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REMOTELY-SENSED MARKET ACTIVITY AS A HIGH-FREQUENCY ECONOMIC INDICATOR IN REMOTE RURAL AREAS

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Abstract

Effective targeting of social policies and their rigorous evaluation require relevant and accurate data. With the majority of the world's poor depending on agriculture and informal businesses for their livelihoods, information on these sectors is particularly valuable. High logistical costs, however, prevent most low-income countries from collecting measures of economic activity frequently and consistently over time. I use high-frequency satellite imagery to map rural marketplaces across large geographies and track activity within them in real-time. The method accurately detects existing markets and measured activity not only displays intuitive variation with respect to exogenous shocks, but also expands their temporal and geographical detail. Focusing on East Africa, I present applications of the novel method to the effects of lockdowns and violent conflict on market activity.

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1 Introduction

There is growing awareness among policymakers and researchers that effective spatial and temporal targeting of social policies as well as their rigorous evaluation require localized, timely and relevant data (World Bank, 2021). With the majority of the world's poor depending on agriculture and informal businesses for their livelihoods (ILO, 2018), information on these sectors across space and time is particularly valuable. However, available sources often have limited applicability to many policy and research questions as they are collected infrequently (e.g. nationally representative household surveys), do not cover the informal sector (e.g. tax records) or do not pick-up short-term fluctuations (e.g. remotely-sensed nightlights or other wealth indicators). This data scarcity is particularly salient for policies that are implemented over large areas, such as road improvements or social safety nets. Here, both local and aggregate effects may be of interest, but unless dedicated data collections are implemented, the coverage of available data may be insufficiently sparse.

In this paper, I present a scalable method generating a high-frequency economic activity measure for rural areas of developing countries. I focus on changes in attendance of rural periodic markets using satellite imagery. Periodic markets are a common and persistent feature of the rural economy across low- and middle-income countries. Typically, buyers and sellers meet once or twice per week in a public space, trading a wide range of goods and services such as vegetables, clothing or kitchenware (Mukwaya, 2016; Kithuka et al., 2020; Balineau et al., 2021). In Ethiopia, for example, the vast majority of crops produced for sale are sold at marketplaces, as opposed to other, more formal channels, and up to a fifth of rural household enterprises operate at marketplaces (von Carnap, 2023). By aggregating otherwise thin supply of rural products and demand for urban goods, these markets function as key locations of trade within and across regions. Beyond direct trading, marketplaces are also where small-scale businesses in sectors such as food processing or tailoring operate, taking advantage of periodic population gatherings there.

Due to markets' close link with rural economies, trends in their activity - i.e. changes in the presence of buyers and sellers - are informative about local economic conditions: busier marketplaces reflect that attendees either have more income to spend, more goods to sell, or both. Observing this activity at scale across large geographies thus holds potential to better understand local and aggregate impacts of social policies. Data collection using remote sensing furthermore allows researchers and policymakers to understand on-the-ground conditions when information is otherwise hard to come by, such as during violent conflict or after extreme weather events.

Tracking rural market activity requires knowledge of marketplaces' locations. However, comprehensive and up-to-date market maps are rarely publicly available. This lack of maps does not necessarily reflect authorities' lack of interest in marketplaces, but rather stems from their nature as modes of trade in informal, non-urbanized economies where traditional, ground-based monitoring systems can be prohibitively expensive to maintain. My method addresses this challenge by first screening imagery of locations where markets may be expected to exist for indicative reflectance patterns. I exploit two characteristic features of periodic markets for their detection. Firstly, stalls, vehicles and crowds are distinctly bright in images taken on market days when compared to the bare ground of the marketplace and surrounding areas on other days. Secondly, markets' regular occurrence provides a temporal signal to distinguish them from other, idiosyncratic changes in the imagery over time.

The high frequency and deep stack of the imagery I use allows me to exploit these regularities: in essence, the method screens stacks of imagery for contiguous areas within candidate locations for periodic changes in brightness. I perform various exercises to show that the method indeed (i) reliably identifies marketplaces where they exist and (ii) does not pick up other periodic events such as religious gatherings. While I focus below on applications in Kenya and Ethiopia, the method can in principle be applied in any relatively cloud-free context where open-air periodic markets exist.

In order to assess the accuracy of market detection, I first examine whether the method indeed identifies weekly markets and not other periodic events such as religious gatherings – a low false positive rate of market detection. I show that detected locations of periodic activity are centered on roads or village squares, as opposed to around known places of worship. Secondly, I show that the method identifies a high share of actual markets – a high true positive rate – by comparing the detected markets and market days against a validated ground sample in Western Kenya (Bergquist and Dinerstein, 2020). Currently available ground-truth data does not allow me to test, however, whether the true negative rate – not detecting a market when there is none – is also high, as maps of locations without markets are not available. It is reassuring in this respect that, conditional on detecting a market in the validation dataset, I always confirm the stated market day and do not detect features on other days. On such non-market days, market locations should look similar to places without markets and can thus approximate a sample of the latter.

Equipped with a sample of marketplaces in a region of interest – in my case East Africa –, I then turn to measuring market activity. For this, I measure the density of participants within the detected market area by extracting the median brightness across all pixels contained therein from each image of a given location. I interpret this measure as tracking *changes* in local GDP – places with larger markets may not necessarily have higher GDP levels than places with smaller or without markets; for a given market, however, days on which measured market activity is high compared to other days likely reflect increased goods exchange and revenue by market participants.

The PlanetScope imagery I use for detection and tracking is available since 2016 and made available in real-time. In Ethiopia and Kenya, I gather between two and five observations for market activity per marketplace and month, depending on seasonal cloud coverage and market frequency. To illustrate that the remotely-sensed market activity can indeed be interpreted as a measure of changes in economic activity, I present three applications using data from 954 marketplaces in Kenya, Ethiopia and Uganda. First, I correlate quarterly changes in market activity with estimates for sectoral GDP in Kenya. I find that the novel indicator varies between quarters at similar magnitudes as official agricultural production statistics, though differences between the two indicators in their respective timing of seasonal peaks suggest that remotely-sensed market activity can provide higher temporal resolution. Second, I show how in areas with rain-fed, small-scale agriculture, market activity is seasonal overall, and levels of harvest-season market activity are causally affected by rainfall during the previous growing season. Thirdly, I illustrate the effects of external events that can be expected to impede economic conditions on market activity, focusing on government-mandated lockdowns during the COVID-19 pandemic and the ongoing war in Tigray and other regions of Ethiopia.

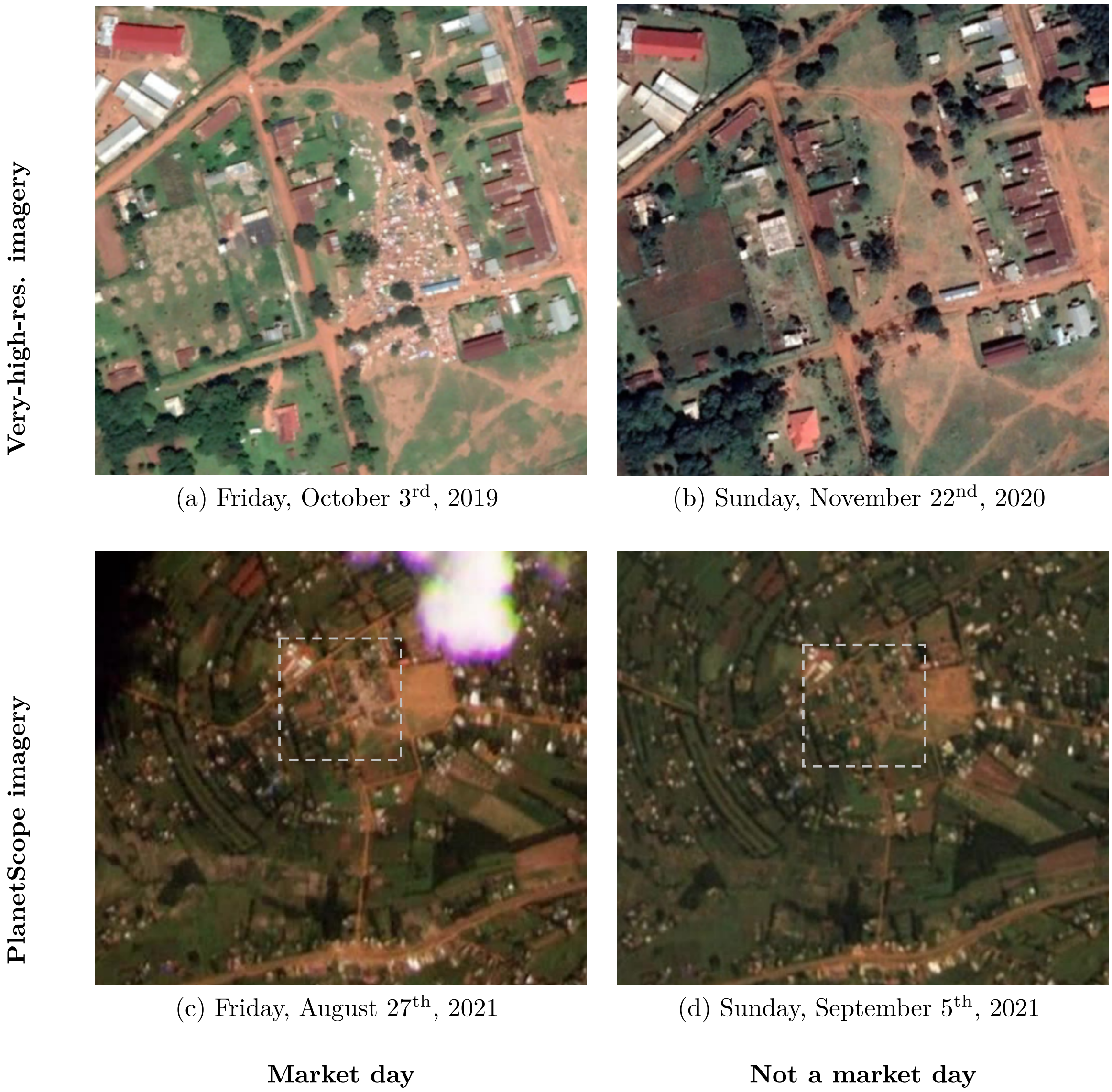
Measuring rural market activity expands the toolkit for data collection in developing countries in various dimensions. Existing micro-level data often captures great levels of detail, but has limited temporal and spatial coverage (e.g. DHS, LSMS surveys), can be difficult to obtain from data proprietors (e.g. call detail records), or does not cover the informal economy (e.g. tax records, tariff data). Remotely-sensed data has some advantages over these aforementioned data sources (see Donaldson and Storeygard (2016) for a review). Compared to commonly used nightlights as an indicator of economic wealth (Henderson et al., 2012; Addison and Stewart, 2015), market activity is available at a sub-yearly frequency, is more likely to pick up short-term changes in economic conditions including downward adjustments[1], and tracks even non-electrified places[2]. Beyond nightlights, other recent work has constructed local poverty estimates from very-high resolution imagery using machine learning (Jean et al., 2016; Huang et al., 2021; Rolf et al., 2021). Here, market activity provides a downward-elastic indicator related to short-term income flows, as opposed to more long-term wealth proxied by village structures and rooftop materials which are commonly used for wealth prediction in this literature. Finally, rural market activity provides a useful complement to the upstream measures of production provided by the agricultural yield estimation literature (Lobell et al., 2019).

Besides providing a novel economic indicator in otherwise data-scarce environments, the method also generates data to study the role of marketplaces and their interactions more broadly (von Carnap, 2023). Previous research on the role of these marketplaces in economic development was hindered by a lack of data. An earlier, cross-disciplinary wave of interest in markets from economists, geographers and anthropologists (see e.g. Hill (1963); Skinner (1965); Wood (1975); Good (1975); Bromley et al. (1975)) died out, with Hill (1963) explicitly mentioning that 'there ought to be much more mapping of marketplaces'. Since then, work on rural marketplaces has been limited to a small number of case studies (e.g., Mukwaya, 2016; Kithuka et al, 2020). Beyond mapping and regarding market-level economic data, available price monitoring programs such as those maintained by the World Food Program or IFPRI typically focus on sets of larger wholesale markets, and lack quantity data. By providing large-scale coverage and local measures of market activity, the method can contribute to our understanding of spatial patterns of economic development.

The rest of the paper proceeds as follows. Section 2 presents the method and validates the market detection. Section 3 presents exercises illustrating the validity and usefulness of the novel activity measure.

[1]Asher et al. (2021) find that nightlights perform well in predicting measures of development, but less so in time series.
[2]This increases spatial coverage addresses a criticism against nightlights raised by Gibson et al. (2021)

Figure 1: Marketplaces in satellite imagery



(a) Friday, October 3rd, 2019
(b) Sunday, November 22nd, 2020
(c) Friday, August 27th, 2021
(d) Sunday, September 5th, 2021

Panels (a) and (b) show Tongaren in Bungoma County, Kenya, in very-high resolution imagery from the GoogleEarth archive. Panels (c) and (d) show a different extent of the same location in PlanetScope imagery. The grey squares in panels (c) and (d) indicate the extent shown in panels (a) and (b)

Section 4 provides an illustration of the method's costs, discusses limitations and concludes.

2 Finding markets & tracking their activity

In the following, I present an overview of the method. I begin by describing how I detect otherwise unmapped periodic marketplaces and explain how I assess the accuracy of the method. I then detail how market activity is measured within the detected markets' extents.

2.1 Finding markets

Figure 1 illustrates the visual pattern underlying the market detection method. It shows in the top row two very-high-resolution images from the Google Earth archive for a Kenyan village, acquired on a Friday and a Sunday. In panel (a), the village square is covered in white, blue and red structures – such as stalls, vehicles and tarps on which goods are displayed – that are typical of periodic markets in the context. While in principle it would be possible to scan an archive of similar imagery for places that look like marketplaces using machine learning or human visual interpretation, in practice, images at the required resolution are only infrequently acquired and made publicly available.

Infrequent captures imply that the few available images may not show a market if they are not taken on market day. This is the case in panel (b): here, the village square appears only as bare ground, indistinguishable from other open common areas around it. My method therefore uses PlanetScope imagery which – compared to images in GoogleEarth – has a slightly lower resolution (3 meters per pixel) but a higher, up to daily revisit frequency at around 11am local time. This allows me to exploit the relative brightness of markets on market days – evident from comparing panels (a) and (b) – as well as their periodic nature – e.g. taking place every Friday, but not on Sundays – in commercially available imagery with global coverage.

Panels (c) and (d) of Figure 1 show examples of the PlanetScope imagery I employ. While the market is not clearly discernible with the bare eye due to the imagery's lower resolution, comparing the area within the grey dashed squares in the two images still reveals a brighter patch in the image taken on a Friday compared to the one taken on a Saturday. This again illustrates the basic idea to screen images for changes in brightness that - unlike the patch of cloud visible in the Friday image - occur at a regular frequency.

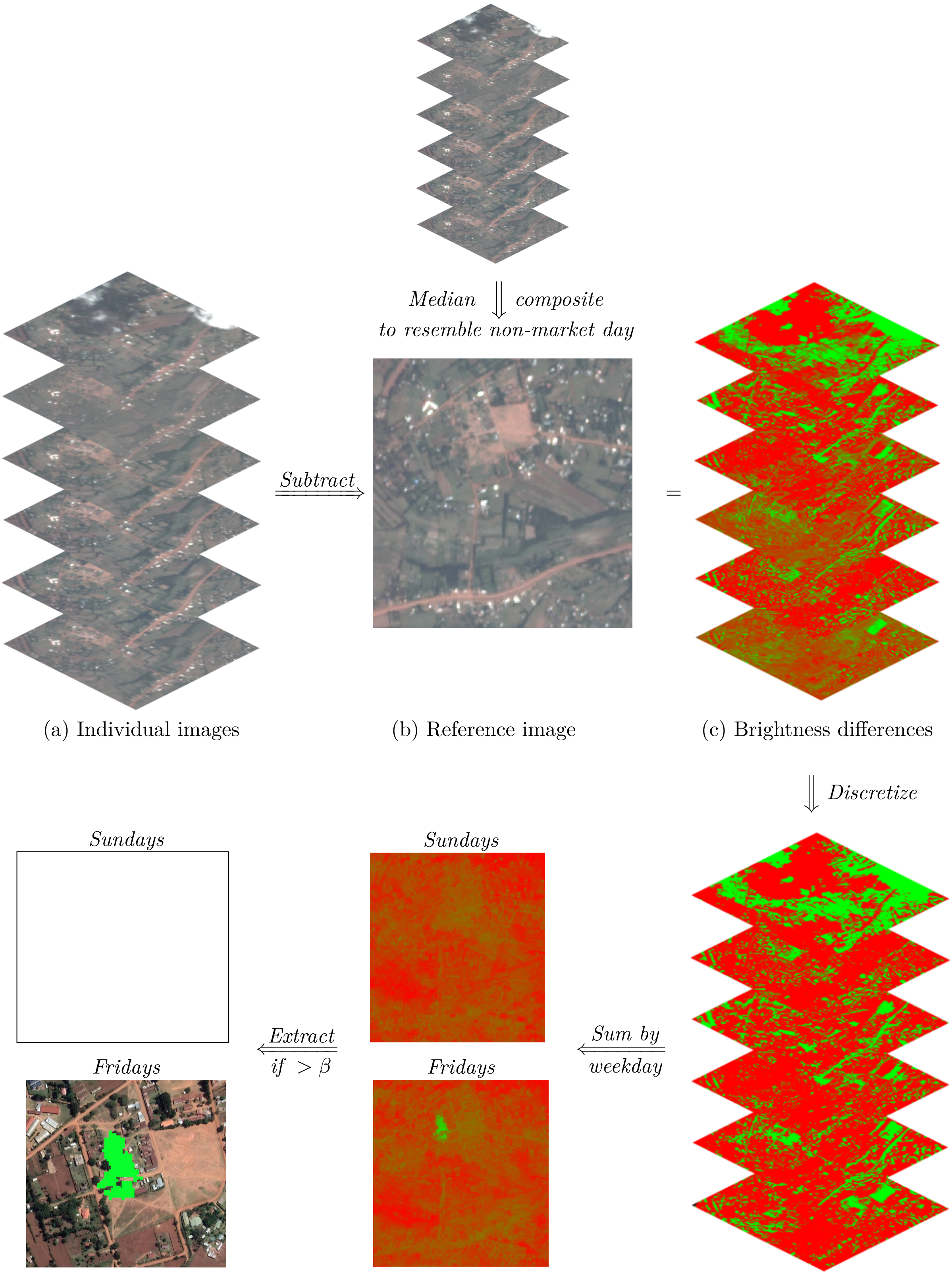
The premise to look for relative changes in brightness between market and non-market days necessitates the definition of a reference image, ideally showing a day on which the market is not held. Given the lack of comprehensive catalogues of market locations, there is also no widespread information on market schedules, including days where markets are not held. To make progress, I exploit the fact that periodic markets are usually held on less than half of the days in a week[3]. With markets being relatively 'rare', a median composite of all images within a time interval (e.g. a quarter[4]) will – given a large enough set of images to construct the composite[5] – look like a 'typical' day which for the vast majority of places is a non-market day (Panel (b), Figure 2).

[3]Previewing the mapping exercise across Ethiopia, Kenya and Uganda, I find that most markets are held on one day (55% of markets in Ethiopia, 70% in Kenya) or two days (37% and 27%) per week, while it is less common for them to occur on three days per week (8% and 3%) (see Figure A.1) This concentrated distribution of market frequencies reflects markets' role as a coordination device in context where farmers have other obligations as well. The dominance of markets held on less than half the days per week also aligns with available evidence from earlier studies of periodic markets in the region (Wood, 1973a; Bromley et al., 1975)

[4]The composition within a set time interval takes into account that relative brightness of market structures relative to the bare ground may differ across seasons.

[5]For a given location of interest, I access all imagery taken since the inception of the PlanetScope product in mid-2016. In practice, I filter out images with high cloud cover (above 20% of the image) and apply a set of processing steps to make scenes comparable over time, including cloud masking and lateral alignment based on reflectance in the red band to account for distortions from the orientation of the sensor.

Figure 2: Identification of periodic markets from satellite imagery



(a) Individual images (b) Reference image (c) Brightness differences

(f) Extracted market area (e) Difference frequency (d) $\mathbb{1}$ (Brightness diff. $> \alpha$)

The figure illustrates how a satellite imagery can be used to identify a market area and its days of operation. First, when median compositing sufficiently many images, this image will look like a non-market day for markets that operate on less than four days per week. Subtracting this composite (b) from the individual images (a) gives continuous representations of brightness differences (c; green = relatively bright). These can be transformed into discretized representations by comparing individual pixel values to a brightness threshold α (d; green = brightness exceeding a threshold). Summing these up by weekday gives heatmaps of the frequency of brightness differences (e; green = frequent). Finally, selecting contiguous pixels that are bright more frequently than a parameter β gives outlines of market area, aligning with the one visible in Figure 1.

Following the same logic, the method can be adjusted to detect markets occurring at other-than-weekly frequencies – such as the 3-4 day cycles in parts of West Africa (Hill, 1966) or monthly gatherings – as long as markets occur on less than half of the days of the cycle.

Using the median composite as the reference image, I can then define relative changes in brightness for each image in the sample. I here match the bands in the visible spectrum (red, green, blue) between individual and respective reference images and subtract the latter from the former. This is illustrated for one band in panels (a-c) of Figure 2.

The individual difference images contain both low-level noise in light green – coming from differing image lighting conditions or sensor properties – and high-level differences in bright green. The latter include the market signal, but also idiosyncratic variation between images stemming from, e.g., remaining patches of clouds after pre-processing or harvested fields.

In order to reduce the influence of noise, I simultaneously filter out the low-level noise – coming from image conditions – and reduce the impact of high-level noise – coming primarily from very bright clouds and reflecting rooftops – by converting the continuous difference measure into a dummy representation (panel (d)). The dummy here indicates whether the pixel-level difference exceeds a threshold value α. In order to account for the observation that e.g. a metal rooftop changes reflectance much more in absolute terms than e.g. fields, I define relative strength in terms of pixel-level standard deviations of the differences.

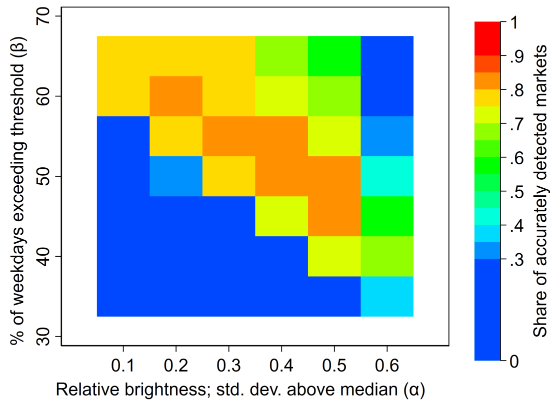
To distinguish between brightness changes from regular market activity or other sources, I rely on the assumption that only markets appear systematically in the same location within an image at a constant periodicity. I can thus filter out remaining high-intensity noise by averaging the relative brightness dummies across all incidents of a given weekday in the sample, as illustrated in panel (e). Here, areas marked in green are those where pixels are relatively bright on a high share of images taken on that weekday. In order to convert these heatmaps into polygons outlining the market areas, I define a second parameter β, defined as the share of weekdays in the sample on which a given brightness threshold is exceeded (panel (f)).

Section 2.2 describes how I calibrate this parameter and evaluates whether assuming markets to be the only visible periodic changes is valid.

2.2 Calibration & validation of market detection

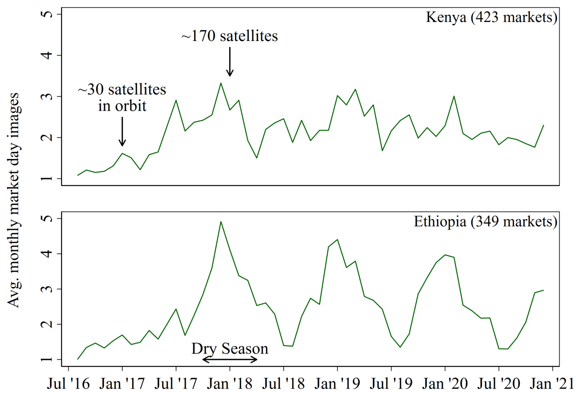
Ideally, the method outlined in the previous section would, when deployed over a large number of locations, detect a high share of existing markets – a high true positive rate – and not detect markets in a large share of locations that do not have markets – a high true negative rate. To assess accuracy in this way, I need a validation dataset containing precise coordinates, timings and sizes of a representative sample of periodic markets in a given region, as well as a sample of locations without periodic markets. To the best of my knowledge, this is not available, at least publicly for any African country where periodic markets

Figure 3: Detection accuracy by parameter combination



The figure shows on the horizontal axis a range of parameter values of what may constitute a brightness change relative to the median composite, measured in standard deviations of brightness per pixel. The vertical axis shows a range of what may constitute a frequent change in brightness over all instances of a given weekday in the sample. The color scale represents detection accuracy as defined in Equation 1 in the validation sample for a given parameter combination.

Figure 4: Monthly observations per detected marketplace



The lines indicate the number of monthly observations per market in the sample. Markets with multiple market days can have more than one observation per week.

are common[6].

Without this ideal validation data, I rely for calibration of the method's parameters and its validation on the set of 56 markets studied in Bergquist and Dinerstein (2020) in western Kenya and still in operation in 2021[7]. The authors specifically sampled periodic markets as opposed to other places of trading and recorded their location and days of operation. The goal here is to find the combination of parameters α and β that maximizes detection accuracy. I assess parameter combinations as 'good' if the method detects market outlines on the correct days in a large share of locations ('true positives'), and does not detect shapes on other days ('true negatives'). More specifically, I define detection accuracy for each parameter combination as the share of locations in which at least a subset of the stated market days are confirmed (true positives) and no other days than these (true negatives).

$$\text{detection accuracy} = \frac{\sum_{i=1}^{56} \mathbb{1}\left(\{\text{detected market days}\}_i \subseteq \{\text{validation market days}\}_i\right)}{56} \tag{1}$$

I perform a grid search over a range of possible parameter combinations of market brightness and brightness frequency, summarized in Figure 3. On the axes, I combine various values of the parameters. The colors of the cells illustrate for each parameter combination the share of sample markets I confirm according to the metric above.

There is an intermediate parameter range in which the method confirms around 85% of the markets. For high values of α and β, the method does not detect a larger number of markets as image - exclusion

[6]Publicly available market monitoring datasets such as those maintained by actors like the WFP or IFPRI focus on aggregation markets in district capitals or other larger towns. Furthermore, the published data typically do not have measures of market extent or timing.

[7]The authors selected 60 markets for their sample in 2016. Moritz Poll kindly collected and shared information on which of these markets were still in operation in 2021. I drop from the validation sample four markets that were found to have permanently ceased operations.

errors - whereas for lower values, inclusion errors increase, typically caused by large rooftops or other reflecting surfaces. I henceforth work with the parameter combination giving the highest accuracy in the validation sample ($\alpha = 3,\ \beta = 55$). This parameter combination may not be optimal in contexts with different atmospheric conditions or where periodic markets consist of differently looking structures[8]. To ensure that the method returns a locally representative sample of market locations, it may be necessary to calibrate the parameters against a context-specific validation sample, collected either on the ground or from secondary sources such as very-high resolution imagery or administrative records.

I show the detected shapes for each location in the validation dataset in Appendix B, where the underlying very-high-resolution images suggest that I indeed identify markets and not another regular patterns. In particular, this is supported by the observation that if more than one market day is detected for a given location, the extents for the various days typically overlap each other closely.

Beyond this visual evidence, a specific confounder may be places of worship that are also frequented on a weekly basis. To address this concern, I calculate the distance from all 879 registered churches and mosques in the Open Street Map database that fall within 1 kilometer of detected marketplaces in East Africa. None of the listed religious buildings falls into the detected market extent. Likely, religious activities rarely spill onto surrounding areas where they may be visible in satellite imagery and confound the market detection.

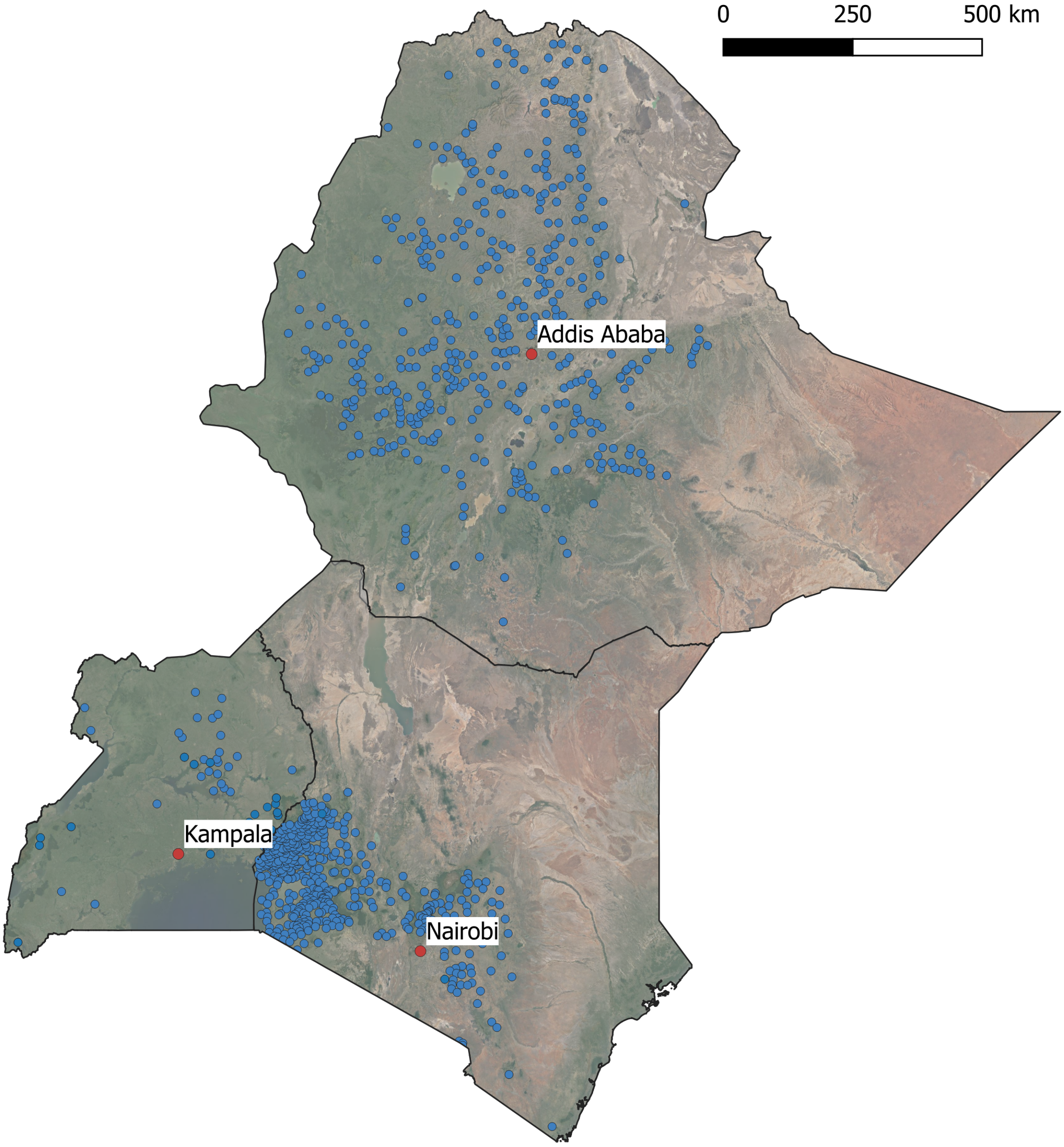
After chosing the method's parameters based on Figure 3, I apply the method to a large set of candidate market locations in Kenya and Ethiopia using GoogleEarth Engine. I select candidate locations based on visual inspection of the GoogleMaps basemap, focusing on clusters of houses along roads. In principle, the definition of candidate locations can be automated using secondary datasets, such as high-resolution population grids and road networks. It is worth noting that the sample is not necessarily representative of all periodic markets in the study countries in a statistical sense, but that it is geographically broad. The sample I work with for the rest of the paper consists of 439 markets in Ethiopia, 452 markets in Kenya and 63 markets in Uganda, mapped in Figure 5.

2.3 Extracting market activity

After having collected information on market locations and their schedules, I now describe the construction of a measure of market activity over time. Here, I again rely on the observation from very-high-resolution imagery that a marketplace is relatively brighter when more cars, tarps and people are present, compared to when the marketplace is empty. I therefore extract the value underlying the market outline detection above, the maximum deviation in brightness measured in standard deviations for each day (including non-market days) across the three bands. Considering maximum instead of average deviations across bands takes into account that some marketplaces may appear bright on non-market days in visual imagery if the ground consists of bright sand. In these cases colorful market structures may not stand

[8]Note that the imaging sampling period included 2020 where, as shown below, market activity ceased for months on end due to COVID-19-related containment measures. This likely affects the optimal choice for the frequency parameter α, as a lower share of actual market days would have looked visually different from other days.

Figure 5: Detected markets in East Africa (blue dots) underlying activity analyses



Blue dots indicate detected markets across Ethiopia, Kenya and Uganda. They form convenience samples based on visually or automatically identified likely locations for marketplaces – such as road intersections and rural settlements – or take as starting point historical mappings (Wood, 1973b; Good, 1973) or mentions of modern markets in administrative documents.

out on average across bands, but should still be markedly different in at least some of them. In order to obtain one observation per day and market location, I compute the median of these deviations across all pixels within each image of the detected market area, including on non-market days. I hence also obtain measures of 'activity', i.e. brightness deviations, on non-market days which can be used to normalize activity on market days within a given time period. I formally define the measure of activity on day d for a market with a set of areas A and set of non-market days $\overline{D}$ as

$$mktAct_d = \sum_{a \in A} \frac{A_a}{\sum_{a \in A} A_a} \underset{p \in A_a}{median} \left(\underset{b \in r,g,b}{max} \left(\frac{v^b_{p,d} - \underset{j \in (d \pm 45) \wedge \overline{D},}{median} \left(v^{b,}_{p,j} \right)}{\underset{j \in T_{\overline{D}}}{sd} \left(v^b_{p,j} - \underset{j \in (d \pm 45) \wedge \overline{D},}{median} \left(v^{b,}_{p,j} \right) \right)} \right) \right), \tag{2}$$

where p identifies pixels and v^b_p with $b \in r, g, b$ are pixel values across the red, green and blue bands of the imagery.

An advantage of remotely sensed market activity is its availability throughout the year, weather permitting. Figure 4 shows for the set of markets in Figure 5 the average number of market activity observations obtained per month. The imagery is relatively infrequently available from mid-2016 onwards and increases with the deployment of a large number of satellites in early 2017. It is furthermore evident that there is a seasonality in image availability, stemming from cloud conditions and particularly so in Ethiopia. In turn though, more markets with two or more market days per week in that country increase the likelihood for successful captures during relatively cloud-free months.

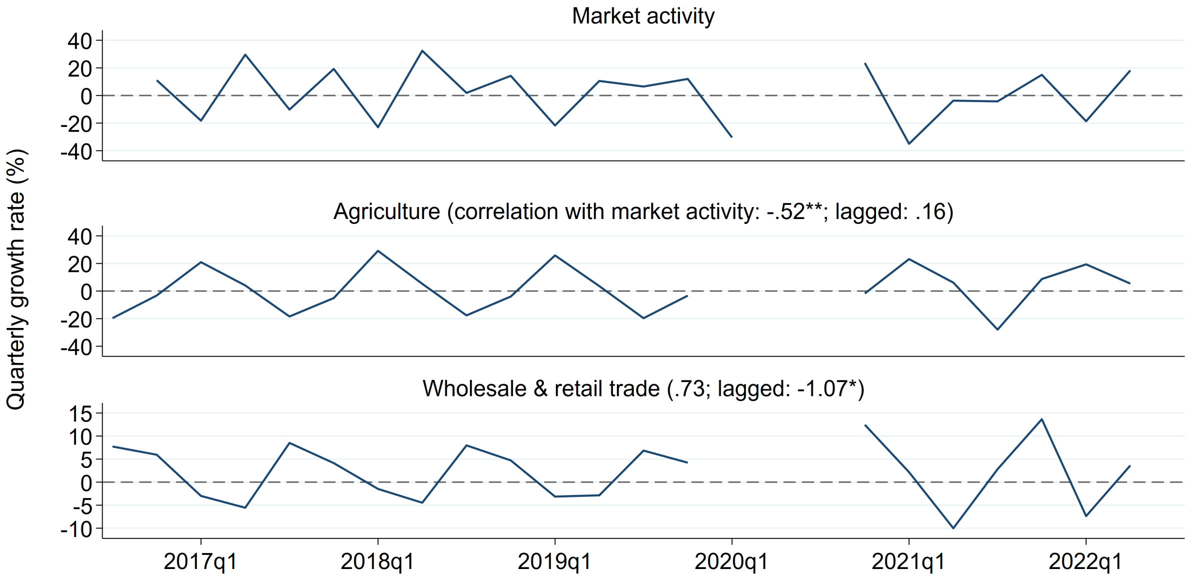
The measure is most useful when interpreting its changes over relatively short periods where fluctuations due to external factors are likely to dominate potential secular trends towards fewer and less busy markets. In particular, a location with a large market is not necessarily more developed than one without if economic activity in the second location is in other sectors. Furthermore, as economies develop, trade may be taking place through more formal networks than those exemplified by periodic markets. Both factors caution against interpreting the level of market activity.

3 Validation of market activity measure

Analogous to the market mapping validation above, the optimal validation data for the market activity tracking is not broadly available at the required temporal and geographical scale: ideally, one would have panels of attendance counts for a large sample of periodic markets in a region of interest, together with measures of traded quantities and prices in order to translate attendance into an easily interpretable economic quantity[9]. Short of this, I present here exercises in which I compare the novel indicator to existing ones, document that it displays intuitive variation with respect to weather patterns, and show how the indicator allows the examination of phenomena at great temporal and spatial detail.

[9]In future work, I will provide such an exercise with the market-level data presented in Egger et al. (2022).

Figure 6: Quarterly growth rates of market activity and sectoral GDP



The figure shows quarterly growth rates for market activity using the measure from Equation 2 for all Kenyan markets shown in Figure 5 and growth rates from official statistics (https://www.centralbank.go.ke/statistics/national-accounts-statistics/), excluding Q1-3 in 2020. The correlation coefficients and their significance levels come from a regression of the quarterly growth rate for market activity on the respective sectoral indicator or its lagged value ($N = 20$), using robust standard errors.

3.1 Remotely-sensed market activity and sectoral GDP

One possible interpretation for the market activity measure is as a proxy for rural GDP. If rural producers valorize their goods and, symmetrically, rural consumers buy their goods to a large extent in periodic markets, then attendance can be interpreted as an indicator of that process. As a first exercise, I hence compare the market activity measure with quarterly statistics on sectoral GDP Kenya[10]. This data is only available on a national level and not disaggregated by rural and urban origins, and as such cannot be directly interpreted as validation data.

I calculate quarterly growth rates of market activity using the following regression:

$$\text{mktAct}_{t,m} = \sum_{q=2016Q1}^{2022Q2} \left(\beta_1^q \text{mktD}_{t,m} * \beta_2^q I\left(t \in T_q\right)\right) + \mu_m + \lambda_q + \epsilon_{m,t}$$

$MktAct_{t,m}$ is the activity in market m on day t from Equation 2, $mktD$ is a dummy indicating whether t is a market day for location m and $I\left(t \in T_q\right)$ assigns days to their respective quarter of a year[11]. Finally, all regressions include a market-fixed effect μ_m and a quarter-fixed effect λ_q. The variables of interest are the β_1^q, yielding quarter-on-quarter market activity growth rates.

Figure 6 presents the estimates compared with quarterly growth rates for 'Agriculture' and 'Wholesale & retail trade') from the national statistics. I exclude quarters during the COVID-19 pandemic (Q1-3

[10] Provided by the Central Bank of https://www.centralbank.go.ke/statistics/national-accounts-statistics/

[11] I use the market activity measure computed from the detected non-market days to normalize the market-day activity measure in order to account for any seasonal differences in marketplace appearance that may be due to e.g. varying image conditions or vegetation.

Table 1: Growing season rainfall and following harvest season market activity

Dep. Var.	Market activity in harvest season			
Country	Kenya		Ethiopia	
	(1)	(2)	(3)	(4)
Market Day	30.94***	30.63***	44.01***	44.11***
	(3.087)	(3.091)	(2.021)	(2.464)
Growing-season rain	0.580*	0.629*	-0.835*	-0.450
	(0.311)	(0.336)	(0.457)	(0.480)
Market Day x Growing-season rain	1.843***	1.393**	1.625*	1.617*
	(0.622)	(0.665)	(0.848)	(0.890)
Growing-season rain (L1)		0.0236		1.810***
		(0.300)		(0.458)
Market Day x Growing-season rain (L1)		-1.069*		-0.0725
		(0.556)		(0.879)
Non-market day (Constant)	4.004***	3.961***	8.191	8.115
	(1.506)	(1.507)	(9.763)	(9.624)
Observations	5,380	5,115	3,505	3,505
R-squared	0.573	0.565	0.657	0.659
Market-FE	yes	yes	yes	yes

The table reports regression estimates of measured market activity during harvest season in Western Kenya in 2017-2020 on rainfall during the current and preceding rainy season. 'Market day' is a dummy indicating whether a given observation falls onto a market day or not. Growing-seasons are defined as the four calendar months per year with the highest remotely-sensed NDVI and harvest-seasons as the three months following each set of growing-season months. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

in 2020). It is evident that all indicators display significant seasonality, in the case of agriculture and market activity of remarkably similar magnitude. Interestingly, however, neither of the official statistics correlates intuitively with the market activity measure. This may be explained by the way the statistical authority attributes agricultural production to seasons, and the regions of the country it covers.

3.2 Remotely-sensed market activity and growing-season rainfall

Periodic markets are where much of agricultural output gets traded and where rural populations buy necessary goods from farming and other income. Absent large-scale irrigation infrastructure, smallholder agriculture continues to be rain-dependent in large parts of Africa, including Kenya and Ethiopia. Rainfall in a given year is thus a key determinant of agricultural production and, consequently, incomes. This link has been used to isolate arguably exogenous variation in household income in the development economics literature (e.g. Björkman-Nyqvist (2013); Sarsons (2015)). It thus seems reasonable to expect growing-season rainfall shocks to affect harvest-season market activity. The following analysis tests this hypothesis.

As a first step, I define locally accurate growing seasons. For this, I rely on the time series of remotely-sensed Normalized Difference Vegetation Index (NDVI) from 2012 until 2020 provided by NASA (Didan and Barreto, 2018). I extract the index for all land within 5km from a market, aggregate markets by pre-2010 Kenyan provinces and Ethiopian regions, and define as the growing season the four months per year where NDVI is highest. I then define as the harvest season the three months following each set of consecutive growing season months. In case of a bimodal rainfall distributions - as is common in parts of both countries - this procedure returns two distinct growing and related harvest seasons.

In order to define rainfall shocks, I match markets to the 1990-2020 time series of remotely-sensed rainfall using the TAMSAT product (Maidment et al., 2017). Rainfall shocks are defined in terms of standard deviations from the long-term mean occurring during the previously defined growing season in a 1km buffer around each market location.

I analyze the relationship using the following regression at the market-season level,

$$\mathrm{mktAct}_{t,m} = \beta_1 \mathrm{mktD}_{t,m} + \beta_2 Rf_{t,m} + \beta_3 Rf_{t,m} * \mathrm{mktD}_{t,m} + \mu_m + \sum_{y=2016}^{2020} \left(\gamma_y \mathrm{mktD}_{t,m} * I\left(t \in T_y\right)\right) + \epsilon_{m,t}$$

where $\mathrm{mktAct}_{t,m}$ is the median measure from 2 for all measured days within harvesting season t at market m and $Rf_{t,m}$ is rainfall during the preceding growing season. Effects of rainfall are estimated separately for activity measures taken on market and on non-market days, in order to account for any effects of changing market surface due to rainfall. Regressions include market-fixed effects and year-effects separately for market days and non-market days[12].

Table 1 confirms the existence of a positive and significant relationship for Kenya and for Ethiopia where widespread unimodal rainfall implies fewer observations and thus a less precise estimate. A one standard deviation increase in growing-season rainfall is associated with markets being $\frac{1.843}{30.94} \approx 6\%$ more active market during the following harvest season. I find that the relationship is robust to controlling for overall changes in reflectance related to rainfall and lagged precipitation, mitigating concerns about general rainfall pattern sequences driving the result.

3.3 Additional illustrations - COVID-19 and war in Ethiopia

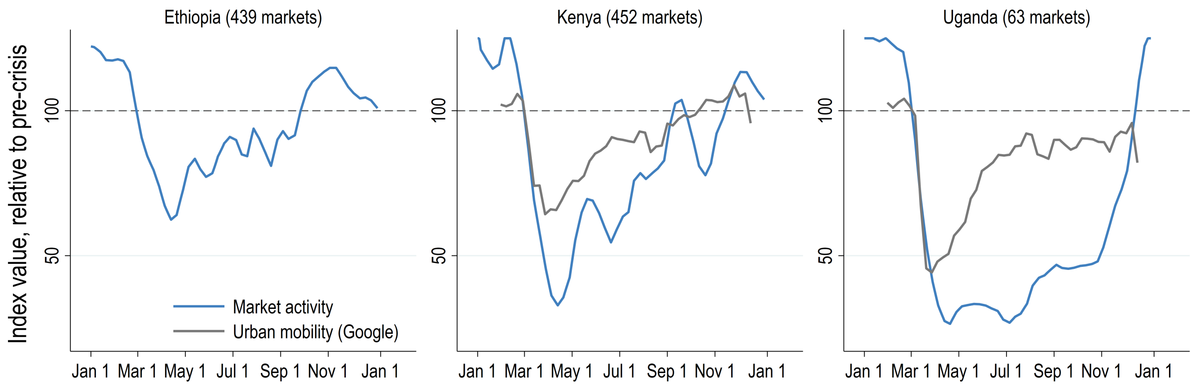
The remote collection of monitoring data has obvious advantages when movement on the ground is constrained. In such contexts, remotely-sensed market activity can provide timely and localized information when traditional forms of data collection are no longer possible. I present here applications from the COVID-19 lockdowns and the 2020-2022 war in Tigray and other regions of Ethiopia as two examples of such episodes.

During the early stages of the COVID-19 pandemic, there was substantial uncertainty around the effects of containment measures in low-income countries on the livelihoods of the poor (Miguel and Mobarak, 2021). Early survey evidence highlighted large income losses in areas where pre-existing panels could be continuously surveyed by phone (Mahmud and Riley, 2020; Abay and Hoddinott, 2020; Egger et al., 2021), though over time survey fatigue meant that samples shrank and information was harder to obtain.

Figure 7 shows how insights from a widely-used, ground-independent measure of economic activity – mobility of urban smartphone users (Google LLC, 2021) – differ from those obtained using remotely-sensed activity in rural markets. It is evident how activity dropped sharply in Ethiopia, Kenya and

[12] Note that this is a conservative approach to controlling for market surface conditions since failure to detect some, possibly minor, market days for a given location would also increase estimates.

Figure 7: Market activity and urban mobility during 2020



Lines indicate time series for remotely-sensed market activity and Google Mobility data (for workplace, retail and transport visits) during 2020. Values are indexed to pre-pandemic levels, i.e. for market activity the 2018-2019 average. Urban mobility data is not available for Ethiopia.

Uganda in March and April 2020 when movement restrictions and other control measures were implemented. Importantly, market activity decreased more relative to baseline levels than urban mobility and – especially in Uganda – remained subdued for longer.

Beyond providing consistent indicators over time, remotely-sensed market activity can also cover large areas and allows for flexible geographical and temporal comparisons. Figure 8a is an example of such an exercise, plotting changes in activity relative to the 2017-19 average by Ethiopian administrative zone. It shows how in early 2022, market activity remained below pre-2020 levels in Tigray where ongoing fighting and a blockade hindered the functioning of markets, while markets elsewhere remained relatively busy. Furthermore and as shown in Figure 8b, market activity in Tigray remained subdued even when available conflict-monitoring data suggested the absence of violent events, while in contrast, markets recovered quickly in Amhara after fighting spreading there in the second half of 2021.

4 Discussion & conclusion

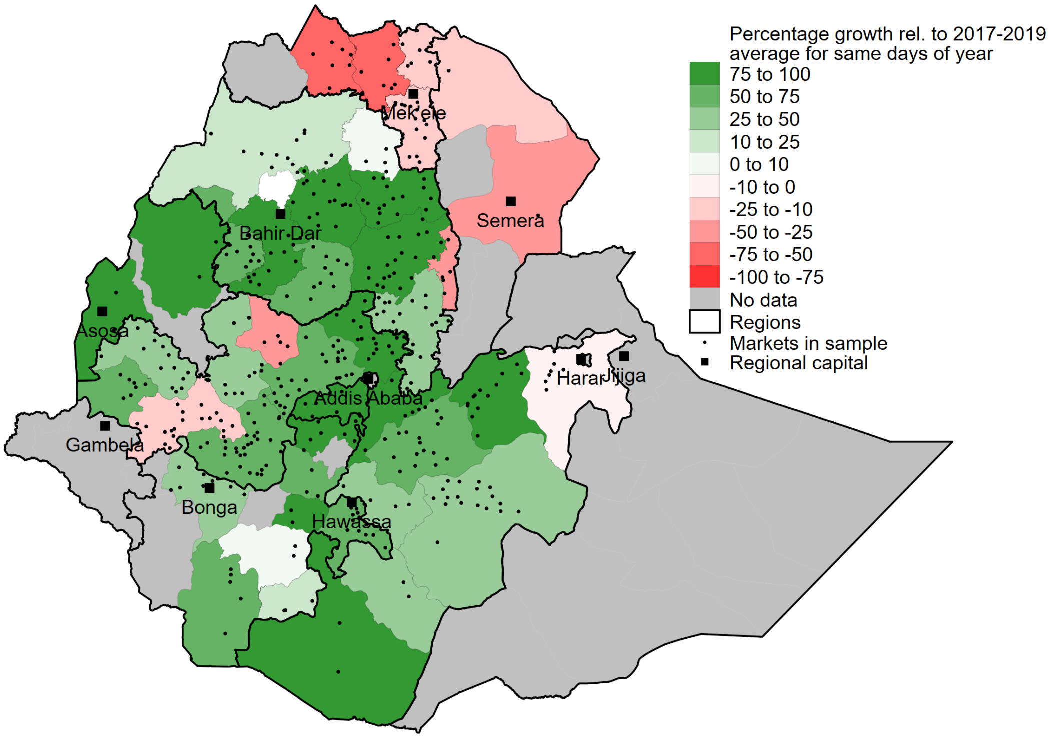
High-frequency satellite imagery allows policymakers and researchers to fill a data gap affecting the millions of people worldwide whose livelihoods are linked to agriculture and small-scale trading. Much economic activity in these contexts takes place in periodic markets. The method presented in this paper allows for the detection of periodic marketplaces and their monitoring over time, thus collecting localized indicators – both retrospectively and in real-time – at a low unit cost.

A back-of-the-envelope calculation suggests that with the imagery that can currently be freely accessed over the course of one year from Planet Labs, around 200 markets can be mapped and their activity for the three preceding years measured. With larger, commercially available licenses, activity data for one year at one market can cost as little as 0.1$, if the method is implemented at scale over large sets of markets (1,000+) or over long time frames.

While in principle the approach outlined above can be transferred to any setting with weekly markets,

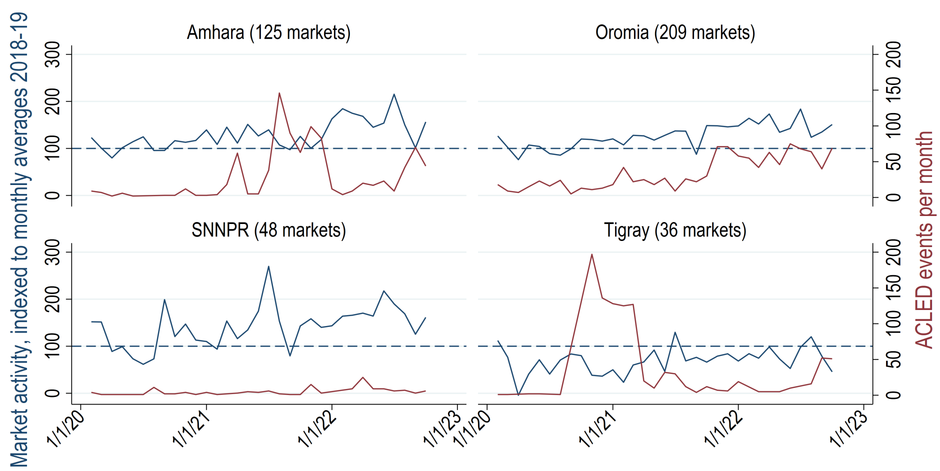
Figure 8: Market activity in Ethiopa 2020-2022

(a) Changes in market activity in Ethiopian zones between Jan 5th and Feb 2nd, 2022 relative to pre-2020 levels



Zones in gray either have less than two detected markets or insufficient images for the given period. Administrative borders are taken from the FAO Global Administrative Unit Layers dataset. Some minor neighboring zones are merged within the same region to increase interpretability.

(b) Market activity and conflict events by Ethiopian region, 2020-2022



The plots show for four major regions of Ethiopia the mean measured market activity across all markets in the region and captures taken on detected market days, indexed per month to the pre-crisis 2018-19 average (blue line) and counts of registered events in the ACLED database (red line). Exlcuding 'agreements', 'establishments of headquarters or bases' and 'non-violent transfers of territory', the most common events are 'battles' (42%), 'violence against civilians' (25%), and 'protests' (15%).

there are some practical limitations to it. Firstly, frequent cloud cover in humid regions leads to relatively few observations per weekday which complicates market detection as periodic reflection changes from markets are more difficult to distinguish from idiosyncratically bright cloud patches. This problem can partly be mitigated by using longer time series, but high-frequency activity measuring will still be more difficult in these cloudy than in drier contexts.

Secondly, smaller, dispersed markets or those whose activity peaks in the afternoon are generally harder to detect. The satellites capture images at around 11am local time for each location, which may or may not be the time when markets are busy. Relatedly, daily markets do not have the regular temporal pattern underlying the detection of weekly markets. If their location is known from other sources, however, a similar methodology as what I present above may be employed to track changes in attendance over time.

Thirdly, the approach may, if at all, only detect the surrounding areas of covered markets. If one's interest is in also measuring their size, a manual post-processing step may be necessary where one expands the detected shape outside of the covered market to also include the covered market.

Keeping these limitations in mind, there is potential in using the novel indicator for the evaluation of social policies, such as large-scale cash transfer or infrastructure programs, where having contemporary, localized data is essential. Furthermore, the data will permit insights during times when traditional data collection becomes infeasible, e.g. during times of violent conflict.

The approach presented here relies on accessible imagery and can be scaled across contexts using similar methodologies. In future work, I will compile a global market map across 20 countries with associated activity measurements since 2017, as well as guidelines on how to adapt existing code to context of interest outside of the countries I will cover. This data will allow new insights into long-standing research questions, including in contexts that are otherwise not covered in existing datasets, such as how changes in economic activity accelerate or prevent the emergence of violent conflict (Burke et al., 2015), how extreme weather events affect rural economies and which investments in rural areas lead to sustained growth.

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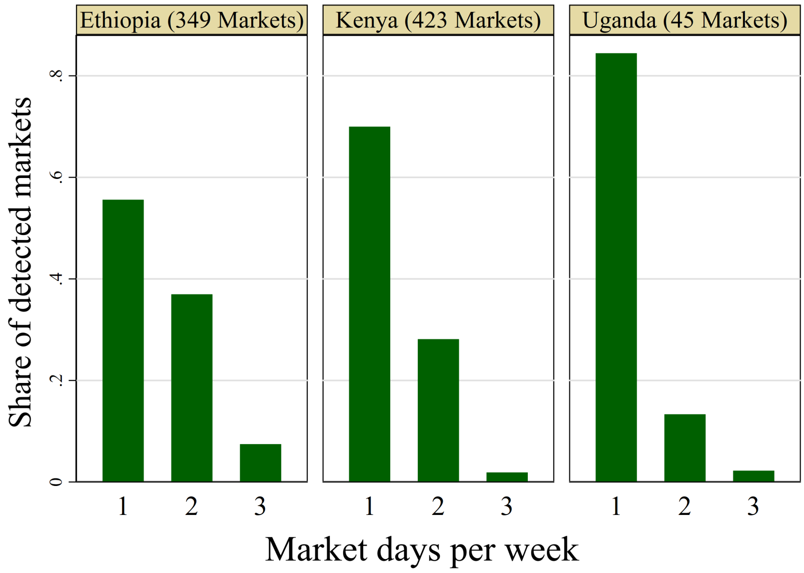
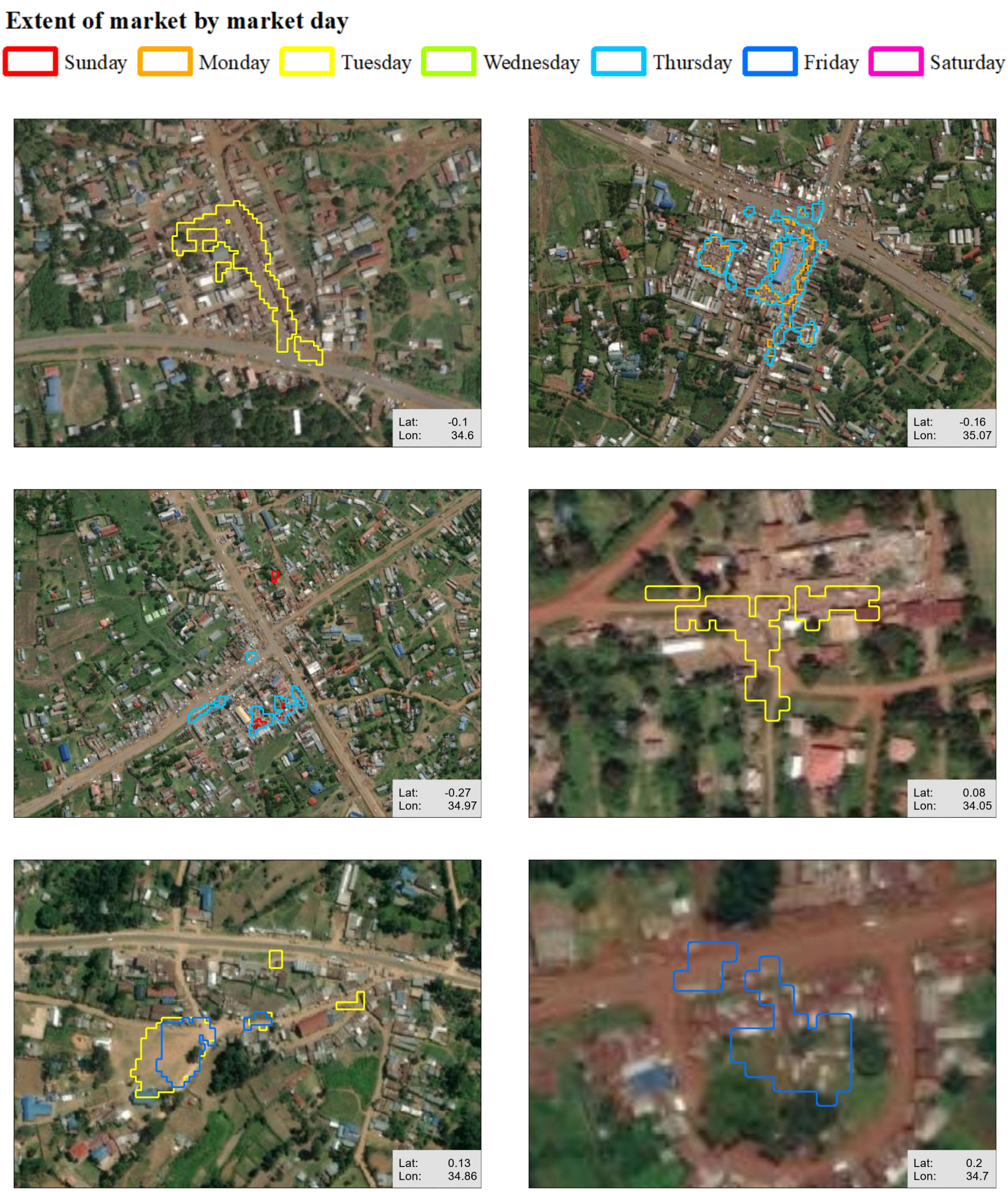
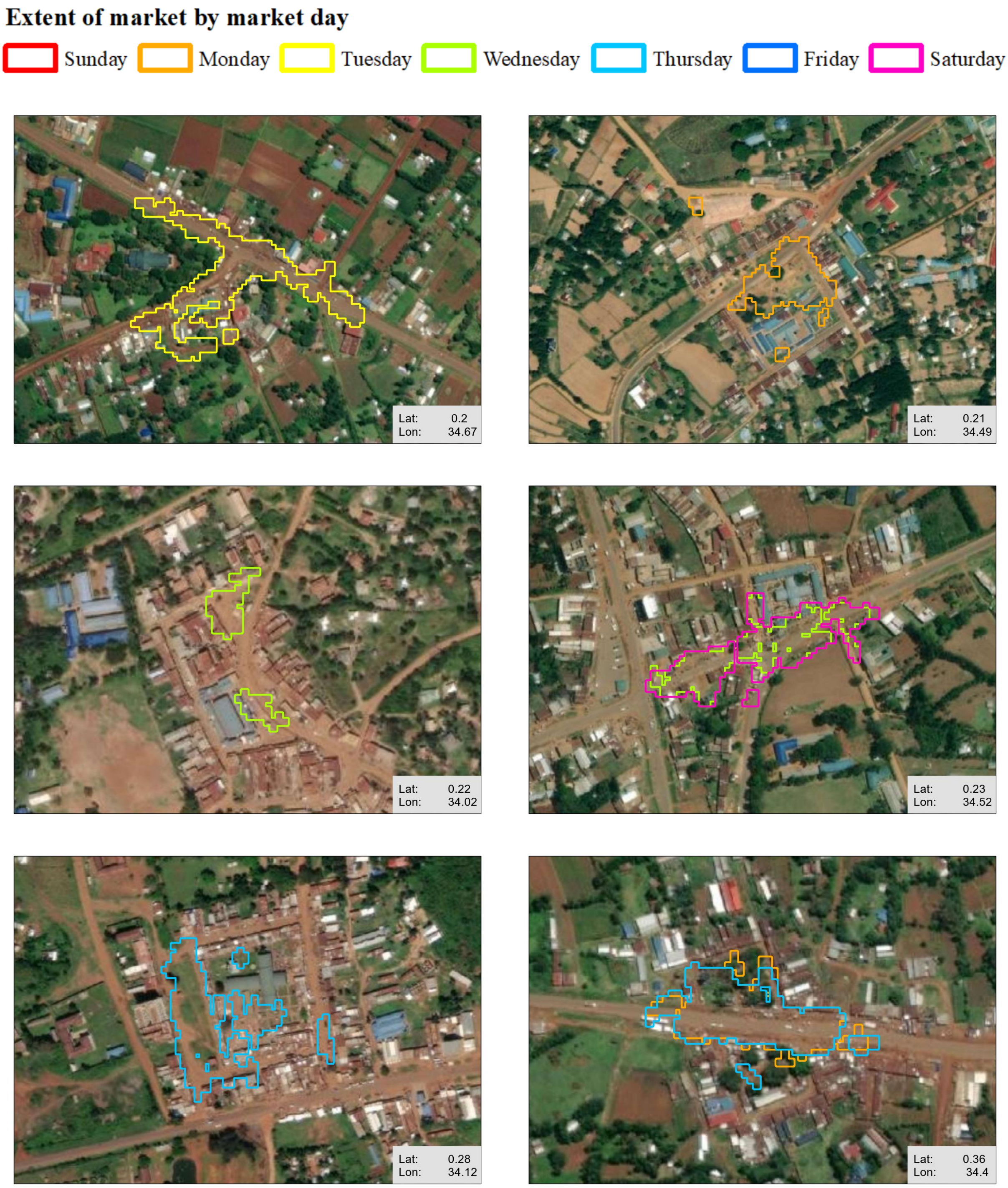
A Additional figures & tables

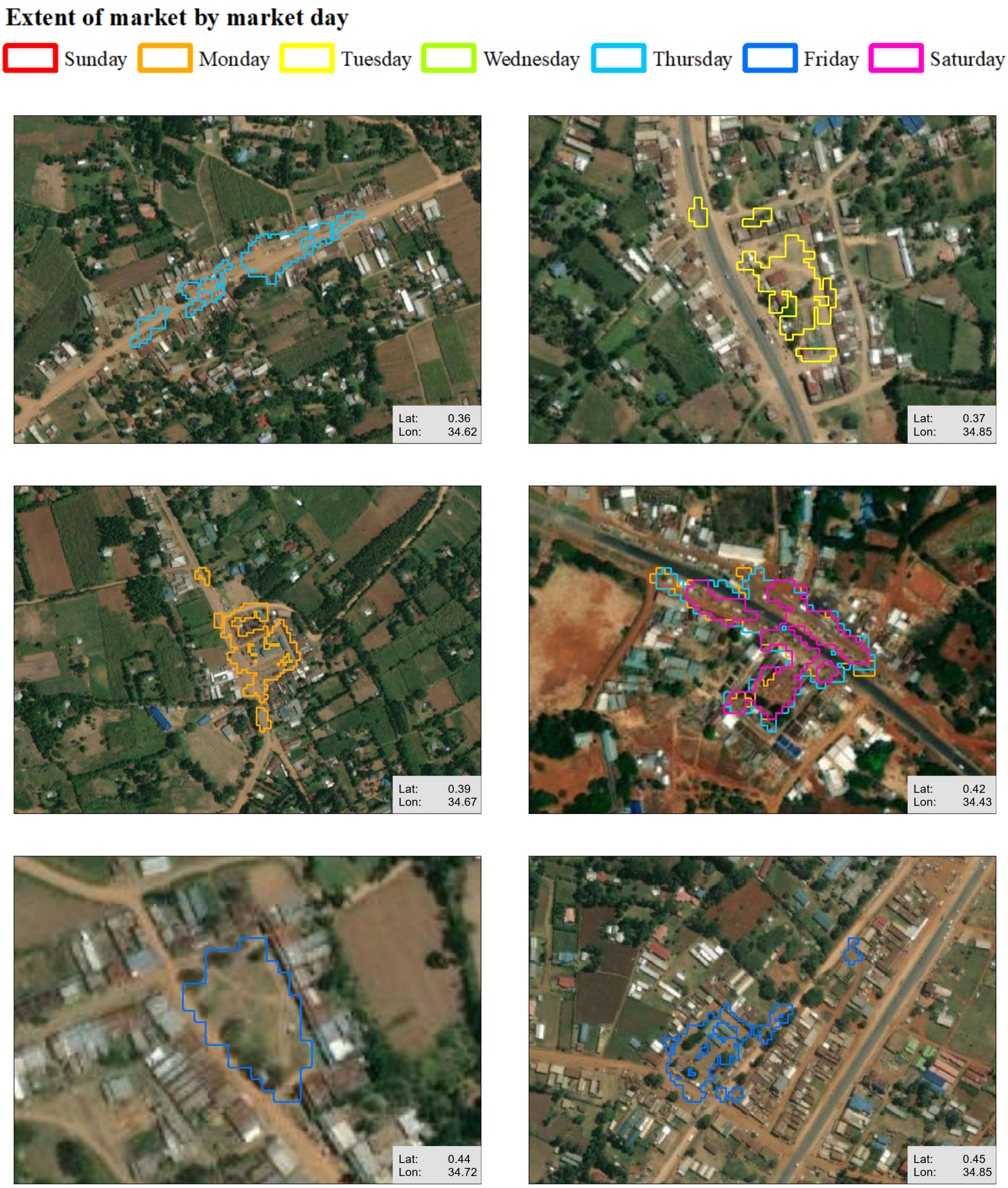
Figure A.1: Shares of detected markets by number of weekly market days



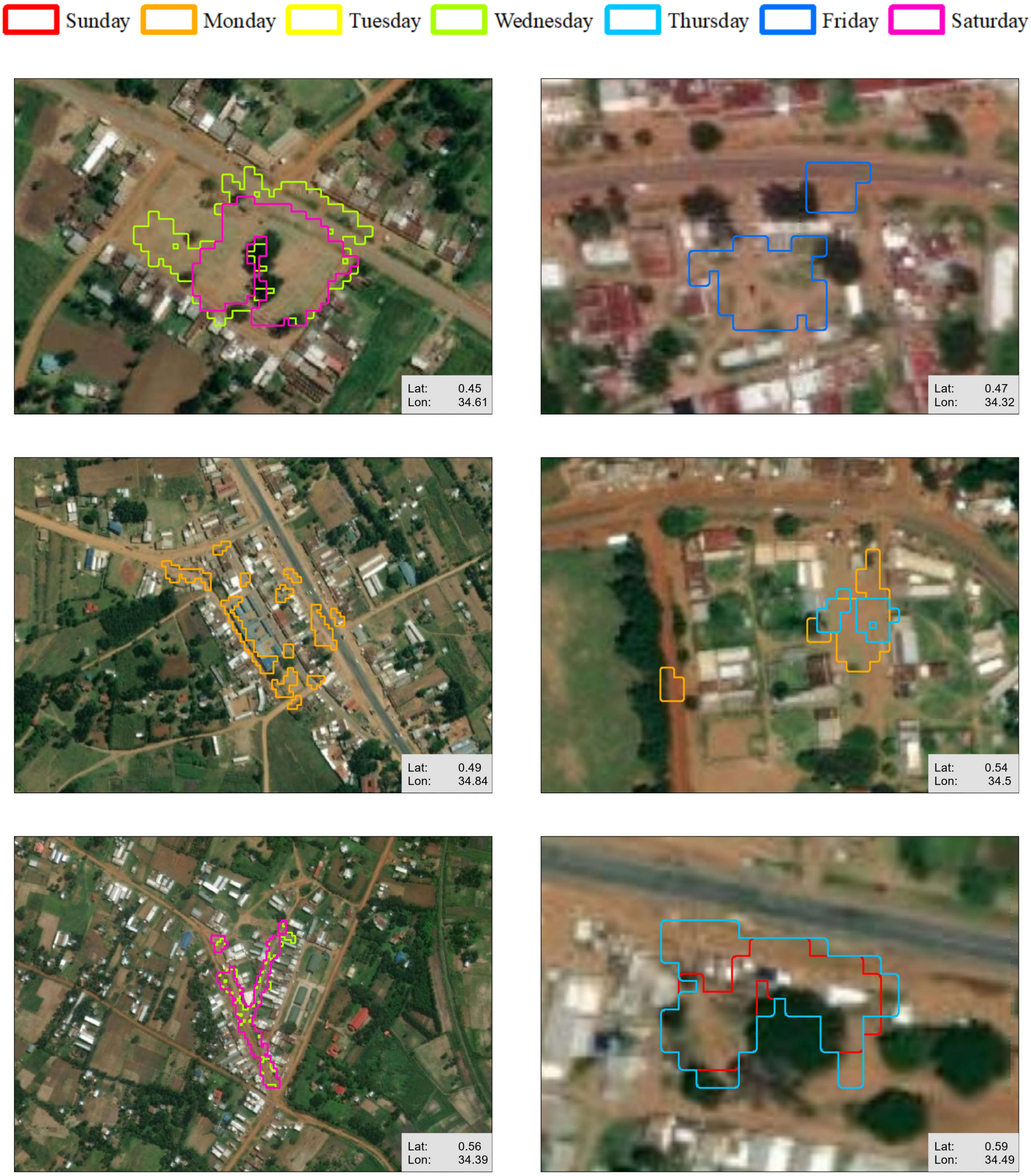
B Detected market shapes from validation sample



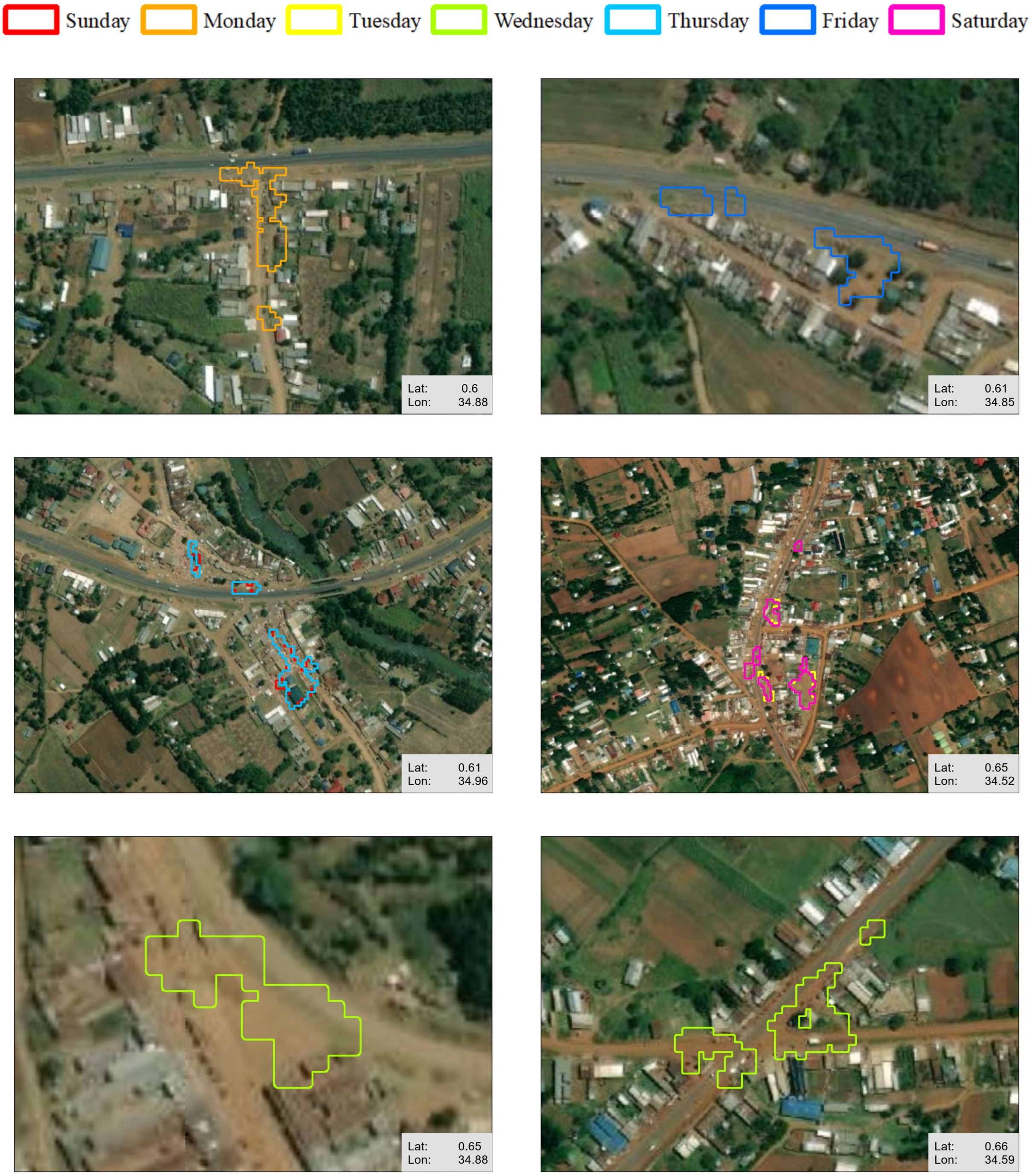

Extent of market by market day
Sunday
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday
Lat: 0.2
Lon: 34.67
Lat: 0.21
Lon: 34.49
Lat: 0.22
Lon: 34.02
Lat: 0.23
Lon: 34.52
Lat: 0.28
Lon: 34.12
Lat: 0.36
Lon: 34.4

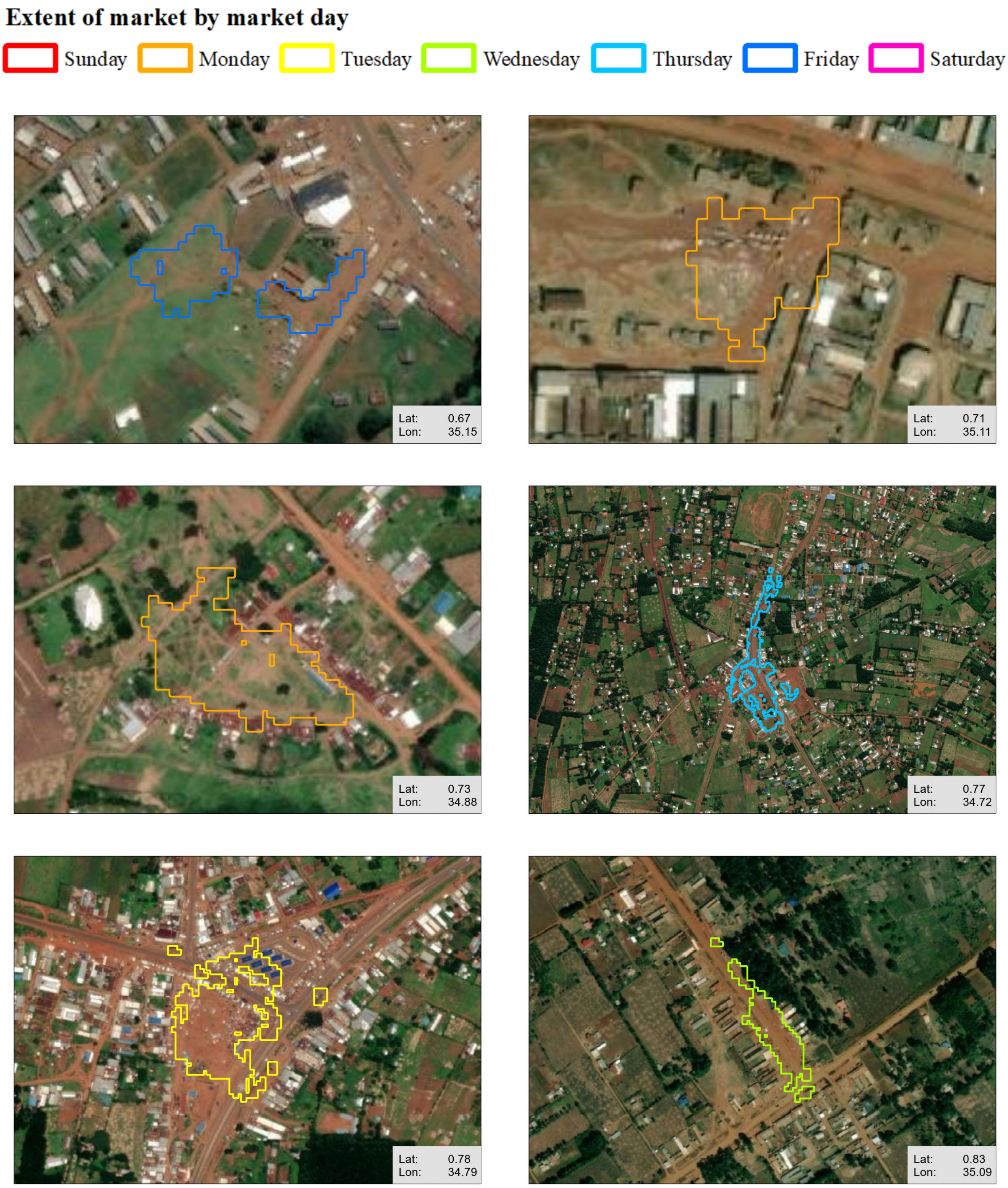

Extent of market by market day
Sunday
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday
Lat: 0.36
Lon: 34.62
Lat: 0.37
Lon: 34.85
Lat: 0.39
Lon: 34.67
Lat: 0.42
Lon: 34.43
Lat: 0.44
Lon: 34.72
Lat: 0.45
Lon: 34.85

Extent of market by market day

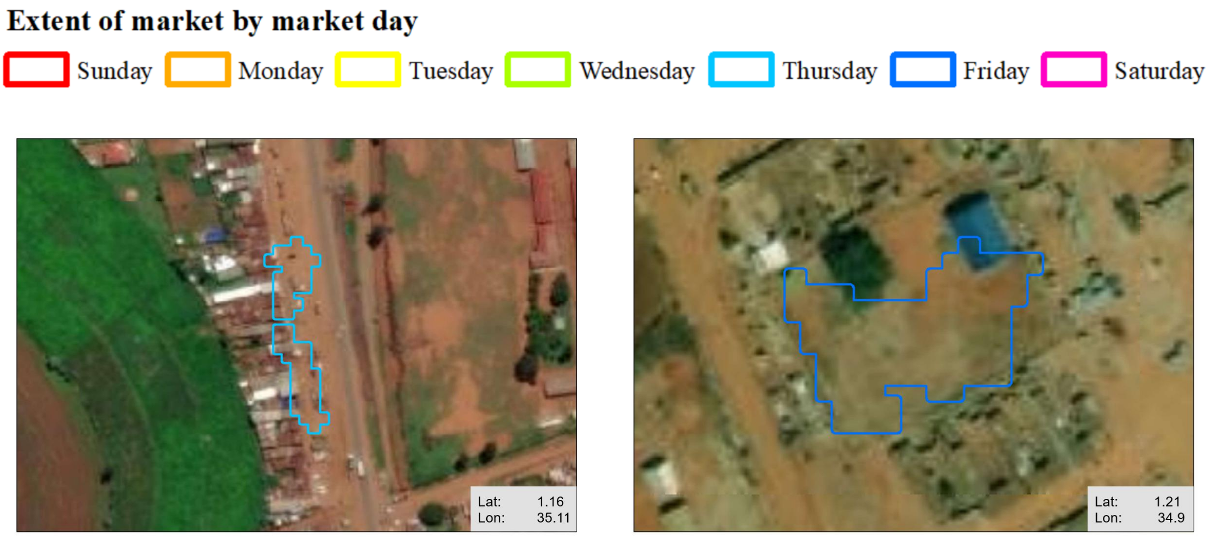


Extent of market by market day




Extent of market by market day
Sunday
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday
Lat: 0.67
Lon: 35.15
Lat: 0.71
Lon: 35.11
Lat: 0.73
Lon: 34.88
Lat: 0.77
Lon: 34.72
Lat: 0.78
Lon: 34.79
Lat: 0.83
Lon: 35.09

Extent of market by market day


Extent of market by market day
Sunday
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday
Lat: 1.16
Lon: 35.11
Lat: 1.21
Lon: 34.9