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Seeing Informal Settlements: the policy implications of different techniques to identify urban growth patterns from satellite imagery using the case of informal construction in Ho Chi Minh City.

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Abstract: In the midst of urban policy institutions taking greater advantage of technological advances for generating data, this paper analyzes the current state of using satellite imagery to monitor informal settlement patterns. Using the issue of informal settlements in rapid urbanization, this paper finds that policy-oriented research agendas needs further development as much as the techniques. The paper first presents an example of how informal urbanization can be detected even with older imagery combined with fieldwork by applying thresholding and texture analysis of remote sensing imagery developed by Kim et al (2004) for data from 1994 and 2001 for Ho Chi Min City, Vietnam. Then this study compares our identification of urbanized areas in Ho Chi Minh City with those identified for 2000 by Angel et al. (2005) and the World Bank (2015). We find that while all three converge on classifying urban areas in the city's core, in the periphery each study's methods systematically identify different kinds of urban spatial patterns. These differences suggest the importance of customizing algorithms to account for the local context and testing through ground-truthing to establish their accuracy. These observations also point to a need for a discussion between urbanization scholars about developing standards in reporting data, methods, and findings. Our study suggests that analysts need to keep a critical eye for marginalized populations when using automated interpretation of satellite images to establish urban settlement patterns. Contextual knowledge gained through fieldwork and collaborative partnerships is necessary to not systematically overlook informal settlements which could have important implications for disaster and resilience, resettlement, climate change adaptation, and public finance policies and planning.

Introduction

As countries around the world urbanize rapidly, their cities have been expanding their land area by converting rural land into urban uses. The new types of land uses, the location of where this conversion takes place, the quality of its infrastructure and construction, and their accessibility has a profound and often differentiated impact on the welfare of city residents. For example, while some residents live in planned communities serviced by high quality public services and built with durable materials, many others settle into self-constructed buildings of temporary materials without access to infrastructure and sometimes positioned in precarious areas at risk of natural or man-made disasters. Between these two extremes exists a wide gradient of situations in between. City governments need data about the patterns and extent of the built environment to make policies and plans for safe, productive, and livable cities. However, local governments find it challenging to keep pace with proliferating land developments, particularly the irregular and undocumented ones. Administrative data are costly to collect, quickly outdated, and usually do not adequately capture urban expansion on the periphery. Therefore, many urban researchers and policymakers are developing the potential of satellite imagery to assist with this information gap.

Recent years have seen important technological changes that make possible the use of satellite imagery to classify urban land use patterns at a fine spatial resolution and with frequent updates. However, it is important that the data produced using this technology do not systematically miss certain forms of settlements, particularly those inhabited by the most vulnerable residents.

The endeavor to generate urban data and metrics is also supported by the international development institutions. The eight United Nations Millennium Development Goals (MDGs) adopted in 2000 were notable for setting explicit and quantifiable international development goals. For example, under the Millennium Development Goal 7 to Ensure Environmental Sustainability, Target 7.C aimed to "halve, by 2015, the population without sustainable access to safe drinking water and basic sanitation" and Target 7.D aimed to "achieve, by 2020, a significant improvement in the lives of at least 100 million slum dwellers," (UN 2016). While one might disagree with the definition of metrics and their applicability to different contexts, the move to quantified indicators and standards helped to give teeth to UN policy goals. Building upon the MDGs, the UN has now set seventeen Sustainable Development Goals (SDGs) to be reached by 2030. The urbanization agenda is framed by SDG 11, to "Make cities and human settlements inclusive, safe, resilient and sustainable." Among the targets associated with SDG 11 is access to "adequate, safe and affordable housing and basic services." Towards tracking this goal, Indicator 66 requires data for the "percentage of urban population living in slums or informal settlements."

Computing UN-Habitat's indicator would require integrating about both population numbers and living conditions. Population data based on household-level surveys and census data is needed to identify the percentage of slum dwellers. However, these surveys usually do not also ask about slum conditions as defined by the United Nations which is identified as a living situation that lacks any one of the following five elements:

1. Access to basic water (access to sufficient amount of water for family use, at an affordable price, available to household members without being subject to extreme effort)
2. Access to basic sanitation (access to an excreta disposal system, either in the form of a private toilet or a public toilet shared with a reasonable number of people)
3. Security of tenure (evidence of documentation to prove secure tenure status or de facto or perceived protection from evictions)
4. Durability of housing (permanent and adequate structure in non-hazardous location)
5. Sufficient living area (not more than two people sharing the same room)."

In addition to incomplete information, survey questions across nations vary and may not be able to address all of these criteria appropriately. Missing data is especially challenging for informal settlements, including large ones, who tend to not be surveyed or to be undercounted (Miller and Small 2003; Barry and Ruther 2005; Carr-Hill 2013). Also, census data generally collected on a decennial basis are insufficient to monitor rapid changes (Alkire and Samman 2014).

In the face of this daunting information gap, using satellite imagery rather than administrative data to identify urban expansion has attracted substantial attention (Antos et al. 2016). This technology has the potential to provide a consistent, reliable and low cost solution to tracking urban expansion and some of the SDG targets, particularly the fourth definition about housing durability. Remote sensing can also make it possible to recover the past using historical imagery in order to track longer periods of changes.

At the same time, it is important to adapt the use of remote sensing imagery to different contexts and to account for the inherent tradeoffs researchers must make in extracting data from them. For example, the same threshold values used in spectral analysis to identify urban construction cannot be applied in all places because of differences in physical geography, construction materials, and seasonal variation. Furthermore, different algorithms may need to be developed to detect informal construction because of differences in settlement patterns and building typologies in different contexts. Also, it is important to reiterate that remote sensing imagery cannot capture many of the other SDG definitions of informality such as the legal status of properties because while settlements may have the physical signature of formal buildings with regular shapes and street patterns they may have been built without permits or do not conform to building codes. We also cannot determine the number of people dwelling in buildings. Still, it is possible to generate information about land use changes and their physical proximity to geographic conditions and infrastructure lines. Accurate information about where people are actually living and working is critical and basic knowledge needed for urban policy and planning.

There have been significant technological advances in the quality and interpretation of remote sensing imagery over the last several decades such that one arena ripe for further development lies at the technology and society interface. In other words, we may be able to to produce more meaningful and policy relevant indicators if the technology is informed by and adapted to field conditions and institutional contexts. This paper capitalizes on the propitious situation of three different research groups who happened to independently utilize satellite imagery to create maps of urban expansion of Ho Chi Minh City, Vietnam in 2000 as a case study with which to discuss how analyst biases can interact with remote sensing data and how they might be better leveraged for different purposes.

As in many cities in the global south, Ho Chi Minh City's rapid urbanization consists of both high quality construction and "informal" construction consisting of non-durable materials, particularly in the urban periphery. The informal land developments invariably house low socio-economic status urban residents, often recent migrants. This population is most likely to be underreported in administrative data, has distinct needs for public services, and is at greater risk for natural disasters since they more often settle in geographically precarious situations.

Kim et al. (2004) noted how in the late 1990s, while cities in transition countries in Asia were undergoing historic rapid urbanization, many government land information systems did not have the capacity to record these changes. Meanwhile de-classified, newly commercialized satellite image archives had systematically collected the only record of what had been happening on the ground. Kim found and purchased cloud-free images of Ho Chi Minh City for years 1991, 1994, and 1998 and then commissioned SPOT-Image to take another image in January 2001 (with a resolution of 10m per pixel). Using this data, Kim et al. (2004) developed algorithms to better interpret urban land use by allowing a lower digital number threshold (i.e. construction materials that do not reflect light as brightly as concrete) if it met a high-pass threshold measure of spatial texture tested by the author's ground-truthing fieldwork (verifying the existence of informal housing settlements through fieldwork). These field-adapted algorithms allowed for the recovery of a larger amount of land use cover change, from rural to urban, than using satellite imagery alone. However, the previous paper (2004) focused on identifying the total urban land area, incorporating informal land development into the overall identification of urbanization. Instead of keeping with the literature's focus on general urbanization patterns, this article proposes to account for them separately, given the MDG and SDG goals of tracking housing conditions. The question for this paper is whether informal spatial patterns differ from formal ones and whether they might have important policy implications.

Furthermore, this paper also takes advantage of the existence of three different studies that used satellite imagery to identify urban land use for Ho Chi Minh City, Vietnam during the same time period, 2000-2001 (Angel et al. 2005; World Bank 2015). This paper compares the classifications obtained by the three approaches to discuss how differences in data and methodology can lead to different answers. Such analysis will contribute to the discussion about whether it may be possible to develop global, standardized indicators to meaningfully capture urbanization patterns and what kind of uses such data can support.

Therefore, this paper addresses two sets of technical research questions with important urban planning and public policy implications: 1) How can informal construction be identified using satellite imagery and are its spatial patterns different from formal construction? 2) In what ways are the classifications of urban areas in Ho Chi Minh City identified by three different research groups systematically different and what accounts for their differences?

The next section reviews the literature on the state of the field of using remote sensing imagery to capture and characterize urban expansion. The second section presents the methodologies we developed to classify urban land uses and to identify informal areas, adapting the algorithms first developed in Kim et al. (2004). The third section then compares these results with two other previously published studies of Ho Chi Minh City by analyzing the areas each identified as urban and tracing how their choice of data and methods shaped their outcomes. The paper concludes with a discussion about policy implications and directions for future study.

I. Literature Review

The World Bank's report "East Asia's Changing Urban Landscape: Measuring a decade of spatial growth" (2015) signaled the growing prominence of spatial data in international development and the move to open access to such data. It builds upon a substantial body of research that has been developing remote sensing imagery to capture changes in urban land use, going back to the 1980s (Riordan 1980; Jensen and Toll 1982; Bertaud 1989; Martin 1989; Gong and Howarth 1990; Gong et al 1992; Ridd and Liu 1998; Li and Yeh 1998; Mas 1999; Zhang 2001; Gluch 2002; Zhang et al. 2002; Kim et al 2004; Angel et al. 2005; Graesser et al. 2012; Pesaresi et al. 2013).

The earlier papers relied on relatively low resolution pictures (30m to 250m) but were still able to provide more information than was previously available about urban expansions occurring beyond official administrative boundaries. More recent research has been able to take advantage of high (5 to 10m) and very high (.5 to 2.5 meter) resolution pictures of the planet in order to provide more detailed images of land use. A number of methods and techniques have been developed to classify urban land uses from remote sensing imagery (please see Appendix for more technical review). Ridd and Liu (1998) and Mas (1999) compared the results of different approaches and found that no single approach was superior in all circumstances. All have their drawbacks due to tradeoffs made between accommodating the heterogeneous nature of urban areas while wanting to standardize techniques (Gong and Howarth 1990).

The World Bank recommends that urban indicators be developed that are "measurable and replicable, easily quantifiable and systematically observable," (Hoornweg et al. 2007: 13). Similarly, the indicators developed to track progress in achieving the SDGs aim to be standardized and obtainable in all countries (Simon, 2015). Accordingly, many policy-oriented researchers have heeded the call to develop and utilize satellite imagery data in order to better understand urbanization patterns and their drivers. For example, Li, Wei and Korinek (2017) used the 2000-

2010 urbanization spatial data released by the World Bank (2015) to model urban expansion in the Greater Mekong Region, which is where this paper's studies are located. They seek to identify factors associated with different urban growth patterns such as distance to coastlines, accessibility, growth and institutional factors like being a capital, or a country political system. Schneider and Woodcok (2008) used changes in urban growth patterns in 25 five international cities to identify four different urban growth types, the indicators being defined by the pace of urban expansion, level of fragmentation, and dispersion patterns. Stewart et al. (2004) used historical imagery for Cairo to analyze urbanization occurring beyond official city limits, finding evidence of decreased density and increased decentralization over time.

However, many of these policy-oriented studies do not give much attention to distinguishing informal settlement patterns that the technically oriented studies have found are challenging to detect. Still the potential is great. Considerable research efforts have been made to develop techniques for identifying informal urban settlements (Rhinane et al. 2011; Graesser et al. 2012; Kit et al. 2012; Taubenbock and Kraff 2014; Vatsavai et al. 2014; Sethi et al. 2015; Antos et al. 2016). As mentioned earlier, utilizing satellite imagery to identify and track informal urban development is particularly valuable due to the general lack of land surveying data about these settlements. Conversely, systematically missing these settlements in studies used to inform urban policy and management could have harmful effects.

These studies have found that there are several challenges to identifying informality in general and relying on remotely sensed satellite imagery in particular. One reason is that the definition of informal settlements is multi-valent. One definition of informality is a legal one, based on the lack of land title and permitting rather than any physical conditions. A limitation of remote sensing imagery is that it does not allow us to directly identify characteristics such as land tenure or service provision (Kit et al. 2012). Some low quality construction settlements could possess security of tenure if there were a large-scale titling program, but these are not common and usually with time lead to better construction quality (Field 2005).

Still, the term "informality" is often used synonymously with sub-standard physical living conditions by the general public and by institutions like United Nations Habitat (2010) which cites non-durable housing materials and insufficient living area. Physical buildings, even small and impermanent ones, can be detected through remote sensing images if we adapt the technology for them. Remote sensing has the potential to be used to develop indicators that distinguish between physically formal and informal settlements because of their differences in building materials, size, and design. Digital processing of remotely sensed images can represent an effective and efficient way to detect these settlements of low construction quality.

Table 1: Methods Used to Classify Urban Land Use Using Remote Sensing Imagery

Indicators	Scale	Resolution	Reference
Spectral analysis	Pixel or pixel clusters	Very High to Low Resolution (<1-30m)	
Spectral threshold			Angel et al.; Hofmann et al.; Kim et al.; Rhinane et al.; Thomson and Hardin; Weber and Puissant;
GLCM PanTex			Graesser et al.
Vegetation Indices			Graesser et al.; Owen and Wong
Texture analysis	Pixel or pixel clusters	High Resolution (1-10m)	
TEXTONS			Barros and Sobreira; Kit et al.; Kim et al.; Graesser et al.
Object-based approach	Pixel clusters	Very High Resolution (<1m) and High Resolution (1-2.5m)	
Lacunarity			Kit et al.; Graesser et al.; Rhinane et al.
Building Density			Taubenbock and Kraff Hofman; Rhinane et al.
Building Size			Taubenbock and Kraff; Hofman;
Road Density			Hofman; Owen and Wong
Scale-Invariant Feature Transform			Graesser et al.
Histogram of Gradients			Graesser et al.
Linear Feature Distribution			Graesser et al.
Line Support Regions			Graesser et al.

Table 1 summarizes the major methods being developed to interpret remote sensing imagery in order to identify informal settlements. It shows the diversity of data resolution and approaches used. The rest of the section briefly reviews the main data and methods being used. Appendix A provides further details on each study.

Remote sensing researchers have attempted to define informality as a particular spatial pattern of settlements characterized by areas with small and highly dense dwellings, of irregular orientations as well as irregular road patterns. In identifying these patterns, some studies use spectral analysis (Thomson and Hardin, 2000; Weber and Puissant, 2003), others focus on texture analysis (Barros and Sobreira, 2005; Kit et al., 2012), while other adopt an object based approach (Hofmann, 2001; Rhinane et al., 2011; Taubenbock and Kraff, 2014). Several studies also combine different methods such as spectral and object based analysis (Hofmann et al., 2008) or spectral, texture, and object based approaches (Owen and Wong, 2013). These approaches navigate taking advantage of the decreasing pixel sizes which can detect more variations in values and re-constituting them into meaningful clusters and objects of urban phenomenon, such as roads and buildings, based on their patterns.

Many studies from a wide range of regions report accuracy above 80 percent, meeting the threshold suggested by the International Expert Working Group on Slum Mapping (Sliuzas et al., 2008). One observation from our literature review that merits emphasis is that researchers utilize the particular building typologies and patterns of a particular city that they identify (smaller red roofs in Rio, limited open space in Hyderabad, etc.) to train algorithms on sites pre-determined as slums. So, while these studies are developing increasingly sophisticated automated techniques, they still need to be based on detailed grounded knowledge about field conditions. And the assumptions utilized are not universal across contexts.

Not surprisingly, the models eventually work well for what it has been trained but this also means that the city must have large areas exhibiting such patterns for it to have high accuracy. Conversely, when slum shelters are situated in ways that deviate into more dispersed and varied patterns, the error rates and particularly the false positives in these studies increase. So, one of the remaining challenges is false positives arising from different levels of land use density that can occur, particularly in the urban periphery. The need for large regular patterns of irregularity implies that thus far larger cities with larger, homogeneous squatter settlements lend themselves well to satellite imagery detection. These studies have found that more isolated squatter households and smaller groupings will not be well identified with such an approach. One implication may be that such households have less economic opportunities than those in more established settlements in the urban center.

Detection strategies have grown increasingly complex to account for the multiple ways to define informal construction under different conditions. These studies all include some elements of unsupervised classification in which an algorithm is used to differentiate between formal and informal built-up area but they also require significant supervised calibration to establish thresholds and filter size based on testing sites. As discussed above, the significant improvements in imagery resolution as well as more complex and sophisticated techniques hold promise for increasingly accurate classifications of urban conditions. Still, as the review of accuracy rates appear to indicate, local geographic conditions and contextual construction patterns usually require some ground-truthing and/or human supervision in the classification. Furthermore, using older images to study change over time necessitates finding ways to work with lower resolution imagery and without the possibility of contemporaneous on the ground verification. The next section proposes an approach to identifying informality in the context of Ho Chi Minh City using mixed spectral and texture analysis.

II. Methodology

Ho Chi Minh City has experienced rapid growth. From 1990 to 2000, the city's population grew by at least 1 million people (Kim et al 2004). Between 2000 and 2010 its urban population had grown by 2.5 million more residents to an estimated total 7.8 million at an annual rate of 3.9 percent and its urban land areas had appeared to have grown at a 4 percent annual rate (World Bank 2015). Rising inflows of population and increasing incomes contribute to an increasing demand for housing. A number of large scale new town development projects built on the periphery such as Saigon South are accommodating the growth in middle and upper income residents. But lower income residents often have to resort to self-construction to obtain a dwelling, finding accommodation in areas that might be located close enough to access jobs but often lack access to urban services. The official city boundaries have grown, incorporating outlying districts in an effort to serve and control growth at the periphery but they have not been keeping up with providing adequate services to these new residents. In addition, administrative data to track these demographic and housing changes remains limited.

This section describes how we apply the methodology developed by Kim et al. (2004) to identify what share of the built-up area is made of informal dwellings built with non-durable materials. In this study, "informal" is defined as construction of lower quality materials with a specific digital signature that can be identified using remote sensing technology and a mixed thresholding and texture approach. It is possible for some high quality buildings to have informal tenure status, and as a result, we are underestimating the share of the built-up area that has informal tenure status. Nonetheless, we posit that the low construction quality buildings we capture with our approach unambiguously constitutes informal urbanism of both building quality and tenure status. These types of recent informal land developments house the lowest socio-economic status residents, often recent migrants, of the city. In many cities in the global south, informal settlements are often located in precarious places prone to flooding or displacement. Therefore, for urban planning and management, it is important to be able to find the extent of informal urban expansion and to identify where these buildings are located.

The spectral signature of dwellings made of plant materials can be similar to its undeveloped rural landscapes. But since the residences' physical patterns are distinct from agriculture and natural environments, a mix of spectral and texture thresholding is able to identify this informal urbanization. Instead of looking at clusters of pixels as in the object-based approaches reviewed above, the approach developed by Kim et al (2004) is at the pixel level based on an algorithm that combines thresholding of the original image to identify the spectral range of low quality constructions and a high pass filter that enhances edges and enables to distinguish built-up areas within that spectral range from the undeveloped areas. The analysis uses panchromatic 10m resolution SPOT imagery for Ho Chi Minh City in 1994 and 2001. The pixel size is close in size to the objects being measured, with the typical building footprint being 5 meters wide and 10 meters deep, which enables the high pass filter to perform effectively in capturing informal construction.

We adopt the same thresholds as in Kim et al (2004). For 2001, we classify as informal built-up areas pixels with a digital number between 53 and 87 and with a normalized 7x7 high pass filter above 0.12. For 1994, the range is 69 to 95 and the normalized high pass filter 0.06. Pixels above an 87 digital number in 2001 and a 95 digital number in 1994 are classified as formal construction built of high reflection materials such as concrete.

Kim et al. (2004) tested the algorithm by using a mix of visual categorization of aerial imagery and ground truth verification for the 2001 data. The original study found an accuracy of about 95 percent in 1994 and 2001. The original paper was only concerned with counting newly urbanized land area, much like the World Bank's East Asia Urbanization Data project. The previous paper's contribution was to increase the count of urbanization by including structures constructed of low reflective materials, implicitly including informal buildings. This paper therefore extends the previous paper by distinguishing between formal and informal construction and analyzing their urban spatial patterns.

The methodology does not capture all informal settlements as defined by the lack of legal tenure or of access to services. Contrary to some of the papers reviewed above that use object-based techniques, this method does not work well to identify larger informal settlements made of durable material that have the same spectral signature as buildings in formal settlements and are homogenous, a limitation of this filtering approach. Still, this method enables the identification of areas that are made of non-durable material in the less dense urban periphery, likely occupied by households among the most economically vulnerable and as we shall see later, those not detected by other studies.

III. Results and Policy Implications of our Findings

Figure 1 shows the formal and informal urban expansion areas for 2001, relative to 1994, based on the Kim et al. (2004) method. As can be seen, the expansion of urbanization, which is a conversion from rural to urban land use defined as new construction, has been large and rapid. Quantified in Table 2 we find that roughly 22 percent of the study area is urban by 2001. Much of the formal construction expanded to the northeast as well as along roads of the southern perimeter of the city and around the airport to the northwest of the city. Coded in yellow, extensive informal construction has occurred mostly in the periphery of the city and in a granular pattern of isolated small dwellings. We calculate that 12 percent of the total urban areas is of informal construction. As discussed in the literature review, it is in these less dense areas in the urban periphery that is challenging to detect informal settlements but not doing so would result in a significant undercount of settlements and populations, which would be detrimental to effective urban policy and policymaking. Figure 1 reveals that the urban area is more extensive than previously considered.

Figure 1: Formal and Informal Urban Land Use in
Ho Chi Minh City, Vietnam January 2001

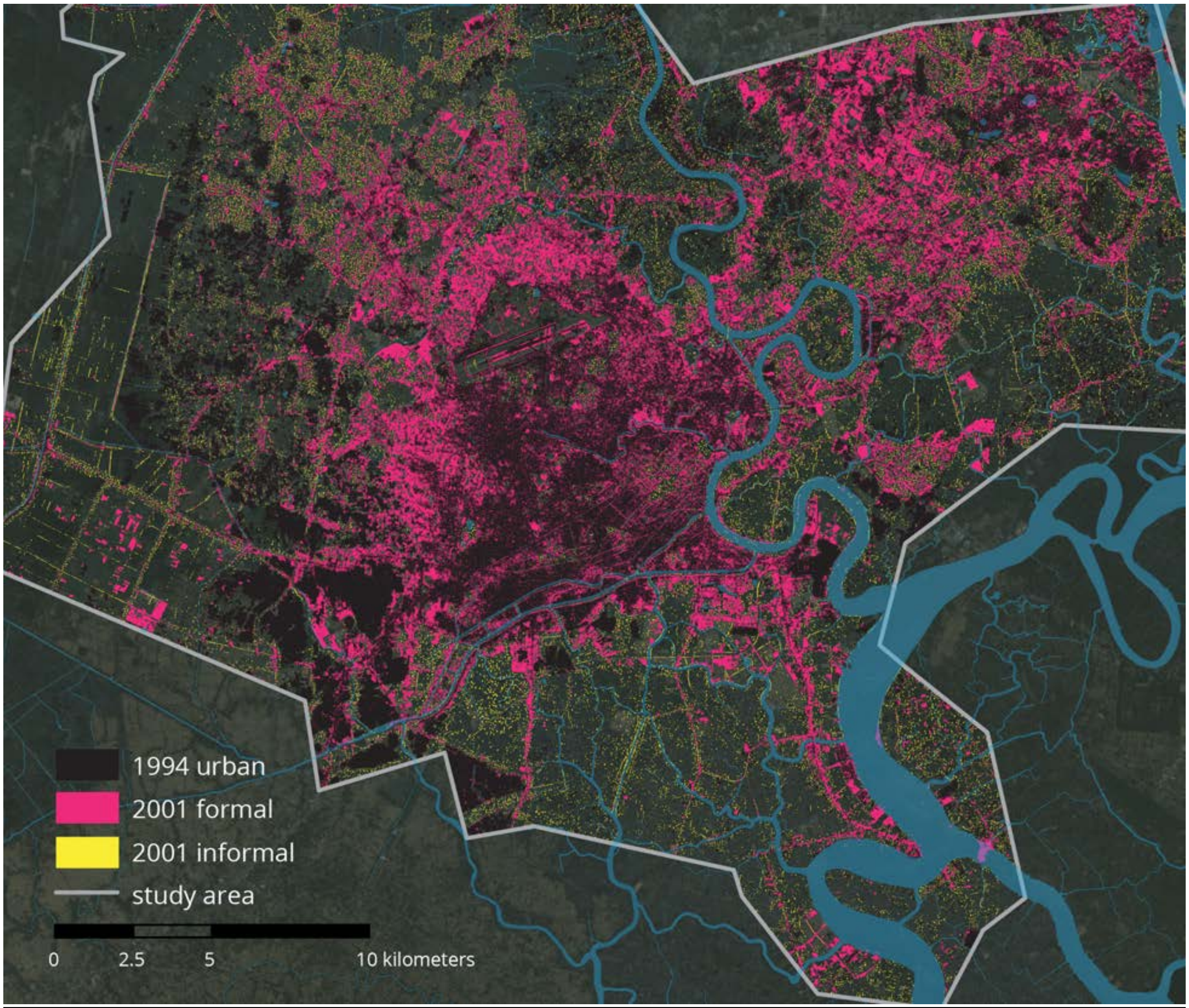


Table 2: A Comparison of Urban Land Use Classifications of Ho Chi Minh City, 2000/2001 by three different studies

World Bank, 2000

Urban Land Use Category	Sq Km	% of total land area	% of total urban area
Urban Fabric	301	34%	100%
Continuous Urban Fabric (S.L. > 80%)	118	13%	39%
Discontinuous High Density Urban Fabric (S.L. 50% - 80%)	124	14%	41%
Discontinuous Low Density Urban Fabric (S.L.: 10% - 50%)	58	7%	19%
Industrial, Commercial and Transport Units	60	7%	
Construction sites	16	2%	
Non-Urban	451	51%	
Water	62	7%	
Total	888	100%	

Angel et al., 2000

Urban Land Use Category	Sq Km	% of total land area	% of total urban area
Urban	207	23%	100%
Non-Urban	625	70%	
Water	56	6%	
Total	888	100%	

Kim et al., 2001

Urban Land Use Category	Sq Km	% of total land area	% of total urban area
Urban	191	22%	100%
Formal Construction	168	19%	88%
Informal Construction	23	3%	12%
Other	697	79%	
Total	888	100%	

However, as we discussed in the literature review, there are a variety of possible ways to generate urbanization data from satellite imagery. This article takes advantage of the serendipitous opportunity created by two other research groups having published satellite image interpretations of HCMC at the same time period as our study. We compare the classification results of the three studies in order to generate a discussion about norms and standards in urban research and their implications for policy.

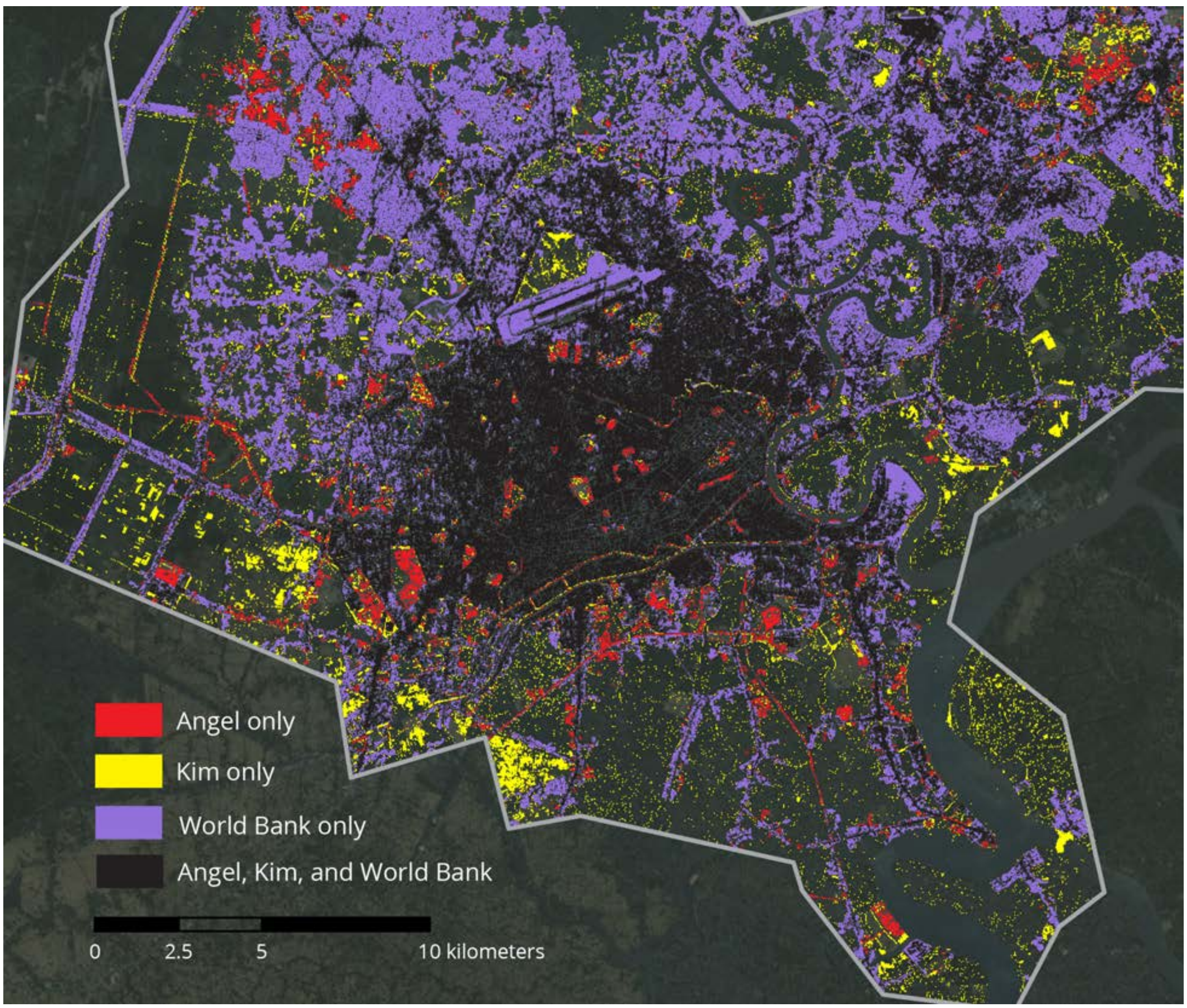
Angel et al. (2005) identified urban areas using 30m pixel size imagery while the World Bank (2015) uses 10m resolution imagery similar to ours. In contrast to our methods of spectral and texture analysis informed by field groundtruthing, both Angel et al. (2005) and the World Bank (2015) used a combination of spectral and cluster analysis as part of an unsupervised classification categorization, followed by supervised reclassification by human analysts. As Table 2 outlines, the three studies also defined land use categories differently. The World Bank study has the most elaborate categories that not only identify a variety of land uses but also categories of densities and urban fabric. One might infer that their category of "discontinuous" patterns could be constituted by a high percentage of unplanned and informal development. In contrast, our study distinguishes between formal and informal land uses by the lower quality of construction materials used. Angel provides the simplest classifications: "urban" and "non-urban." To begin the comparison of these studies, we first simplify Kim et al.'s and the World Bank's various classifications of urban land use into a single urban category. In this way we can see what each study counts as urban and not urban.

Table 3: A Comparison of the three different studies mapping Ho Chi Minh City Urban Expansion through Satellite Imagery Interpretation

Paper	Methods	Resolution	Accuracy	Strengths	Weaknesses
Angel et al.	Spectral and Cluster	30m	89%	- Consistent measure of urban land covers for over 120 cities in 1990 and 2000	- Limited categories - Lower resolution misses phenomenon smaller than 30 sqm
Kim et al.	Spectral and Texture, Field verification	10m	94%	- Captures more informal developments	- Limited categories - Misses road networks
World Bank	Spectral and Cluster	10m	Unknown	-Consistent measure of urban land covers for 5 cities in 2000 and 2012 - Detailed categorization	- over identification of land areas -Lack of accuracy assessment and limited documentation

When comparing the areas classified as urban by the three studies, we find overlap as well as differences despite the fact that the imagery used are from similar periods (2000 for Angel et al. and the World Bank and January 2001 for Kim et al). Figure 2 visualizes the areas that were classified as urban by the three studies. Coded in black are the areas that all three studies agreed were urban. The urban core is unambiguous to all three studies. However, each of the three studies also identified urban areas that the other two studies did not: these are colored in yellow (Kim et al.), lavender (World Bank), and red (Angel et al). Overall the World Bank (2015) identifies much more urban area than the other two studies: 301 square kilometers or 34 percent of the study area is classified as urban and another 60 square kilometers or 7 percent are classified as "Industrial, Commercial and Transport Units", as compared to 207 square kilometers or 23 percent for Angel et al. (2005) or 191 square kilometers or 22 percent for Kim et al. (2004). Many of Kim's unique areas are granular areas of isolated dwellings on the southern periphery whereas the other two tend to pick up clusters. The differences can primarily be attributed to different procedures being used, pointing to the importance of understanding the limits of each algorithm and of ground-truthing the results of the classification in order to make sure that they capture local conditions appropriately and estimate the margin of error.

Figure 2: A Comparison of urban land use classification maps for Ho Chi Minh City 2000-2001 by three different studies[1]



[1] Angel et al. 2005; Kim et al. 2004; World Bank 2015

But before further elaborating the reasons for the differences, we should note the striking similarities between Kim et al. and Angel et al.'s overall urbanization rates despite different data quality and methods. This impels a basic question: what is the minimum resolution image needed for examining urban expansion?

Angel et al. conducted a multi-city study that used 30m resolution imagery to classify urban and nonurban areas, while both the World Bank and Kim et al. used 10m resolution imagery. Since the 1990s, 10m imagery has been widely, commercially available with images archived since the 1980s. The increasingly available Very High Resolution (VHR) imagery at submeter resolution has enabled the development of cluster based categorization based on object extraction algorithms (Vatsavai 2014; Sethi 2015; Antos et al. 2016) but this requires significantly more computing capability. Also, another drawback is that very high resolution images are limited for historical images because of the recent technological advances.

Obviously, more can be detected with higher resolution. However, for urban applications these potential gains require knowledge about the contextual conditions on the ground since submeter imagery requires identifying patterns of pixels that constitute urban phenomenon such as buildings. In the Vietnamese context, 10m pixels roughly match a typical residential building's footprint which allowed the World Bank and Kim et al to use them productively. On the other hand, the 30m pixel resolution images used by Angel et al which require mostly spectral approaches was also able to detect much of the same urban areas at lower cost, which facilitated their study of over 120 city comparisons. However, with larger resolution images they are susceptible to missing houses that are built in discontinuous patterns, of sizes smaller than the pixel size, and of low quality materials, such that it does not significantly cross the spectral threshold.

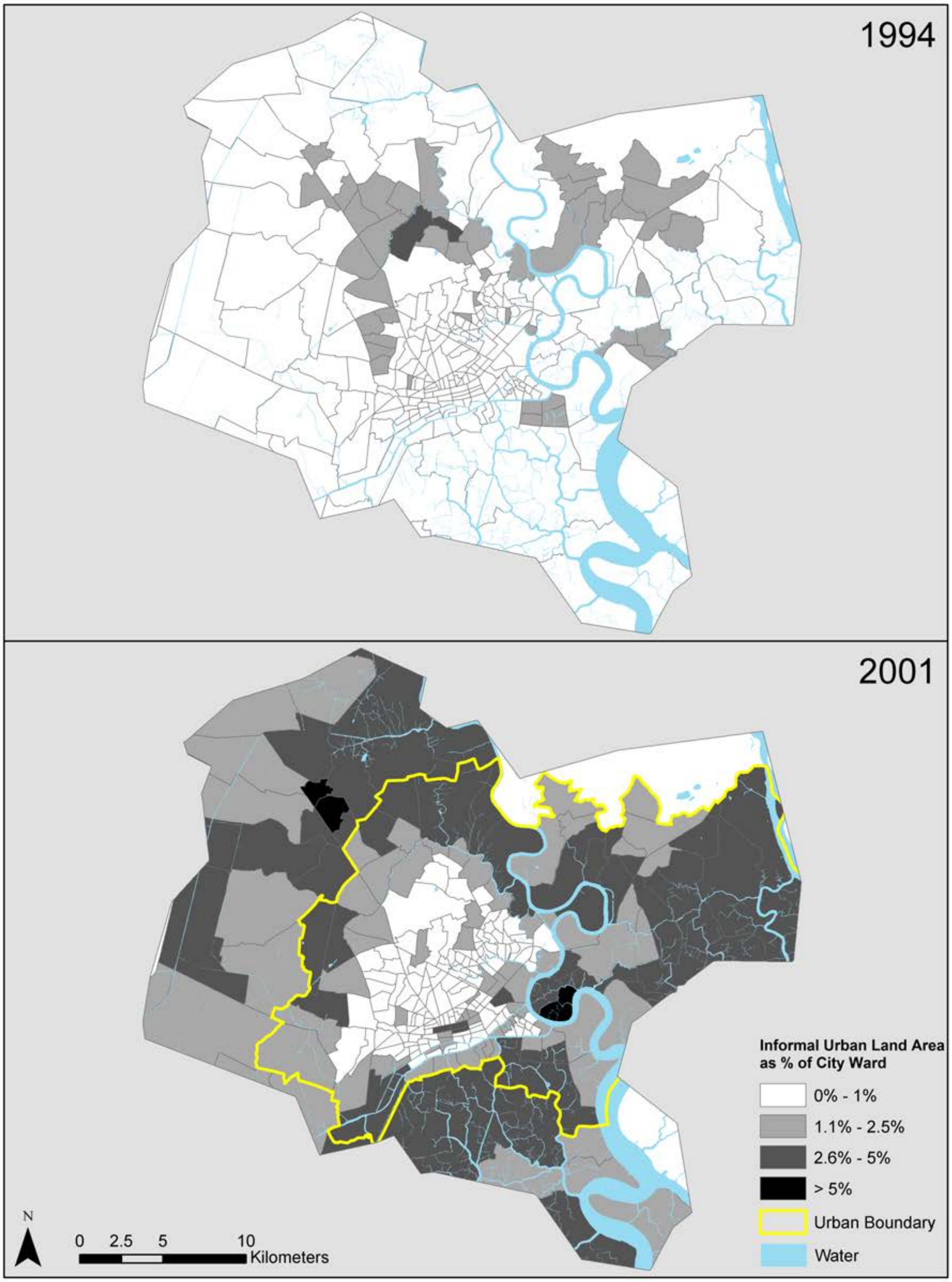
These studies indicate that different resolution images and methods for interpreting urban expansion are possible. The comparison also displays systematic differences in results emanating from the detection methods deployed. In Figure 2 we see that the World Bank study alone identified most of the northern half of the study area as urban. This probable over-identification results from their classification schemes which looked for different densities of "urban fabric" rather than identifying urban objects such as houses. Meanwhile, most of the pixels that were classified as urban by only Kim et al. are located on the southern low-lying outskirts of the city, capturing informal land developments that exist in a dispersed pattern on the periphery. This identification results from the author's fieldwork that groundtruthed the existence of isolated structures in this region. This texture analysis would not be possible using 30m resolution imagery such as the Landsat data used by Angel et al. (2005) as the size of a pixel needs to roughly match the size of a typical object (building) to be effective. Approaches that use a pure thresholding approach without taking into account differences in texture for informal construction are likely to miss the buildings that can be identified through the high-pass filter texture approach developed by Kim et al.

Another difference between methods is the treatment of streets, which was best classified by the World Bank and was a weakness of the Kim et al.'s method, although Angel et al. and Kim et al. were able to detect a few roads in the west that the World Bank did not (presumably unpaved roads). In other words, the Kim et al. study's algorithm focused on gaining detections of lower quality buildings with its texture analysis of these variegated patterns while not sufficiently accounting for higher spectrum roads. Still, for planning and policy purposes, since roads are generally formally planned and documented with maps, one could add this information as a GIS layer. In other words, urban land use detection through satellite imagery would ideally be integrated with and verified by other data sources. Then, a key question becomes, what kinds of new data might satellite imagery provide that other sources cannot? Figure 3 starkly reveals that Kim's identifications in yellow of dispersed informal settlements not lining major roads would most likely be missed were it not for satellite imagery.

Accordingly, we can take advantage of this unusual situation of comparing three classification studies to further investigate the interaction between the spatial data we produce and the possible policy implications. How can we assess the quality of this data and use it responsibly? While a city might not usually have the luxury of three different research teams providing data, Figure 3 provides a useful exercise for discussing issues from a policymaker's point of view. If a city were to just use one study, there would be some systematic differences in its understanding of where its population resides and works. With the World Bank map, there would be more focus on the north whereas with the Kim study one would have smaller settlements, particularly in the south. This raises questions about how city leaders might manage the veracity and implications of satellite imagery interpretation. How confident should they be of a study's claims of identifying urban settlements? They should want to know if there had been field verification and the reporting of error rates.

The attention to informal urbanization distinguished the Kim et al study. In addition to showing that historical 10m resolution images could be interpreted to detect informal urbanization, this paper asked whether these informal settlements displayed different spatial patterns than formal construction. Figure 3 shows the percentage share of each administrative ward's area that we classified as consisting of informal urban development. As expected, city wards at the periphery have the highest levels of informal areas. The yellow line represents the official boundary of Ho Chi Minh City that was expanded in 1997 and in 2004 to accommodate the city's rapid urban growth. 1993 was a momentous year because the government signaled with the 1993 Land Law that it was legally possible for citizens to own and trade land use rights privately, unleashing a rapid migration to Vietnam's largest city. We see in 1994 that informality first started in the northern edge of the city, which was sensible given the firmer geological foundation upon which to build. However, by 2001 we see significant expansion to the swampy south because of the national decision to support the large private Saigon South developments (Kim, 2008). Other smaller developers took advantage of the high quality trunk infrastructure developments invested in this area of the city and its associated high land values. We can see increases in informal construction in areas adjacent to but outside the official urban boundary in the south and northwest of the city.

Figure 3: Share of Informal Urban Land Area by City Ward Jurisdiction



Besides being located in the periphery, we also analyzed whether informal land uses in Ho Chi Minh City were located in physically vulnerable areas. We found two spatial patterns of higher risk for informal settlements. Table 4 summarizes the share of formal and informal urban areas that fall within a 250 m buffer around the waterways shown in Figure 3.[2] We find that while 26 percent of urban areas classified as formal construction falls within 250 m of a waterway, 52 percent of urban areas classified as made of informal construction fall within that buffer zone that is potentially more exposed to risks of flooding. It is common for informal settlements to locate in less desirable places because they are less likely to be contested. But, by being less noticed, they are also more challenging to incorporate into disaster and resilience planning. We also performed a similar buffer around arterial roads since these locations will be relatively higher valued because of their accessibility to jobs and urban services and the potential for supporting commercial activities that will benefit with the traffic.

Not surprisingly, a large share of formal construction is located within 250m of major roads (53%) but there is also a substantial share of informal construction that falls within the 250 buffer around major road (30%) consistent with informal constructions taking place in locations with access to the rest of the city. However, informal developments are likely to be displaced by formal urban development because of the high land market value of locations with transportation access. Overall, informal settlements in Ho Chi Minh City are more likely to be located in areas that might be at risk for flooding and also near roads that can provide access to jobs but put them at risk for eventual displacement and resettlement. The methodology developed by Kim et al. enables this distinction in risks between formal and informally built construction and captures some informal built up areas that might not have been detected by the other classifications reviewed here. Missing such data observations would limit the planning capacity of cities, particularly for catastrophic risk preparation and infrastructure needs assessment.

[2] The shapefiles for arterial roads and waterways were obtained from Open Street Map. We use waterways as a proxy for areas at risk of flooding, which has been a major issue of policy concern in low-lying Ho Chi Minh City.

Table 4: Share of a Given Land Use Type within a 250m buffer of Roads and Waterways

Ho Chi Minh City, 2001

Land Type	Total Area (Sq Km)	Land Type Within Waterways Buffer (Sq Km)	% Land Type Within Waterways Buffer[1]	Land Type Within Arterial Roads Buffer (Sq Km)	% Land Type Within Arterial Roads Buffer2
Total Land Area of Study	889	399	44.9%	249	28.0%
Total Urban Land Area	191	54	28.1%	94	49.4%
Formal Construction	168	43	25.7%	88	52.5%
Informal Construction	23	12	51.7%	7	29.8%
Non-Urban Area	698	343	49.1%	155	22.2%

[1] % Within Waterways Buffer = Sq Km of land type area within 250m of waterways / Total Sq Km of land type. For example, for Informal Land Area: % Within Waterways Buffer = 12/23 = 51.7%

[2] % Within Arterial Roads = Sq Km of land cover within 250m of waterways / Total Sq Km of land cover. For example, for Total Land Area: % Within Waterways Buffer = 249/889 = 28.0%

Conclusion

This paper analyzes and discusses the potential and tradeoffs in using supervised algorithms to classify remote sensing satellite imagery to generate data about formal and informal urban land expansion as part of the monitoring of the Sustainable Development Goal 11.1 on slum housing. Using remote sensing imagery to detect patterns of informal development is of primary importance because unlike formal construction, alternative sources of data (such as building permits, taxes) to manage them are limited. The Kim et al. study also showed that it is possible to take advantage of older 10m resolution images of urban areas from the 1980s and 1990s when many cities particularly in the global south were just starting to grow explosively. Often these are the only record of what was happening on the ground during that time period. Therefore, this methodology has the potential to be used to identify changes in the patterns of informality over decades which would allow studies of policy impacts as well as other factors.

This paper also discussed the exciting growth in technology and scholarship in generating urbanization data from satellite imagery. It found there are tradeoffs to consider by comparatively analyzing the results of three different studies of the same place, using slightly different data sources and employing different methods and metrics. While these experts agreed about the urban core of which there was little question, we found substantial differences between the studies in the areas that are classified as urban in the newer urban expansion areas on the periphery. Developing policy-useful and parsimonious approaches to classifying urban land uses with limited supervision is an important research agenda for this field.

The comparison emphasizes the importance of customizing automated interpretations to the local context. In particular, this paper focused attention on informal urbanization occurring in potentially hazardous areas. Our study adapted its detection method for distinguishing formal and informal urban development within the particular context of Ho Chi Minh City, based on field knowledge about the particular range of reflective properties of building materials, building typologies, and development patterns. Missing the areas classified as urban by Kim et al. has policy implications. We found that in the case of Ho Chi Minh City, as expected, more informality happens in the periphery. Informal settlements also anticipate future growth by locating adjacent to where formal investment occurs and along roads. But, we also found a higher percentage of informal construction happening near rivers. If experts use algorithms that systematically miss the presence of residents in these areas, the missing data would encourage policymakers to underestimate the number of vulnerable residents in risky locations.

Spatial indicators developed from satellite imagery can be powerful tools for measuring urban expansion. They can provide consistent and lower cost estimates, particularly in cases in which administrative data is unavailable or limited. However, it is important to make sure that the algorithms used are adapted to local context, especially for construction typology and material, to ground-truth results to ensure accuracy, and to estimate margins of error. Depending on the objectives of the study, the verification and ground-truthing efforts can take different forms but some measure of accuracy is needed. As further indicators are developed based on remote sensing imagery, the adoption of standards to verify and report accuracy will be important to make the indicators useful and compare different results. It is also important for these indicators of urban land use to ensure that they do not systematically miss certain settlement types and populations.

Knowing the preponderance and location of informal urban land developments can help local governments serve those in need and plan for more sustainable and inclusive cities as well as to be used to inform a broad number of policies. These include planning future infrastructure development, climate change flood adaptation, resettlement needs, and public transportation. Furthermore, different algorithms may be necessary to capture the different dimensions of the urban environment: for example, urban land cover, dispersed irregular development, concentrated irregular development, differences in density. In effect, the differences between the three studies of Ho Chi Minh City emanate from the researchers' particular interests in using satellite imagery. Kim et al.'s 2004 study is most interested in accounting for informal construction given the international development policy community's focus in improving sub-standard housing. Angel et al. (2005) also provided an analysis of urban expansion of Ho Chi Minh City between 1990 and 2000, as a part of a larger research project of 120 cities that seeks to develop comparative global urban indicators using lower resolution imagery (30m per pixel). Such a broad study could help give a more comprehensive historical picture of which countries and areas of the world are urbanizing more rapidly, and general typologies of urbanization patterns. Meanwhile, the World Bank (2015) commissioned the interpretation of its PUMA dataset for Ho Chi Minh City 2000 from a research group at the University of Wisconsin Madison as a part of its East Asia urbanization data initiative. It was one of 5 cities for which the Bank publicly provided higher resolution imagery (10m) to encourage the further development of research. The Wisconsin group developed categories of land use pattern densities that are common to studies of urban sprawl in order to assess how costly it would be to provide infrastructure. What is clear from the comparative analysis is that in addition to tradeoffs between accuracy and coverage, it is important to match the methods of generating urbanization data for the specific policy and urban planning purpose.

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Appendix A: Principal Studies Identifying Informal Settlement Using Remote Sensing Imagery

A number of methods and techniques have been developed to classify urban land uses from remote sensing imagery such as image differencing (Jensen and Toll 1982, Ridd and Liu 1998); image ratioing (Howarth and Boasson 1983); image regression (Ridd and Liu 1998); and principal component analysis (Li and Yeh 1998) amongst others. In addition to overall urbanization, substantial research advances have been made to automate the detection of different urban land uses areas such as roads and open spaces, as well as data about the area, height and density of built structures (Pesaresi et al. 2013). Hofmann (2001) applies principal component analysis to segment 1m and 4m IKONOS images of a subset of Cape Town, South Africa into individual objects. The objects are defined by a combination of scale, color, shape and smoothness. This article does not provide accuracy estimates but mentions misclassifications that require further ground-truthing or images of higher resolution. Hofmann et al. (2008) use an object-based approach that includes a spectral component to identify informal settlements in Rio de Janeiro, Brazil. This article uses very high resolution four channel .69m resolution QuickBird data. [3] Informal settlements are characterized by smaller than average building sizes and road segments (object component) as well as lower than average areas of red roofs combined with a higher area of small shadows/dark objects (spectral component). The article defines informal settlements as contiguous settlements of that nature that form an area of more than 1,800 square meters. Review of the accuracy of the automated classification compared to a manual classification on a sample of the study area find a 68 percent concordance rate. Rhinane et al. (2011) use an object based-approach to detect slums in Casablanca, Morocco. They use 2.5 m resolution SPOT data and produce a supervised classification of the data. The segmentation is based on spectral parameters, object size and context of the object based on training sites pre-identified as slums or not. The accuracy of the classification is 85 percent in identifying slums but 31 percent of non-slums were incorrectly classified as slums. The authors report that most of the omissions are associated with small areas made of isolated buildings. Taubenbock and Kraff (2014) use panchromatic .60 m resolution QuickBird images of Mumbai to identify squatter housing. They use an object-based approach to identify individual buildings and rely on building density, size and height to categorize a settlement

[3] The resolution of satellite data changes slightly depending on the angle between the sensor and the area captured across studies, the changes are small but result in noticeable difference for very high resolution imagery like QuickBird's (increase in the angle result in lower accuracy).

as informal based on a threshold estimated from areas classified as such through field surveys. They do not provide accuracy estimates.

Kit et al. (2012) identify slums in Hyderabad, India using a texture-based approach applied to multispectral 2.44-2.88 m resolution and panchromatic .61-.72 m QuickBird imagery. The methodology is based on priors about the internal spatial structure of slums in terms of building density, size and organization. It relies on lacunarity, a measure of surface texture that represents the distribution of gaps within an image, to classify slums. Slums are expected to have lower lacunarity values, reflecting denser settlements with limited open spaces. The lacunarity measure is applied to a training image of slum/nonslum areas in order to define the threshold and the window size that obtains the best results. They are able to identify slums 83 percent of the time while non-slum areas are classified as such about 10 percent of the time. This method appears to work best in identifying slums larger than 3,600 square meters.

Owen and Wong (2013) combine several approaches to identify informal settlements in Guatemala City: spectral, texture, scale-based, geomorphology and road accessibility. They use panchromatic .6 m resolution QuickBird imagery and 30 m resolution ASTER elevation data to test the contribution of 24 separate indicators to differentiating between informal and formal settlements. The indicators are based on existing studies (a number of which are reviewed above). They find that the following 6 variables were most effective: entropy on roads (captures increased debris or randomness of surface materials on roads), vegetation patch size (smaller), vegetation compactness (more circular), profile convexity (capturing slope), road density (higher) and soil coverage (higher). They report an accuracy of 92 percent in correctly classifying the sample into formal or informal based on these indicators using the discriminant function analysis approach. Indicators may vary across cities and over time, but this approach of combining different measure and estimating what indicators can contribute to differentiate between formal and informal appear promising for further research on developing a standardized approach to identification using high resolution remote sensing imagery.

Graesser et al. (2012) also combine different criteria to identify informal settlements in Caracas, Kabul, Kandahar and La Paz) using panchromatic .6 m resolution QuickBird imagery. They combined 8 different approaches combining spectral, texture and object extraction at the pixel and neighborhood levels (grey-level co-occurrence matrix, histogram of oriented gradients, lacunarity, linear features distribution, line support regions, vegetation indices, scale invariant feature transform and textons). They classify land use into formal, informal and non-settlement. The informal settlement class is further divided into two types with Type 1 characterized by "small to medium-sized building and typically narrow and irregular streets." Type 2 is characterized by "very small building size and high building density, and unidentifiable roads." (Graesser et al., 2012: 1166).