

Poster - Mapping Opium Poppy Cultivation in Afghanistan Using Satellite Imagery

Xiao Hui Tai

xtai@berkeley.edu

University of California, Berkeley
Berkeley, California, USA

Suraj Nair

suraj.nair@ischool.berkeley.edu
University of California, Berkeley
Berkeley, California, USA

Shikhar Mehra

mehra.shikhar@berkeley.edu
University of California, Berkeley
Berkeley, California, USA

ABSTRACT

Afghanistan accounts for around 70-80% of the world's supply of opium. This production provides livelihoods to millions of Afghans, while also funneling hundreds of millions of dollars to insurgent groups every year, exacerbating corruption and insecurity, and contributing to high domestic levels of drug addiction. Remote sensing and field surveys are currently used to estimate total poppy cultivation area; these are costly and difficult to implement under poor security conditions. Counter-narcotics efforts have focused on reducing total cultivation area, rather than trying to understand local socioeconomic or political conditions, and have largely been unsuccessful. We develop and test a new approach to mapping cultivation using freely available satellite imagery. Such a method could provide timely estimates at a high level of granularity. These data can then be combined with other data sources, such as grid-level data on climate, population, and healthcare, allowing us to study the causes and consequences of opium poppy cultivation quantitatively and in great detail. In Helmand, a province responsible for over half of all cultivation, we find that our aggregate area estimates track official statistics closely at a district level. Future work will involve refining the methodology and extending it to the rest of Afghanistan over multiple years.

KEYWORDS

illicit drugs, agriculture, satellite imagery

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1 INTRODUCTION

Since 1999, Afghanistan has been the world's largest supplier of illicit opium, accounting for an estimated 70-80% of supply [19]. In 2019, this generated an estimated income of \$1.2-\$2.1 billion domestically, or around 10% of Afghanistan's gross domestic product [24]. The illicit drug economy has provided livelihoods to millions of

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Afghans [14], but has also had numerous negative effects, including funding insurgent groups, exacerbating corruption and insecurity [19], and contributing to high domestic levels of drug addiction [25]. From 2002 to 2017, the U.S. government spent over \$8 billion on counter-narcotics efforts in Afghanistan, achieving little long-term success. The lack of reliable data contributed to the failure of counter-narcotics efforts; the robustness and interpretation of top-line estimates of area under cultivation have been questioned and criticized [17]. The lack of granularity in official cultivation statistics has also impeded efforts by aid agencies to evaluate the impact of various interventions aimed at transitioning cultivators away from poppy.

Currently, official statistics on poppy cultivation are released annually by the United Nations Office on Drugs and Crime (UNODC) at a district level [24]. These are produced using commercial high-resolution (0.5m × 0.5m) imagery, manually annotated by analysts and verified with ground imagery. In districts with substantial cultivation, a limited number of sites are sampled for labeling, while in other districts, all known cultivation areas are annotated. Only aggregate district-level cultivation figures are published; no detailed maps are available. The UNODC also conducts in-person surveys to characterize socioeconomic conditions. These methods, while undoubtedly valuable, are costly and difficult to undertake under poor security conditions. Furthermore, reports are released after long delays, with the government being suspected of blocking publication in some years [2].

This paper investigates the possibility of using publicly available satellite imagery to generate poppy cultivation maps at high resolution. Some advantages of this source of data include its timeliness and cost-effectiveness, easy availability of data, and high level of granularity. These maps can then be combined with other data sources to further our understanding of the socioeconomic circumstances associated with poppy cultivation, a complex and persistent development challenge. This work complements official estimates, as well as related work that relies on commercial high-resolution satellite imagery, manual labelers, expert knowledge or qualitative methods [e.g., 12, 13, 15]. In developing these methods, we build on work using automated methods and spectral imagery to classify opium poppy, wheat, as well as other agricultural crops [5, 7, 10, 22, 26, 27, 29].

2 METHODS

We make use of multi-spectral, high-resolution (up to 10 meters) Sentinel-2 imagery made publicly available by the European Space

Agency (ESA) and accessible on Google Earth Engine.¹ These images are available for Afghanistan from 2016 to the present day. We infer areas under poppy cultivation by carefully choosing image acquisition dates based on crop cycles, and measuring levels of vegetation growth in the pre- and post-harvest stages. In initial work, we limit the analysis to Helmand, a province accounting for more than half of all cultivation, where crop cycles are well-known and there are few major alternative crops. Examples of the imagery are in Figure 1.

Our classification approach relies on the premise that major crops have different crop cycles and have unique spectral properties [7, 22, 23, 29]. Helmand has two major crops, poppy and wheat (barley is also cultivated to a smaller extent, and there are some orchards). The distinguishing characteristics of poppy and wheat in the pre- and post-harvest periods for poppy, are summarized in Table 1. Our goal is to acquire imagery from these two periods, subject to the constraints of cloud cover and Sentinel-2's global revisit frequency of 5 days, and noting that different areas have different harvest seasons; the harvest begins in the south and moves north [23]. The first pair of acquisition dates we consider are the second half of March (March 15 to 31) for pre-harvest images, and the two-week period starting from the end of April (April 25 to May 9) for post-harvest images. We also consider a second set of dates a week later, and a third set two weeks later. If cloud cover is substantial, we increase the length of acquisition periods.

We mask cloudy pixels, compute the normalized difference vegetation index (NDVI) (using the near-infrared (B8) and red (B4) bands, as $\frac{B8-B4}{B8+B4}$), and take the median composite of available imagery during the acquisition periods. To classify poppy pixels, we first select pixels that have $NDVI > .5$ in the pre-harvest period, and $< .3$ in the post-harvest period. The rationale is that both wheat and poppy pixels will be selected using the first cutoff, and wheat pixels would be filtered out using the second cutoff. Since earlier-ripening wheat fields may have NDVI values $< .3$ at the second acquisition date, when possible we add a condition on the reflectance value of the green band (B3) to the first acquisition date ($B3 > 850$). These thresholds were derived by visual inspection (Table 1) and known crop characteristics [7, 22, 23]; future work will involve developing more flexible approaches (Section 4).

3 RESULTS

Using this simple rule-based classification strategy, we check the accuracy of generated maps by comparing our estimates to (i) aggregate district-level UNODC estimates [24] (Figure 2), (ii) published poppy cultivation maps in specific regions [13] (Figure 3), and (iii) by visual inspection of RGB images (Figure 4). Field-level ground truth data are not available.

We first demonstrate that in 2018 and 2019, relatively cloud-free years and the two most recent years with official district-level estimates, our estimates of poppy cultivation area aggregated to a district level track UNODC estimates closely (Figure 2; Pearson's correlation $\rho \geq .8$). Figure 2 also highlights the effect of acquisition dates. In southern districts (Lashkar Gah, Nad Ali and further south), the first set of acquisition dates generally gives the best

estimates, while the second and third sets result in some overestimation, due to ripening wheat being misclassified as poppy. In the remaining districts, the first set of dates results in underestimation, as the poppy has not been harvested by the "post-harvest" dates. For two districts (Nahri Sarraj and Washer), the second set of acquisition dates works best, while for the remaining northern districts, the third set works best. Figure 2D plots the results using these "best" sets of acquisition dates, generating the most accurate predictions. Ideally we would time acquisition dates to generate the "best" predictions, although in practice this might not be possible due to image availability and quality.

Next, we compare our maps to other available published maps, specifically a desert area around Nad Ali and Washer districts, north of the Boghra Canal. A reference published figure, labeled using commercial high-resolution imagery as well as fieldwork [12–14], is available,² and we visually compare our predictions in the same area in Figure 3. We see a close correspondence, with similar patterns of agricultural expansion into desert areas, as documented in [14].

Finally, we visually inspect RGB images in multiple districts to see if the results correspond to the known characteristics in Table 1. An example is in Figure 4. In the pre-harvest image (Figure 4A), there is a clear difference between bright green fields (expected to be poppy), and dark green fields (expected to be wheat). In the post-harvest image (Figure 4B), the fields that were bright green are a beige color, which is consistent with being post-harvest, after the fields have been plowed. The fields that were dark green have a variety of shades: some remain dark green, while the remainder are green to dark brown, indicating various stages of ripening. The predicted poppy pixels are in Figure 4C. In general, the results are as expected, although we do observe some false negatives: for example there are poppy fields that are less lush and do not exceed the threshold of $NDVI > .5$ in pre-harvest images. An example of false positives occur at the edge of wheat fields (not observable in Figure 4), where the green band exceeds the threshold of 850 in pre-harvest images; the NDVI drops below .3 in post-harvest images (due to an early harvest), and these are erroneously classified as poppy.

4 DISCUSSION

We have developed a rule-based classification method to map opium poppy cultivation in Helmand at a $10m \times 10m$ resolution, using only free, publicly available imagery and tools. Ground truth data of cultivation at a field-level are not available, but we evaluate the accuracy of our results using several alternate means.

The ability to produce country-level, granular maps over multiple years, without the need for manual annotation, has numerous advantages over traditional methods. First is the timeliness, easy availability and ease of production of estimates. Traditional methods are possibly more accurate, but appear to be extremely costly to produce. Furthermore, the future availability or reliability of these estimates is unclear, given the impending U.S. troop withdrawal. In the past, the Afghanistan government has been accused of blocking publication of poppy cultivation-related statistics [2], and the robustness of estimates has also been questioned [17]. The 2021

¹<https://developers.google.com/earth-engine/datasets/catalog/sentinel-2>

²Figure 5 on Page 12 of [14], available at <https://reliefweb.int/sites/reliefweb.int/files/resources/2006E-When-the-Water-Runs-Out.pdf>.

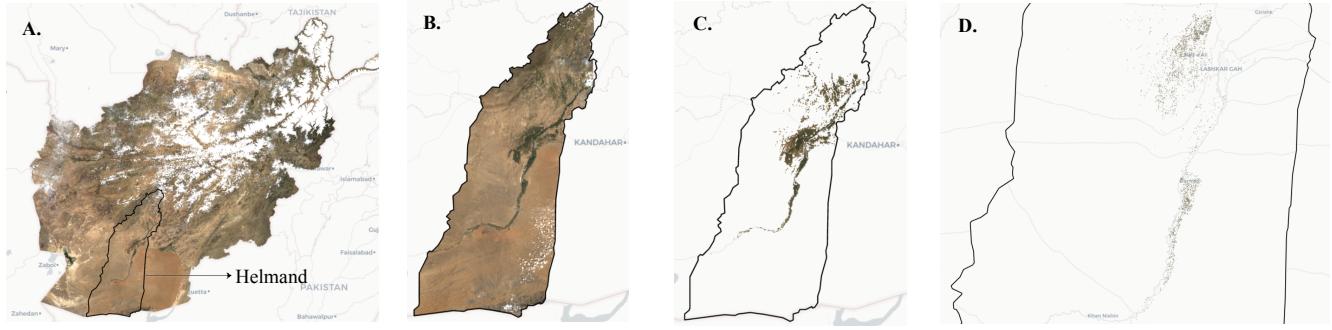


Figure 1: Inferring poppy fields from satellite imagery. (A) Sentinel-2 imagery for Afghanistan in 2020. Our initial study area, Helmand province, is highlighted. (B) Helmand province after cloud masking. (C) Areas with vegetation, measured using the normalized difference vegetation index ($NDVI \geq .2$). (D) Identified poppy growing areas.

Crop	Harvest dates [6]	Pre-harvest dates for poppy	Post-harvest dates for poppy
Poppy	April 1 to May 15	NDVI: generally $> .6$ Bright green; B3 (green) band ≈ 1100 and higher	NDVI: $< .3$ Fields plowed immediately after harvest [24]
Wheat	May 20 to July 1	NDVI: generally $> .7$ Dark green; B3 (green) band ≈ 600 and lower	NDVI: .2 to .7; early-harvest wheat have lower values Golden-brown just before harvest

Table 1: Distinguishing characteristics of the main crops in Helmand. Specific values for NDVI and green bands are obtained by examining Sentinel-2 imagery; cloud cover and image quality could affect these values.

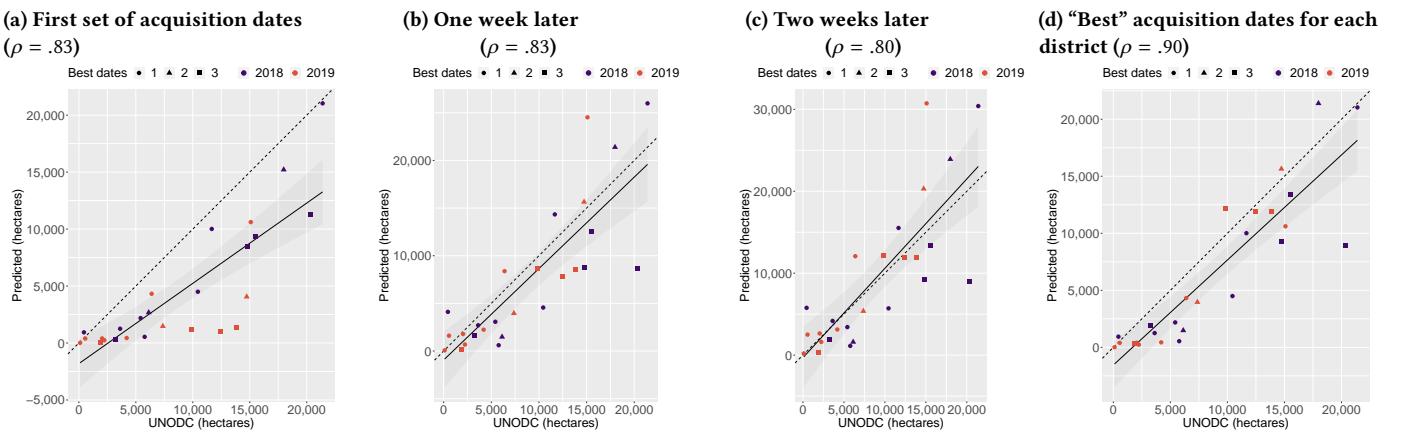


Figure 2: UNODC estimates vs. our estimates for districts in Helmand in 2018 and 2019, using different sets of acquisition dates (see Section 2). Dashed lines are 45-degree lines, and solid lines are best fit lines. Shapes represent districts in which the first, second or third set of acquisition dates produce the best results. Circles are Lashkar Gah, Nad Ali and districts south, triangles are Nahri Sarraj and Washer, and squares are the remaining districts. ρ is the value of Pearson's correlation between actual and predicted values.

harvest is currently underway, and the immediate availability of satellite imagery will allow the rapid mapping of cultivation areas. Next, the production of granular maps can contribute to the evaluation of development policies over multiple growing seasons. These maps can be paired with other sources of granular data, in order to better understand the causes and consequences of poppy cultivation in a localized manner. With the recent proliferation of such

granular data, for example: grid-level data on population [11, 20], healthcare accessibility [28], climate and drought [1, 18], wealth [4], as well as violence [21], there are many potential avenues for further investigation.

Despite the promises of the use of satellite imagery for mapping poppy cultivation, there are numerous challenges. First, our method relies on high quality, cloud-free imagery during multiple

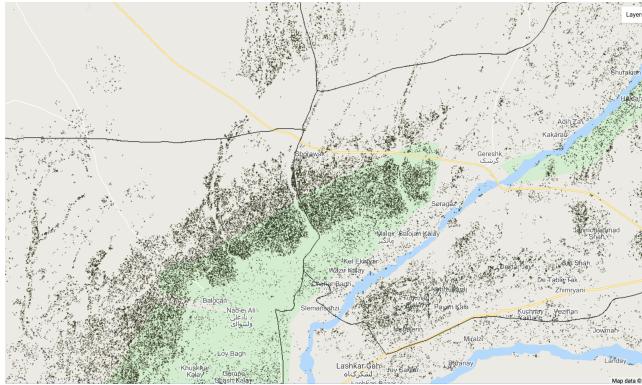


Figure 3: Our predictions for the area as shown in Figure 5 of [14], in 2019, using the second set of acquisition dates. This is the area north of the Boghra Canal in which agricultural expansion into previously desert areas has been documented. Using our methodology and comparing to published results, we are able to see similar patterns.

well-timed acquisition windows; this is a major challenge as we extend this work to additional years and to the rest of Afghanistan. Our current methodology requires experimentation and manual visual examination of classified pixels to diagnose errors and determine best acquisition dates. Early analysis suggests that this approach generalizes with minimal adjustment to other provinces in Southern and Western Afghanistan, but we expect to face more difficulty in the Northern parts of Afghanistan, due to a combination of smaller plot sizes, mixed cultivation patterns, complex terrain and the close proximity of agriculture to natural vegetation. Some potential solutions that we are exploring include automated strategies to infer best acquisition windows, and classifying agricultural land and opium poppy using more flexible approaches, such as unsupervised clustering methods using other spectral bands or differences in values between pre- and post-harvest imagery. Another potential area of investigation is the use of synthetic aperture radar imaging, which is insensitive to cloud cover, to monitor crop growth and harvest [8, 9]. Methods to estimate prediction intervals can also be explored.

Finally, we recognize that there are a number of ethical challenges associated with this work. Even though the use of satellite imagery for crop detection has become fairly commonplace, it is important to be cautious about its applications in sensitive contexts. While it is not possible to identify or locate individual cultivators using our approach, the granularity of the estimates is a cause for potential concern, especially since our approach is easily reproducible and thus has the potential to be misused. Every precaution must be taken to ensure that the privacy and welfare of cultivators are protected. Related concerns, and frameworks for the ethical use of big data in development are discussed in more detail in [3, 16] and others.

To conclude, we have demonstrated how freely available satellite imagery can allow us to study poppy cultivation patterns in great detail. We hope that an extension of such an analysis can provide additional insight to the local circumstances surrounding poppy

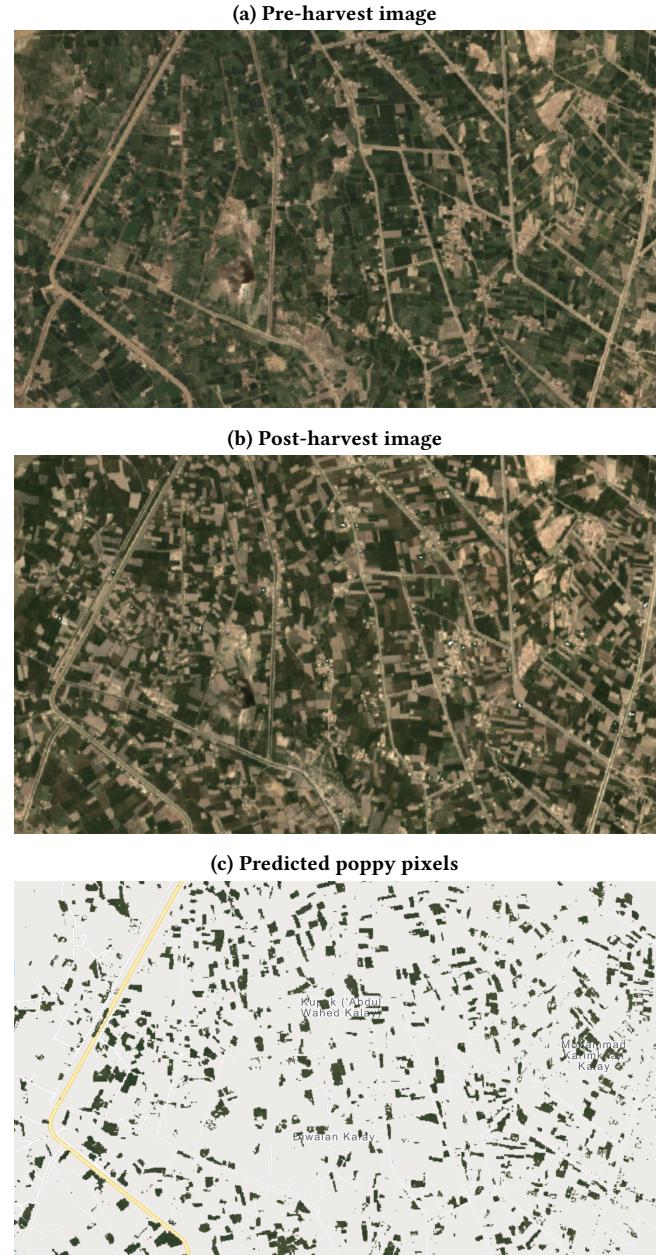


Figure 4: Example RGB images of an area in Garmser district in 2019, using the first set of acquisition dates.

cultivation, and ultimately contribute to the design of effective policies to protect the welfare of farmers while governments work towards their counter-narcotics goals.

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