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Urban land expansion in Indonesia 1992–2012: evidence from satellite-detected luminosity*

Susan Olivia, Geua Boe-Gibson, Glen Stitchbury,
Lars Brabyn and John Gibson[†] 

Land conversion to urban use typically accompanies economic development but raises concerns about food security. Debates of these issues often rely on incomplete and incompatible evidence. This study uses satellite-detected luminosity, from 1992 to 2012, to examine the urban land expansion of 41 major urban areas in Indonesia. The trend annual expansion rate is 2.0 per cent, which is comparable to the rate for India and just one-third of the rate for China, as estimated with the same data and methods. Prior to the Asian Financial Crisis in 1997/98, the rate of urban expansion was faster, and the income elasticity of urban expansion was much higher. About 85 per cent of the area of urban expansion had formerly been grassland, shrub or woodland, and just 7.0 per cent was former cropland so food security concerns about urban expansion may be overstated.

Key words: food security, land conversion, land cover, night lights, urbanisation.

1. Introduction

The conversion of land to urban uses is one of the most visible changes that come with economic development. Growing urban areas can help countries to escape from mass poverty (Gibson *et al.* 2017), but loss of agricultural land may conflict with national food security goals. One view in the literature is that the conversion of land to urban uses is often wasteful, in that it entails potentially greater loss of productive land – and greater risk to food security – than may be needed by the urban activity associated with a given level of economic development. Thus, urban sprawl is often viewed with alarm (e.g. Sudhira *et al.* 2004). A case study of spatial externalities and sprawl in Jakarta (Fitriani and Harris 2011, p.17) provides an example of this view:

The main concern about sprawl in Jakarta Metropolitan is the scattered or leapfrog development pattern has expanded the spatial size of the metropolitan more than if the development was managed to achieve a more compact pattern.

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[†] Susan Olivia (email: susan.olivia@waikato.ac.nz), Geua Boe-Gibson, Glen Stitchbury, Lars Brabyn and John Gibson are with University of Waikato, Hamilton 3240, New Zealand.

Yet despite compact cities being desired by urban planners, issues about outwards versus upwards urban expansion remain contentious. First, urban growth boundaries can distort land markets and contribute to high urban house prices (Grimes and Liang 2009). Second, rural living standards may benefit from outward rather than upward expansion of urban areas, as found, for example, in the effect of urban growth on rural poverty in India (Gibson *et al.* 2017). Third, urban growth may save agricultural land; urbanites use less land than do rural dwellers, so moving people into the city can save land. For example, just 40 square metres of new urban land was added in Indonesia for each new urban resident between 2000 and 2010; the smallest amount of any country in East Asia (World Bank, 2015). If the footprint for rural dwellers exceeds 40 square metres, which is highly likely, moving someone from a rural area to an urban one can be land saving. Along these lines, Deng *et al.* (2015) show how pre-2000 urbanisation in China saved cultivated land.

In this study, we report on the rate of urban expansion for Indonesian cities. This new evidence is relevant to a hypothesis that is suggested by the Fitriani and Harris quotation above:

H1: The rate of urban area expansion in Indonesia is unjustifiably fast.

This hypothesis is deliberately vague because claimed effects on food security of agricultural land loss to urban expansion typically do not have any explicit benchmark for assessing the deviation from optimality. In order to provide such a benchmark, we consider whether urban area expansion in Indonesia exceeds what is observed internationally in other demographically large countries that are undergoing a structural rural-to-urban transformation.

Our study also has evidence that is relevant to a second hypothesis that is commonly seen in some of the negative views about urban expansion:

H2: It is mostly cropland that is being lost to the expansion of Indonesia's urban areas.

For example, in discussing land-use change in Yogyakarta, Indonesia, König *et al.* (2010, p.1993) state that:

Given the fact that most natural forests in this region have been cleared already (with the remaining area being under strong protection), *the demand for settlement space is mostly met by changing rice paddies into settlements.* (emphasis added)

The idea that urban expansion causes a loss of cropland, rather than a conversion from other land uses, persists despite evidence that more forest or grassland may be converted to urban use (Gibson *et al.* 2015) and also ignores the fact that urban expansion strengthens the incentives to improve

land quality and so may actually increase the effective amount of cropland (Deng *et al.* 2006).

In addition to the somewhat negative view of urban expansion, a further problem is much of the literature is about expansion of particular cities, with few accounts of urban expansion across a whole country. Moreover, it is rare to find national level studies that use comparable data and methods to what has been used in other countries. In the light of these weaknesses in the literature, the goal of this study was to help inform debates about food security and land-use change in Indonesia, by providing comprehensive, and internationally comparable, estimates of urban land expansion. In order to achieve this goal, we use satellite-detected luminosity, from 1992 to 2012, to study the spatial expansion of 41 major urban areas. An advantage of our study is that the same data and methods have recently been used to study urban expansion in China and India (Gibson *et al.* 2014, 2015), and this enables the results to be considered alongside comparable ones for other populous countries.

The importance of accurately measuring urban expansion, and studying its driving forces, means that our study is not the first in this area. A related study, by the World Bank (2015), uses satellite imagery and demographic data, for 2000 and 2010, to estimate urban area for countries in East Asia. This provides a valuable resource for comparing urban expansion across countries, but the restriction to just two years, ten years apart, is a limitation. Ideally, food policy would be informed by ongoing analysis of urban expansion, because the driving forces may change at any time; for example, as occurred in China as urban expansion switched from saving land to becoming a source of pressure on cropland (Deng *et al.* 2015). In contrast to the World Bank (2015) study, this research covers more urban areas in Indonesia, for a longer period and with annual data. We also estimate the income elasticity of urban expansion and show what was previously on land that became urban.

The next Section provides a brief background on urbanisation in Indonesia. Section 3 describes the data, paying particular attention to night-time lights as a measure of urban area, and explains our econometric model, which is estimated on a panel of satellite–year–city cells. Our results are then presented in Section 4, and Section 5 concludes the paper.

2. Urbanisation in Indonesia

Over the last 40 years, Indonesia has gone from having less than one-fifth of the population in urban areas to being over one-half urbanised. In the particular time period that we study, from 1992 to 2012, Indonesia's urbanisation rate rose from 33 to 51 per cent, according to the *World Development Indicators* of the World Bank. This urban transformation was slightly slower than in China, where the urbanisation rate rose from 28 to 52 per cent (again, according to *World Development Indicators*) but is quite a lot faster than for other populous Asian countries. For example, urbanisation

rates went from 26 to 32 per cent for India, from 31 to 37 per cent for Pakistan and from 21 to 32 per cent for both Bangladesh and Vietnam, while in the Philippines, the urbanisation rate declined slightly, falling from 48 per cent in 1992 to 45 per cent in 2012 according to *World Development Indicators*. Another country that is sometimes compared with Indonesia is Nigeria, where the urbanisation rate increased from 31 per cent in 1992 to 45 per cent in 2012. Thus, it appears that Indonesia has undergone one of the more rapid urban transformations observed in the recent past, and this should be borne in mind when interpreting findings about the rate of urban area expansion.

The urbanisation process is especially marked for Java, the home of almost 60 per cent of Indonesia's population despite having just 7 per cent of the area. Java's urban population grew from below 60 million in 2000 to 80 million by 2010 (Firman 2017). Urban development in Java is marked by massive urban belts connecting large cities, including the Jakarta–Bandung, Yogyakarta–Semarang and Surabaya–Malang corridors. This development along infrastructure corridors, and also around toll ring roads, especially for Jakarta, has seen the growth of private industrial parks in the peripheries (Hudalah *et al.* 2013), contributing to the spatial spread of urban areas. The effects of this type of development are also seen in population data; Jones and Mulyana (2015) compared 1990, 2000 and 2010 population censuses and found population growth rates for Java's largest cities (namely Jakarta, Surabaya, and Bandung) are relatively low, due to rapid growth taking place in areas outside their official boundaries. An advantage of using remote sensing data rather than administrative area data is that this 'spillover' growth in the built-up area can be detected from satellites irrespective of where it occurs relative to administrative boundaries.

Urban growth rates outside of Java are even higher in some cases, although for cities that typically start out much smaller (except for Medan). Some of the faster growing cities include Batam on the Riau Islands, across the Strait from Singapore, and Pekanbaru in Riau Province, Sumatra. The close proximity to Singapore has helped Batam to become an important service centre, attracting migrants from throughout Indonesia and contributing to a population growth rate at the last census of over 7 per cent (Firman 2017). Another rapidly growing city is Makassar, in Sulawesi, which is a key commercial centre for Eastern Indonesia. We provide ground-truthing evidence for Makassar in our appendix (and also for two larger cities, Surabaya and Medan) to show how the footprint of each city, as detected by satellite observation of night lights, corresponds to particular types of urban development on the ground.

3. Data and methods

As noted above, a problem for measuring growth of urban areas (and their populations) is that these areas spill over boundaries, so data based

on administrative collections can be misleading. For example, just four of the 21 Indonesian urban areas with population above one million are within a single administrative boundary, with the others spilling across boundaries (World Bank, 2015). Satellite remote sensing is not affected by boundaries, so in this study, we use satellite-detected night lights to measure urban area. Artificial light is present wherever urban areas occur, and light from larger urban settlements is of sufficient density to be detected from space. In contrast, it takes more light than is typically found in rural areas to be detected by the satellites supplying the data we use. For example, Tuttle *et al.* (2013) show that it takes 800 times more light than what comes from a typical incandescent bulb in order to be detected from space with these satellites, and this sort of intense light is not typically found in rural areas.

Within economics, night lights data are increasingly used as a proxy for GDP, at both the national and subnational level (Donaldson and Storeygard 2016), but outside of economics, there is a longer tradition of using night lights data to measure urban area and urban dynamics (Imhoff *et al.* 1997; Henderson *et al.* 2003; Small *et al.* 2005). The lights data are from the Defense Meteorological Satellite Program (DMSP), processed by the National Oceanic and Atmospheric Administration and available at <http://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html>. The six satellites from the DMSP provide annual estimates over 1992–2012 at a one square kilometre resolution (in some years, two satellites are in orbit, so there are 33 satellite–year observations). In applications related to food security, Gibson *et al.* (2015) use these data to study area expansion for 47 Indian agglomerations with populations above one million and also show that most of the land that cities expanded on to had previously been woodland and grassland, and only one-quarter had been cropland. In a related study, Gibson *et al.* (2014) use the same data to examine expansion of the urban cores of 225 prefectural cities in China (with average populations of 1.6 million).

In comparison with Landsat, which is used by Deng *et al.* (2006) to study urban expansion, or Moderate Resolution Imaging Spectroradiometer (MODIS), which is used by the World Bank (2015), the DMSP stable lights data tend to make urban areas look bigger. Moreover, the amplification on the DMSP sensors changes over the lunar cycle, given that their primary purpose is to measure moonlit cloud, to help with Air Force weather forecasts, although the annual composite of nonephemeral lights that we use should converge to an average amplification level. Research has shown there is only a small proportionate error in area estimates for medium to large settlements (Small and Elvidge 2013) and there is a strong linear trend at city level between area estimates derived from night lights and other measures of urban area that use data from satellites with higher resolution sensors (Ma *et al.* 2012). For example, Gibson and Li (2017) report a correlation of 0.86 between night lights derived measures of city area for over 200 cities in China and estimates based on more finely grained Landsat data.

In this study, we use night lights to examine the spatial expansion of 41 urban areas in Indonesia. These areas had an average population of 0.9 million in 2013, and so measurement errors at this scale should be small. A further advantage of using the night lights is that the results can be compared to other countries. Figure 1 provides a location map for these 41 urban areas and classifies them by population. These areas are located in 27 different provinces and include provincial capitals and other major cities.

A key decision with night lights is the brightness threshold to classify a pixel as urban. A lower threshold makes urban areas seem larger and they can merge together, especially if they are linked by built-up corridors along major transport routes. However, with a higher threshold, some smaller or less brightly lit urban areas are not bright enough to be detected. In this research, we use detection thresholds of 30, 40 and 50 per cent of the maximum brightness value (which is Digital Number [DN] = 63) captured by the DMSP satellites. This range is a compromise between consistency with previous studies using night lights, which used detection thresholds of 40, 50 and 60 (India) and 50 per cent (China), consistency with other data, as 21 of the areas we study are in the 2010 *Demographia World Urban Areas* compilation and best match those estimates at a 60 per cent threshold; and maintaining sample size, especially in earlier years when cities were less brightly lit. For example, at a 60 per cent detection threshold, 21 of the 41 urban areas were not visible in 1992, while at a 30 per cent threshold, only

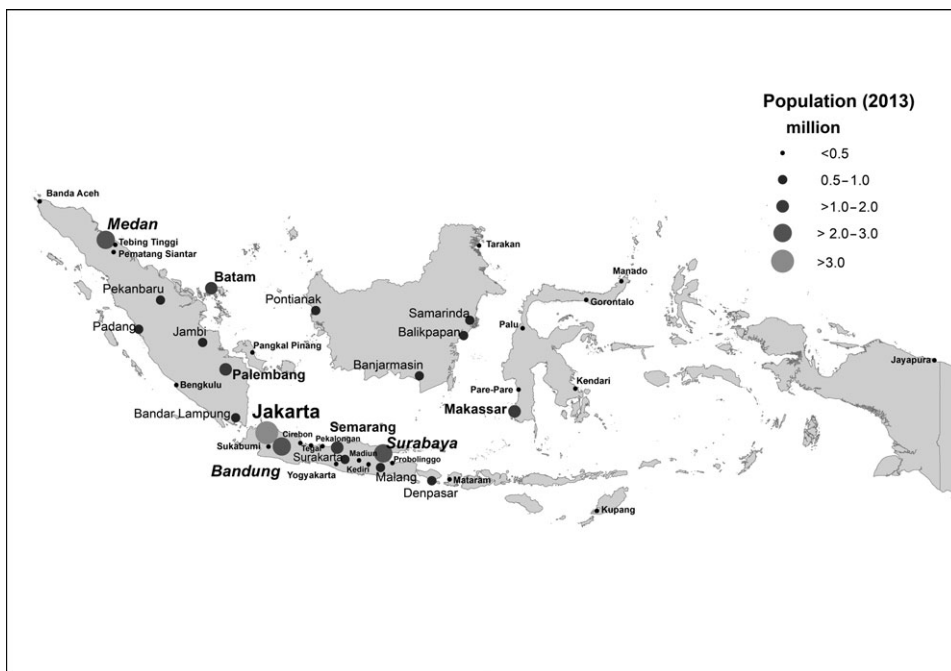


Figure 1 Location map for the 41 urban areas

two were not visible, and so lower thresholds reduce problems of changes in sample composition affecting the estimated trend expansion rate (because with a lot of missing areas in some years the panel becomes unbalanced). A final point to note is we use multiple thresholds to see if the patterns are robust, and so concern with the accuracy of any one particular threshold is less important if one finds the same patterns across several thresholds.

Our measurement procedure is as follows: starting at the centre of each urban area, where lights are brightest, and moving outwards, as the algorithm comes across pixels less illuminated than the threshold, it searches in a different direction. If the algorithm finds no contiguous pixels with light above the threshold, except those closer to the city centre that it has already scanned over, it sets a boundary. This procedure traces out edges of urban areas, as defined by the brightness threshold. To confirm that the edge areas are indeed urban, we carried out ground-truthing for Surabaya, Medan and Makassar (see Appendix S1, S2 and S3). Our online appendix has maps of the urban area of these cities, according to the night lights, with photographs for edge spots that were obtained by the lead author and/or from *Google Earth*. These photographs all show built-up area and urban activities in these edge locations.

In order to extract trend expansion rates, we model the (log) area, A_{its} , of urban area i in year t , as measured by satellite s , with a fixed effects regression:

$$\ln A_{its} = \beta_0 + \beta_1 T + \delta_s D_s + \gamma_i D_i + \varepsilon_{its} \quad (1)$$

where T is a time trend, the D_s are fixed effects for each satellite, the D_i are fixed effects for each urban area, and ε_{its} is a random error. The $\hat{\beta}_1$ gives the percentage change in area for a one unit increase in T and estimates the trend annual rate of expansion, after controlling for any time-invariant characteristics of each urban area (such as topography) and of each satellite (such as differences in the sensitivity of sensors). Unlike the approach suggested by earlier studies, of averaging the observations in years with two satellites (Lowe 2014), which implicitly gives equal weight to both satellites, our regression approach uses data-determined weights (the size of the $\hat{\delta}_s$). The measurement errors in the A_{its} should be random, conditional on D_s , so any errors go into the residuals, β_{its} , and so should not bias coefficient estimates (but do create heteroscedasticity, so robust variance estimators are used).

In order to estimate trend expansion rates for each urban area, the model can be extended as follows:

$$\ln A_{its} = \beta_0 + \beta_1 T + \lambda_i (T \times D_i) + \delta_s D_s + \gamma_i D_i + \varepsilon_{its} \quad (2)$$

with the trend expansion rate for the i th urban area obtained from $\hat{\beta}_1 + \hat{\lambda}_i$. Of course, a small urban area may expand at a faster rate than a larger one does, but still contribute much less to the total change in urban area. The regression

in equation (2) can also be used to examine absolute changes in area over time, and in the results below, we do this for two three-year averages; 1992–94 for the start of the two decades of night lights observations, and 2010–12 for the end (the advantage of the three-year averages is that they should smooth out any single-year fluctuations).

A further variant of equation (1) is to consider changes in the trend rate of expansion. This is one advantage of the annual data rather than studying two years, ten years apart, as was done by the World Bank (2015). A key breakpoint for Indonesia is likely to be the economic crisis that began in late 1997. This caused a sharp contraction in economic activity and movement of workers from cities back to the countryside (Smith *et al.* 2002). These events would be expected to lower the rate of urban expansion.

4. Results

The growth in urban areas over the two decades is illustrated in Figure 2, which maps Java in three parts: West; Central; and East. We pay special attention to Java because it has 80 per cent of Indonesia's urban population, and a previous study that defined urban regions by minimums of population size and density and travel time considered nearly the entire island as one large urban area (World Bank, 2012). In contrast to that finding, it is apparent from Figure 2 that large parts of Java remain unlit (according to the 40 per cent threshold) and therefore are not highly urbanised. The radial nature of urban development along infrastructure corridors is apparent, especially for Jakarta and Surabaya, and at a smaller scale for Semarang, Surakarta and Malang (by 2012, there is almost a continuous lit corridor connecting Malang to Surabaya, 90 km to the north).

The results of estimating equation (1) are reported in Panel A of Table 1, with detection thresholds of 30, 40 and 50 per cent used. The results for the middle threshold are emphasised, with the other two sets of results providing a sense of how robust the patterns are. The trend annual rate of expansion in these 41 urban areas is 2.0 per cent over 1992–2012, using our preferred detection threshold of 40 per cent. The trend expansion rate is the same if the 30 per cent threshold is used and is slightly higher (2.8 per cent) if the 50 per cent threshold is used. The results also show the importance of controlling for both sets of fixed effects, with the null hypotheses that the fixed effects for urban areas and for satellites can be excluded from the model being decisively rejected.

If these trend rates of expansion continue, these urban areas would be expected to double in size after 36 years. However, the rate of expansion appears to have slowed down, which is shown in Panel B of Table 1 by the negative coefficient on the deviation term in a piecewise trend. Specifically, if the time trend is allowed to have a different slope after 1997, there is a statistically significant fall in the slope of between nine to eleven percentage points. In other words, the rate of urban area expansion was significantly

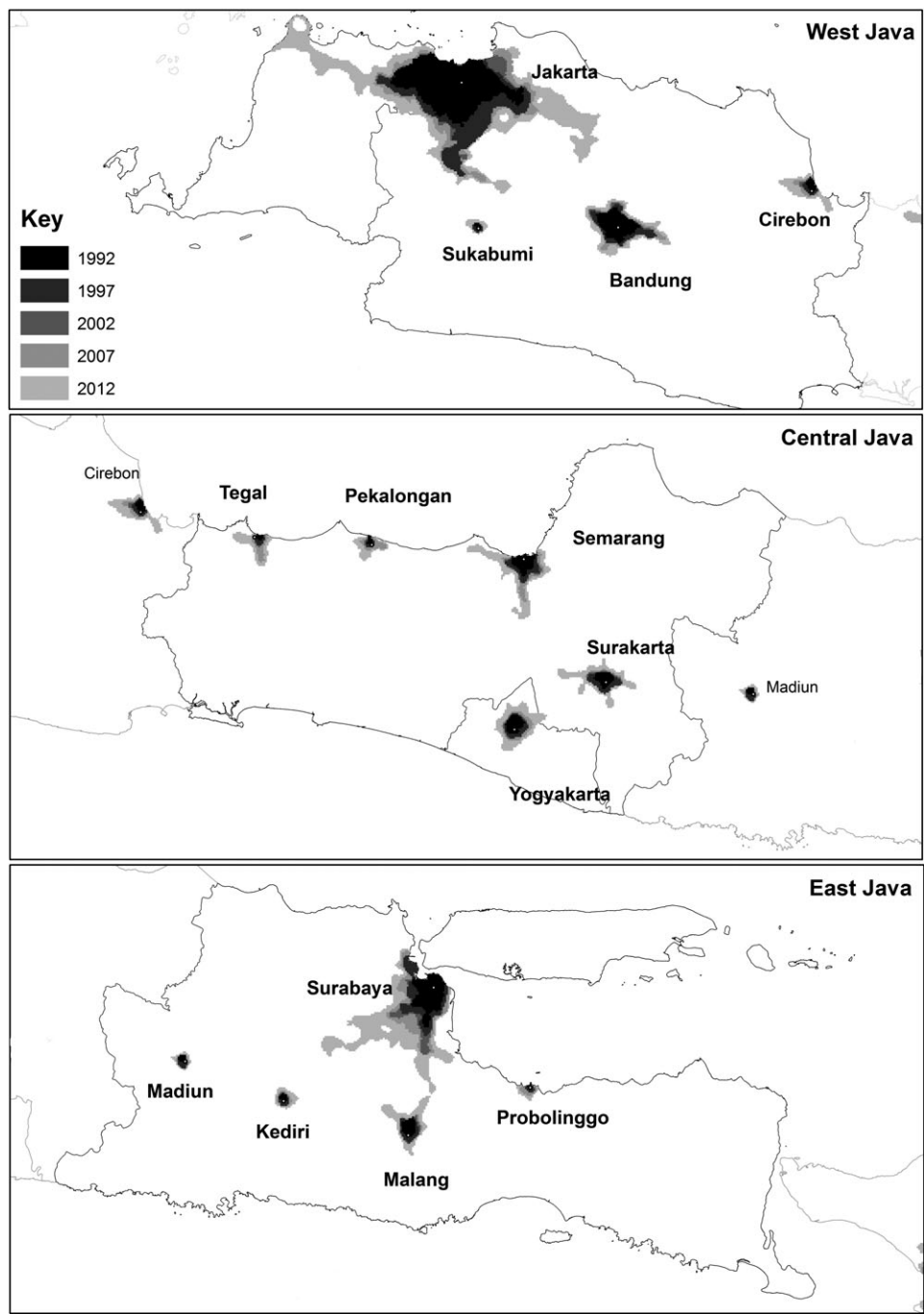


Figure 2 Urban area expansion for major cities in Java: 1992–2012 (at 40 per cent threshold)

faster in the years up to the Asian Financial Crisis in 1997 than in the years since then. In contrast, the more recent Global Financial Crisis from 2008 onwards seems to have had almost no effect on Indonesia’s urban expansion

Table 1 Average trend expansion rates of main Urban Areas in Indonesia, 1992–2012

	Trend at 40% threshold	H_0 :Fixed Effects = 0		R^2	Trends at other thresholds	
		Cities	Satellites		30%	50%
Panel A: Linear trend						
Trend expansion rate (% per annum)	2.0% (2.77)***	842***	120***	0.937	2.0% (4.11)***	2.8% (5.75)***
Panel B: Piecewise trend						
Trend 1992–1997	12.9% (8.10)***	874***	89***	0.939	10.8% (10.51)***	13.6% (8.92)***
Deviation 1998–2012	−10.9% (6.52)***				−9.2% (7.74)***	−10.6% (5.94)***

Notes: *t*-statistics for the trends in () and *F*-statistics for fixed effects = 0 are from robust standard errors, ***, ** and * denote statistically significant at 1, 5 and 10 per cent level. *N* = 1,308 city–satellite–year observations.

rate. If an additional slope shifter is added to the regression reported in panel B, it has a coefficient for the period from 2008 of just 0.01 per cent higher than the trend growth rate after the Asian Financial Crisis.

The results in Table 1 account for fixed effects, like topography, which may affect the expansion rate for each urban area, and the measures of precision and the hypothesis tests are based on robust standard errors that account for various forms of heteroscedasticity. However, one other statistical concern is spatial autocorrelation, where the regression errors are not independent of the errors for nearby observations. For example, nearby cities may share a common regional growth process, and if this is ignored, standard errors and statistical inferences may be misleading. To allay this concern, we estimated several spatial panel models, using routines provided by Belotti *et al.* (2017). One feature of Indonesia, which Figure 1 shows, is the great variation in distance between cities; if the distance from Jayapura to the nearest city is also used to define who are neighbours of, say, Jakarta, then it would seem that almost every city is a neighbour of Jakarta. Therefore, the weights matrices that define which cities may have regression errors potentially correlated with which other cities uses routines provided by Jeanty (2014) that allow both nearest neighbour and distance weights.

It turns out that allowing for spatial autocorrelation in the error terms only slightly reduces the precision of the estimated trend rates of urban area expansion (Table 2). Compared with the OLS results in Table 1, where the *t*-statistic for rejecting the hypothesis of zero trend expansion is 2.77, with the spatial error models, the equivalent *z*-statistic ranges from 2.09 to 2.69. The results are slightly less precise as more cities are added as nearest neighbours in the spatial weights matrix or as inverse distance weights are defined so as to not decline as rapidly (e.g. not squaring distance). The log-likelihoods suggest the nearest neighbour models are a better fit than the inverse distance weights. In these models, the spatial error term has a

Table 2 Selected estimates from spatial error models of Urban Area Expansion Rates, Indonesia 1992–2012

Type of spatial weights matrix	Trend expansion rate at 40% threshold		Spatial error term		Maximized value of log-likelihood function
	Coefficient	z -statistic	Coefficient	z-statistic	
Inverse distance weights	2.0%	2.38	0.214	5.82	−818.62
Inverse distance-squared weights	2.0%	2.69	0.119	3.95	−827.12
Six nearest neighbours	1.9%	2.09	0.046	6.76	−813.74
Five nearest neighbours	1.9%	2.23	0.049	6.44	−815.48
Four nearest neighbours	2.0%	2.40	0.056	6.28	−816.24

Notes: z-statistics for the trend expansion rate and for the spatial error term are statistically significant at $P < 0.04$. The spatial error panel regression models also includes fixed effects for each urban area and for each satellite. Other notes, see Table 1.

coefficient of about 0.05, which is the strength of the relationship between the equation error for a particular urban area and satellite–year and the average of the errors for the k nearest neighbours (where k ranges from 4 to 6 in the table). Given that the results in Table 2 are fairly close to those in Table 1, we infer that the findings are robust to the presence of spatial autocorrelation and so do not further use the spatial error model.

4.1 How does Indonesia’s rate of urban expansion compare with elsewhere?

By comparing the urban expansion rates for Indonesia with other Asian countries undergoing a rural-to-urban structural transformation, we can assess the validity of hypothesis H1 that the rate of urban expansion in Indonesia is somehow excessive. Recall from Section 2 that the share of Indonesia’s population in urban areas rose 18 percentage points between 1992 and 2012, which was a faster increase than for most of the populous Asian countries other than China (where there was a 24 percentage point rise). Conveniently, there are estimates of urban area expansion for two comparison countries – China and India – that also use night lights data and similar methods to what is done in the current study.

Results for the cores of 225 prefectural cities in China are reported by Gibson *et al.* (2014). These urban cores had an average resident population of 1.6 million and so are a little larger than the average population of the urban areas that we study. The trend annual expansion rate in lit area for these urban cores in China was 8.0 per cent, using a 50 per cent threshold to detect the urban boundaries. This compares with the 2.8 per cent trend expansion rate for Indonesia at a 50 per cent luminosity threshold, and so the trend rate of urban expansion in Indonesia appears to be only one-third as high as for China when using the same data and definitions.

Gibson *et al.* (2015) estimate a 1992–2012 trend expansion rate for Indian urban agglomerations of at least one million population of 2.0 per cent per annum. This was measured using a 40 per cent luminosity threshold so the estimates are directly comparable to the ones for Indonesia. Another commonality between the results for India and for Indonesia is the apparent slowing in the expansion rate; in India, the annual expansion rate was around six per cent from 1992 to 2001, and then, it dropped to around two per cent per year. For Indonesia, the break in the trend occurred around 1997/98; before then, the annual expansion rates exceeded even those of China, but after that, they fell back to a two per cent per annum trend.

While urban areas in Indonesia appear to be expanding at the same trend annual rate as in India, there has been a much more rapid rural-to-urban transition in Indonesia. Specifically, the increase in the share of the population in urban areas was three times as large for Indonesia as for India, even though the rate of urban area expansion was the same in both countries. This comparison also corroborates the finding from the World Bank (2015) that Indonesia added the smallest amount of urban land for each new urban resident between 2000 and 2010, for any country in East Asia. Thus, in terms of international comparisons, there is nothing to suggest that the rate of urban area expansion in Indonesia is unjustifiably high, and so hypothesis H1 is not supported by the evidence.

4.2 How does the rate of urban expansion vary between cities?

The results of estimating equation (2) are reported in Table 3, using a detection threshold of 40 per cent. There is considerable variation in trend annual expansion rates across urban areas, ranging from just over ten per cent in Kendari and Pangkal Pinang to around zero in some others. Amongst the most populous cities, Surabaya is expanding at a faster rate than any of the other very big cities (those having more than two million people in 2013). In terms of total area of expansion rather than expansion rates, Surabaya's area increased by three times more than the increase for the city with the third largest expansion (Medan) and was not much less than the area of expansion for Jakarta. In general, the less populous urban areas (which are listed in the bottom rows of Table 3) are expanding at a faster rate than more populous ones. Along these lines, while Jakarta had the largest absolute increase in area, because it was starting from such a large base, the annual trend growth rate was insignificantly different from zero. These spatial patterns are quite stable when the different luminosity thresholds are used, with a correlation of 0.90 between the results for 40 and 50 per cent thresholds, and a correlation of 0.92 for the results at 40 and 30 per cent thresholds.

These differences in expansion rates are likely to affect the future ranking of cities in terms of their area. At the beginning of the period (1992–94), the area of Semarang made it just the seventh largest city, while Batam was just the 21st largest. However, these two cities had moved into fifth and seventh

Table 3 Trend expansion rates and areas for each Urban Area (Based on 40% Luminosity Threshold)

Urban Area	Province	Expansion rate (annual)	t-statistic H_0 : rate = 0	Area (square km)		Change in lit area (sq km)
				1992–94	2010–12	
Jakarta	Jakarta DKI	0.1%	0.14	7,203	10,177	2,974
Surabaya	East Java	2.9%	4.95	1,543	3,863	2,320
Bandung	West Java	0.1%	0.79	1,196	1,621	425
Medan	North Sumatra	0.4%	0.54	1,037	1,833	795
Semarang	Central Java	1.6%	2.55	519	985	466
Palembang	South Sumatra	1.2%	1.17	649	779	131
Makassar	South Sulawesi	1.8%	1.70	249	572	324
Batam	Riau Islands	6.6%	5.68	137	914	777
Pekanbaru	Riau	5.2%	7.12	221	809	587
Bandar Lampung	Lampung	0.5%	0.65	264	437	173
Padang	West Sumatra	2.4%	2.93	174	386	212
Denpasar	Bali	1.8%	2.22	523	920	396
Malang	East Java	1.0%	1.46	319	614	295
Samarinda	East Kalimantan	0.2%	0.24	306	436	130
Banjarmasin	South Kalimantan	0.6%	1.93	309	619	310
Balikpapan	East Kalimantan	0.4%	1.50	263	297	33
Pontianak	West Kalimantan	0.5%	0.57	236	324	88
Jambi	Jambi	0.6%	0.89	246	371	125
Surakarta	Central Java	0.5%	0.50	364	553	189
Mataram	West Nusa Tenggara	3.0%	2.90	75	178	103
Manado	North Sulawesi	1.3%	1.66	77	159	82
Yogyakarta	Yogyakarta DIY	2.1%	3.15	407	807	400
Kupang	East Nusa Tenggara	2.1%	1.70	35	83	48
Palu	Central Sulawesi	1.0%	1.04	33	149	115
Bengkulu	Bengkulu	0.4%	0.18	48	83	35
Kendari	Southeast Sulawesi	10.4%	5.60	3	85	82
Sukabumi	West Java	−0.7%	0.58	61	102	41
Cirebon	West Java	2.4%	3.28	172	344	172
Pekalongan	Central Java	5.6%	6.38	67	251	184
Kediri	East Java	2.2%	2.72	102	193	91
Jayapura	Papua	3.3%	1.52	33	120	86
Tegal	Central Java	4.4%	3.74	93	313	221
Pematangsiantar	North Sumatra	−0.4%	0.20	31	63	32
Banda Aceh	Aceh	2.1%	2.12	87	218	131
Probolinggo	East Java	4.6%	3.83	48	121	73
Tarakan	East Kalimantan	1.9%	0.79	44	80	36
Gorontalo	Gorontalo	5.3%	2.51	7	91	84
Pangkal Pinang	Bangka-Belitung	10.4%	7.87	9	126	117
Madiun	East Java	1.7%	0.31	92	116	25
Tebing Tinggi	North Sumatra	3.4%	2.40	8	68	61
Pare-Pare	South Sulawesi	0.7%	0.46	5	23	18

Notes: Urban areas are ranked by 2013 population. The results are from regressions that include fixed effects for each satellite and each area, estimated on a sample of $n = 1308$ city–satellite–year observations. t -statistics and P -values are from robust standard errors.

position by the end of the period (2010–12). It is also clear that there is variation in average density across these cities, given that Denpasar stayed in sixth position in terms of area but was just the 12th most populous city. Also noteworthy from the last two columns of Table 3 is that the total area covered by these 41 urban areas rose by about 13,000 km² between 1992–94 and 2010–12. The same amount of Indonesia's land is converted, every year, from forest to agricultural use (Warr and Yusuf, 2011). Thus, in terms of food security, conversion of land to urban use is much less important than is forest to agricultural land conversion.

4.3 The elasticity of urban area with respect to local income and population growth

The space needed for urban living is a normal good, so as people get richer, they demand more of it. Consequently, it is expected that one determinant of urban expansion will be the rate of local economic growth. Indonesia reports annual GDP at the second level of the administrative hierarchy (that is, for regencies, *kabupaten* and cities, *kota*), and we match these data to each of our urban areas (for the Jakarta urban area, this involves aggregating, because it covers five *kota* prior to 2001 and five *kota* and one *kabupaten* since then). We also consider the sectoral composition of GDP, in terms of agriculture, manufacturing, services and transport. These data are available since 1993, so we have a 20 year panel, and the estimated relationship between local growth and urban area includes city-level fixed effects. These let us deal with one possible threat to the causal interpretation of the estimated relationship, which is that unobserved characteristics, such as difficult topography, affect both the rate of income growth and the prospects for the city to expand over space.

Over the 1993–2012 period, these urban areas appear to increase in size by 1.1 per cent for every ten per cent rise in local GDP per capita and this effect is precisely measured, with a coefficient that is statistically significant at the one per cent level (Table 4, column 1). While urban expansion is sensitive to per capita income growth, it does not appear sensitive to growth in the local population, with coefficients on the population variable in Table 4 always having confidence intervals that include zero. This lack of independent effect for population growth suggests that these urban areas have become denser, given that the effect of income growth (mediated by its coefficient of just 0.11) in causing area to expand would not outweigh the effect of population growth in increasing density. This result is consistent with the finding of the World Bank (2015) that population density for urban areas in Indonesia increased from 7,400 people per square kilometre in 2000 to 9,400 in 2010, which was the largest increase in urban density of any country in East Asia.

The results are largely unchanged if the industrial structure of each city is considered. Specifically, in column 2 of Table 4, the elasticity of urban area with respect to local GDP falls only slightly, from 0.11 to 0.10, when the industrial structure variables are included in the regression model. These industrial

Table 4 Effects of income and population growth on Urban Expansion in Indonesia, 1993–2012

	1993–2012		1993–1997		1998–2012	
	(1)	(2)	(3)	(4)	(5)	(6)
ln (GDP per capita)	0.114 (3.23)***	0.099 (3.17)***	0.653 (5.56)***	0.675 (5.25)***	0.124 (3.12)***	0.082 (2.58)**
ln (population)	−0.064 (0.30)	−0.084 (0.39)	−0.211 (0.55)	0.248 (0.58)	−0.157 (0.65)	−0.140 (0.57)
Share of GDP from						
Agriculture		−1.185 (1.44)		5.719 (1.59)		−3.334 (2.31)**
Manufacturing		0.544 (1.55)		0.130 (0.14)		0.810 (2.07)**
Services		0.011 (0.02)		−1.237 (1.29)		0.607 (1.46)
Transport		0.303 (0.42)		4.521 (2.19)**		0.462 (0.61)
Constant	2.792 (0.92)	3.167 (1.07)	−3.151 (0.76)	−10.147 (1.90)*	4.274 (1.22)	4.488 (1.36)
Observations	1,224	1,224	247	247	977	977
R-squared	0.53	0.54	0.57	0.60	0.55	0.56

Notes: The dependent variable is the log area of each city in each year, according to each satellite, as detected with a 40 per cent luminosity threshold. Unreported variables from the regressions include fixed effects for each satellite and each city. The values in () are t-statistics from robust standard errors, with ***, ** and * denoting statistical significance at 1, 5 and 10 per cent.

structure variables remain (mostly) statistically insignificant in the subperiod analyses, except that urban area is smaller, all else the same, when agriculture is a larger share of GDP (for 1998–2012) and is larger when more of GDP is from the transport sector (in 1993–97) or from the manufacturing sector (in 1998–2012). At least two of these patterns are consistent with the monocentric model of urban growth, because with a more important agricultural sector, higher rural land prices should limit city growth, while a larger transport sector should enable easier commuting which favours expansion of the urban area.

In keeping with the results in Table 1 that considered differences in trend expansion rates before and after the 1997 Asian Economic Crisis, the relationship between income and urban expansion appears to have changed substantially over time. The results in columns (3) and (4) show that growth in urban area was much more elastic with respect to income in the period before 1998 than after then, with an elasticity of 0.65 (or 0.68 if industrial structure of each city is controlled for). In contrast, for the period from 1998 to 2012 (in columns (5) and (6)), the elasticity of urban area with respect to per capita GDP is just 0.12 (or 0.08 if industrial structure is controlled for). This much diminished elasticity is still precisely estimated (the coefficient is statistically significant at the one per cent level), and so the change in the elasticity suggests a change in the urban growth process in Indonesia following the Asian economic crisis in 1997.

4.4 What type of land was converted to urban area?

A common theme in the literature is that urban expansion takes away valuable cropland (e.g. König *et al.* 2010). This view informs our second hypothesis, H2. However, the remote sensing data do not support this hypothesis because most of the land converted to urban area for the 41 cities that we study over 1992–2012 had previously been grassland or woodland and just seven per cent had been cropland. To establish this fact, we use a data set developed by Hansen *et al.* (2000) that has 14 different land cover classes at one square kilometre resolution. Four of these land cover classes are vacant for the areas we consider, and we aggregate some of the others to give a breakdown into six categories: bare and/or already built-up land; water; woodland; shrub; grassland; and cropland. The land cover data set is cross-sectional and gives a composite from satellite images that were acquired over the period from 1981 to 1994. Thus, it should give a good baseline to establish what type of land in Indonesia was converted to urban area since the early 1990s.

The land expanded on to by each urban area can be thought of as a stylised ‘doughnut’ shape where the hole in the middle is the starting period urban area and the outer perimeter is the edge of the urban area by the end period. We use a 2011 end period to match the estimates of urban area in Table 3, which are a 3-year average centred on 2011. An example of this type of shape is shown in the left panel of Figure 3 for Yogyakarta, which had a somewhat symmetric expansion pattern. The overlay of the baseline land cover map

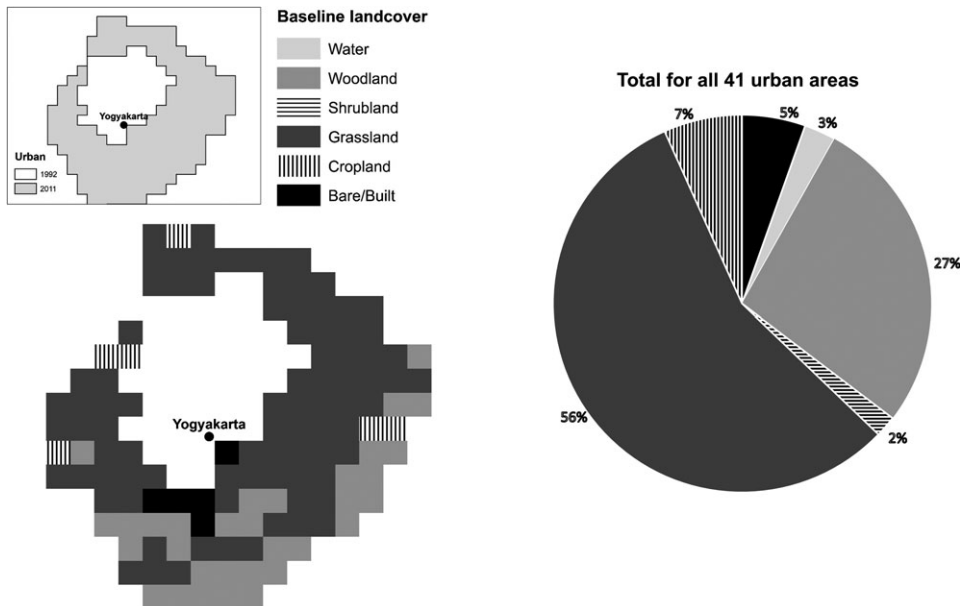


Figure 3 Composition of baseline land cover in areas of urban expansion (example of Yogyakarta, *left* and all urban areas, *right*)

with the ‘doughnut’ of newly urbanised area shows that most of the land that the urban area expanded onto was previously grassland and there were only a few pockets of cropland. In the panel to the right of Figure 3, a pie chart shows the breakdown over all 41 urban areas. The expansion over the two decades was on to land whose predominant former land cover was grassland (56 per cent) and woodland (27 per cent), with just 7 per cent formerly cropland.

It may seem surprising that grassland is the largest component of the land that these cities expanded onto, given that grassland is not the typical land cover one associates with Indonesia. In fact, Indonesia has up to 20 million hectares of *alang-alang* grass (*Imperata cylindrica*) which is often used for thatched roofs. While there is an ecosystem service provided by this land cover, from a food security point of view, the loss of this type of land cover to urban area expansion may be rather less concerning than is suggested by the previous literature that links the growth in settlements to a reduction in rice paddy land.

5. Conclusions

The land area of cities reflects the demand for living space of growing urban populations, along with the needs of commercial and urban industrial development. Indonesia’s ongoing urbanisation, with just over one-half of its population in urban areas, along with the rising affluence of that urban population, can be expected to lead to continued expansion in urban area. It is therefore important that agencies concerned with land use and land conversion are aware of the most recent patterns across a variety of areas, rather than relying on earlier or more limited case study evidence. In this analysis, we have used satellite-detected luminosity to estimate the rate of urban area expansion for 41 cities in Indonesia. We use this new empirical evidence to assess two hypotheses about whether Indonesia’s urban expansion is ‘excessive’ and about whether it mainly results in a loss of cropland.

The results suggest a trend annual rate of spatial expansion for Indonesia’s major urban areas of two per cent, which is consistent with a doubling time of 36 years. This is much slower than it was prior to the 1997 economic crisis, and the sensitivity of urban area expansion to income growth has also fallen sharply. Amongst comparator countries, the trend rate of urban land expansion for major cities in Indonesia is much more like that of India than of China. Notably, Indonesia has moved a far higher share of the population into urban areas than has India, despite the similar rates of urban area increase, and this attests to the comparative land-use efficiency of the urbanisation process in Indonesia. Although a different source of satellite data is used, and the time period differs, the recent findings by the World Bank (2015) that Indonesia’s rate of urban land expansion has been modest, relative to urban population growth, and compared to the patterns elsewhere in East Asia, are consistent with our own findings.

Neither of the two hypotheses that we presented, which were informed by the previous literature, is supported by these new findings. In particular, in terms of the food security implications of this urban area expansion, less than one-tenth of the newly urbanised area had formerly been cropland, while over four-fifths had been woodland, shrub or grassland. Given that food security is less reliant on these types of land cover than it is on land devoted to crops (and especially rice), the assumed threat posed by excessive urban expansion might be less than what the previous literature suggests. However, the experience of China, where urbanisation switched from saving cultivated land to becoming land using (Deng *et al.* 2015), shows that food policy should be informed by ongoing analysis of urban expansion and the driving forces behind competing land uses more generally. Fortunately, the accuracy and availability of satellite remote sensing data are ever improving, and so future analysts and policymakers interested in food security can be informed in a more timely and comprehensive way about changes in land cover.

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Appendix S1. Ground-truthing Map for Surabaya.

Appendix S2. Ground-truthing Map for Medan.

Appendix S3. Ground-truthing Map for Makassar.