images for a given month, record all image dates. If there is looting present in some but not all images for a given month, record *only* the image dates where looting occurs. This is because in the aggregate, recording the image dates without any looting as well as image dates with looting will give an inaccurate representation of the proportion of the month with looting evidence.

Notes *(notes)*: Records any notes on the coding of individual images during a given month.

Socio-Political Data Coding

The data on sociopolitical stress come from three sources: the Global Terrorism Database (GTD), the Armed Conflict Location Event Dataset (ACLED), and the Uppsala Conflict Data Program (UCDP). Some variables were imported from the ACLED and GTD datasets (e.g., **Event type**). All incidents were coded according to all variables below. Variables with an asterisk (*) are those I created and added to the data.

***Id (*id*):** A unique identifier for each incident of armed conflict. The IDs for the GTD, ACLED, and UCDP were kept and merged together.

Date of incident (*year, month, day*): code in 3 columns, one for year, one for month, and one for day.

Event Type (*eventtype*): From the ACLED, describes the granular type of event for each incident. Some incidents are coded twice if there are two event types present. These duplicates were removed from the data during cleaning.

***First Actor (*actor1*):** From the ACLED, describes the type of actor involved in the conflict incident. Where a specific group or individual is known, they are identified. Where not, a more general type of actor is recorded (e.g., protesters). I combine this with the *assoc_actor_1* variable in the ACLED so that there is more granularity to the actor type.

***Second Actor (*actor2*):** From the ACLED, describes the type of actor involved in the conflict incident. Where a specific group or individual is known, they are identified. Where not, a more general type of actor is recorded (e.g., protesters). I combine this with the *assoc_actor_2* variable in the ACLED so that there is more granularity to the actor type.

Admin1 (*admin1*): From the ACLED. The governorate or region in which the incident took place.

Admin2 (*admin2*): From the ACLED. The city or area in which the incident took place.

Province and State (*provstate*): From the GTD "admin1". The governorate or region in which the incident took place. During cleaning was renamed *admin1* so that it could be merged with the ACLED variable.

City (*city*): From the GTD "admin2". The city or area in which the incident took place. During cleaning was renamed *admin2* so that it could be merged with the ACLED variable.

Location (*location*): From the ACLED. The specific location of the incident.

Latitude (*latitude)*: From the GTD & ACLED. The latitude of the incident. Latitude and Longitude were used to compare incidents during cleaning to determine whether there were any overlapping events between the GTD and the ACLED.

Longitude (*longitude)*: From the GTD & ACLED. The longitude of the incident. Latitude and Longitude were used to compare incidents during cleaning to determine whether there were any overlapping events between the GTD and the ACLED.

Description of incident (*description)*: Provides a brief 1-2 sentence overview of the incident from the database as applicable. During cleaning the variables were made to both be named "description" and so could be merged into one variable.

From GTD = *incident summary* variable
From ACLED = *notes* variable

Geographic precision (*geo_precision)*: A variable from the ACLED that indicates their confidence in the reported location.

1 = Event reported for a specific town with coordinates provided
2 = Event reported in a small region or general area with georeferenced coordinates
3 = Event reported in a larger region – in this case the ACLED choses the provincial capital

Fatalities (*fatalities*): The number of fatalities recorded and verified in the source material from the ACLED.

***Multiple incident (*multincident)*:** Code according to the following scheme. This variable accounts for acts that occur as part of a series. Police killings of suspected assailants or attackers are not coded as "multact," unless the alleged incident is recorded elsewhere already.

1 = Yes
0 = No

***Related incident (*relatedincidents)*:** The IDs of the other related rows in the coordinated/series of incidents. If it is a series of incidents, then the first instance records the ID of the last one and the others record the ID of the first one.

***Conflict type (*conflicttype*):** Code according to the following scheme. In the GTD, coding for 2 (i.e. terrorism) means that there was a "0" for the variable *doubterr*. In the GTD, all others from the variable *doubtterr* should be evaluated and coded as appropriate. In the ACLED, each sentence is coded individually, regardless of the *event_type* variable. Generally, "riots and protests" corresponds to "riots/protests," "remote violence" and "strategic development" correspond to terrorism and "battle no change of territory" to police-militant clashes. "Violence against civilians" contains terrorism, religious violence, and violence against civilians. Riots/protests includes riots, protests, and skirmishes between different groups of demonstrators. If the incident focuses on the action of the protest itself, then code it as a riot/protest. If the protest/riot/protesters are the victims or tangential to the action, then code it as terrorism. Both successful and unsuccessful attacks are coded as their intended type of attack (e.g., a foiled terrorism attack is still a terrorist attack). In the UCDP, the field *source_headline* was used to determine which type of conflict occurred.

1 = Riots/protests
2 = Terrorism
3 = Religious violence
4 = Violence against civilians
5 = Police-militant clashes
6 = Other

***Attack Type (*attacktype*):** This variable combines the attack types from the GTD, and additional forms of attack based on the content of each dataset. Code according to the following scheme. Information for this variable comes from the GTD variable *attacktype1*. When combining with ACLED's type of incident, refer to the descriptions of each type of attack below: #1-9 come from the GTD, #10-18 are based on the ACLED codebook. In the UCDP, the field *source_headline* was used to determine which type of conflict occurred. There is a hierarchy rule in place for the attack type coding. The primary incident is the one coded. The primary incident is the one that motivates the contact between the two individuals or groups. This is often the first incident in a sentence, but not always.

Examples:

- "The driver of the former presidential candidate Abdel Moneim Abul Fotouh was kidnapped and tortured whilst on his way to the Fifth Settlement district. His family blamed the Homeland Security apparatus. The reason behind the arrest of the driver is unknown, but some observers speculate it was a slap on Abouel Fotouh's hand for critical remarks he recently made against the government of President Abdel Fattah al-Sisi."
    - Kidnapping is the primary incident because the torture could not occur without the kidnapping

- "At least 17 people were killed on Sunday in clashes between police and protesters in Cairos eastern Matariyah district."
    - The protest is the primary incident. The killings would not have occurred without the protest.

Code	Label	Description
1	Assassination	An act whose primary objective is to kill one or more specific, prominent individuals. Usually carried out on persons of some note, such as high-ranking military officers, government officials, celebrities, etc. Not to include attacks on non-specific members of a targeted group. The killing of a police officer would be an armed assault unless there is reason to believe the attackers singled out a particularly prominent officer for assassination.
2	Armed assault	An attack whose primary objective is to cause physical harm or death directly to human beings by use of a firearm, incendiary, or sharp instrument (knife, etc.). Not to include attacks involving the use of fists, rocks, sticks, or other handheld (less-than-lethal) weapons. Also includes attacks involving certain classes of explosive devices *in addition to* firearms, incendiaries, or sharp instruments. The explosive device subcategories that are included in this classification are grenades, projectiles, and unknown or other explosive devices that are thrown.
3	Bombing/explosion	An attack where the primary effects are caused by an energetically unstable material undergoing rapid decomposition and releasing a pressure wave that causes physical damage to the surrounding environment. Can include either high or low explosives (including a dirty bomb) but does not include a nuclear explosive device that releases energy from fission and/or fusion, or an incendiary device where decomposition takes place at a much slower rate. If an attack involves certain classes of explosive devices along with firearms, incendiaries, or sharp objects, then the attack is coded as an armed assault only. The explosive device subcategories that are included in this classification are grenades, projectiles, and unknown or other explosive devices that are thrown in which the bombers are also using firearms or incendiary devices.

Code	Label	Description
4	Hijacking	An act whose primary objective is to take control of a vehicle such as an aircraft, boat, bus, etc. for the purpose of diverting it to an unprogrammed destination, force the release of prisoners, or some other political objective. Obtaining payment of a ransom should not the sole purpose of a Hijacking but can be one element of the incident so long as additional objectives have also been stated. Hijackings are distinct from Hostage Taking because the target is a vehicle, regardless of whether there are people/passengers in the vehicle.
5	Hostage taking (barricade incident)	An act whose primary objective is to take control of hostages for the purpose of achieving a political objective through concessions or through disruption of normal operations. Such attacks are distinguished from kidnapping since the incident occurs and usually plays out at the target location with little or no intention to hold the hostages for an extended period in a separate clandestine location.
6	Hostage taking (kidnapping)	An act whose primary objective is to take control of hostages for the purpose of achieving a political objective through concessions or through disruption of normal operations. Kidnappings are distinguished from Barricade Incidents (above) in that they involve moving and holding the hostages in another location. Note that if kidnapping lasts for multiple months, it should be coded for each month as a series of incidents.
7	Facility/infrastructure attack[66]	An act whose primary objective is to cause damage to a non-human target, such as a building, monument, train, pipeline, etc. Such attacks include arson and various forms of sabotage (e.g., sabotaging a train track is a facility/infrastructure attack, even if passengers are killed). Facility/infrastructure attacks can include acts which aim to harm an installation, yet also cause harm to people incidentally (e.g. an arson attack primarily aimed at damaging a building but causes injuries or fatalities).

[66] My coding for facility/infrastructure differs from the GTD in that I include explosives in this category.

Code	Label	Description
8	Unarmed assault	An attack whose primary objective is to cause physical harm or death directly to human beings by any means other than explosive, firearm, incendiary, or sharp instrument (knife, etc.). Attacks involving chemical, biological or radiological weapons are considered unarmed assaults.
9	Unknown	The attack type cannot be determined from the available information.
10	Political protests	Events involving individuals and groups who demonstrate against a political entity, government institution, policy, group, tradition, businesses or other private institutions. Political protests involve individuals and groups peacefully protesting against actions by the government that are political in nature. A rally is a more aggressive form of political protest.
11	Economic protests (famine)	Events involving individuals and groups who peacefully demonstrate against a political entity, government institution, policy, group, tradition, businesses or other private institutions. Economic protests focusing on famine involve individuals and groups demonstrating against policies or actions that reduce the amount of food available to the public.
12	Economic protests (labor)	Events involving individuals and groups who peacefully demonstrate against a political entity, government institution, policy, group, tradition, businesses or other private institutions. Economic protests focusing on labor involve individuals and groups demonstrating against policies, businesses, institutions, or traditions that affect the labor market. This can include wages, forced conscription, unfair market practices, etc.
13	Religious protests	Events involving individuals and groups who peacefully demonstrate against a political entity, government institution, policy, group, tradition, businesses or other private institutions. Religious protests involve individuals and groups demonstrating against other religious groups or against policies, traditions, institutions, or actions that are perceived to infringe on one group's religious rights or traditions. A group of Muslims may protest against the construction of a new Coptic church in an area with a mosque. Similarly, Christians may protest against the government for their lack of representation in governance.

Code	Label	Description
14	Police protests	Events involving individuals and groups who peacefully demonstrate against a political entity, government institution, policy, group, tradition, businesses or other private institutions. Police protests involve individuals and groups demonstrating against actions by the police, military, and security forces (all of which are under the authority of the Ministry of the Interior in Egypt).
15	Other protests	Events involving individuals and groups who peacefully demonstrate against a political entity, government institution, policy, group, tradition, businesses or other private institutions. Other protests involve demonstrations against issues not described above.
16	Arson	An act whose intent is to cause destruction or damage to property, persons, or places through the use of fire. Arson must be intentional. A house that catches fire incidentally after an altercation is not arson.
17	Torture	An act whose intent is to obtain the information from individuals or groups through violent means. Torture may include armed assault (e.g., through electroshock, stabbing, sodomy, etc.) and unarmed assault (e.g., through beatings). In addition to obtaining information such as a confession, these acts may be designed as a warning or punishment for behavior that threatens or is perceived as threatening to the torturer. Police may torture a confession for a crime or may torture a human rights lawyer for their work. A terrorist organization may torture to obtain strategic information on future attacks or to issue a warning to the other side not to pursue their current course.
18	Riots	Spontaneous acts of violence by disorganized groups, which may target property, businesses, other disorganized groups, or security institutions.

***Domestic/International (*domestic*):** Code according to the following scheme. A domestic incident is one that is domestic in focus and perpetrated by citizens of Egypt. An international incident is on that is international in focus and/or is perpetrated by people from other countries, regardless of whether it was within the borders of Egypt. This variable was coded by conducting a search of all summary information for key words of known countries to be active or have international relevance to Egypt, including Palestine, Lebanon, the US, Israel, and France. In addition, most internationally focused incidents appear to have occurred around or in embassies, so the key word search also included 'embassy.' It is important to note that this variable was in no way coded based on the 4 "international" variables in the GTD (*INT_LOG, INT_IDEO, INT_MISC, INT_ANY*).

1 = International
2 = Domestic
3 = Unknown

***Violence (*violence*):** A binary indicator of whether violence occurred as part of the conflict. Violence is defined both as physical violence between individuals (either armed or unarmed) and as an act of violence, such as an explosion, regardless of whether there were any casualties. This is intended to get at whether protests contain violent clashes with police. Many of Egypt's peaceful protests contained other elements like the Ultras, or the Ahrar movement, which sought out protests to instigate violence and turn them into riots. In other cases, 'riotous' behavior is intentionally planned as an element of the protest. However, this should be coded for all sentences, regardless of whether it is a protest or not as violence could be subsumed under other types of attacks. Unless specified, security forces dispersing a march or protest is not inherently violent.

1 = Yes
0 = No

***Check (*check*):** Binary indicator for whether further review of the case is needed. For example, if a story reports an arrest for alleged bombing, code "check" to make sure you don't duplicate the bombing and that the date (month) of the bombing is accurate.

1 = Yes
0 = No

***Notes (*notes*):** Additional notes on coding.

***Source (*source*):** Code according to the following scheme.

1 = ACLED
2 = GTD
3 = UCDP

Economic Indicators Data Coding

The data on economic stress come from three sources: Egypt's Centralized Agency for Public Mobilization and Statistics (CAPMAS), the Food and Agriculture Organization of the United Nations (FAO), and the World Bank. CAPMAS provides quarterly data on unemployment at a governorate level. The FAO provides monthly data at the national level on consumer price indices. The World Bank provides yearly data at a national level on consumer price indices, national debt, inflation, and tourism. The variables below were downloaded from their respective sources and compiled into an economic indicators dataset to be transformed as needed.

Unemployment *(totunem, totythun)*: CAPMAS measure unemployment as all individuals between the ages of 15 and 64 years who have the ability to work, would like to work, and actively search of it, but who are unable to find any work. They report both total unemployment and unemployment by age ranges (from which a youth measure can be constructed) for each governorate as well as at the national level.

Consumer Price Index – General *(cpigen)*: According to the FAO, the consumer price index measures the price change between the current reference periods (in this case month) of an average basket of goods and services purchased by households and the baseline (in 2010). A general CPI includes both goods and services in the calculation.

Consumer Price Index – Food *(cpifood)*: According to the FAO, the consumer price index measures the price change between the current reference periods (in this case month) of an average basket of goods and services purchased by households and the baseline (in 2010). A food CPI includes only food-based purchases in the calculation.

Short-term Debt as Percent of Total Reserves *(stdres)*: The World Bank defines this indicator as, "all debt having an original maturity of one year or less and interest in arrears on long-term debt, including reserves of gold."

Short-term Debt as Percent of Total External Debt *(stdext)*: The World Bank defines this indicator as, "all debt having an original maturity of one year of less and interest in arrears on long-term debt. Total external debt is debt owed to nonresident repayable in currency, goods, or services – it is the sum of public, publicly guaranteed, and private nonguaranteed long-term debt, use of IMF credit, and short-term debt."

International Tourism Arrivals *(tourarr)*: The World Bank defines this indicator as, "the number of tourists who travel to a country other than that in which they have their usual residence, but outside their usual environment, for a period not exceeding 12 months and whose main purpose in visiting is not business-related." These data refer to the number of arrivals, not the number of people traveling – a person who makes several trips to a country during a given period is counted each time as a new arrival.

Inflation based on the Consumer Price *(infconpr)*: The World Bank defines this indicator as, "inflation as measured by the consumer price index and which reflects the annual percentage change in the cost to the average consumer of acquiring a basket of goods and services that may be fixed or changed at specified intervals."

Environmental Indicators Data Coding

Data on environmental stress come from the National Aeronautics and Space Administration (NASA), the National Oceanic and Atmospheric Administration (NOAA), and the Food and Agriculture Organization of the United Nations (FAO). NASA provides access to data on soil moisture content and vegetation health. NOAA provides information on precipitation, and FAO provides data on crop health and production. The variables below were downloaded from their respective sources and compiled into an environmental indicators dataset to be transformed as needed.

Soil Moisture Content *(GWETPROF)*: Data on the soil moisture content come from the Modern-era Retrospective analysis for Research and Applications version 2 (MERRA-2) data, which focuses on providing historical climate analyses for a broad range of weather and climate time scales (GMAO, 2015). Data were downloaded as a monthly mean, time-averaged, single-level, assimilation land surface diagnostic with coverage from 1980 to 2018 at approximately 0.5-degree spatial intervals. From this file a single variable on the average profile of soil moisture was used. This profile represents the degree of saturation of the soil measured to the bedrock from 0 to 1. For example, a value of 0.51 would indicate that just over half of the soil is saturated with moisture from the surface to the bedrock.

Vegetation Health *(NDVI)*: Data on vegetation health come from a Normalized Difference Vegetation Index (NDVI), which is one of the longest continual remotely sensed time series observations, using both the red and near-infrared (NIR) bands to create an index that reflects the health of vegetation on a scale between 0 and 1 (Didan & Barreto, 2018). The data were collected as part of the Suomi National Polar-Orbiting Partnership (S-NPP) NASA Visible Infrared Imaging Radiometer Suite (VIIRS) Vegetation Indices, which provides the indices through a process of selecting the best available pixel over a monthly acquisition period at 0.05-degree resolution (Didan & Barreto, 2018). From these data, a single NDVI variable was used.

Precipitation *(prec)*: Data on precipitation come from the GLDAS Noah Land Surface Model monthly version 2.1 dataset available from NOAA or the ArcGIS Living Atlas. The data from this dataset are the result of a simulation from 2000 to 2019 that created historical estimated precipitation amounts (and other atmospheric measures) by forcing together three sources. Specifically, this dataset combines the National Oceanic and Atmospheric Administration/National Center for Environmental Prediction's Global Data Assimilation System (GDAS) atmospheric analysis fields, spatially and temporally disaggregated Global Precipitation Climatology Project (GPCP) precipitation fields, and observation based downward shortwave and longwave radiation fields derived using the method of the Air Force Weather Agency's AGRicultural METeorological modeling system (AGRMET) (Beaudoing et al., 2016; Rodell et al., 2004). The combined used of simulated and observed data provides a reliable source of precipitation estimates (in millimeters) at a 0.25-degree spatial resolution. From this dataset, estimated precipitation amounts were extracted for Lower Egypt from 2015 to 2017.

Crop Production *(totprod)*: Data on crop production come from a detailed FAO report on crop harvested area, yield, and production. FAO provides data on individual crops as well as aggregate crop type. Because harvesting occurs at different points during the year depending on the type of crop, these data are reported annually as a compilation of all crop production (in tonnes). From this dataset, only the aggregate crop types were used for crop production from 2015 to 2017.

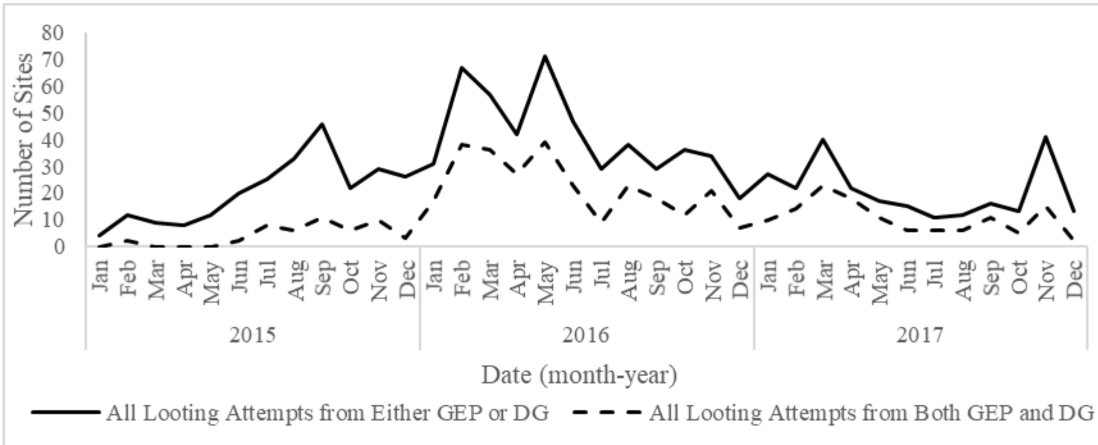
Appendix 2: Spatial Methods

Method	Analysis	Description	Data Format	Relevant Hypothesis
Spatial Autocorrelation	*Global Moran's I*	Measures spatial autocorrelation based on both feature locations and their values concurrently. Based on location and attribute information, it calculates an index value by creating a deviation from the mean. This index is compared to a test statistic to determine whether or not to reject the null hypothesis that the feature is randomly distributed in space.	Point data, polygon data	Spatial Distribution Descriptive Statistics
	Local Moran's I	Measures whether there is clustering based on the surrounding features in a "neighborhood." If a neighborhood distance (threshold) is specified, this will look only within that distance for each feature. If not, it will calculate the optimal threshold. Identifies whether a feature is surrounded by similarly high values (high-high cluster), similarly low values (low-low cluster), high values (low-high outlier), or low values (high-low outlier).	Point data, polygon data	
	Incremental Spatial Autocorrelation	Calculates the Global Moran's I statistic at multiple distances to determine how clustering and spatial dependence changes at different thresholds. The results indicate whether each distance measured is clustered, random, or dispersed and identifies peaks at which the identified pattern is more pronounced.	Point data	

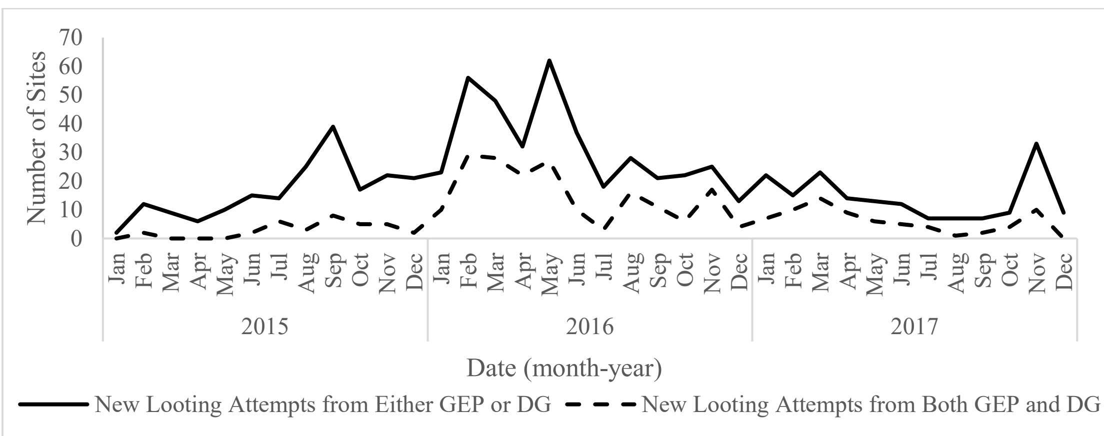
Method	Analysis	Description	Data Format	Relevant Hypothesis
Clustering	*Ripley's K Function*	Provides a summary of the spatial dependence of a variable over a range of distances, illustrating how clustering or dispersion changes as neighborhood size changes. At each distance, observed and expected "K-values" are calculated. When the observed K-value is greater than the expected K-value for a given distance, then it is more clustered than would be expected by random chance. When weighting the K-value (e.g., by counts of incidents), results can indicate: the clustering of feature values (as opposed to locations) relative to the baseline unweighted k-values or relative to complete spatial randomness.	Point data, polygon data	Hypothesis 3
	Voronoi Maps	Creates a set of polygons that divide the study area into proximal zones. Each polygon is created such that any location within the zone is closer to its input point than to any other input point.	Point data	
Proximity	*Geodesic Distance*	Calculates the shortest path between two points without reference to the road network or any physical barriers in the landscape. This distance is calculated using the geodesic method, which accounts for the curvature of the earth.	Point data, polygon data	Hypothesis 2 and Hypothesis 3
	Nearest Incident	Calculates the shortest path along a road network between two variables. It is possible to assign costs/barriers to the network map that determines which routes are considered "shortest." Also specified the type of distance being calculated including, driving time/distance, rural driving time/distance, and walking time/distance.	Point data, polygon data	
Ordinary Least Squares Regression clustered on Site (or grid-cell)		Multivariate regression using ordinary least squares to look at the effect of site characteristics (e.g., ownership status) and distance to key locations on looting attempts. Clustering on the site (or grid-cell) controls for potential spatial autocorrelation.	Point and gridded data where the unit is the site or grid-cell containing at least one site, respectively.	Hypothesis 1, Hypothesis 1a, and Hypothesis 2

Appendix 3: Additional Descriptive Statistics and Information

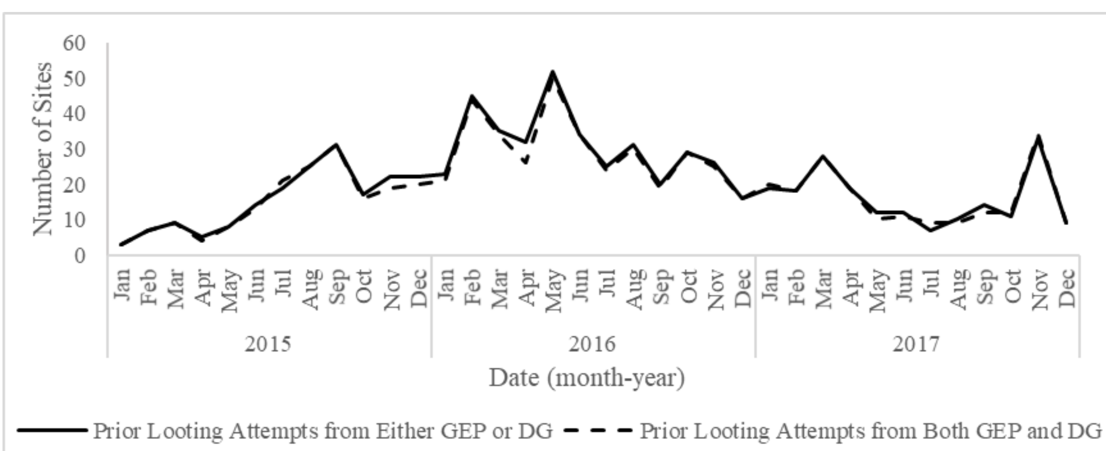
Looting Attempt Evidence Types by Coding Strategy (2015 – 2017)



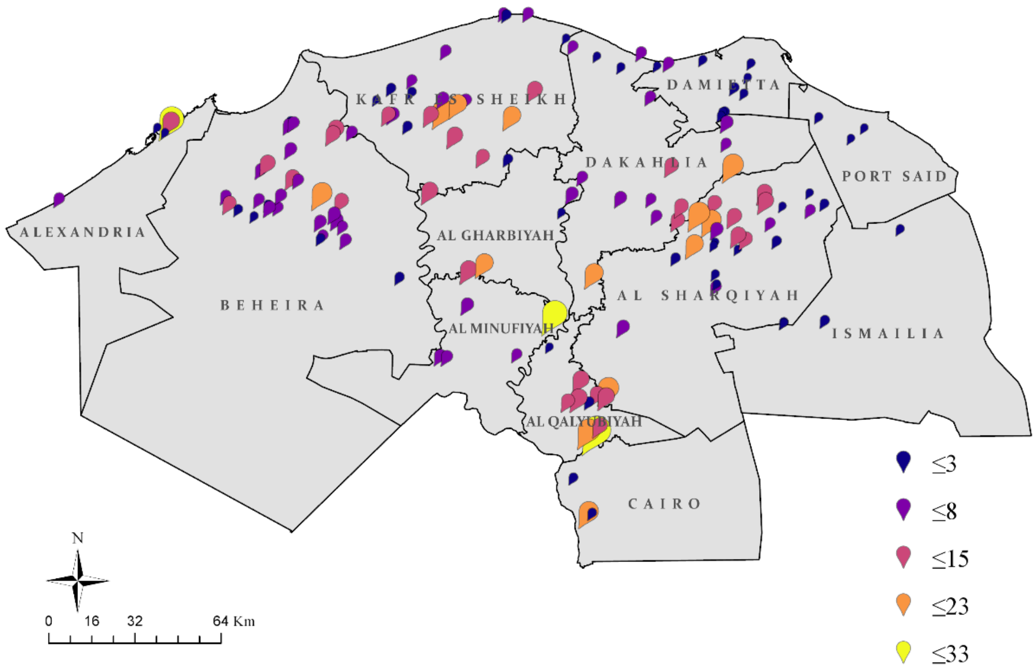
Temporal comparison of all looting attempts evidence from either source and from both sources.

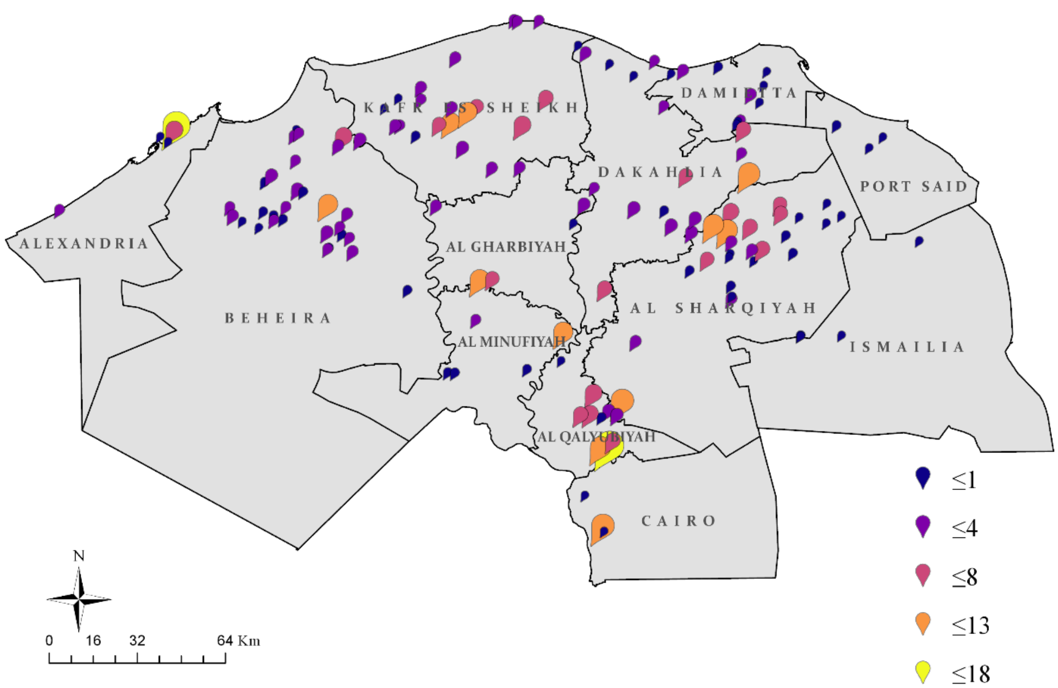


Temporal comparison of new looting attempts evidence from either source and from both sources.

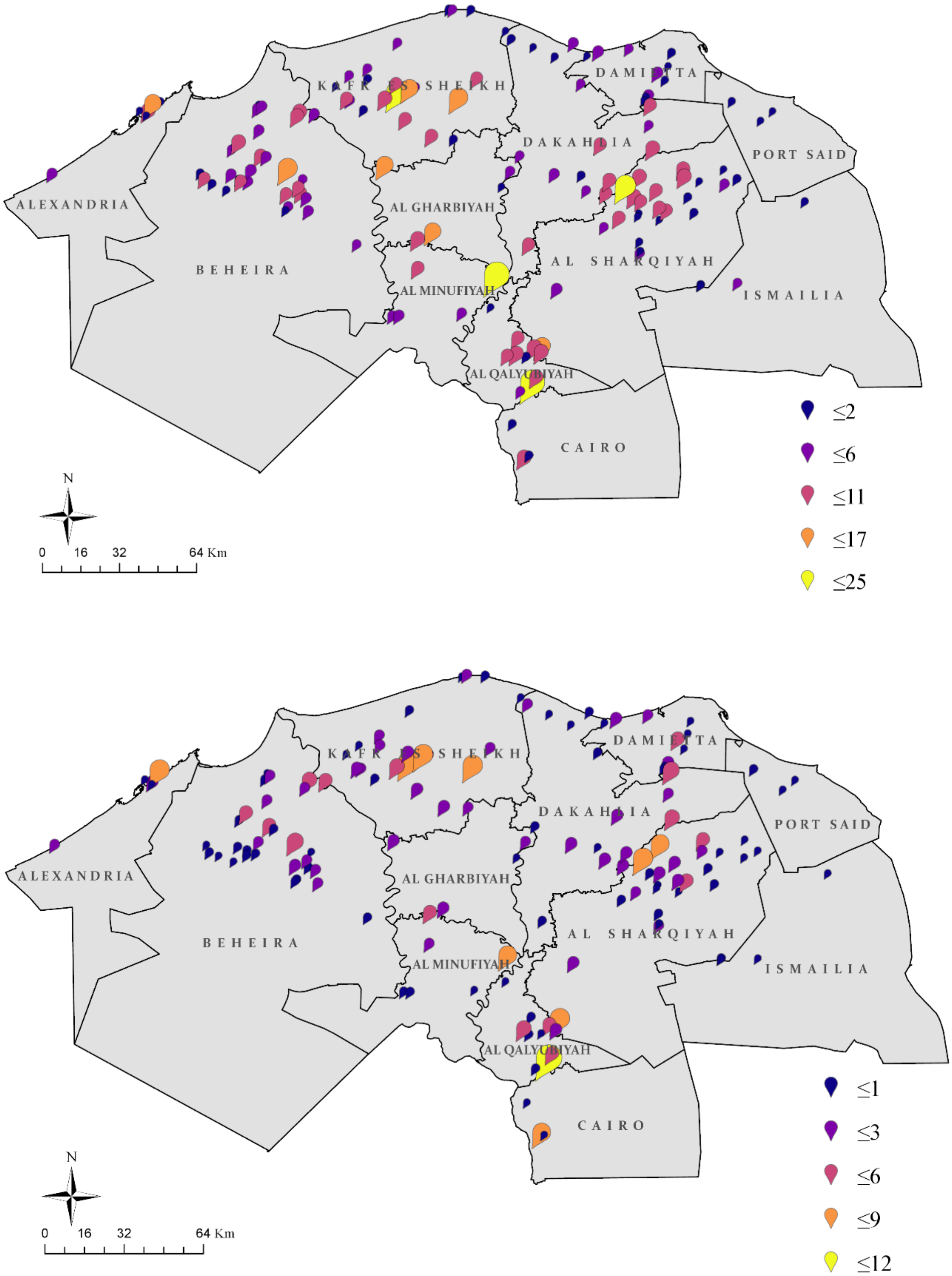


Temporal comparison of prior looting attempts evidence from either source and from both sources.

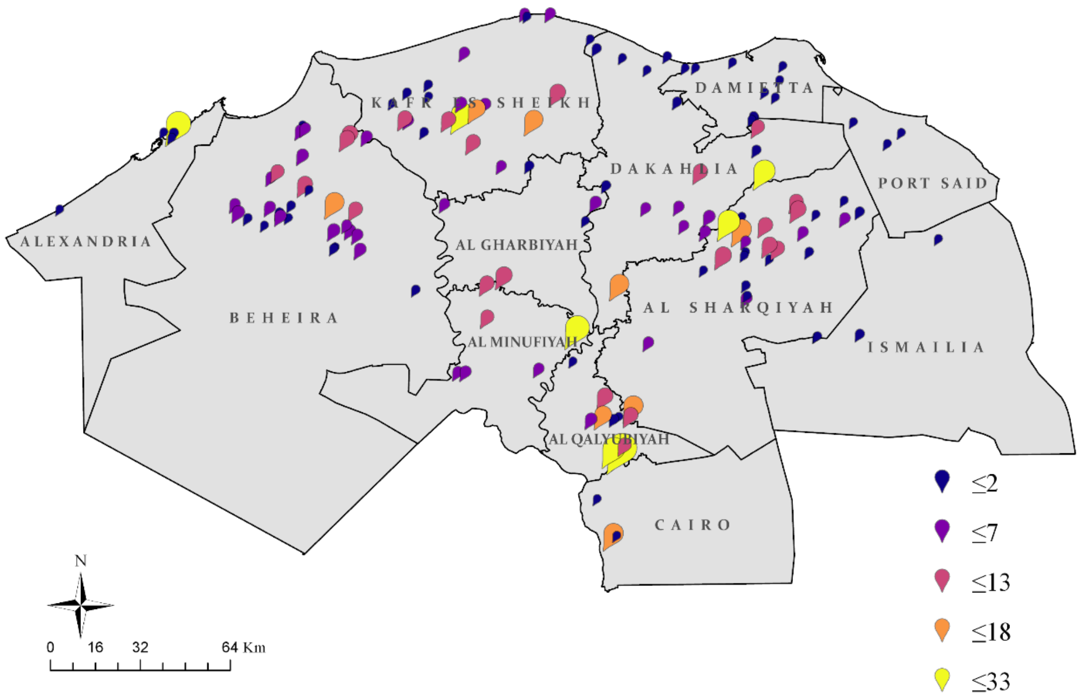


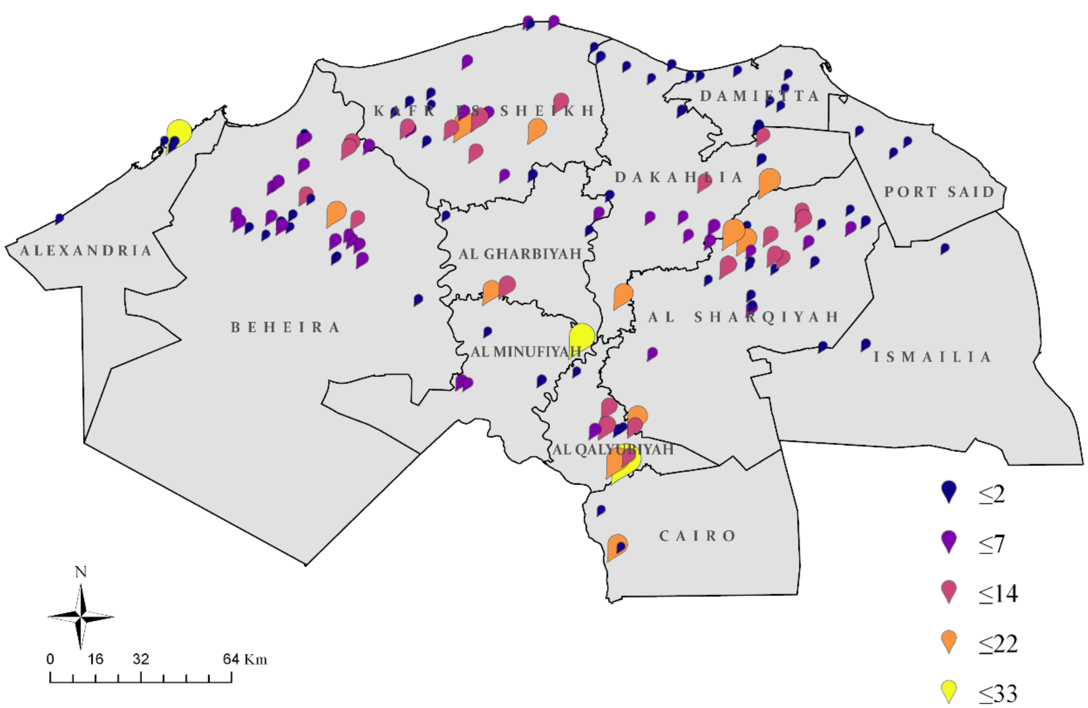


Spatial comparison of all looting attempts evidence from either source (top) and from both sources (bottom).



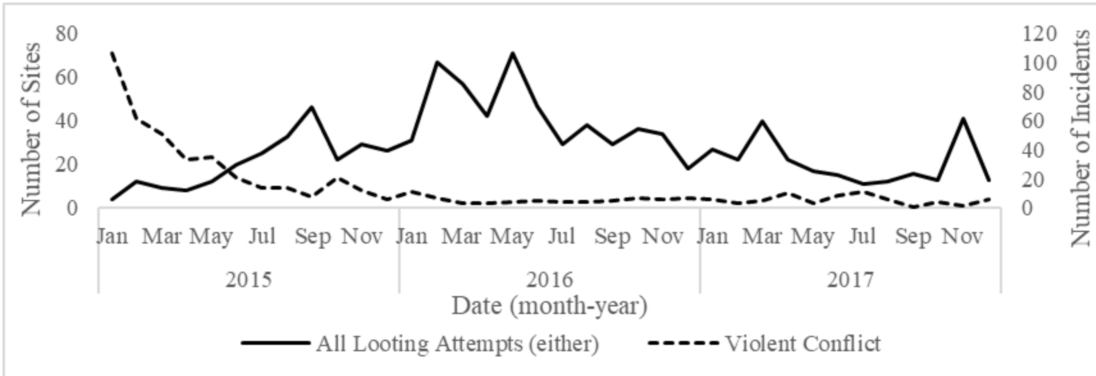
Spatial comparison of new looting attempts evidence from either source (top) and from both sources (bottom).



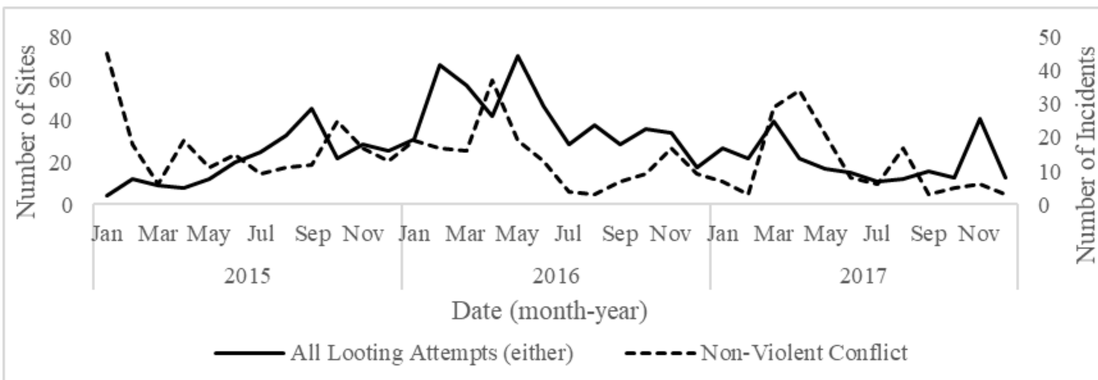


Spatial comparison of prior looting attempts evidence from either source (top) and from both sources (bottom).

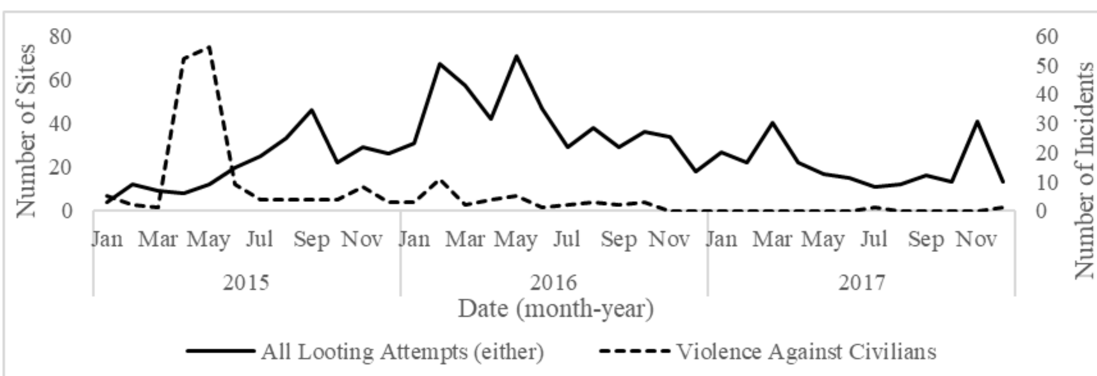
Looting Attempts versus Sociopolitical Stress Indicators (2015 – 2017)



Number of archaeological sites with any evidence of looting attempts compared to incidents of violent conflict from 2015 to 2017.

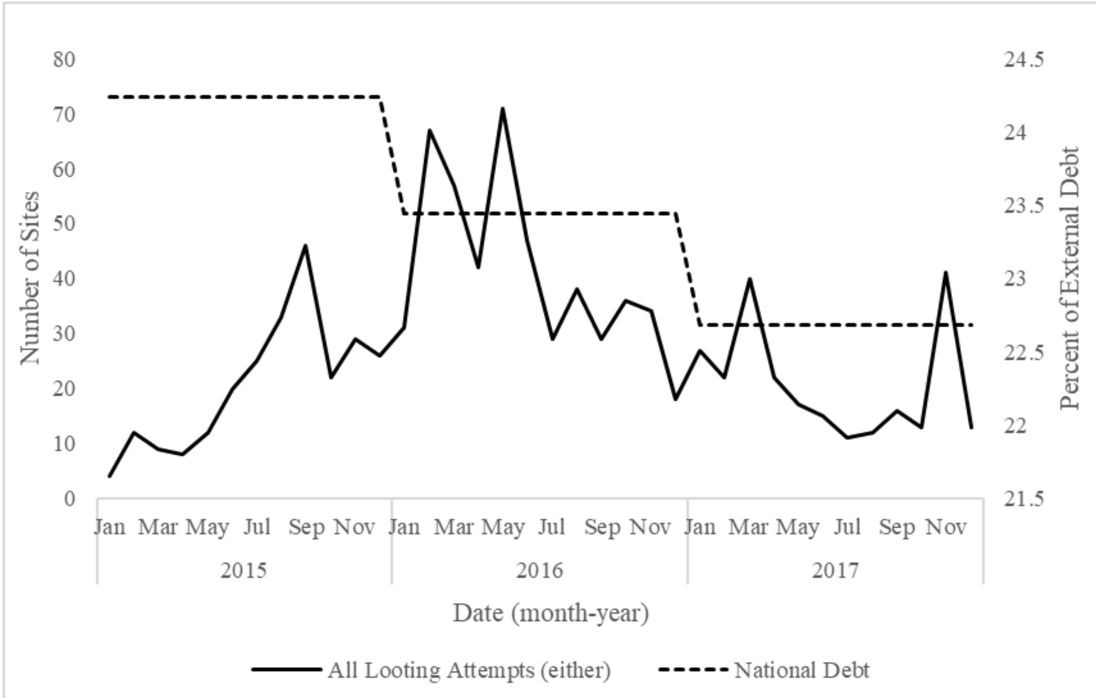


Number of archaeological sites with any evidence of looting attempts compared to incidents of non-violent conflict from 2015 to 2017.

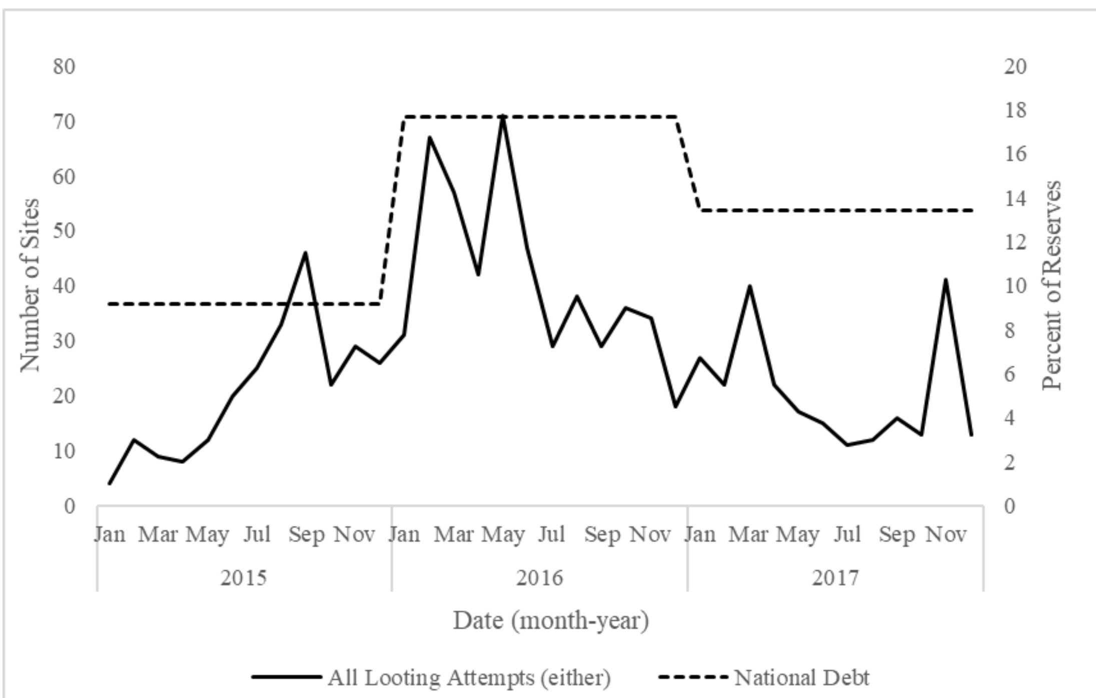


Number of archaeological sites with any evidence of looting attempts compared to incidents of violence against civilians from 2015 to 2017.

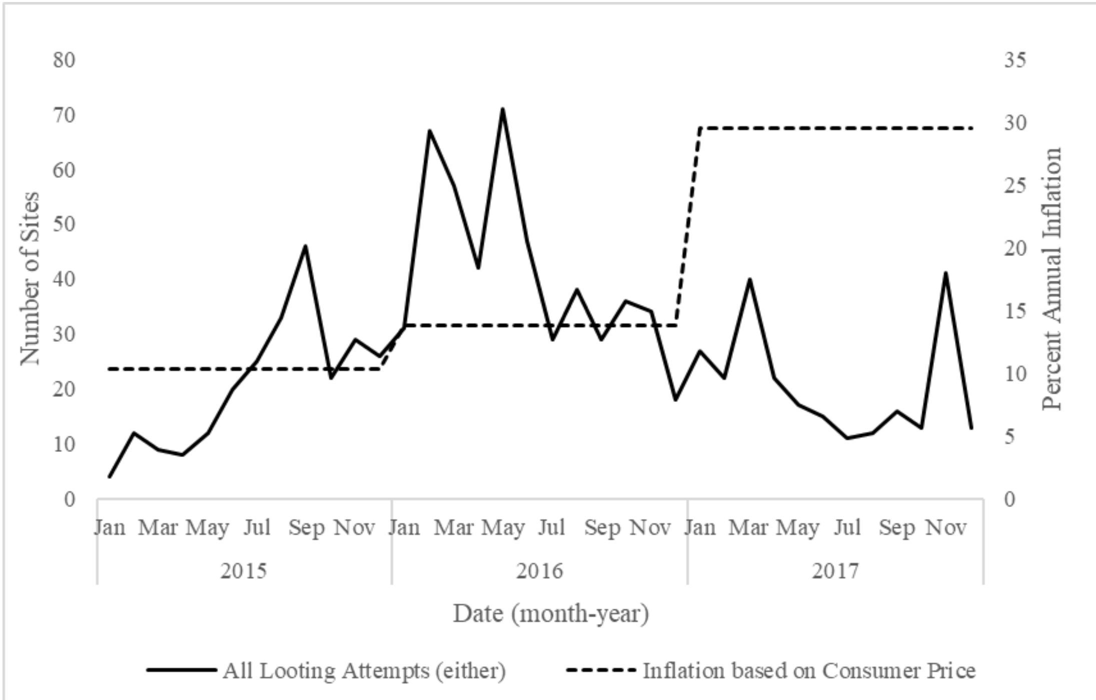
Looting Attempts versus Economic Stress Indicators (2015 – 2017)



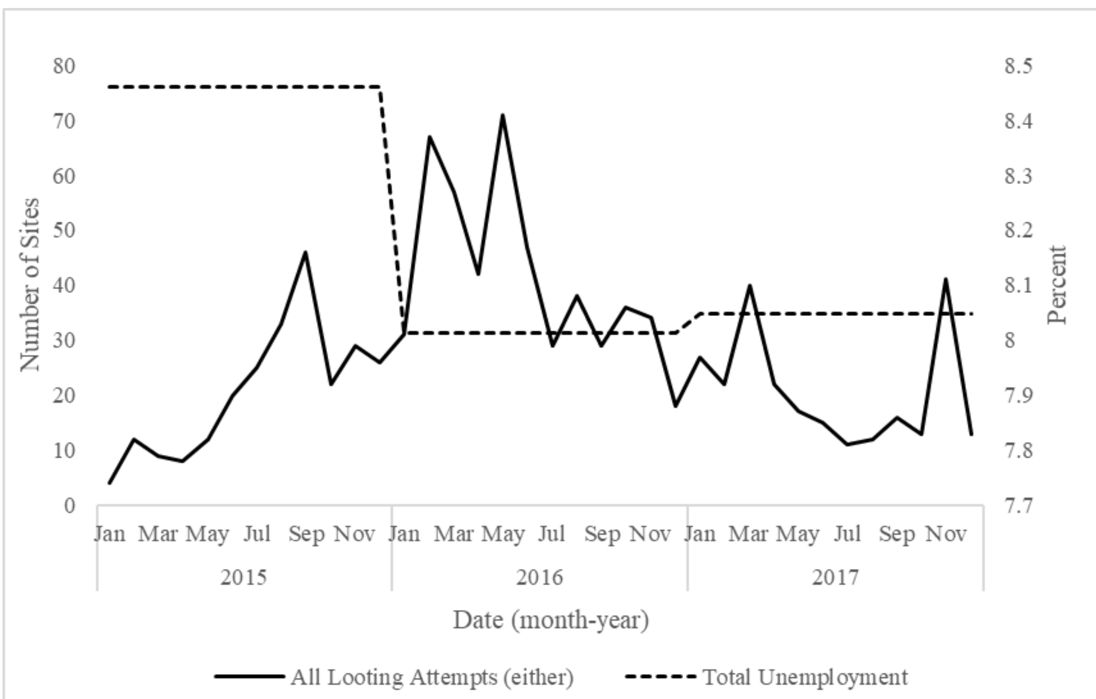
Number of archaeological sites with any evidence of looting attempts compared to the national debt (as % of external debt) from 2015 to 2017.



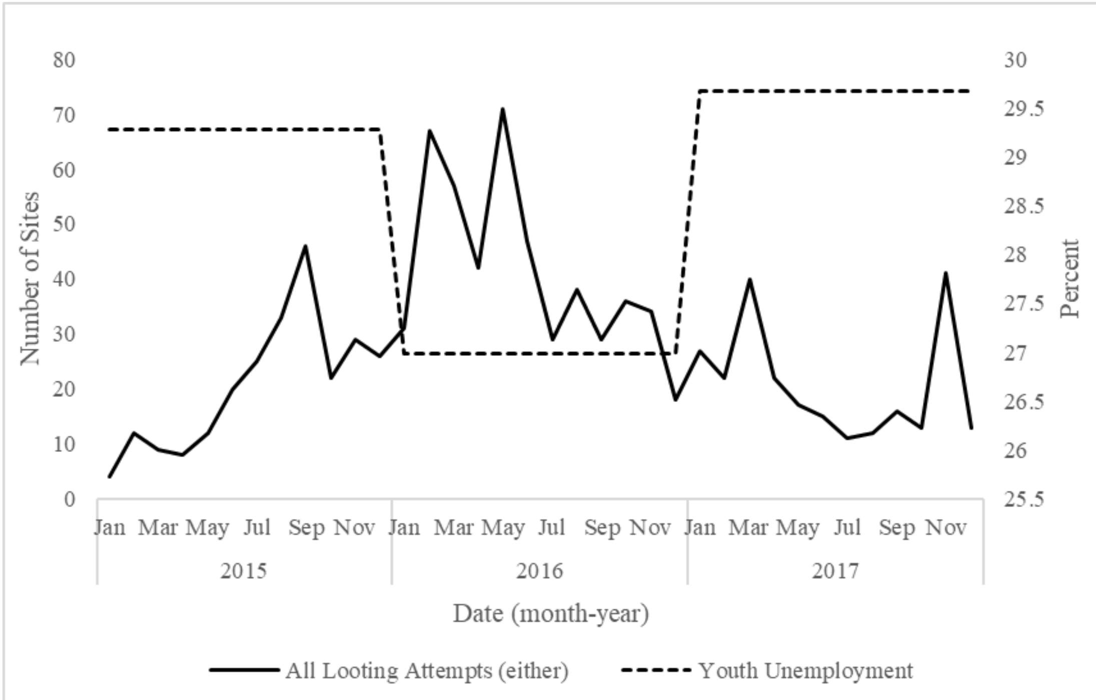
Number of archaeological sites with any evidence of looting attempts compared to the national debt (as % of reserves) from 2015 to 2017.



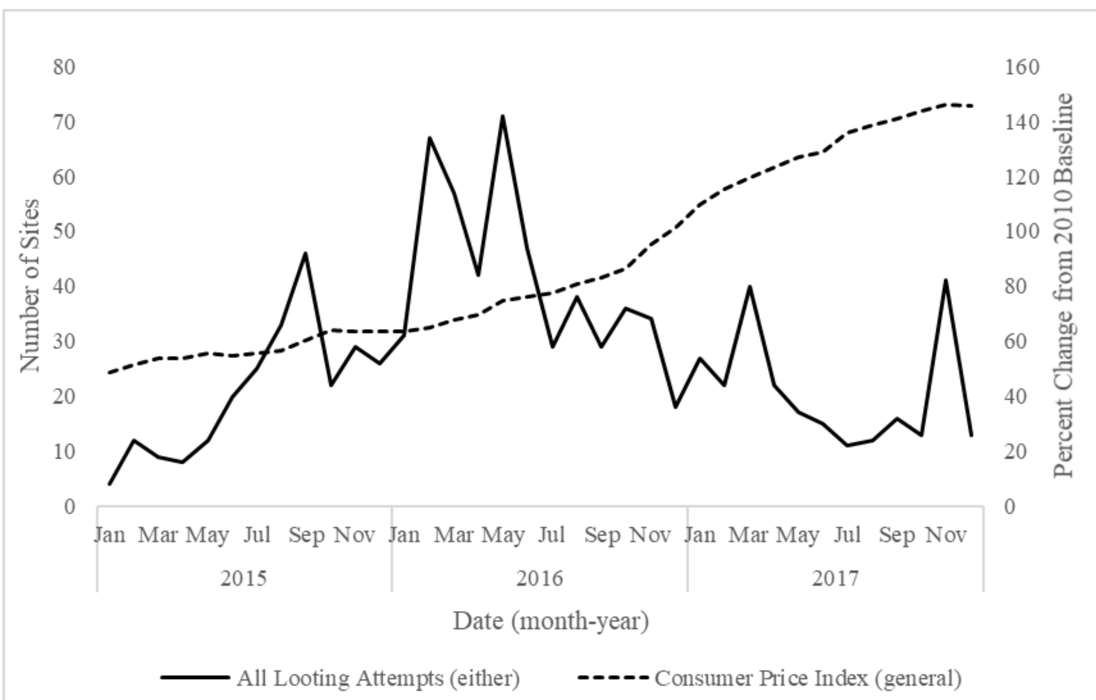
Number of archaeological sites with any evidence of looting attempts compared to inflation based on the consumer price index (% of annual inflation) from 2015 to 2017.



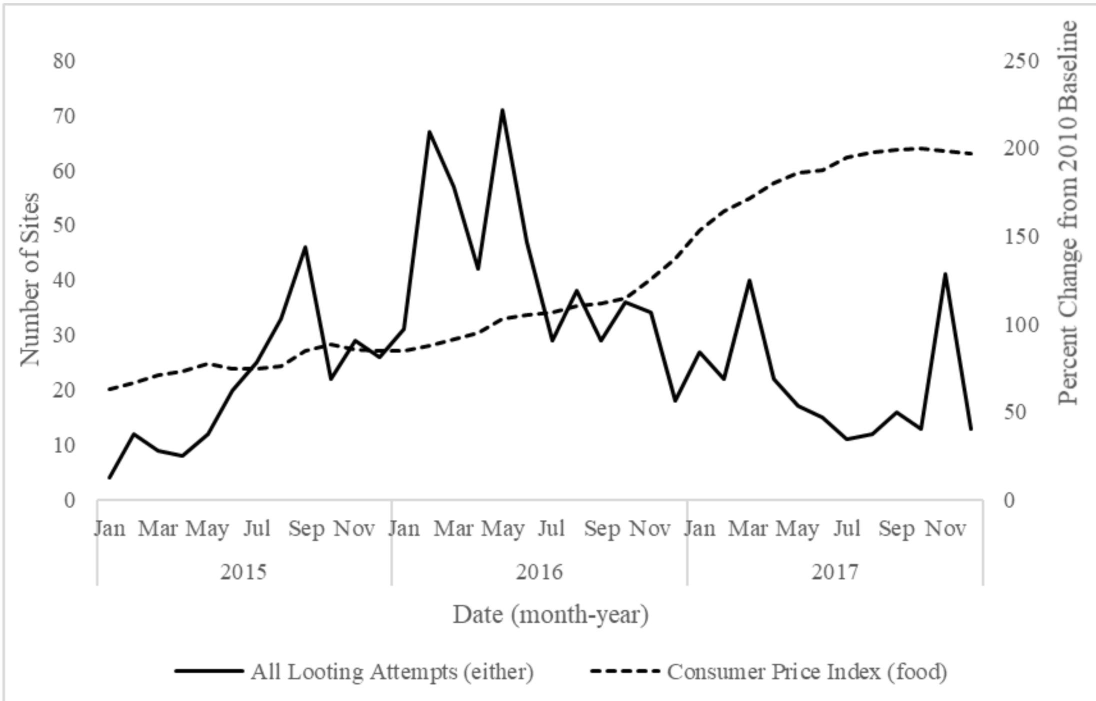
Number of archaeological sites with any evidence of looting attempts compared to the total percent unemployment in Lower Egypt from 2015 to 2017.



Number of archaeological sites with any evidence of looting attempts compared to the percent youth unemployment in Lower Egypt from 2015 to 2017.

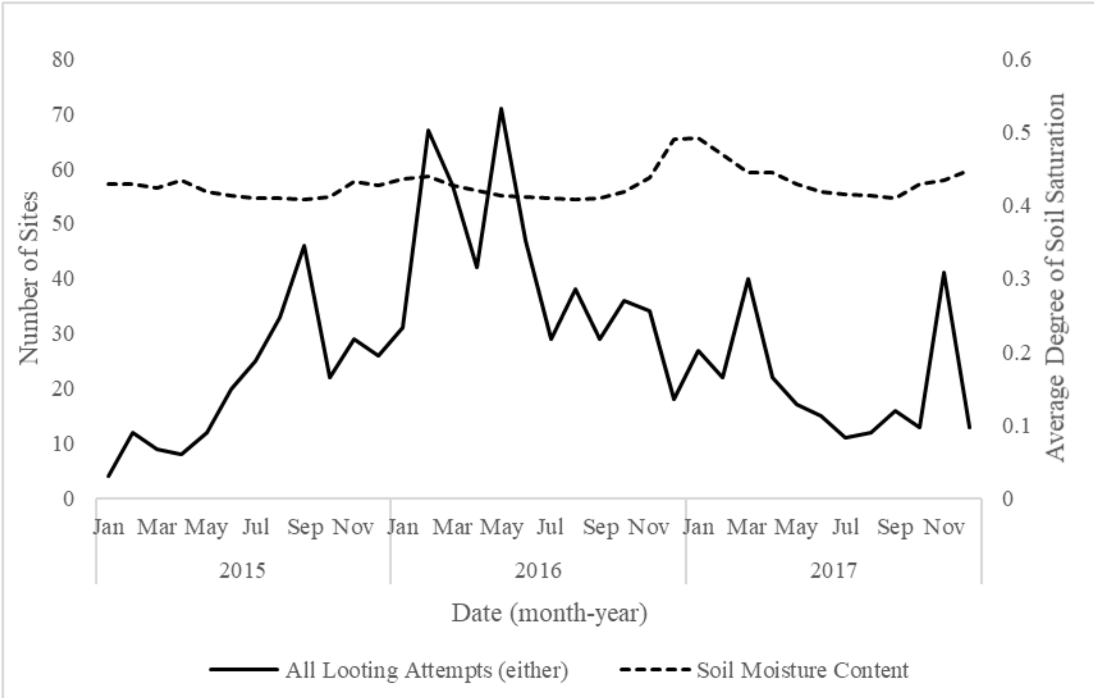


Number of archaeological sites with any evidence of looting attempts compared to the consumer price index for general goods from 2015 to 2017.

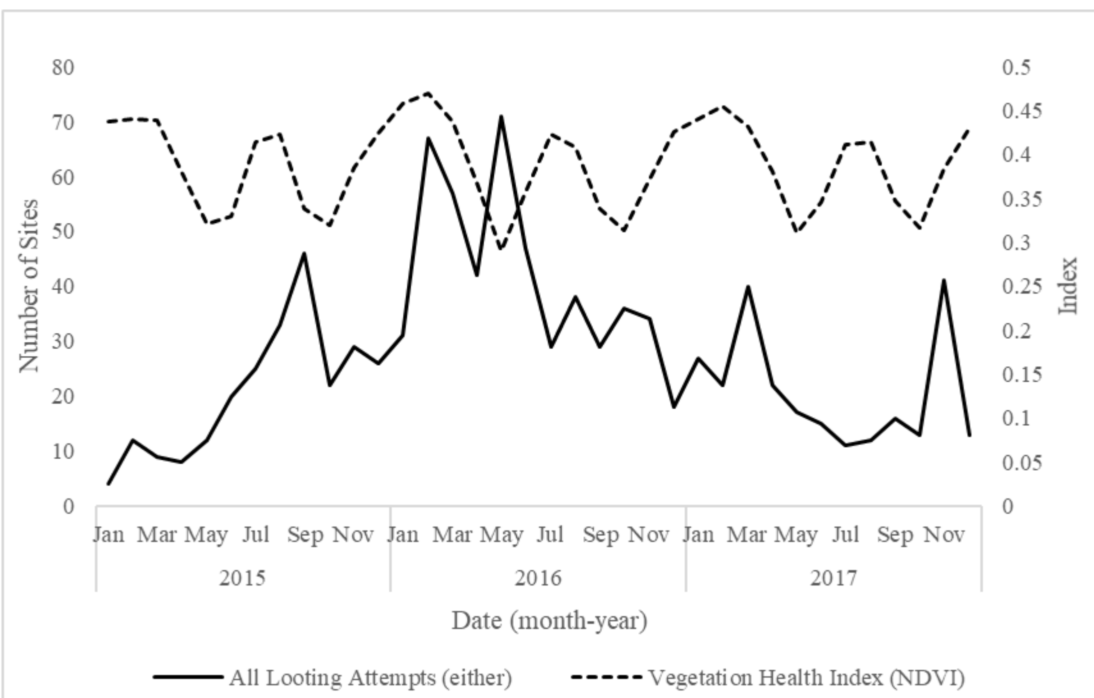


Number of archaeological sites with any evidence of looting attempts compared to the consumer price index for food from 2015 to 2017.

Looting Attempts versus Environmental Stress Indicators (2015 – 2017)

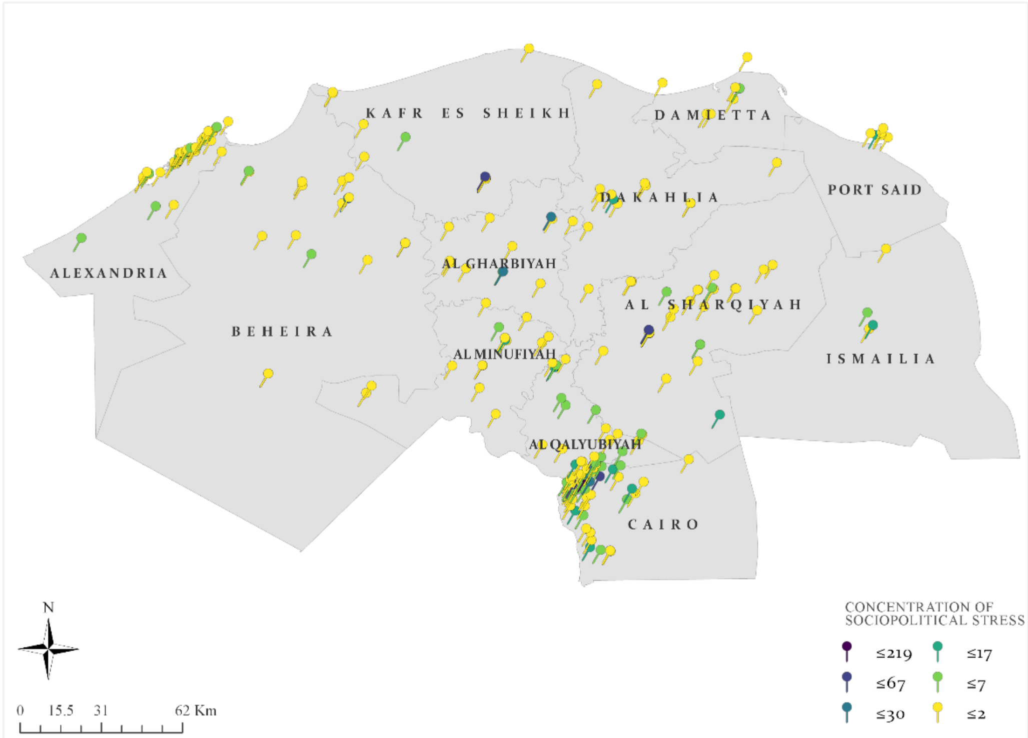


Number of archaeological sites with any evidence of looting attempts compared to the average degree of soil saturation for a given 0.5-degree grid-cell between the surface layer and the bedrock from 2015 to 2017.

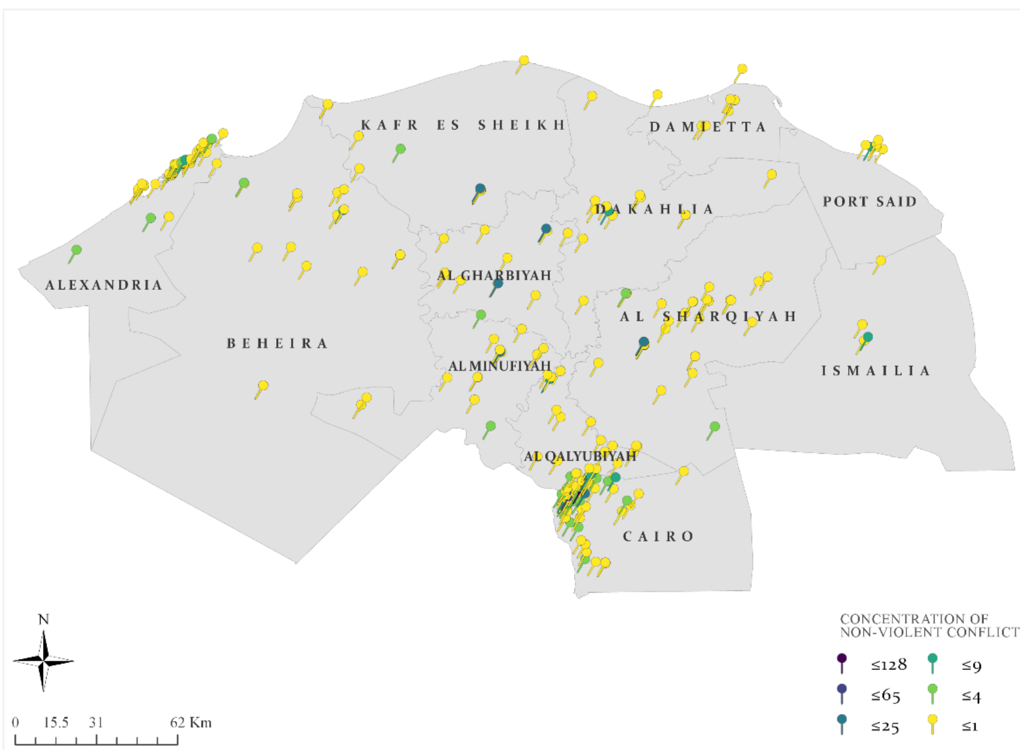


Number of archaeological sites with any evidence of looting attempts compared to the average vegetation health index (higher values indicate healthier vegetation) for a given 0.05-degree grid-cell from 2015 to 2017.

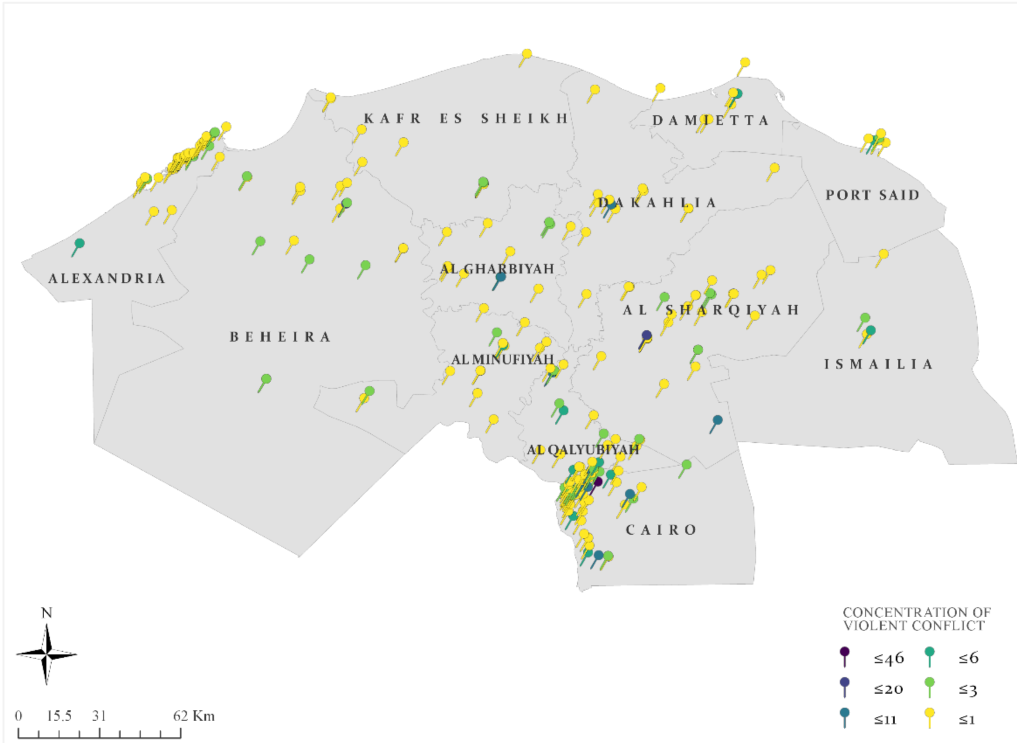
Sociopolitical Stress Descriptives



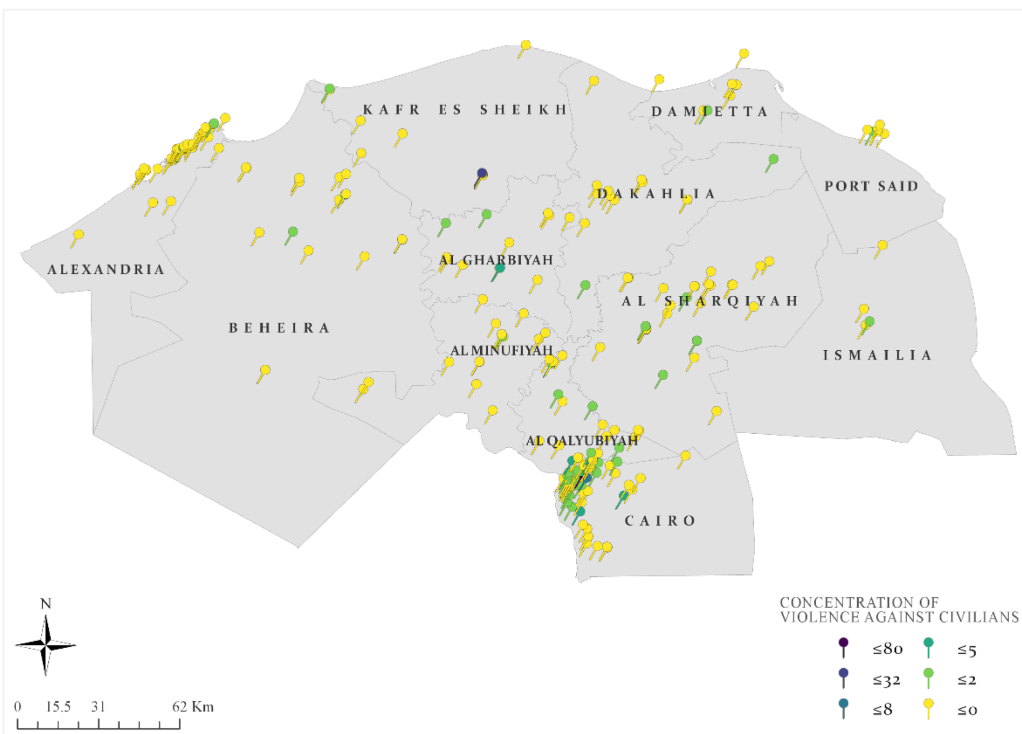
Spatial distribution of all sociopolitical stress from 2015 to 2017.



Spatial distribution of non-violent conflict from 2015 to 2017.

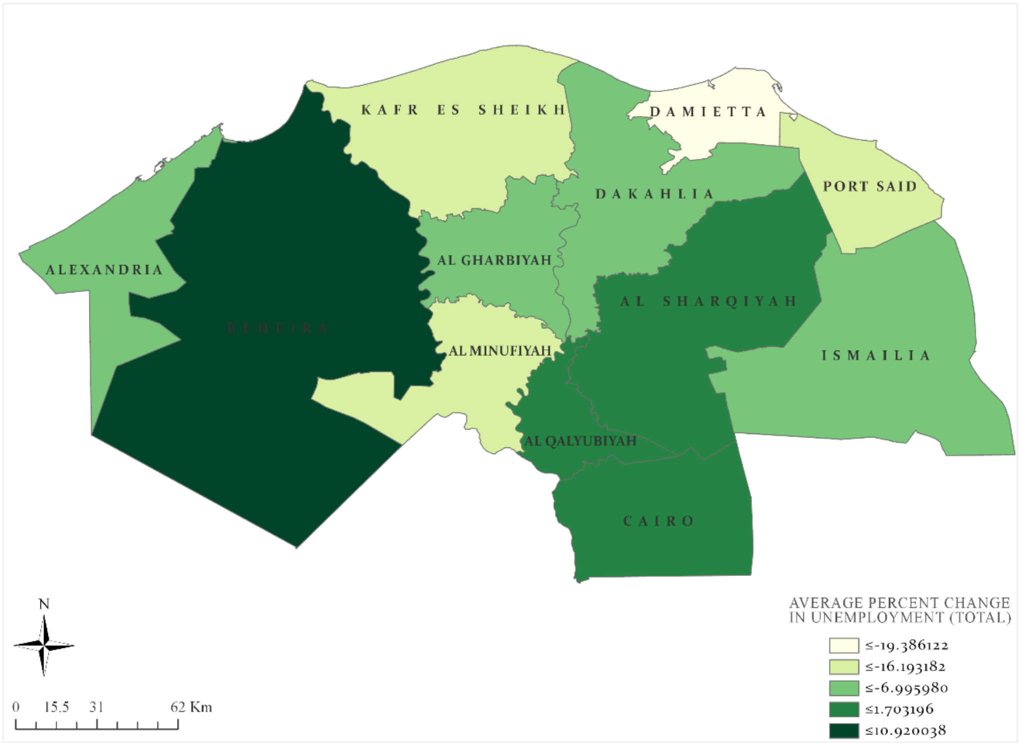


Spatial distribution of violent conflict from 2015 to 2017.

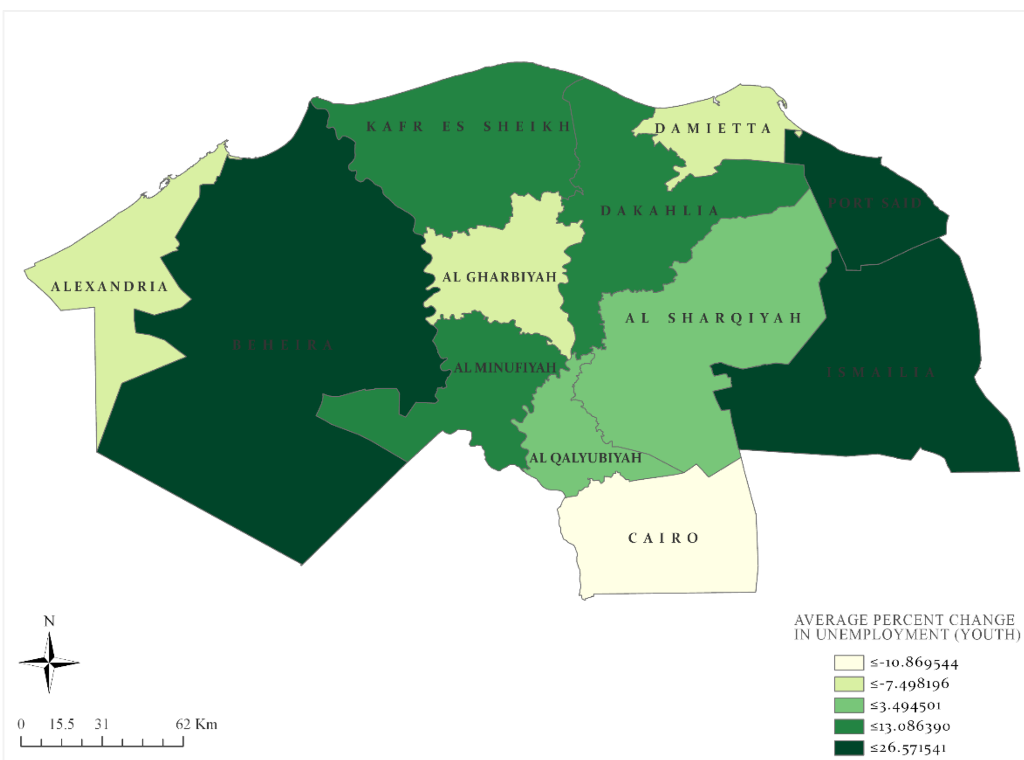


Spatial distribution of violence against civilians from 2015 to 2017.

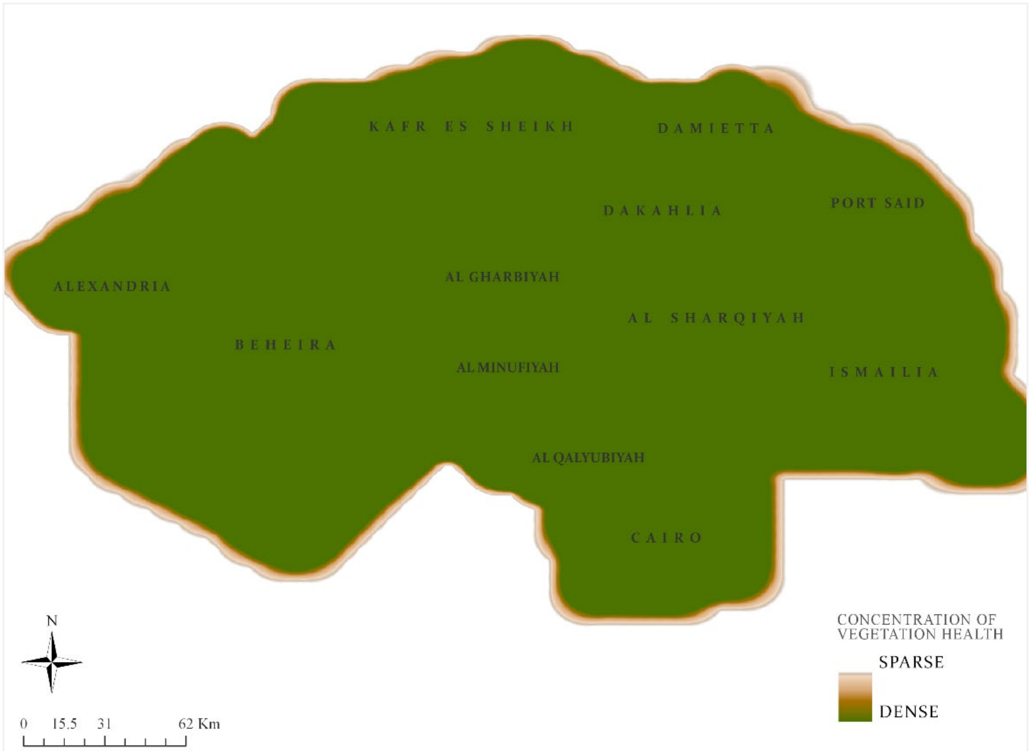
Economic Stress Descriptives



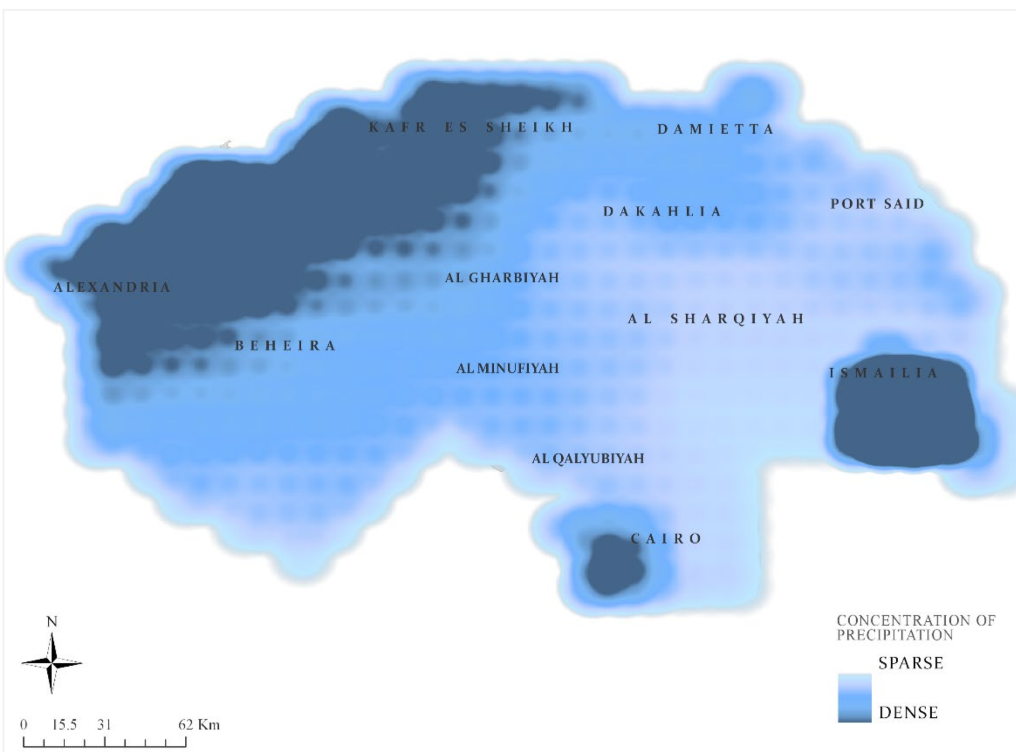
Spatial distribution of the average percent change in total unemployment from 2015 to 2017.



Spatial distribution of the average percent change in youth unemployment from 2015 to 2017.



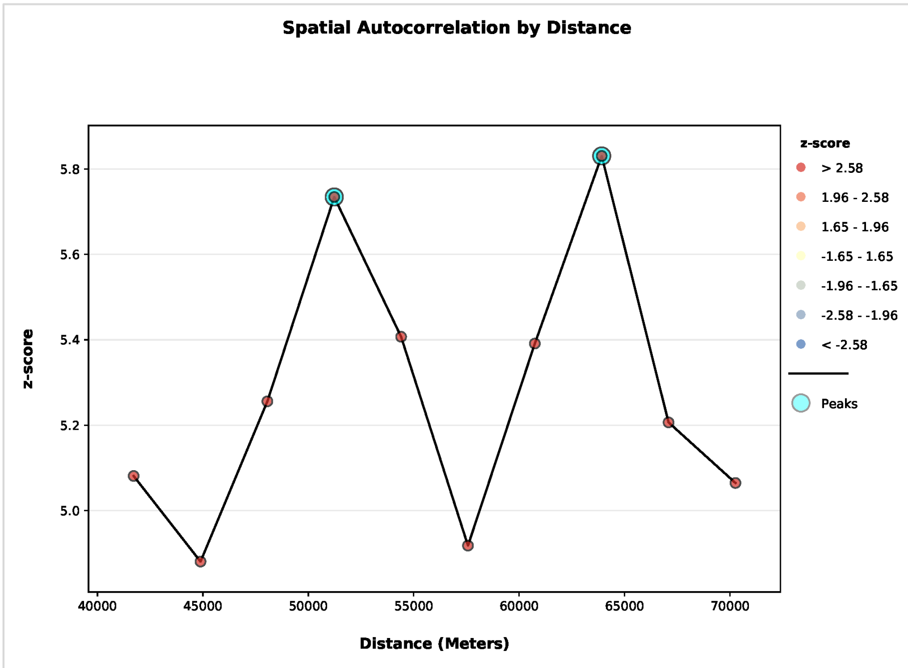
Spatial distribution of the average percent change in vegetation health from 2015 to 2017.



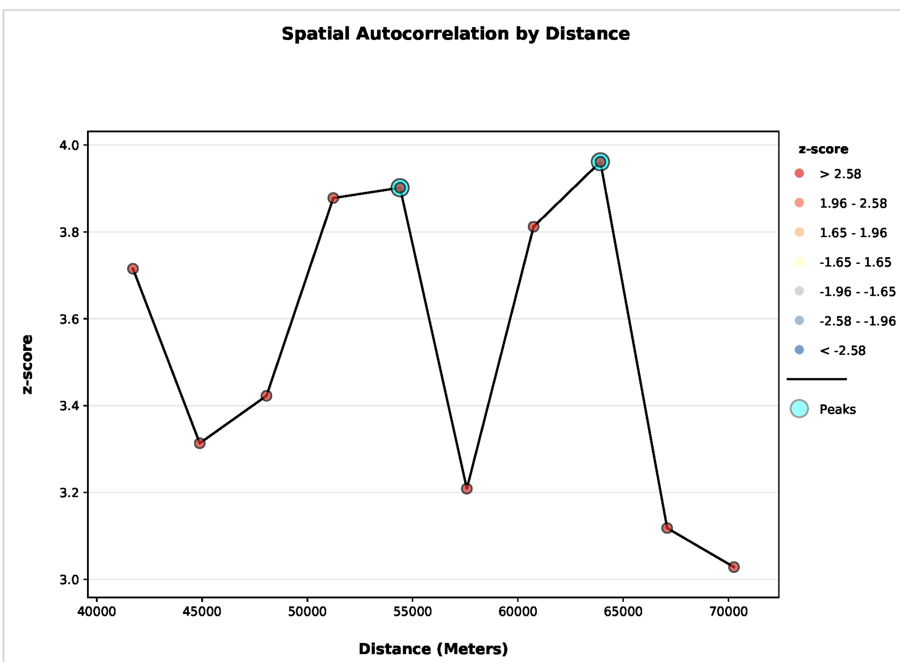
Spatial distribution of the average percent change in precipitation from 2015 to 2017.

Appendix 4: Spatial Results

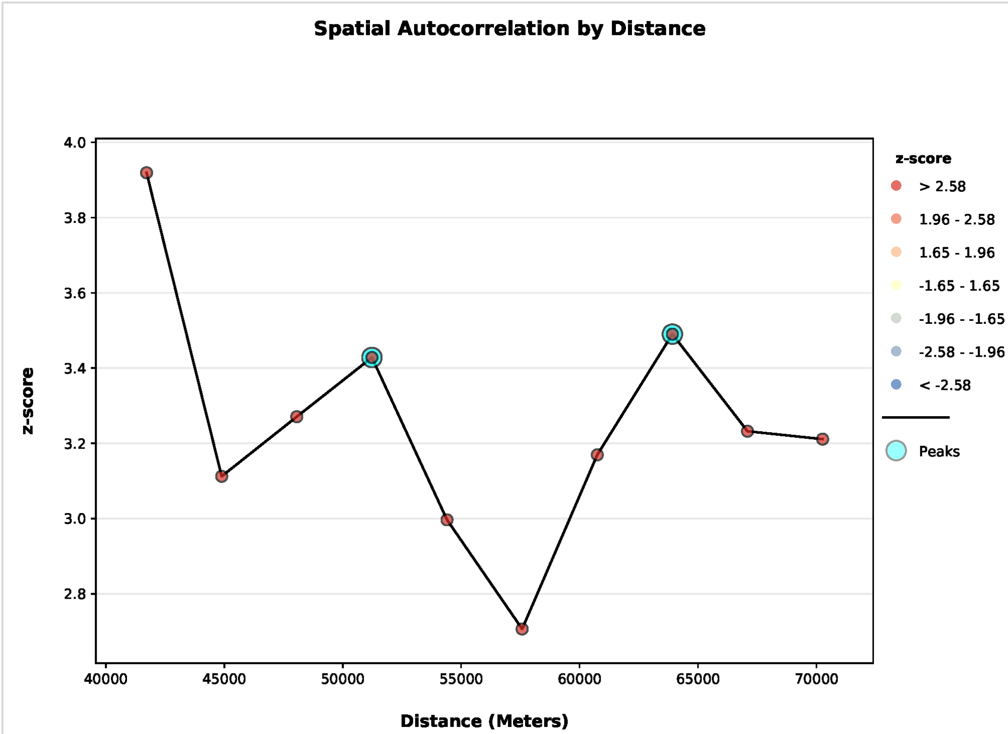
Incremental Spatial Autocorrelation Results



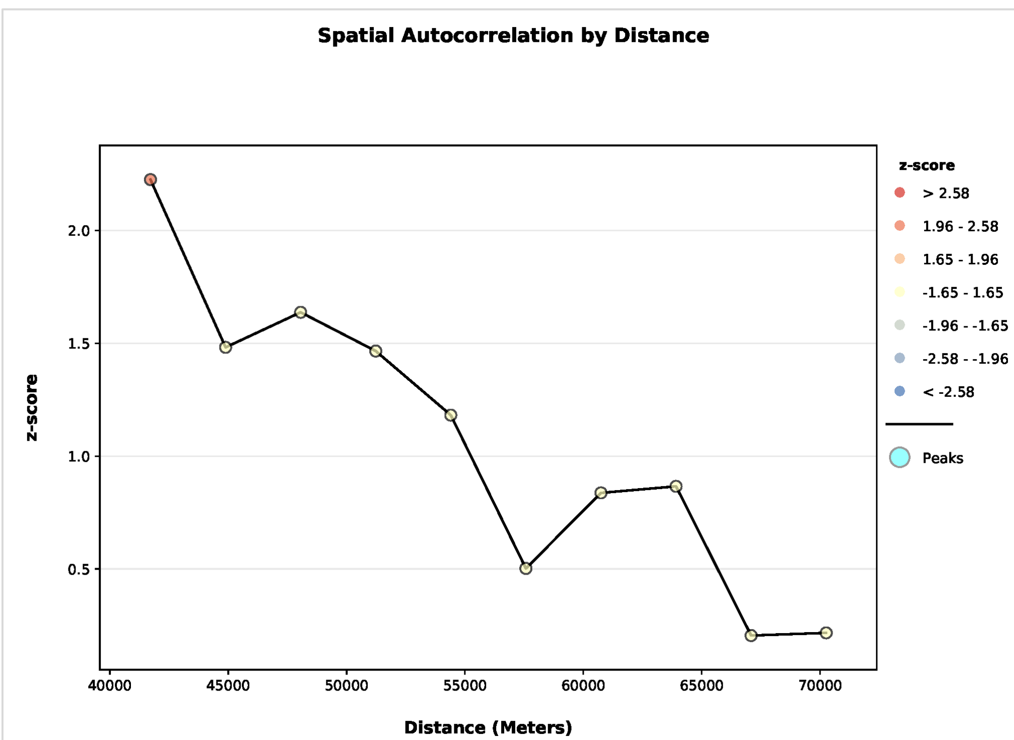
Incremental spatial autocorrelation for all evidence of looting attempts (either)



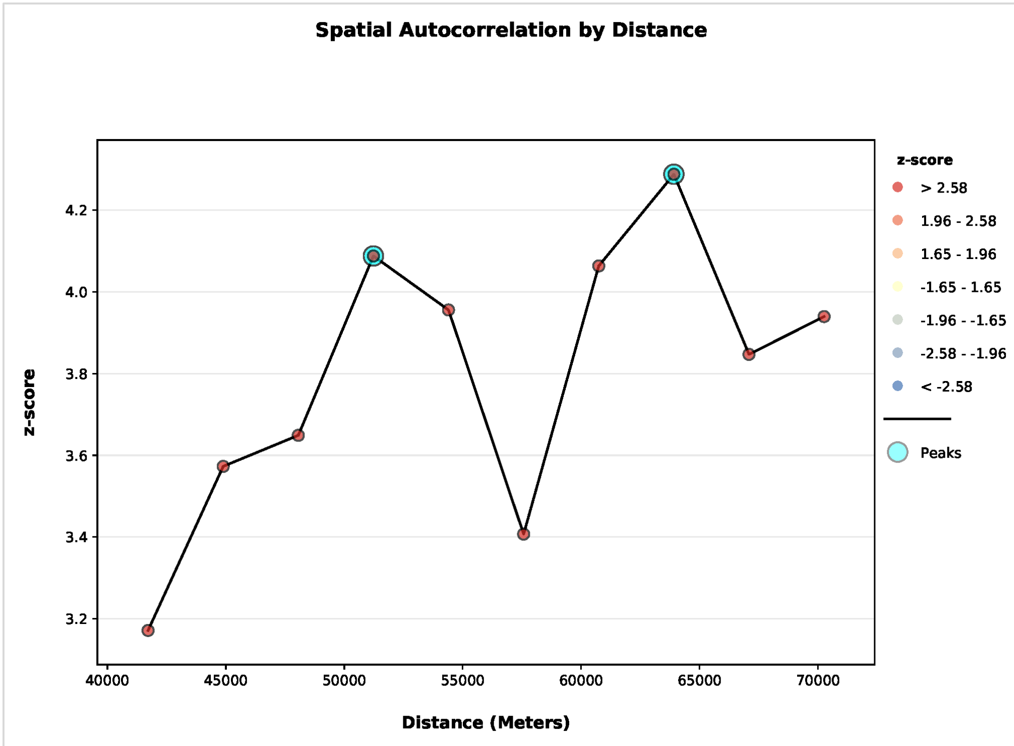
Incremental spatial autocorrelation for all evidence of looting attempts (both)



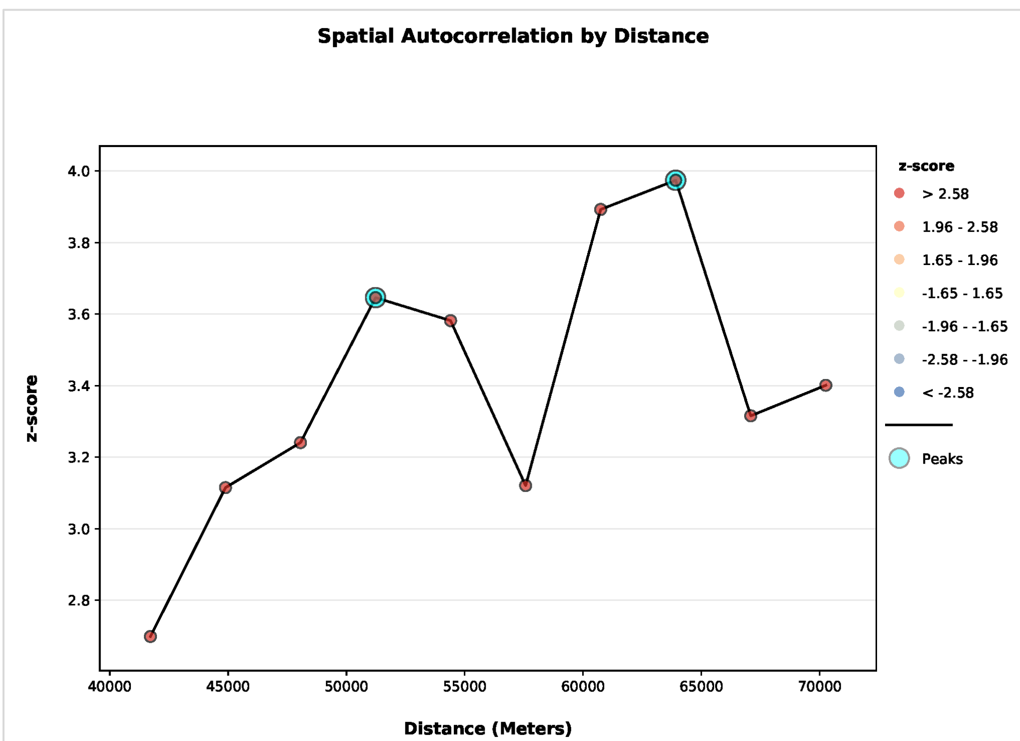
Incremental spatial autocorrelation for new evidence of looting attempts (either)



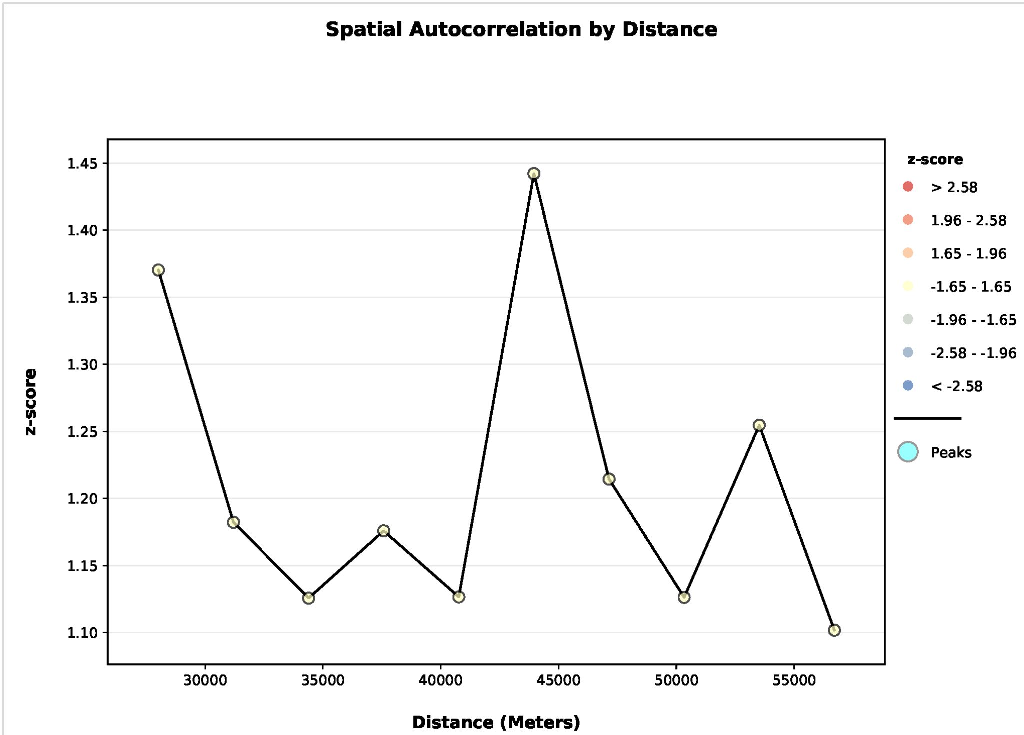
Incremental spatial autocorrelation for new evidence of looting attempts (both)



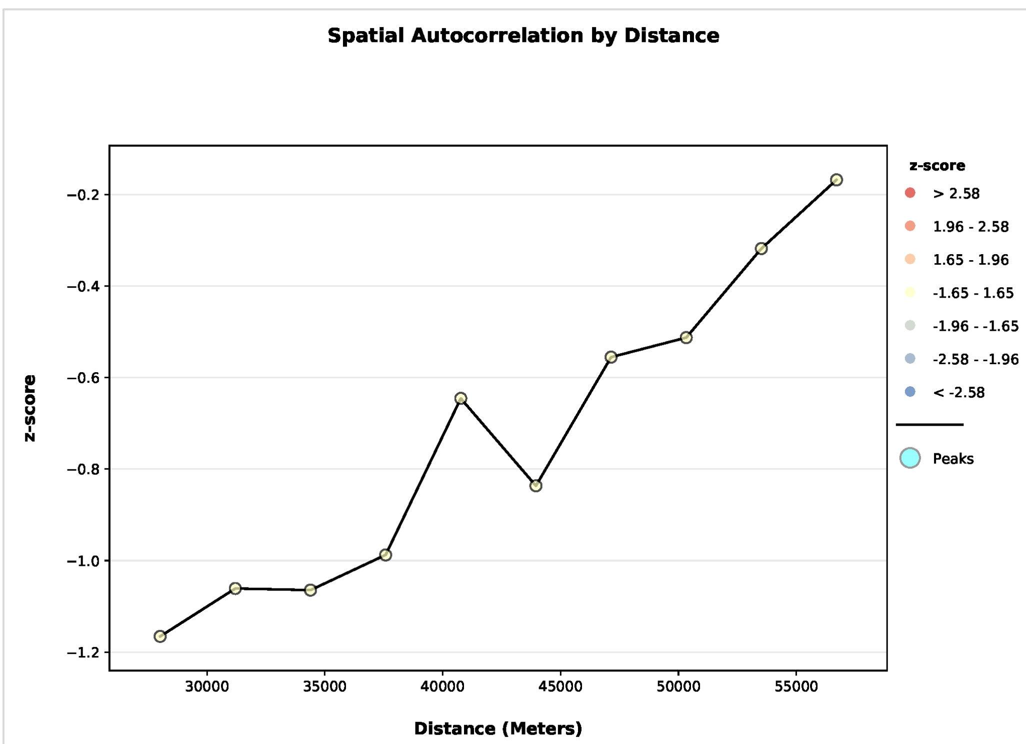
Incremental spatial autocorrelation for prior evidence of looting attempts (either)



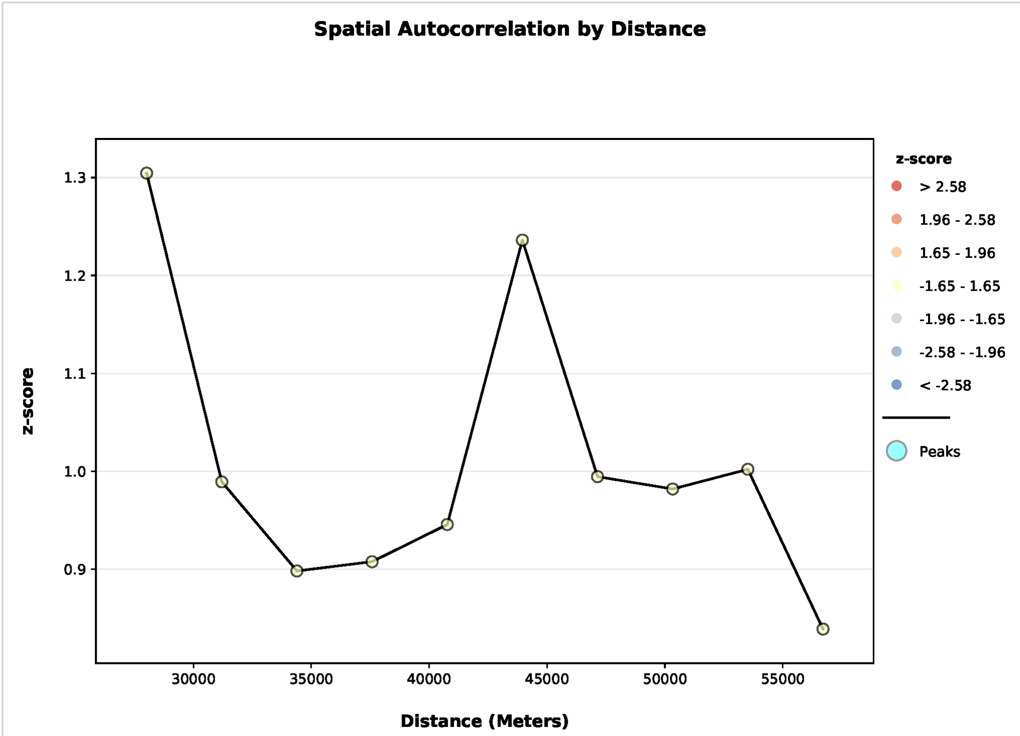
Incremental spatial autocorrelation for prior evidence of looting attempts (both)



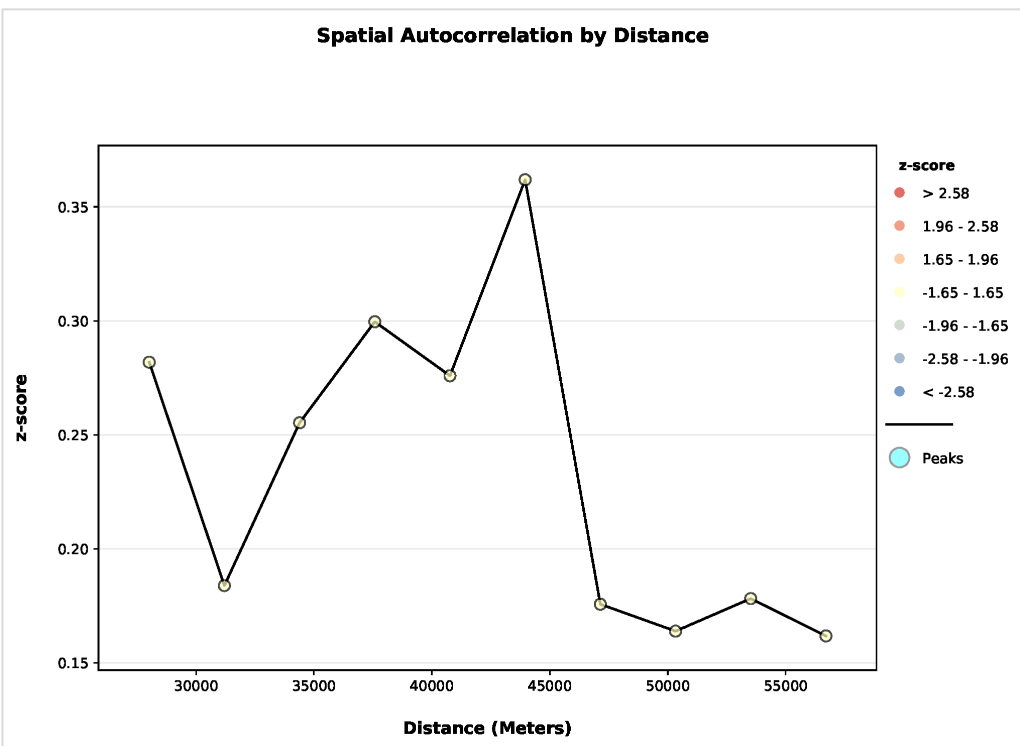
Incremental spatial autocorrelation for all sociopolitical stress incidents



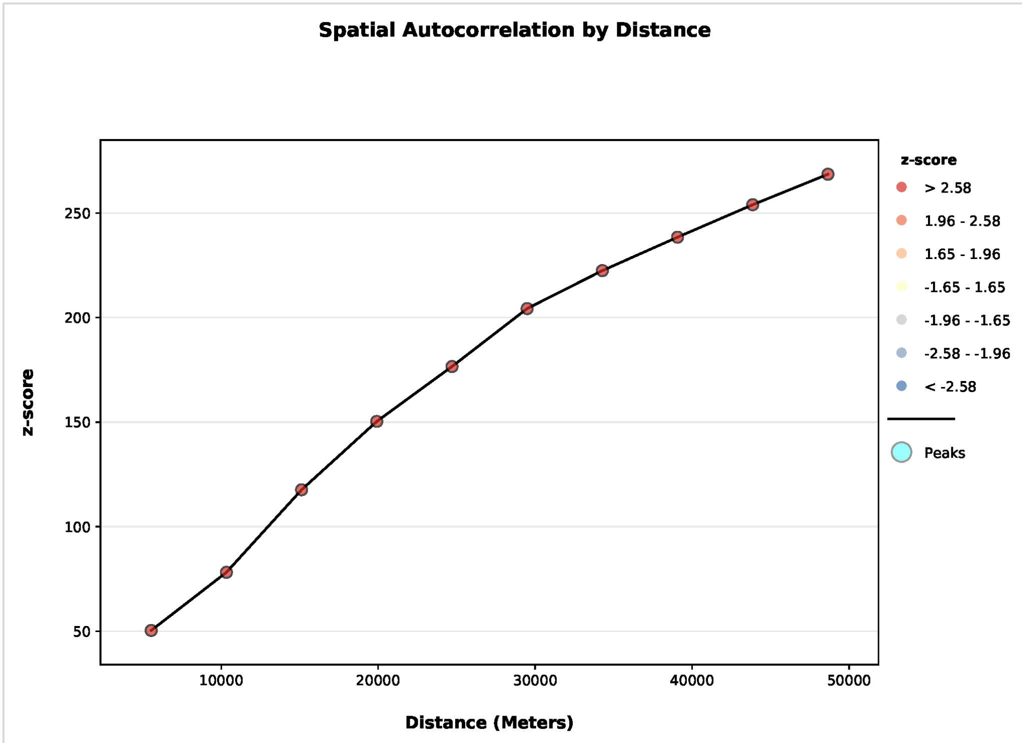
Incremental spatial autocorrelation for violent conflict incidents



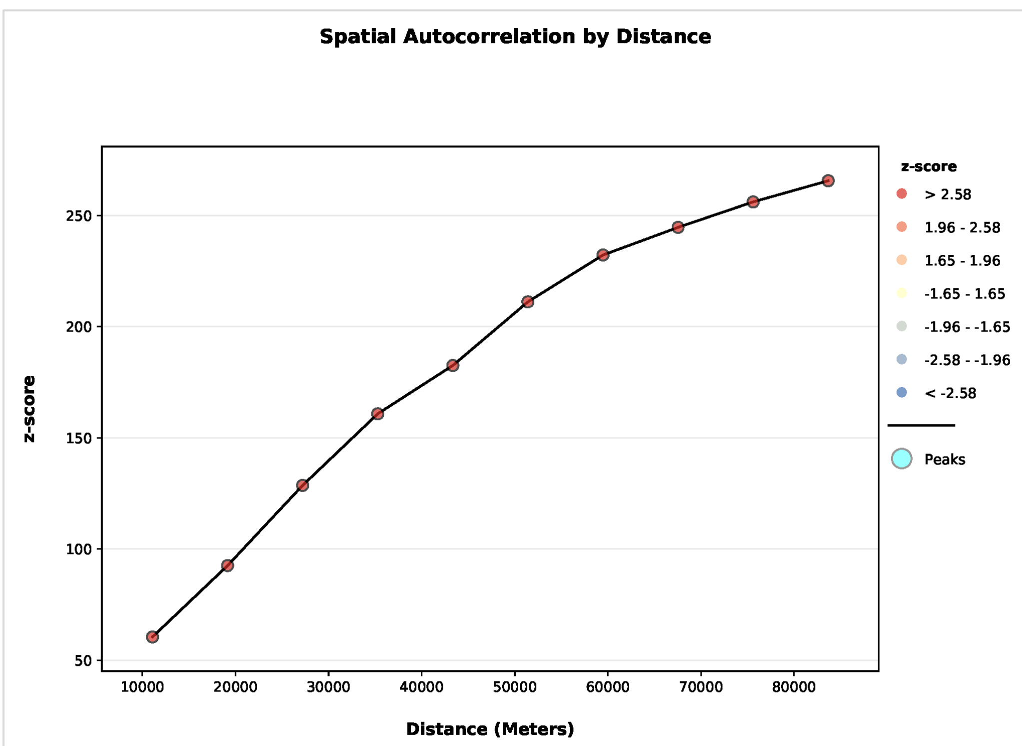
Incremental spatial autocorrelation for non-violent conflict incidents



Incremental spatial autocorrelation for incidents of violence against civilians



Incremental spatial autocorrelation for average change in vegetation health index (NDVI)



Incremental spatial autocorrelation for average change in precipitation

Weighted Analyses for Site Characteristics

DV: All looting attempts (either)	**Clustered on Hex-cell (n=211)**	**Clustered on Grid-cell (n=231)**	**Site-level (n=128)**
Owned by SCA (compared to not)	0.40872 (1.26033)	-0.47816 (1.15462)	0.70491 (1.30961)
Owned by SCA	-0.17934 (1.27927)	-0.70428 (1.18306)	0.34166 (1.370275)
Protected under Law	-0.45188 (1.62951)	-1.45693 (1.45533)	-0.42382 (1.65321)
Submitted for Protection	0.98816 (2.00899)	2.29952 (1.75639)	2.02799 (2.40049)

* p ≤ 0.10, ** p ≤ 0.05, *** p ≤ 0.01

Weighted Proximity Analyses

Straight-Line Distance to Key Locations

Sample Size: 140	**All Looting Attempts**		**New Looting Attempts**		**Prior Looting Attempts**	
	Either Source	*Both Sources*	*Either Source*	*Both Sources*	*Either Source*	*Both Sources*
Distance from Site Location						
Capitals	-0.0699 (0.057)	-0.0159 (0.0313)	-0.0730 (0.04524)	-0.02134 (0.01996)	-0.0463 (0.0587)	-0.03014 (0.05970)
Cities	-0.2088 (1.362)	-0.148* (0.0767)	-0.1249 (0.1116)	-0.09677* (0.05284)	-0.2154 (0.1441)	-0.22313 (0.14435)
Urban Area	0.0002 (0.0001)	-0.0001** (0.00005)	0.0002** (0.0001)	0.00004 (0.00004)	0.000*** (0.0001)	0.000*** (0.0001)
Road	-1.046** (0.5228)	-0.5332** (0.2661)	-0.6977* (0.4185)	-0.3215* (0.17684)	-1.0779** (0.45281)	-0.9474** (0.4596)
Distance from Site Boundary Polygons						
Capitals	-0.01225 (0.0604)	0.0169 (0.0341)	-0.04309 (0.04270)	-0.01835 (0.02076)	0.05828 (0.05807)	0.05114 (0.05783)
Cities	-0.1367 (0.2486)	-0.06458 (0.1445)	0.02026 (0.1888)	0.00592 (0.09377)	-0.23547 (0.24802)	-0.19453 (0.25044)
Urban Area	-0.0625 (0.0815)	-0.02805 (0.04732)	-0.00357 (0.05425)	0.01495 (0.02666)	-0.12719 (0.07964)	-0.13071 (0.07912)
Road	-0.5059 (0.8692)	-0.24858 (0.4209)	-0.14693 (0.73007)	-0.02198 (0.33084)	-0.71660 (0.71133)	-0.78501 (0.68651)

* p ≤ 0.10, ** p ≤ 0.05, *** p ≤ 0.01

Road-network Distances to Key Locations

Sample Size: 140	All Looting Attempts		New Looting Attempts		Prior Looting Attempts	
	Either Source	*Both Sources*	*Either Source*	*Both Sources*	*Either Source*	*Both Sources*
Driving Distance & Time						
Km to Capital	-0.03702 (0.04305)	-0.00344 (0.02343)	-0.04661 (0.0308)	-0.01212 (0.01342)	-0.01458 (0.04479)	-0.00621 (0.04510)
Km to Cities	-0.19472** (0.09647)	-0.1350** (0.05375)	-0.11456 (0.07336)	-0.0848** (0.03426)	-0.20634** (0.10388)	-0.2080** (0.10312)
Min to Capital	-0.01611 (0.02929)	0.000412 (0.15735)	-0.02219 (0.02110)	-0.00464 (0.00919)	-0.00730 (0.03040)	-0.00163 (-0.0307)
Min to Cities	-0.10636 (0.06747)	-0.07343* (0.03762)	-0.06369 (0.05346)	-0.0558** (0.02418)	-0.10424 (0.06936)	-0.10226 (0.06943)
Rural Driving Distance & Time						
Km to Capital	-0.06640* (0.03530)	-0.02196 (0.01863)	-0.06203** (0.02755)	-0.02180* (0.01187)	-0.04528 (0.03618)	-0.03796 (0.03654)
Km to Cities	-0.10000* (0.05471)	-0.0688** (0.03006)	-0.06203 (0.04407)	-0.0448** (0.02074)	-0.01000* (0.05973)	-0.09658 (0.05931)
Min to Capital	-0.01257 (0.02625)	0.00209 (0.0139)	-0.01677 (0.02025)	-0.00422 (0.00910)	-0.00567 (0.02761)	0.00046 (0.02783)
Min to Cities	-0.20664 (0.07233)	-0.121*** (0.04329)	-0.145*** (0.05423)	-0.077*** (0.02860)	-0.1865** (0.07909)	-0.1848** (0.07836)

* p ≤ 0.10, ** p ≤ 0.05, *** p ≤ 0.01

Distance between Sociopolitical Stress and Looting Attempts

Sample Size: 140	All Looting Attempts		New Looting Attempts		Prior Looting Attempts	
	Either Source	*Both Sources*	*Either Source*	*Both Sources*	*Either Source*	*Both Sources*
Distance from Site Location						
All Sociopolitical Stress (SPS)	0.06063 (0.09837)	0.051746 (0.51575)	0.06420 (0.07712)	0.03608 (0.03774)	0.089882 (0.09283)	0.08648 (0.09114)
Violent Conflict	0.14228 (0.09778)	0.0885* (0.05119)	0.12213 (0.07657)	0.04273 (0.03656)	0.15413 (0.09536)	0.15123 (0.09414)
Non-violent Conflict	-0.04152 (0.06694)	0.01575 (0.03567)	-0.03015 (0.05307)	0.01314 (0.02422)	-0.04062 (0.06191)	-0.04571 (0.06174)
Violence Against Civilians	-0.13026 (0.03881)	-0.05533 (0.01936)	-0.10877 (0.02875)	-0.032358 (0.01366)	-0.11467 (0.03995)	-0.11025 (0.03999)
Distance from Site Boundary Polygons						
All Sociopolitical Stress (SPS)	-0.25697 (0.23622)	-0.09870 (0.10794)	-0.11048 (0.20444)	0.00930 (0.08984)	-0.18784 (0.23585)	-0.15268 (0.23324)
Violent Conflict	0.00797 (0.10607)	-0.01976 (0.05689)	-0.05066 (0.08322)	-0.03420 (0.03821)	-0.00255 (0.09966)	0.02580 (0.09883)
Non-violent Conflict	-0.04146 (0.08610)	0.031188 (0.04688)	-0.03139 (0.07184)	0.02111 (0.03229)	-0.03547 (0.08285)	-0.04356 (0.08204)
Violence Against Civilians	-0.04955 (0.04689)	-0.03417 (0.02442)	-0.00374 (0.03762)	-0.00368 (0.01798)	-0.04770 (0.04700)	-0.05878 (0.04594)
Driving Distance & Time						
Km to SPS	0.04029 (0.06706)	0.03113 (0.03461)	0.044234 (0.05264)	0.018516 (0.02361)	0.063261 (0.06367)	0.06055 (0.06281)
Min to SPS	0.05367 (0.04928)	0.03115 (0.02569)	0.05114 (0.03900)	0.01830 (0.01742)	0.06498 (0.04654)	0.06366 (0.04608)

* $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$

Appendix 5: Temporal Results

Path Diagrams for Structural Equation Models

Model 1 Path Diagrams

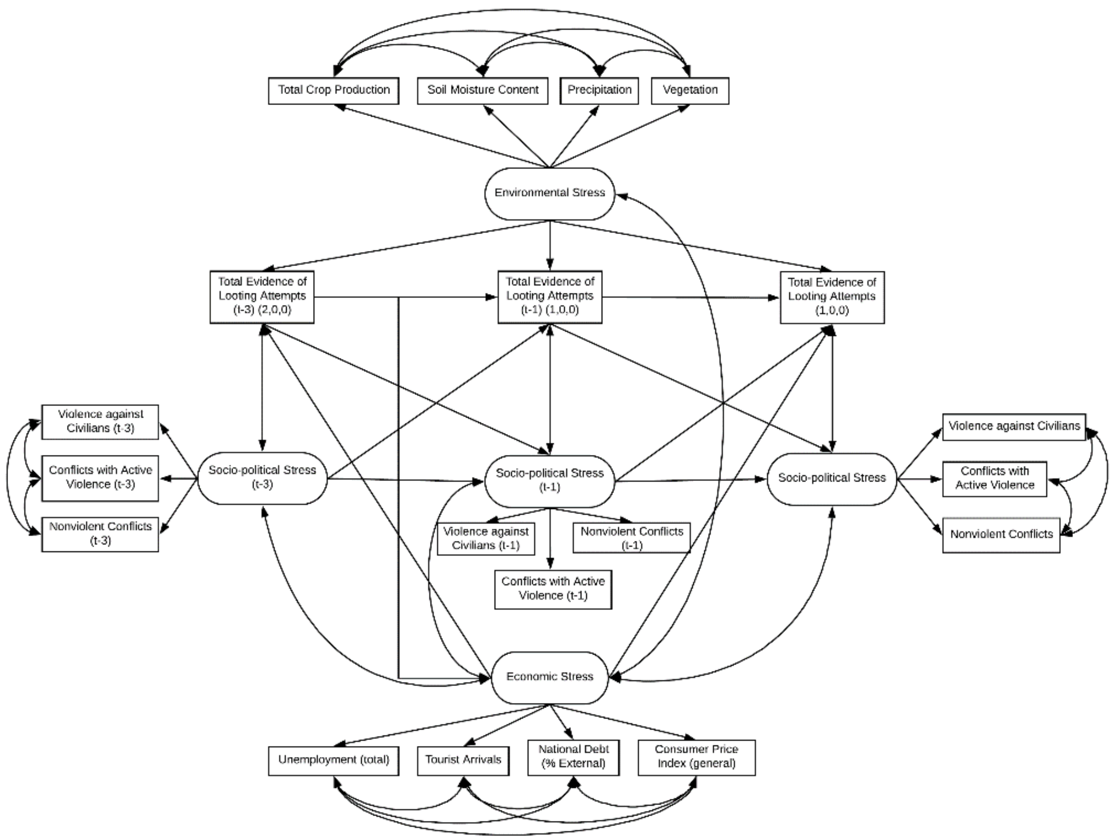


Figure 49. Model 1 version 2. 3 latent variables (2 exogenous, 1 endogenous)

Model 2 Path Diagrams

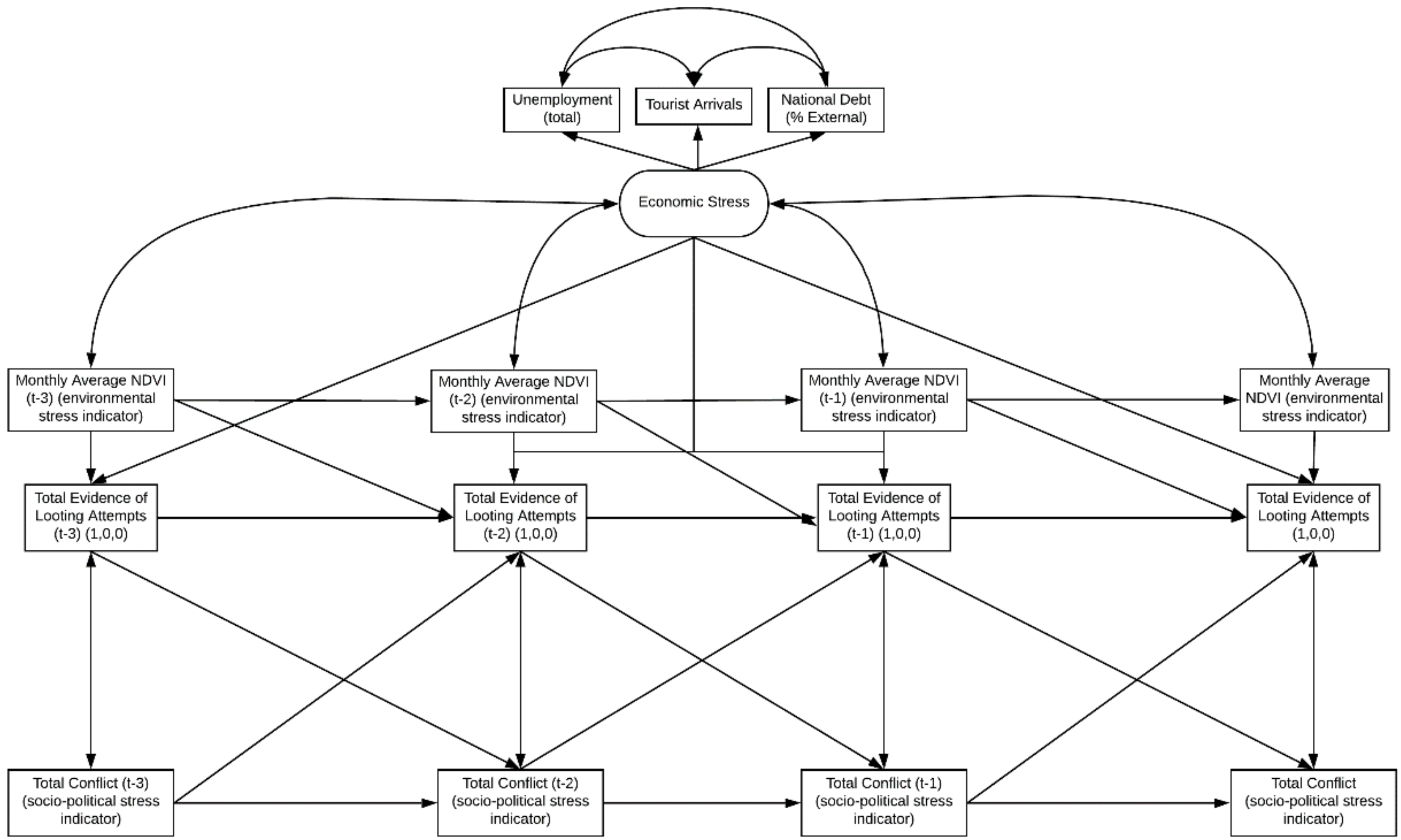


Figure 50. Model 2 version 1 – 1 exogenous latent variable (Economic Stress) and 2 observed variables (example with 3 lags)

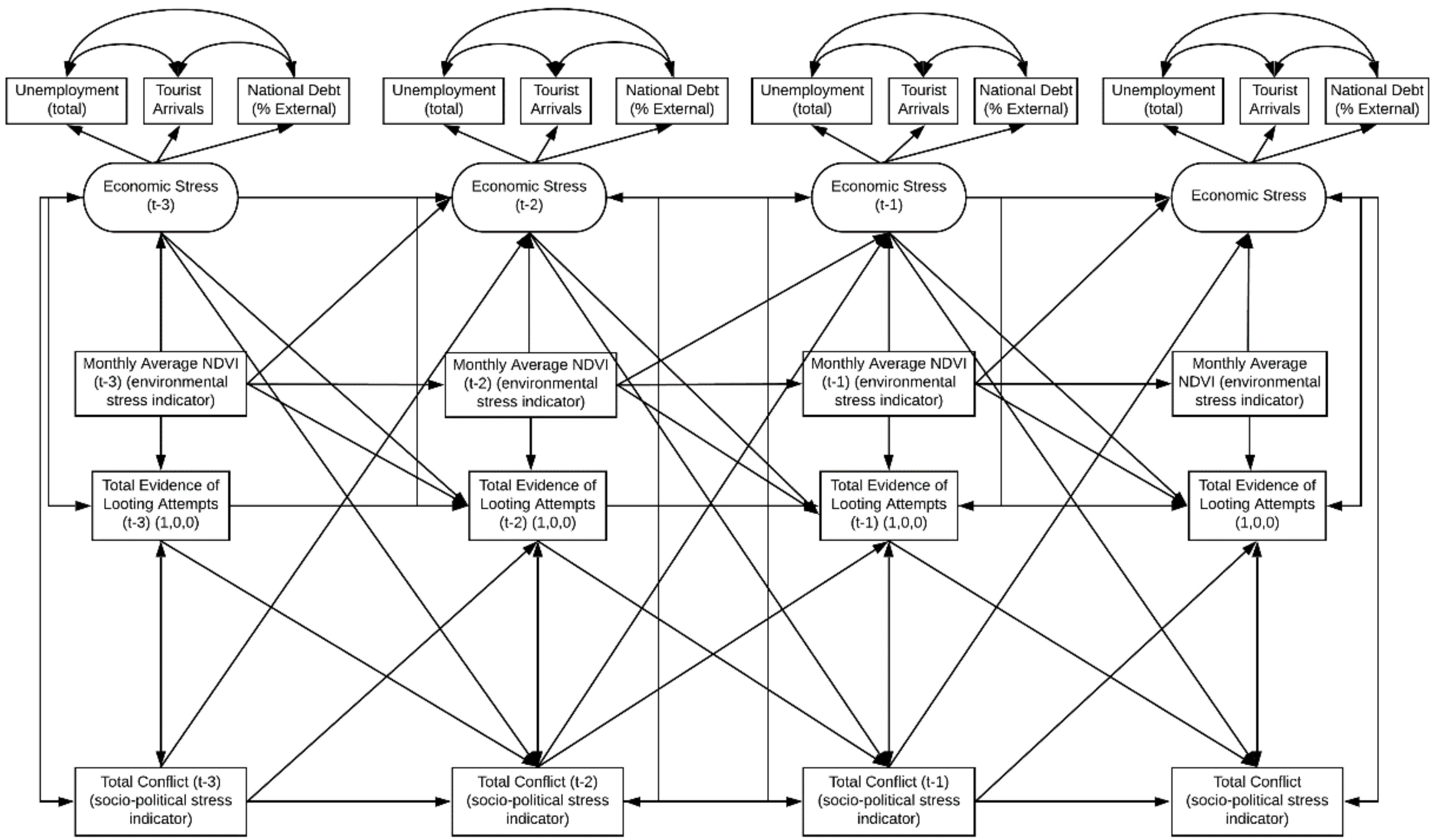


Figure 51. Model 2 version 2 – 1 endogenous latent variable (Economic Stress) and 2 observed variables (example with 3 lags)

Model 3 Path Diagrams

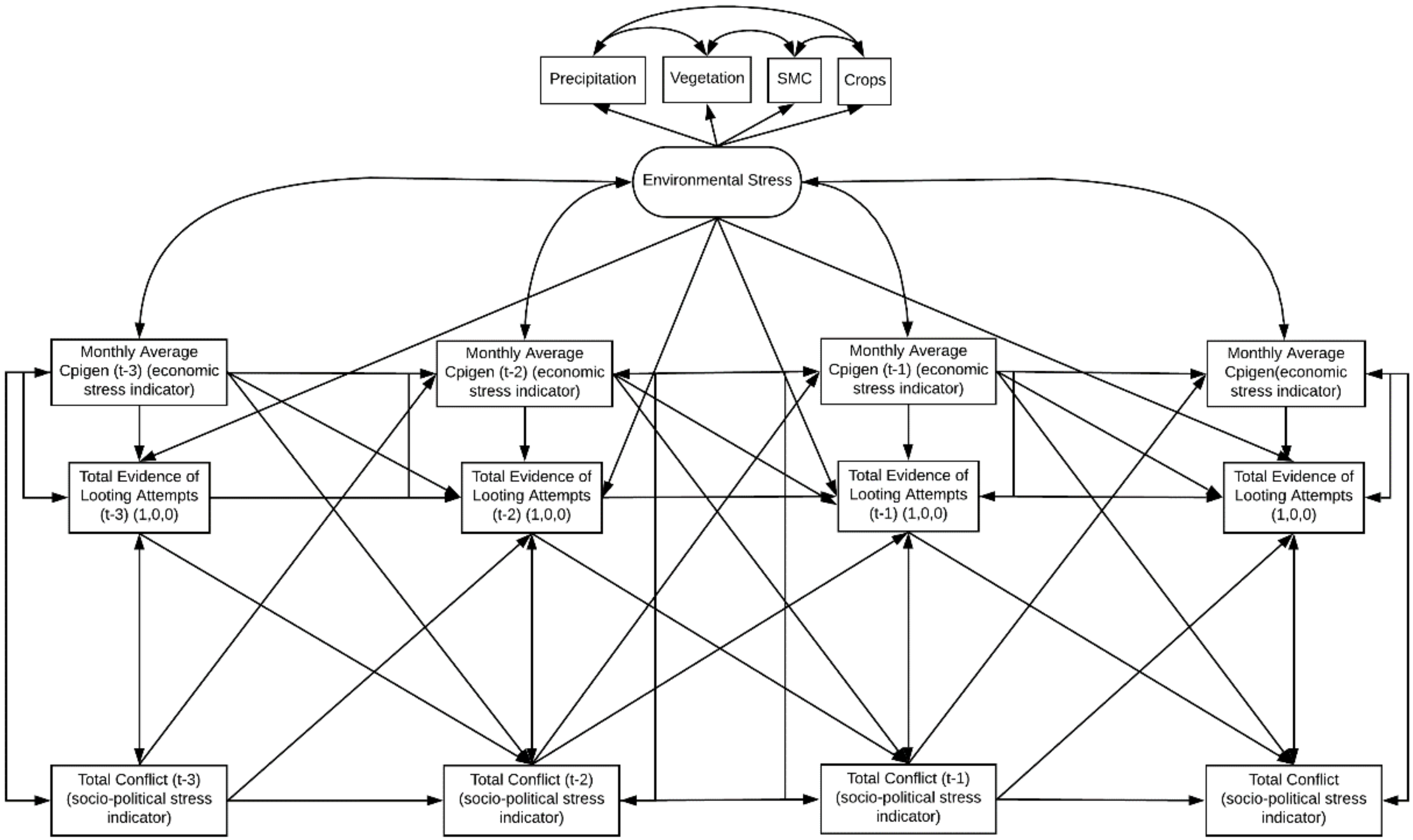


Figure 52. Model 3 version 1 – 1 exogenous latent variable (Environmental Stress) with 2 observed variables (example with 3 lags)

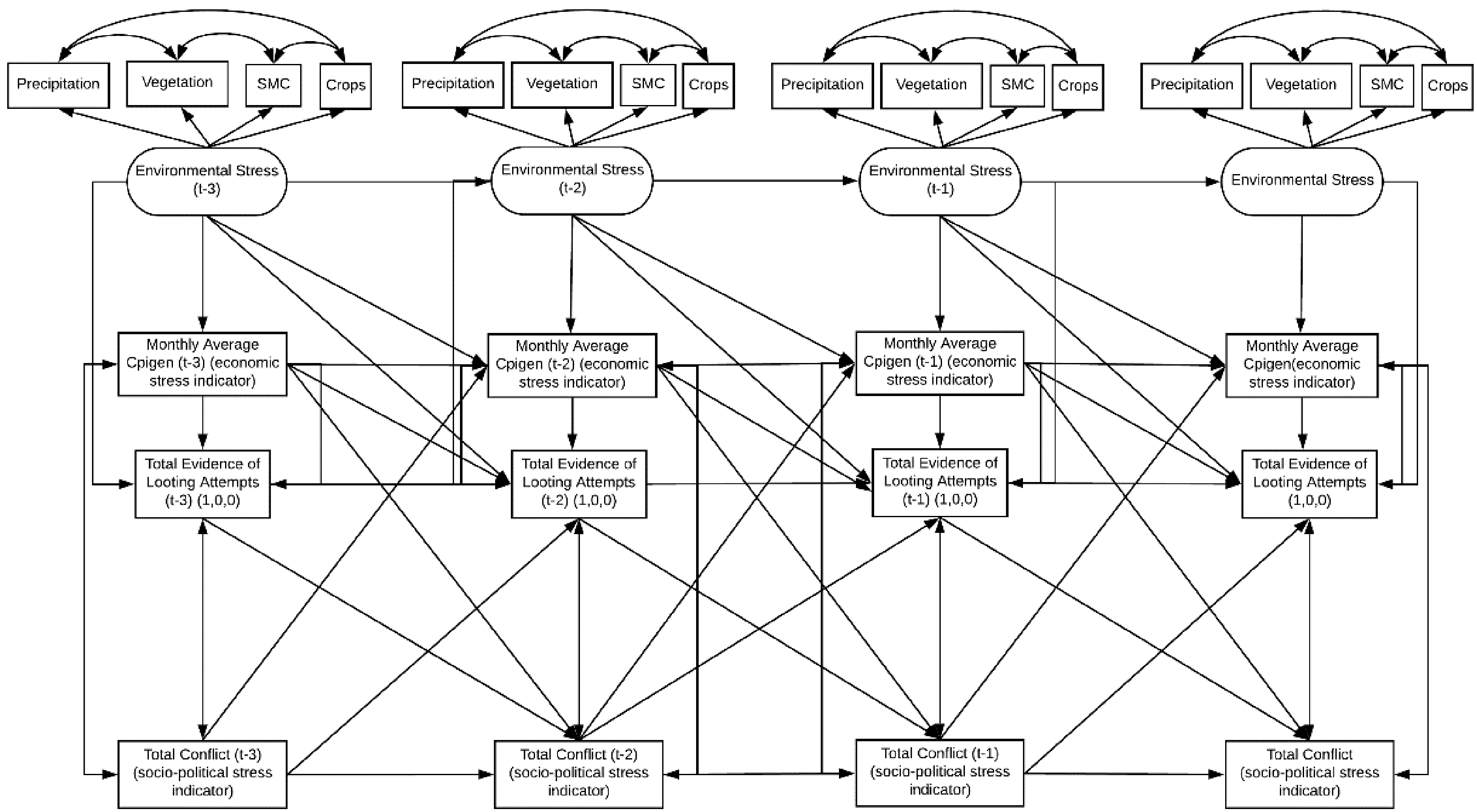


Figure 53. Model 3 version 2 – 1 exogenous latent variable (Environmental Stress) with 2 observed variables (example with 3 lags)

Model 4 Path Diagrams

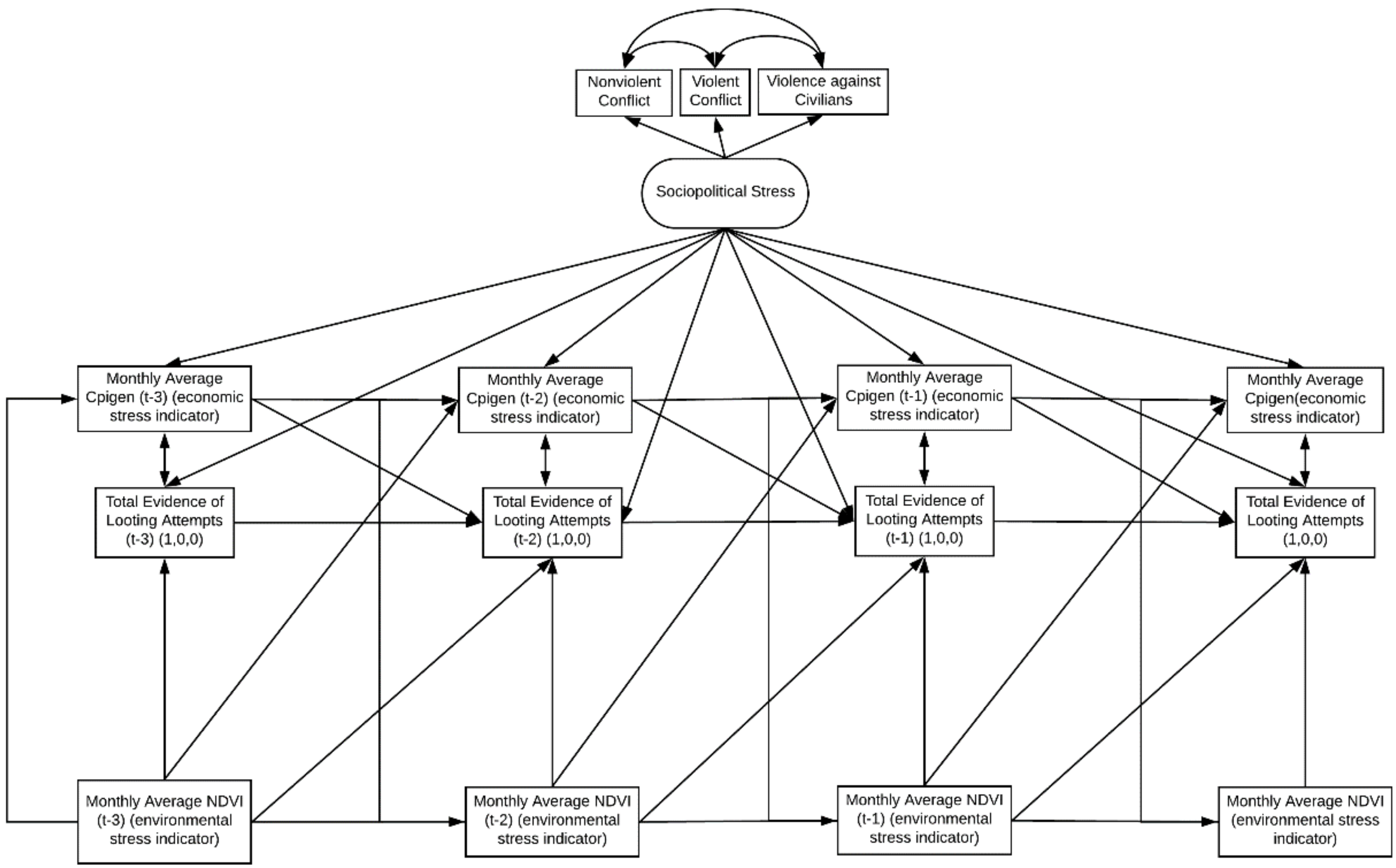


Figure 54. Model 4 version 1 – 1 exogenous latent variable (Sociopolitical Stress) with 2 observed variables (example with 3 lags)

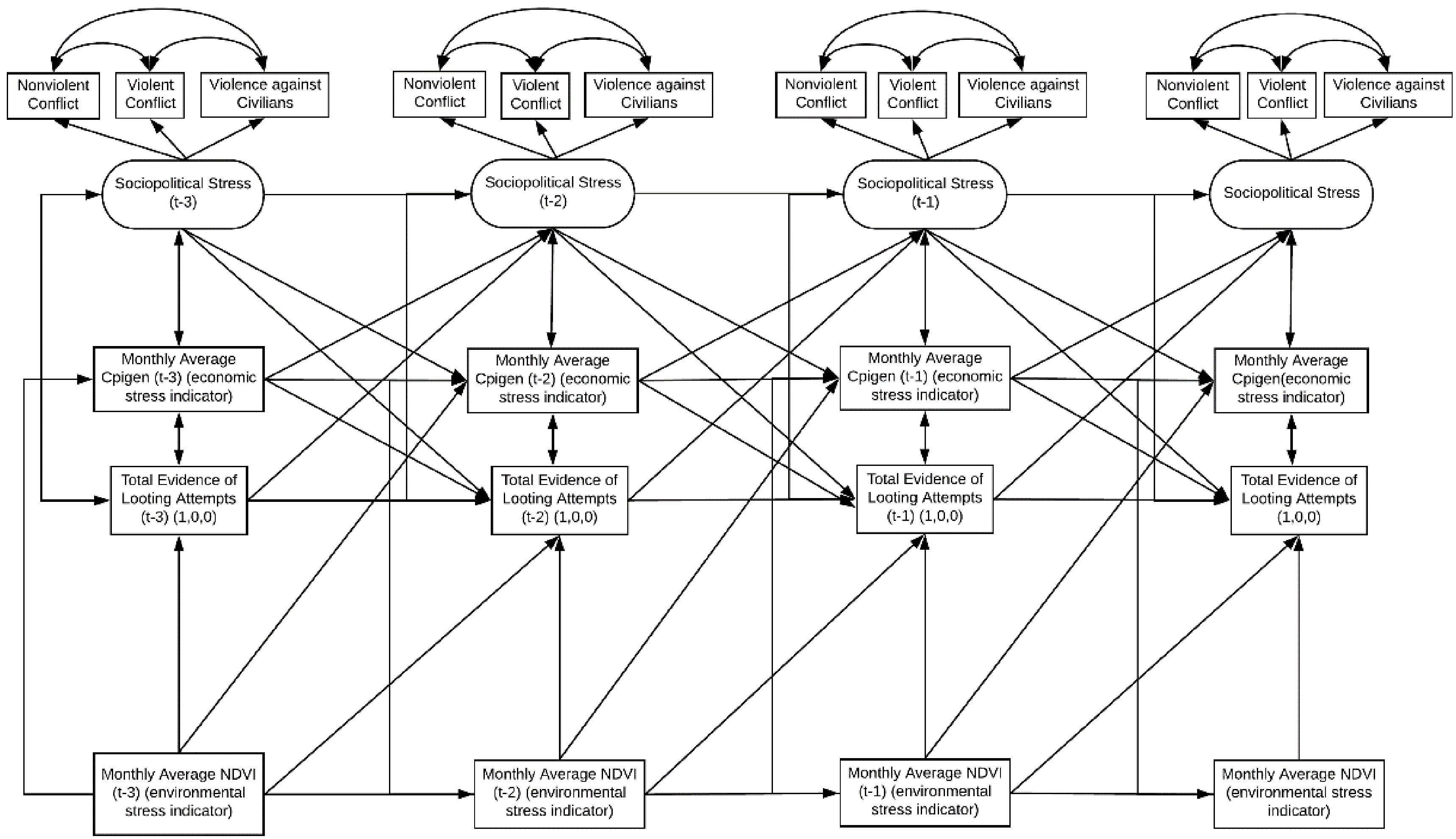


Figure 55. Model 4 version 2 – 1 exogenous latent variable (Sociopolitical Stress) with 2 observed variables (example with 3 lags)

Model 5 Path Diagrams

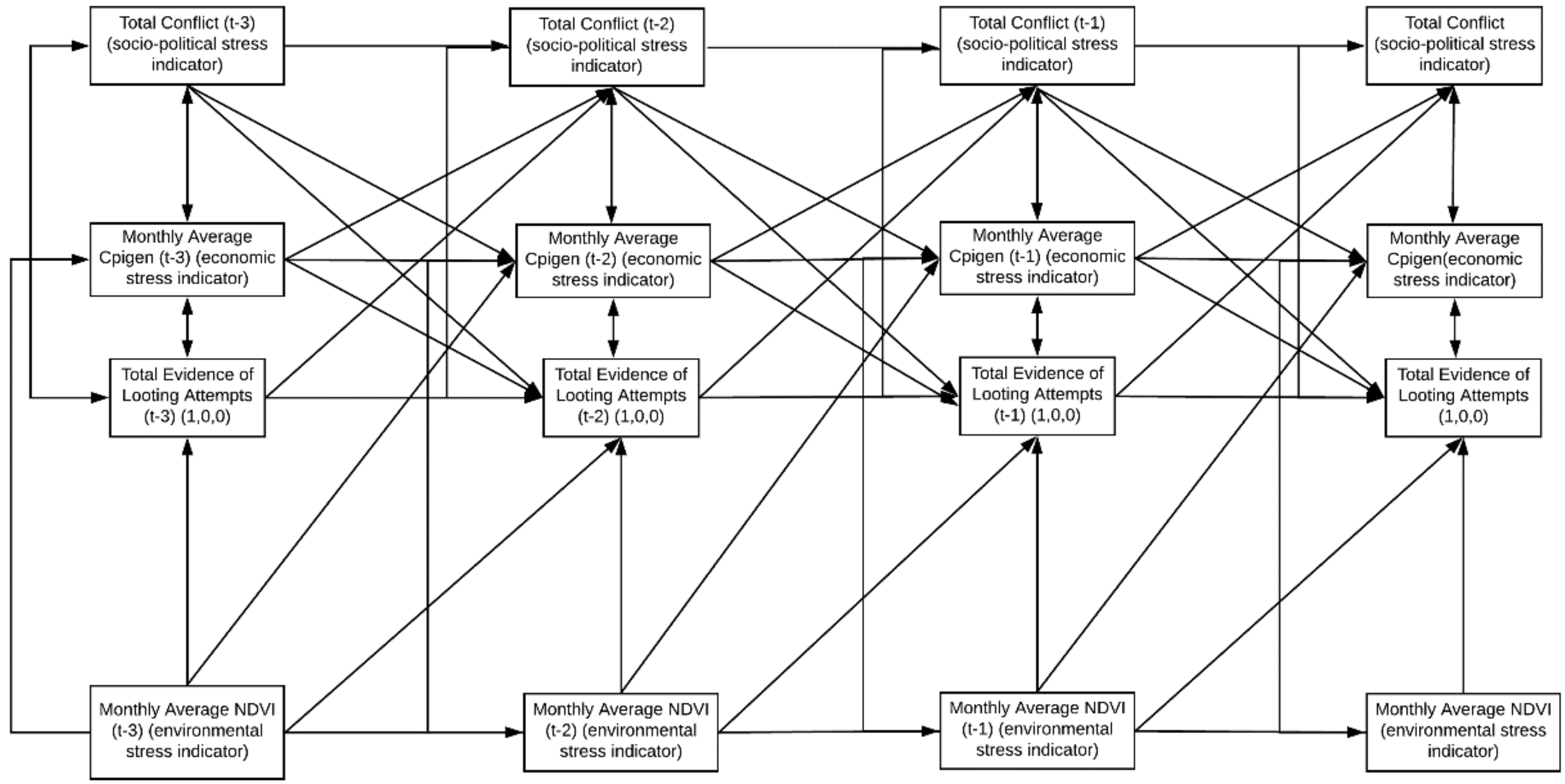


Figure 56. Model 5 version 1 – 0 latent variables and 3 endogenous observed variables (example with 3 lags)

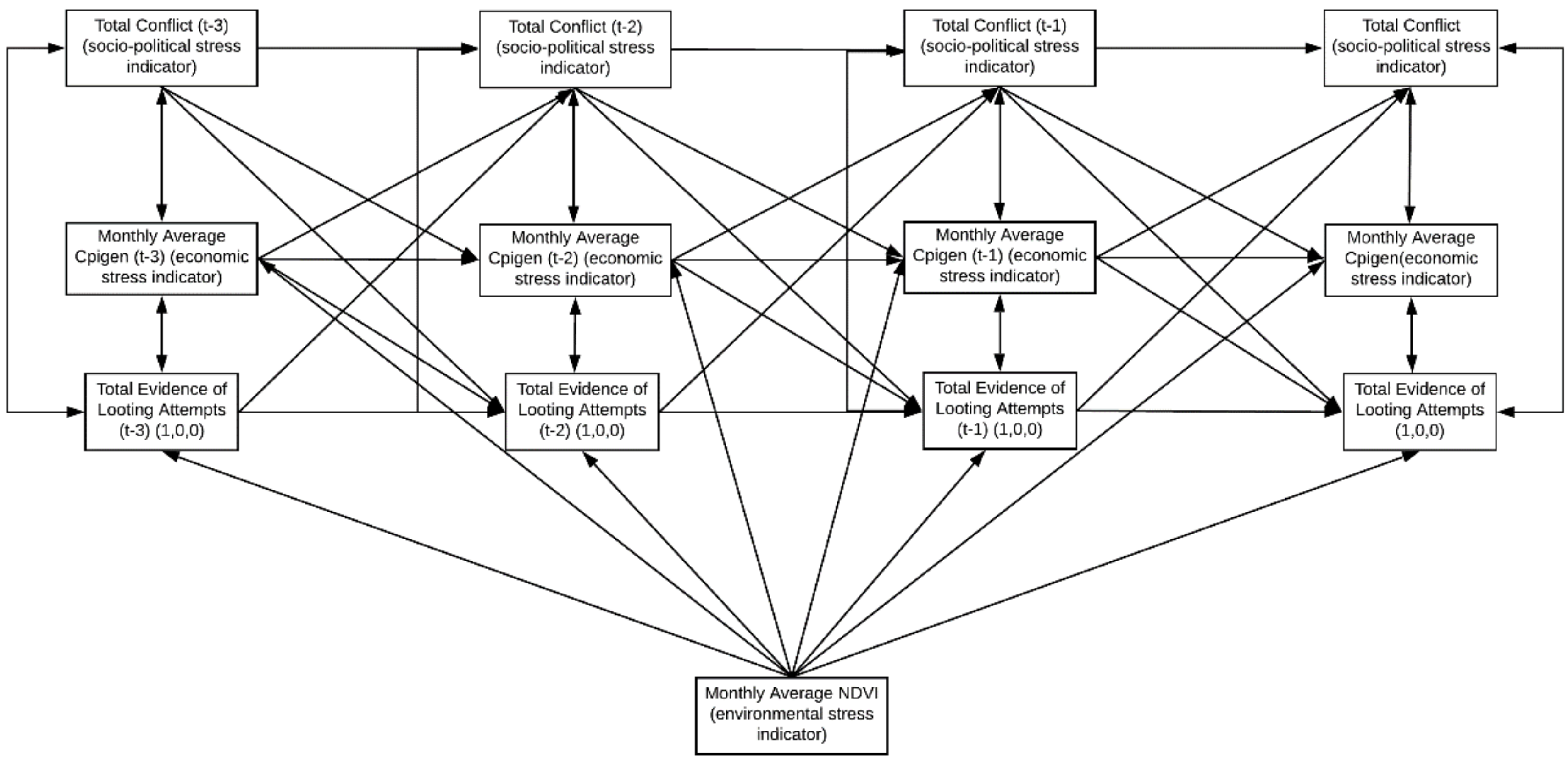


Figure 57. Model 5 version 2 – 0 latent variables with 1 exogenous observed variable and 2 endogenous observed variables.

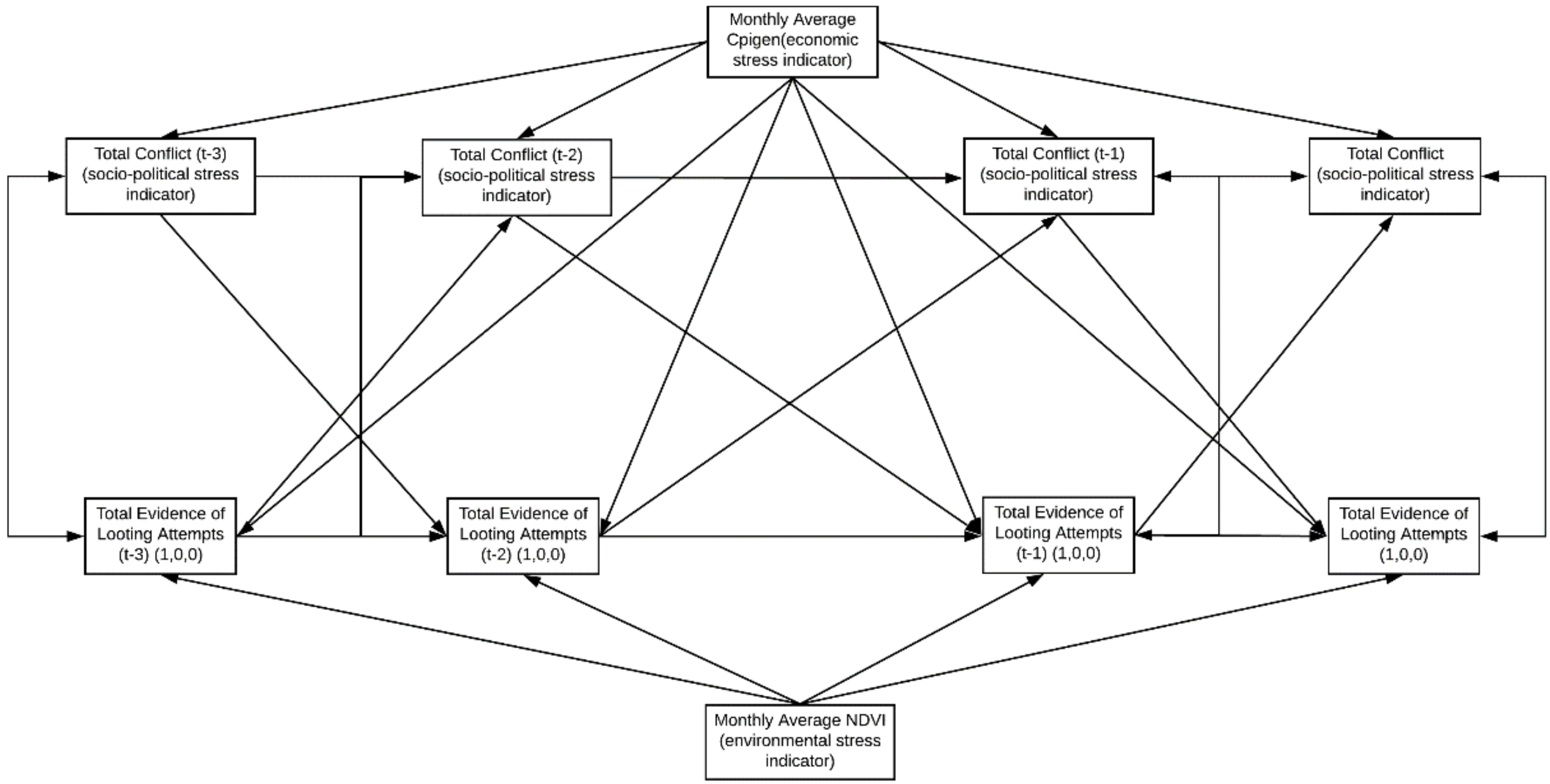


Figure 58. Model 5 version 3 – 0 latent variables with 2 exogenous observed variables and 1 endogenous observed variables (example with 3 lags)

ARDL Model Results with Sociopolitical Stress as the Dependent Variable

DV: Violent Conflict	Variable	Coefficient	Std. Error
Error Correction Term	Violent Conflict (-1)	**-3.1264******	0.6378
Short-term Relationships	D(Violent Conflict)	**1.3100****	0.4334
	D(Violent Conflict (-1))	**0.4972****	0.2227
	D(Looting Attempts)	**0.2703****	0.1028
	D(Looting Attempts (-1))	**0.1248***	0.0628
	D(Violence Against Civilians)	-1.0137	0.3078
	D(Violence Against Civilians (-1))	-0.3824	0.1327
	D(Violence Against Civilians (-2))	-0.2592	0.0979
	Vegetation Health Index	1.5760	14.1461
	Precipitation	0.2639	0.3640
	Soil Moisture Content	0.1534	29.8654
	National Debt (% external)	0.8569	3.1152
	Tourist Arrivals	-0.0123	0.0090
	Consumer Price Index (general)	**0.7350****	0.2928
Long-term Relationships	Looting Attempts	-0.1943	0.0280
	Violence Against Civilians	**0.5493*****	0.0526
	Non-Violent Conflict	0.0162	0.0241

* p ≤ 0.10, ** p ≤ 0.05, *** p ≤ 0.01

DV: Violence Against Civilians	Variable	Coefficient	Std. Error
Error Correction Term	Violence Against Civilians (-1)	**-2.0846*** **	0.2024
Short-term Relationships	D(Violence Against Civilians (-1))	**0.7892*** **	0.1030
	D(Violence Against Civilians (-2))	**0.3341*** **	0.0780
	D(Violence Against Civilians (-3))	**0.2729*** **	0.0597
	D(Violent Conflict)	-1.2611	0.3142
	D(Violent Conflict (-1))	-0.9965	0.1844
	D(Violent Conflict (-2))	-0.9126	0.1393
	D(Violent Conflict (-3))	-0.4470	0.0995
	D(Looting Attempts)	-0.2095	0.0795
	D(Looting Attempts (-1))	-0.1183	0.0510
	D(Looting Attempts (-2))	-0.0537	0.0404
	Vegetation Health Index	2.7772	9.8527
	Precipitation	-0.0434	0.2968
	Soil Moisture Content	-19.3578	20.4869
	National Debt (% external)	1.5501	2.2888
	Tourist Arrivals	-0.0072	0.004132
	Consumer Price Index (general)	0.0280	0.0631
Long-term Relationships	Looting Attempts	**0.1098***	0.0534
	Violence Against Civilians	**0.5642*** **	0.1474
	Non-Violent Conflict	-0.0265	0.0248

* p ≤ 0.10, ** p ≤ 0.05, *** p ≤ 0.01

DV: Non-Violent Conflict	Variable	Coefficient	Std. Error
Error Correction Term	Non-Violent Conflict (-1)	**-2.066*****	-0.5683
Short-term Relationships	D(Non-Violent Conflict)	**1.2561****	0.5649
	D(Non-Violent Conflict (-2))	**1.0735***	0.5082
	D(Non-Violent Conflict (-3))	0.3146	0.3064
	D(Violence Against Civilians (-1))	0.6369	0.4140
	D(Violence Against Civilians (-2))	0.3161	0.2646
	D(Violence Against Civilians (-3))	0.3906	0.2361
	D(Looting Attempts)	-0.4132	0.2093
	D(Looting Attempts (-1))	-0.3554	0.1828
	Vegetation Health Index	112.1397	74.3958
	Precipitation	-0.3479	1.3820
	Soil Moisture Content	**-332.7429***	165.5333
	National Debt (% external)	-14.9218	9.2365
	Tourist Arrivals	-0.0271	0.0272
	Consumer Price Index (general)	1.3131	0.7451
Long-term Relationships	Looting Attempts	**0.2643***	0.1318
	Violent Conflict	0.4411	0.3274
	Non-Violent Conflict	-0.3423	0.2697

* $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$

Appendix 6: Spatio-temporal Results

Hot and Cold Spot Patterns

	Evidence of Archaeological Looting Attempts					
	All Looting Attempts (either)	*All Looting Attempts (both)*	*New Looting Attempts (either)*	*New Looting Attempts (both)*	*Prior Looting Attempts (either)*	*Prior Looting Attempts (both)*
New Hot Spot	0	0	0	0	0	0
Consecutive Hot Spot	25	34	24	20	29	29
Intensifying Hot Spot	0	0	0	0	3	3
Persistent Hot Spot	0	0	0	0	0	0
Diminishing Hot Spot	0	0	0	0	0	0
Sporadic Hot Spot	4	2	8	5	2	4
Oscillating Hot Spot	14	3	5	0	11	7
Historical Hot Spot	0	0	0	0	0	0
No Pattern Detected	60	95	83	115	61	60
New Cold Spot	1	0	0	0	0	0
Consecutive Cold Spot	17	3	8	0	25	28
Intensifying Cold Spot	2	0	0	0	0	0
Persistent Cold Spot	1	0	0	0	0	0
Diminishing Cold Spot	0	0	0	0	0	0
Sporadic Cold Spot	16	3	12	0	9	9
Oscillating Cold Spot	0	0	0	0	0	0
Historical Cold Spot	0	0	0	0	0	0

	Sociopolitical Stress				Environmental Stress	
	All Sociopolitical Stress	*Violent Conflict*	*Non-Violent Conflict*	*Violence Against Civilians*	*Vegetation Health Index (NDVI)*	*Precipitation*
New Hot Spot	0	0	0	0	0	0
Consecutive Hot Spot	1	0	1	0	10	38
Intensifying Hot Spot	0	0	6	0	237	0
Persistent Hot Spot	2	0	0	0	1	0
Diminishing Hot Spot	4	0	0	0	0	15
Sporadic Hot Spot	0	0	0	0	4	21
Oscillating Hot Spot	0	0	0	0	0	0
Historical Hot Spot	1	4	0	0	0	0
No Pattern Detected	91	95	92	99	26	224
New Cold Spot	0	0	0	0	0	0
Consecutive Cold Spot	0	0	0	0	18	69
Intensifying Cold Spot	0	0	0	0	206	0
Persistent Cold Spot	0	0	0	0	0	0
Diminishing Cold Spot	0	0	0	0	0	0
Sporadic Cold Spot	0	0	0	0	10	18
Oscillating Cold Spot	0	0	0	0	0	0
Historical Cold Spot	0	0	0	0	0	0

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