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A global assessment of market accessibility and market influence for global environmental change studies

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Abstract
Markets influence the global patterns of urbanization, deforestation, agriculture and other land use systems. Yet market influence is rarely incorporated into spatially explicit global studies of environmental change, largely because consistent global data are lacking below the national level. Here we present the first high spatial resolution gridded data depicting market influence globally. The data jointly represent variations in both market strength and accessibility based on three market influence indices derived from an index of accessibility to market locations and national level gross domestic product (purchasing power parity). These indices show strong correspondence with human population density while also revealing several distinct and useful relationships with other global environmental patterns. As market influence grows, the need for high resolution global data on market influence and its dynamics will become increasingly important to understanding and forecasting global environmental change.

Keywords: accessibility, land use, environmental change, markets, economy, global, GDP, world

1. Introduction

Human interactions with local environments have far reaching consequences for the functioning of the Earth system, including global climate, biodiversity, and biogeochemistry (Rockstrom *et al* 2009). Human–environment interactions vary greatly in type, intensity and duration across Earth's land surface, depending on a wide variety of dynamic influences at global, regional and local scales, including climate, land suitability for use, governance and economic systems and their history of interaction at specific locations (Ellis and Ramankutty 2008, Gallup *et al* 1999, Liverman and Cuesta 2008, Rindfuss *et al* 2008). For this reason, high spatial resolution data on both human and environmental systems are needed to understand and assess the local causes and consequences of global environmental change processes driven by human interactions with land.

High spatial resolution global data for land cover, soils and other biophysical variables are now widely available from remote sensing and the coordinated efforts of global observation networks (Achard *et al* 2007, Batjes 2009, Herold *et al* 2008, Hijmans *et al* 2005, Sanchez *et al* 2009, Schneider *et al* 2009). High spatial resolution data on human systems are much less available (Hibbard *et al* 2010, Verburg *et al* 2011). While global agencies including the FAO and the World Bank produce annual harmonized inventories of many human variables at national level, these data are not generally available at sub-national scales. As a result, global level analysis of environmental change tends to be biased toward biophysical processes or restricted to national levels (Rudel 2009). Exceptions include high resolution gridded data for human population density (Dobson *et al* 2000, ORNL 2008) the use of land for urban settlements, crops, pastures and livestock created by disaggregating national and sub-national datasets using spatial models (Achard *et al* 2007, Herold *et al* 2008, Klein Goldewijk *et al* 2011, Kruska *et al* 2003, Ramankutty and Foley 1998, Schneider *et al* 2009) and even for crop management (Monfreda *et al* 2008, Sacks *et al* 2010).

For socioeconomic variables, globally standardized data have been limited to population density and gross domestic product (GDP) related measures. Most socioeconomic datasets are the result of spatial downscaling of (sub)national statistics with the help of topographic data (Baer 2009). Gallup *et al* (1999) produced the first global gridded map of 'GDP density' by multiplying national level GDP by human population density. Poverty data have been downscaled by nighttime lights observed from remote sensing (Elvidge *et al* 2009). In this study correlations between national level poverty statistics and average national level nighttime light intensity were used to assign poverty values to individual pixels. Doll *et al* (2006) similarly use nighttime light intensity to map regional economic activity. Influential maps of economic activity have been prepared using national and sub-national statistics and global gridded population data (Nordhaus 2006, Nordhaus and Chen 2009). These studies show that variation within nations of such socioeconomic parameters is often larger than variation of average values between nations. If only average values from national level datasets are used there is a large risk for misinterpretations due to the many non-linear relations within human–environment interactions and the notion of ecological fallacy (Easterling 1997).

Markets have become one of the most important factors driving human activities and their interactions with the global environment. Markets link local activities to larger regions and global processes through trade. For farmers, markets are a means to sell their products to consumers while at the same time markets provide access to inputs such as fertilizer and pesticides to increase production (Keys and McConnell 2005). Markets also provide a strong incentive for investments and production choices (Chomitz and Gray 1996, Walker 2004). In one of the early theories on the geography of land use Von Thünen describes land use choices as a result of market prices and transport costs to the market. The location of markets is therefore since long considered an important determinant of land change, especially in a strongly globalizing world. Peet (1969) describes the role of markets within the colonial system indicating that markets influence production decisions over large distances. Since colonial times, global trade has increased many fold and improved accessibility has made global market conditions even more important (Britz and Hertel 2011, Lambin and Meyfroidt 2011, Meijl *et al* 2006). Market access is also listed as one of the main determinants of deforestation in a meta-analysis of case studies around the world (Geist and Lambin 2002, Rudel 2005) and is used in many regional studies of land change as an important determinant (Nelson *et al* 2004, Pfaff 1999, Verburg *et al* 2004).

Transportation infrastructure largely determines the access people have to markets, and this market access tends to drive further infrastructure expansion (Hansen 1959). Infrastructure construction and operation is by itself a primary driver of environmental change (Doyle and Havlick 2009). Infrastructure expansion and associated environmental changes, are driven by economic demand for the services that infrastructure provides, combined with the political will and ability to facilitate the implementation of the infrastructure construction and operational programs. As a result, the processes of increasing market influence and improving market access tend to be interwoven.

For global-scale studies, high spatial resolution data on the influence of markets is lacking. This letter develops and demonstrates the first high spatial resolution global datasets of market influence indices, including their strengths and weaknesses as predictors of the global spatial patterns of land use and land cover, human populations, biomes, anthromes (anthropogenic biomes: globally significant ecological patterns created by sustained interactions between humans and ecosystems), plant species richness, and net primary production.

2. Data and methods

2.1. Development of market influence indices

To derive a globally consistent indicator of market influence, the concept of market influence was matched with available, independent, global datasets. It is assumed that market influence at a specific location is determined as a function of accessibility to markets and the importance of these markets. While the importance of individual markets is difficult to measure and consistent data at the level of individual markets are lacking, national level GDP is a general indicator of market importance across individual nations, as it measures a nation's overall economic output in terms of the market value of all final goods and services made within the borders of a nation in a year.

Accessibility to markets may be measured in many different ways and a wide literature of accessibility measures is available (Geurs and van Wee 2004, Kwan *et al* 2003, Lei and Church 2010). Accessibility is loosely defined by Ingram (1971) as the inherent characteristic (or advantage) of a place with respect to overcoming some form of spatially operating source of friction (for example time or distance). Different authors have discussed various measures of accessibility varying from simple line distance between two locations to measures that account for the infrastructure network and travel costs. Distance measures (also called connectivity measures) are the simplest class of location-based accessibility measures. We have chosen to base the accessibility not solely on distance but also account for the infrastructure and a number of terrain characteristics that impede access to the markets. Therefore, our measure is based on travel time rather than on the absolute distance. Many studies have modified such simple location-based accessibility measures by accounting for some aspects related to behavior and perception. In

Table 1. List of global datasets used for calculating the market influence index.

Variable	Year	Spatial characteristics	Source
Road network, rivers	1979–1999	Vector map, 1:1 M	National Geospatial Intelligence Agency (NGA); VMAP0
Slope	—	Slope derived from resampled altitude data; so the slope only captures the overall topography and is no measure of the real slope	Based on SRTM elevation data (Farr *et al* 2007) resampled to 1 km
Wetlands	Approx. 1990–2000	30 s resolution map containing different wetland types	(Lehner and Döll 2004)
Cities >750 000	2003	Point data	Selected from UNEP major urban agglomeration database (www.geodata.grid.unep.ch)
Cities >50 000	Approx. 2000	Point data	Database compiled by the Joint Research Centre of the European Commission (Nelson 2008) based on the GPW database, CIESIN, Columbia University and the World Bank database of air pollution in World cities
Maritime ports	2005	Point data; harbors with size 'large' are selected[a]	Global Maritime Ports Database produced by General Dynamics Advanced Information Systems
Population density	2000	30 s resolution grid	GPWv3 database; Center for International Earth Science Information Network (CIESIN), Columbia University; and Centro Internacional de Agricultura Tropical (CIAT). 2005. Gridded Population of the World Version 3 (GPWv3). Palisades, NY: Socioeconomic Data and Applications Center (SEDAC), Columbia University. Available at http://sedac.ciesin.columbia.edu/gpw.
Gross domestic product (on a purchasing power parity basis)	2010, in case of missing data earlier years	National level	CIA World factbook (www.cia.gov/library/publications/the-world-factbook)

[a] The size classification in the database is based on a combination of attributes including area, facilities, and wharf space. Ports classified as large must at least be able to accommodate vessels over 500 feet.

so-called potential accessibility measures the influence of a location is diminishing by travel time (Geurs and van Wee 2004, Guy 1983, Ingram 1971). By integrating measures of economic strength and accessibility we have created a simple and straightforward indicator for market influence.

2.2. Data

A variety of publicly available global datasets were used in calculating market influence indices (table 1). For a number of variables, different alternative datasets were available and a selection was made based on global consistency and fit with the specific application. International data on roads are extremely patchy and inconsistent, with frequent gaps and many large changes in time that are often quickly reversed (Canning 1998). Most available datasets are based on sources of individual nations (Nelson *et al* 2006). Different nations define roads differently, and the definition of a road often changes within nations over time. Rural roads above a certain quality threshold are often centrally controlled, while urban roads are controlled by municipal authorities, leading to an underreporting of urban and low-quality rural roads controlled by the central authority. We have used the VMAP0 database of infrastructure given its public availability and global consistency as compared to more recent databases. Though more recent databases contain much more detail in road patterns for a number of nations, differences in detail between countries is also much greater, derailing the construction of globally consistent accessibility indices (Nelson *et al* 2006). Rivers were also taken from VMAP0 which is generally considered to provide the most comprehensive and consistent global river network data currently available. It is based on the US DMA (now NGA) Operational Navigation Charts. Although more detailed, satellite-based river network data are available (Lehner 2005), these include many smaller streams that are not navigable and therefore not adding to accessibility. Gross domestic product (GDP) values on a purchasing power parity (PPP) basis were obtained from the CIA Factbook and a link with a map of national territories was made to allow spatial representation. GDP measured in PPP was chosen over GDP measured at market exchange rates to standardize international comparisons.

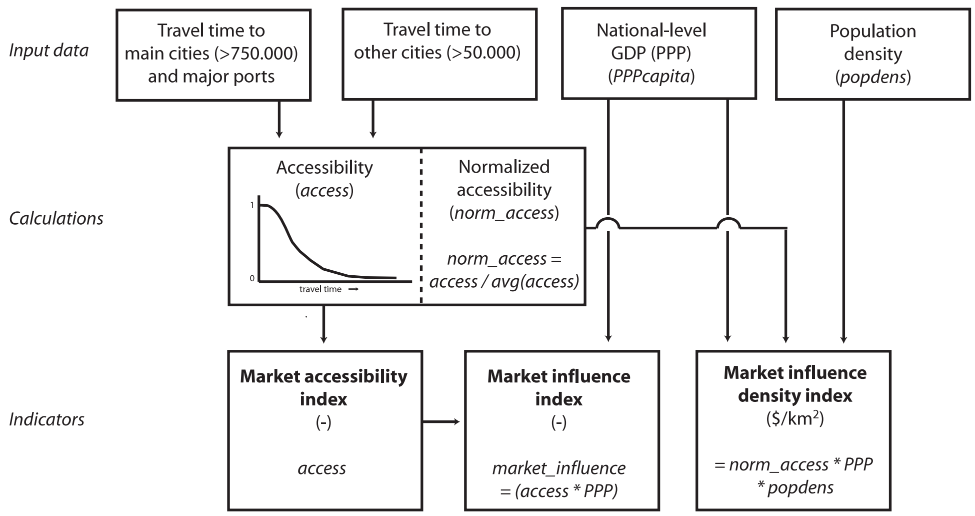

Figure 1. Overview of the different steps involved in calculating the market influence indices.

2.3. Calculation of market access and market influence indices

Calculation of market influence indices consisted of two distinct steps (figure 1): first, an index of access to national and international markets was calculated, and second, two indices of market influence, one by combining national GDP data directly with the access index, and the other by downscaling national GDP using a measure of economic density. All calculations are made at a spatial resolution of 1 km^2 in Eckert IV Equal Area Projection using a geographical information system (GIS).

2.3.1. Market access index The calculation of market access is based on a set of destinations that people travel to and a measure of the costs of traveling, either in distance, time or monetary costs. For this study we have used two groups of locations as destinations. The first group represents large domestic and international markets. Consistent data are not available at global scale representing the locations of markets. Therefore, as a proxy for these locations cities or urban agglomerations with more than 750.000 inhabitants were used. Cities/agglomerations of such a size are in any case locations of important domestic markets while they often have airports important for the import/export of the country. In addition to these, large maritime ports are included as important locations representing the influence of international markets. The second group represents locations that are important destinations as regional and domestic markets. All towns and cities with a population of more than 50.000 inhabitants were selected.

Travel time accounting for infrastructure and some aspects of terrain was used to measure the accessibility to the selected destinations. Although costs of travel, means of transport and the quality of infrastructure have a high variation a globally uniform approach was used to represent differences in travel time to each of the two groups of destinations. Table 2 provides an overview of the assumed velocities to calculate the total travel time. Assumed velocities are within the range of 75–100% of the most common speed limits for the different road types while the speed on large rivers is accounting for waiting times at sluices etc. It is assumed that it is also possible to travel outside the infrastructure network represented in the data as many smaller roads are available. Off-road speed is however assumed to be relatively low to account for deviations from straight-line connections, especially in mountain and wetland landscapes that pose barriers and often have a lower density of smaller roads. Because the calculated travel times are converted to an index it is the relative speed across different types of infrastructure and terrain that is important rather than the absolute values. Air transportation is ignored in the analysis as it mainly links urban areas that are designated as destinations in the analysis and consequently have a high accessibility.

Table 2. Speed assumed for different types of infrastructure and terrain to calculate the travel time to the nearest market.

Infrastructure/terrain type	Speed (km h^{-1})
Highways	100
Primary/secondary roads	65
Tertiary roads	40
Railways	70
Large rivers	10
Canals	5
Seas, lakes and reservoirs	2
Off-road:	
Flat or gentle slopes, small rivers	5
Moderate slopes	3
Steep slopes	1
Marshes, Swamps, Bogs, Peatlands[a]	3
International borders	Speed is divided by 10 over a distance of 1 km

[a] Only wetland classes covering more than 50% of the designated area in the database are considered.

The calculated travel times to the two different types of destination are integrated into one index accounting for travel behavior. As distance or travel time increases people are less likely to travel to certain locations and curvilinear functions of distance are more suitable than linear relationships. Ingram

(1971) and Guy (1983) compare different functional forms and conclude that a Gaussian curve is the most applicable for the quantitative measurement of accessibility. A Gaussian function has a slow rate of decline in the region close to the origin, thus allowing for the zone where the frictional effects of distance on accessibility is low following:

$$a_{ij} = S_j \exp\left(-\frac{d_{ij}^2}{v}\right) \tag{1}$$

where a_{ij} is the relative accessibility of point i to destination j and $d_{i,j}$ is the distance between points i and j. For each location i, a_{ij} is calculated for the closest destination j for respectively the national/international market locations and the regional markets. The importance (size or frequency of visit) of destination j is Sj and v is a constant specific to the study. In our study we have assigned Sj a value of 1 for the national and international market locations (including ports) and a value of 0.5 for the regional market locations. This arbitrary choice of values allows us to distinguish the influence of the different types of market. Within equation (1) v is a constant. According to Ingram (1971) this constant may be set at the average squared distance between all points considered. However, no rational is provided. Guy (1983) indicates that a value for v may be chosen such that the steepest part of the graph (that is, the point of inflexion) is at a predetermined distance from the origin. In this case it can be shown that:

$$v = 2d_*^2 \tag{2}$$

where d_* is the distance from i at which accessibility is deemed to decline at the most rapid rate. Since we assume that the influence of large market locations is stronger than the influence of regional markets we have calculated the constant for the two groups of destinations with values for the inflection point of respectively 2 h for large markets and 45 min for smaller regional markets. In the final accessibility index we have used the maximum value a_{ij} for the national/international markets and the regional markets. Figure 2 provides an illustration of the decline in accessibility index with the travel time from a large market.

2.3.2. Market influence indices Two different indices of market influence were developed (figure 1). The simplest, market influence index, characterizes market influence by simply multiplying the accessibility index by national level per capita GDP values, independent of population density data. This creates an index of market influence expressed in \$ per capita (market access is dimensionless), essentially treating market influence as the multiplicative effect of local market access and national market importance (GDP/capita measured in PPP). A second index, market density, incorporates population density data in an effort to allocate market importance (GDP/capita) across space before combining it with market access, thereby describing market influence as a density expressed in \$ km^{-2}. This is accomplished by dividing the local market accessibility index by the national average of the market access index and then multiplying this by the PPP and population density as illustrated in figure 1. The global data for both indices are available for download at www.ivm.vu.nl/marketinfluence.

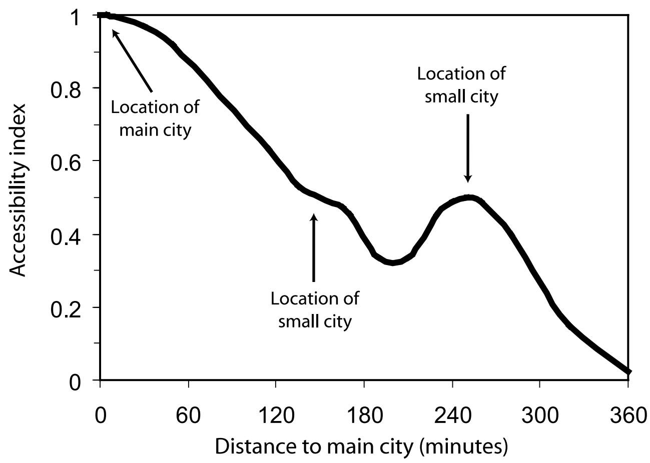

Figure 2. Illustration of the decrease in market access index with travel time from the location of a large city. At 150 and 250 min from the large city two regional markets are located.

2.4. Analysis of market influence in relation to other global patterns

To investigate the utility of our new global market indices, their relationships with existing global data for human and environmental variables were assessed. Global land cover data were obtained from the GlobCover v2.2 dataset (http://ionia1.esrin.esa.int/) and simplified into ten land cover classes by merging forest and scrubland types. Spatial data at 5 arc min resolution were obtained for human population density in year 2000 (Klein Goldewijk *et al* 2010 based on Landscan (Dobson *et al* 2000)), anthromes (Ellis *et al* 2010), potential vegetation biomes (Ramankutty and Foley 1999), potential net primary productivity (NPP; Haberl *et al* 2007), and potential plant species richness in regional landscapes (based on Kreft and Jetz 2007). For analysis, population density, NPP and plant species richness were stratified into 11 classes (including a 'zero class') covering their full range of variation. Global data were processed at 5 arc minute resolution using zonal statistics in a GIS to create a database allowing calculation of land area-weighted statistics for market indices and population density in relation to other global patterns.

3. Results

3.1. Spatial patterns in market influence indices

Figure 3 illustrates global patterns in market influence described by each of our three indices. As expected, market influence is strongest near large cities in all indices, declining to zero in regions without human populations. Also as expected, the market access index is saturated near 1.0 in large cities (figure 3(a)), declining to moderate values in densely populated regions which have an abundance of smaller cities and towns, as intercity distances are so small that the index never declines below 0.2. Examples of such regions are West Africa, Central America and parts of South America, India and China.

The market influence index (figure 3(b)) differs from the market access index most clearly in areas with similar

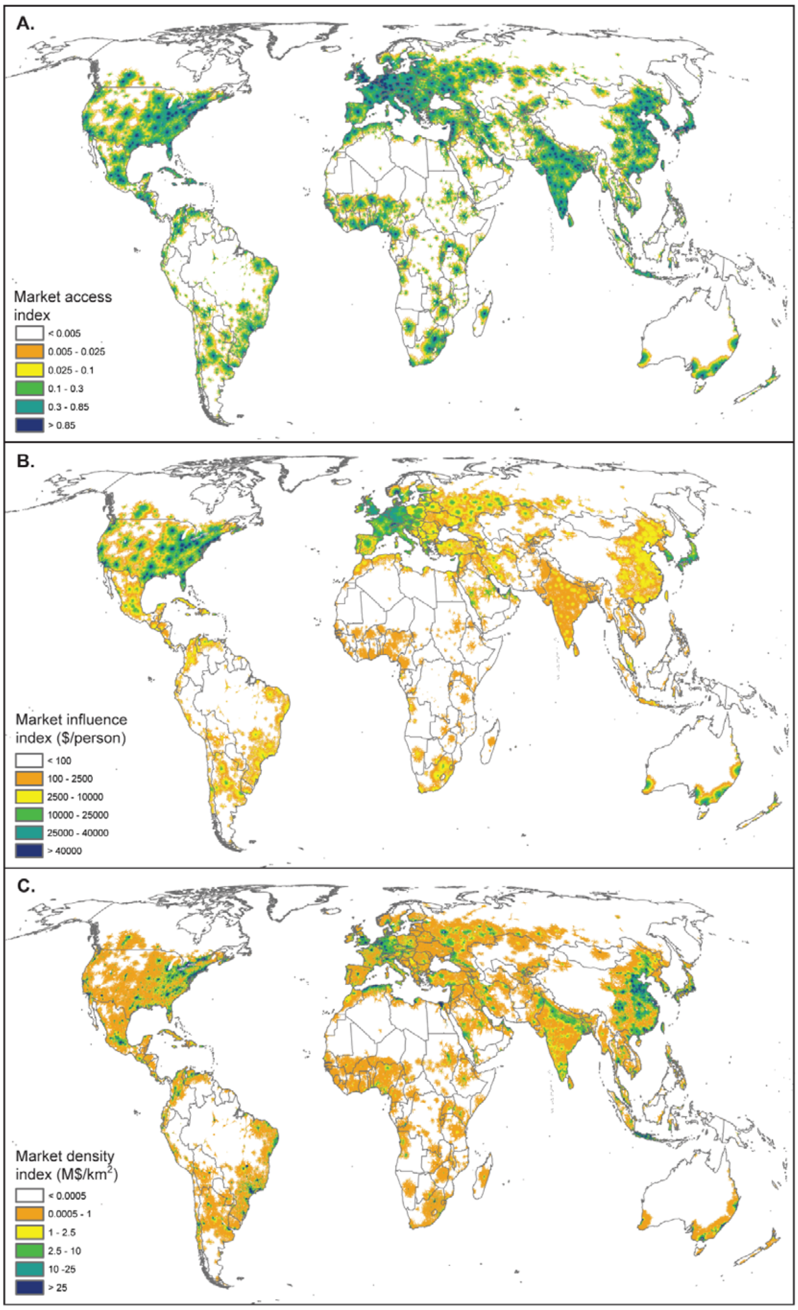

Figure 3. Global overview of the market access index (A), the market influence index (B) and the market influence density index (C).

population densities but different levels of market strength (GDP per capita). These differences originate in the different economic conditions of these regions. For example, India has high scores in the market access index, similar to Europe, yet the market influence index is much lower than Europe as a result of the region's relatively low GDP per capita. The effects of differences in GDP are even clearer if we look at the maps in more detail, as in figure 4 which zooms in to a part of the South-East Asian region. Market access is strong in Peninsular Malaysia around Kuala Lumpur and also around the city of Medan in Indonesia. The major differences between these two regions only become apparent when market influence is expressed in per capita units using the market influence index, with the lower GDP of Indonesia clearly creating different spatial patterns of market influence than in Malaysia, areas that are otherwise similar in terms of population densities and environmental conditions. Only when market influence is adjusted for human population density, as it is in the market density index, do the most densely populated developing regions of the world tend to become more prominent, as in China (figure 3(c)) and the island of Java in Indonesia (figure 4).

3.2. Global relationships between market influence and human and environmental patterns

Figure 5 illustrates global relationships between our three market indices and major global patterns in human population

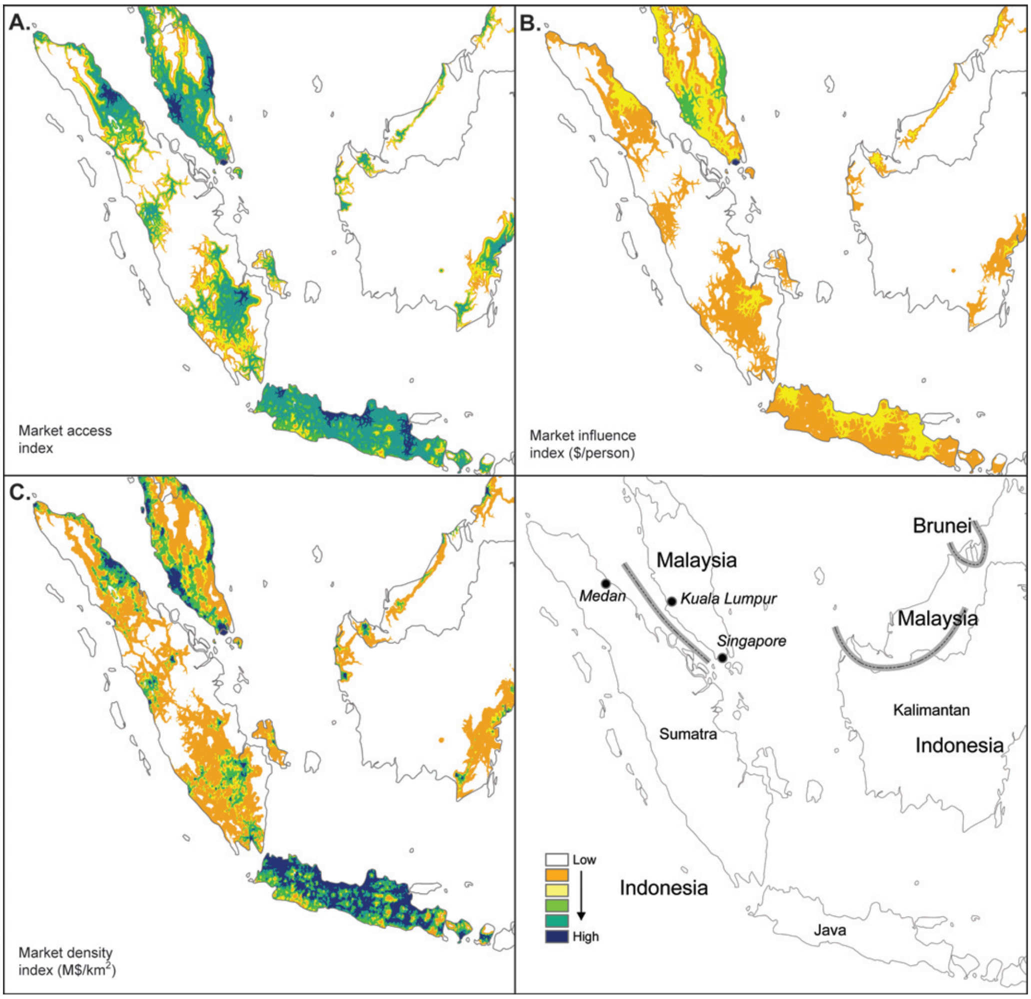

Figure 4. Detailed views of the accessibility and market influence indices for part of the South-East Asian region.

density, land cover, anthromes, biomes, potential NPP and potential plant species richness (an indicator of biodiversity). Global relationships with human population density are also depicted at the top of the figure, illustrating the strength of this most basic measure of human influence and allowing the relative utility and additional strengths of different market indicators to be observed. Moreover, the means, medians and inter-quartile ranges in these charts make clear that the global variables used to assess relationships among variables are highly non-linear, skewed, and full of inherent variation, often because large numbers of low and zero values are combined with small numbers of extremely high values, in some cases even causing mean values to exceed the inter-quartile range.

The strongest relationships evident in the charts of figure 5 depict the strong positive correspondence between market influence and human population density. Urban areas in particular tend to score 'off the charts' on all three indices of market influence; an obvious result given that the location of cities was used to derive these indices. The very strong relationship of all three market influence indices with population density outside urban areas is also unsurprising, given that maps of market access and population density are both derived from similar input maps, including not only settlement maps but also maps of transportation and land use. Therefore, the distributions of other indicators with respect to market influence are more interesting, especially those that deviate from patterns indicated by population density by itself.

The clear global relationships between market influence and agricultural land cover in figure 5 appear to correspond to the classical 'Von Thünen' patterns, in which (intensive) arable agriculture predominates in areas of highest market influence followed by mosaic landscapes (crop/natural being mostly crops, natural/crops, vice versa), grazing land and savannahs, and natural land cover types. All of the market influence indices show these patterns, as does human population density.

Relationships between anthrome classes and market influence indices also resemble those with population density, with notable exceptions. Villages tended toward higher population densities than dense settlements, yet their market access was similar and their market influence tended to be significantly lower in terms of market density. This makes sense, in that villages generally persist only in developing nations with long histories of subsistence economies, while dense settlements, which have low levels of agricultural land use, mostly occur in wealthier nations relying solely on commercial agricultural systems. Comparisons among croplands, rangelands and semi-natural anthromes with similar population densities are also interesting ('Residential'

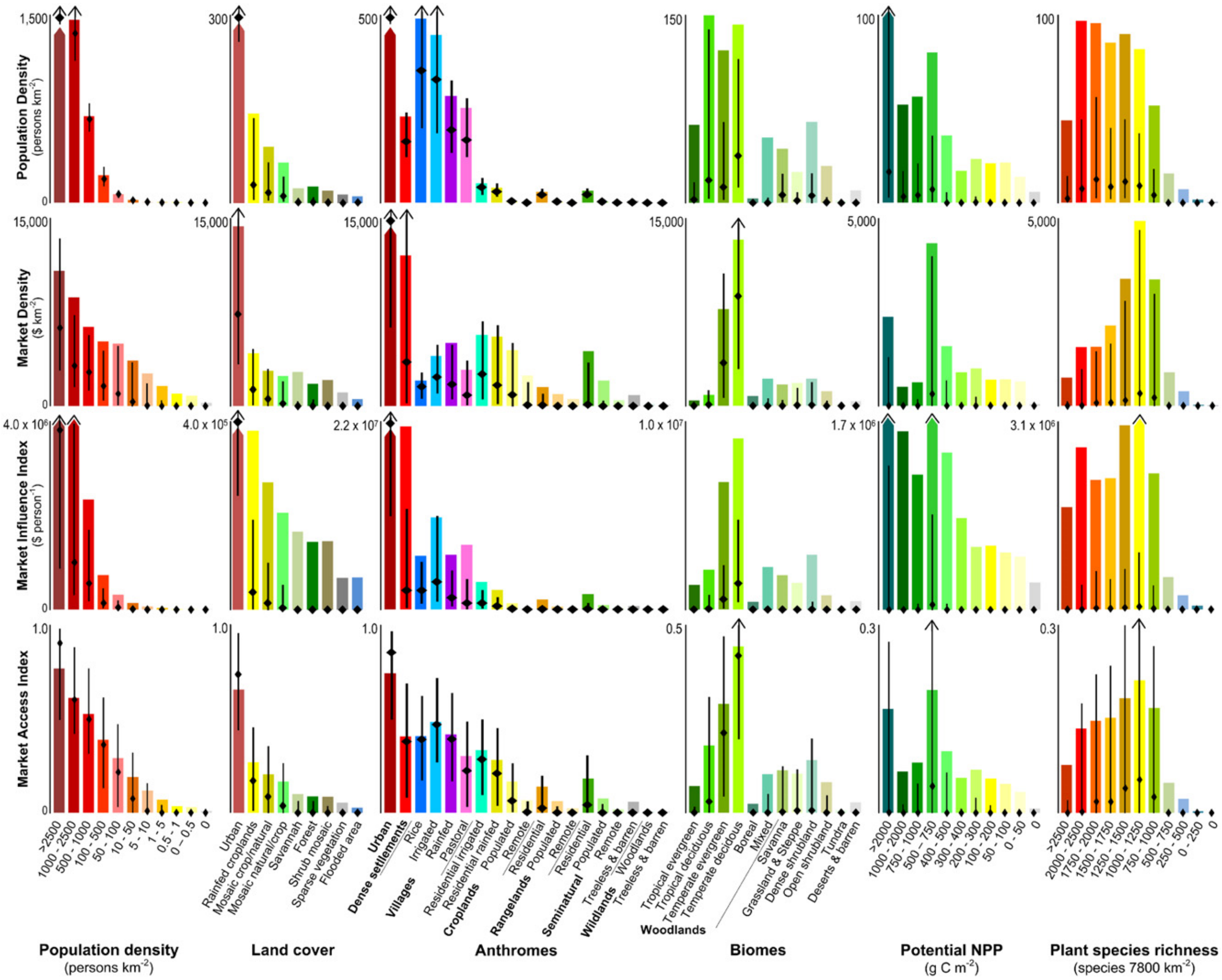

Figure 5. Global patterns in population density, market access and market influence indices in relation to population density, land cover (sorted by access value), anthromes (Ellis *et al* 2010), biomes (Ramankutty and Foley 1999), potential net primary productivity (NPP; Haberl *et al* 2007) and potential plant species richness (Kreft and Jetz 2007). Colored bars are area-weighted means, diamonds are medians; error bars depict inter-quartile range.

anthromes have 10–100, 'Populated' 1–10, and 'Remote' anthromes <1 persons km^{-2}). As predicted by Von Thünen, market access and influence are greater in croplands than in rangelands and semi-natural lands. Further, market influence is on average higher in semi-natural woodlands than in rangelands, indicating perhaps the abandonment of agriculture or conservation of nonagricultural areas in more market influenced areas.

Relationships between markets and biomes, NPP and plant species richness are weaker than those with anthromes and anthropogenic land cover. The strongest relationship observed was between market influence and biomes, with a significantly higher market influence by all indices in the temperate woodlands, confirming the prevalence of dense and wealthy populations across the temperate woodlands. Interestingly, market density and market access appeared to be more strongly associated with temperate woodlands than population density, a fairly exceptional result across all measures in figure 5. Population density appeared to have slightly stronger relationships with NPP and plant species richness than did market influence indices, with very low levels of NPP and plant species richness strongly associated with low populations, market access and influence, and all of these have, on average, higher at intermediate middle levels of NPP and plant species richness, though inherent variation in the values is greater than the apparent trends.

4. Discussion and conclusions

4.1. Evaluation of results

The global market influence indices presented in this letter offer an important addition to the data available for analysis and modeling of global environmental change and land use. Existing global models, such as IMAGE (Eickhout *et al* 2007, van Vuuren *et al* 2010), which is used in a wide range of global environmental assessments, account for accessibility effects using only a simple distance to city measure. The market influence data presented here can be used directly in IMAGE and other such models. Compared to earlier published global accessibility datasets (Nelson 2008) this new dataset distinguishes different types of destinations, including important maritime ports, and accounts for the strength of markets, allowing derivation of multiple distinct and useful indicators of the global patterns of market influence. The inclusion of ports in this study is especially important, as these can drive environmental changes such as deforestation and plantation development wherever these are constructed to support commodity export markets, such as bananas in central America (Kok and Veldkamp 2001).

The market influence indices presented here do have some similarities with earlier efforts to downscale gross domestic product. The simplest method for determining the spatial spread of GDP is to assume that GDP is equally distributed among the inhabitants of a nation or region, so that the spread and influence of GDP is directly related to the distribution of population (Metzger *et al* 2010, Nordhaus 2006). The G-Econ database uses sub-national GDP values as a basis for such downscaling, thereby capturing to some extent the differences in GDP/capita within countries (Nordhaus and Chen 2009). The representation in this database does, however, not explicitly incorporate income differences between urban and rural regions, and it also creates data that are very tightly and artifactually correlated with population density. Grübler *et al* (2007) have downscaled national level GDP values using income distribution statistics by assuming that the richest 20% of a country's population reside in urban areas. The remaining 80% of the population and their income share is assumed to be distributed according to the remaining rural–urban population distribution. A third alternative to account for sub-national differences in per capita GDP is the use of nighttime lights as a measure of economic activity (Doll *et al* 2006, Sutton and Costanza 2002). While the indices presented here, especially market density, in some ways resemble existing GDP downscaling efforts, they differ in one very important way: all three of the new indicators couple market strength (GDP) with variations in market access across Earth's land using detailed infrastructure datasets enabling much higher spatial resolutions than earlier studies.

4.2. Relating markets to land use and anthropogenic global change

Associations between market influence indices and land cover demonstrate that the most intensive modifications of natural land cover, urbanization, land clearing and cultivation, are found in areas with the highest market influence. In that sense, market influence is a proxy for the intensity of human alteration of natural environments and shows similar patterns as the human footprint calculated by Sanderson *et al* (2002). However, such an interpretation should be made with extreme care: large areas in South Asia and Africa are densely populated with intensive agricultural systems focused mainly on subsistence. In spite of the large impact of these systems on the environment, the influence of markets is (still) relatively small—and this can be differentiated by comparing market density with the market influence index, with lower values of the latter highlighting subsistence regions.

Besides altering land cover patterns, market access is also believed to determine the intensity of land management practices including use of irrigation, fertilizers and other agrichemicals (Lambin *et al* 2001). Easy access to markets is likely to raise land prices and favor intensive cultivation practices and access to inputs such as fertilizers and other chemicals (Keys and McConnell 2005, Verburg *et al* 2000, 2004). In a global-scale analysis of the spatial distribution of grain yields Neumann *et al* (2010) used the market influence index presented in this letter as one of the factors explaining the gap between actual yield and the highest attainable yield (as defined by a frontier function). For all three crops analyzed (rice, wheat, maize) the market influence index yielded a significant relation with the efficiency in production; i.e. upon higher values of the market influence index yields tended to be closer to the maximum attainable yield. The authors used both the market influence and a standard accessibility index. Both indicators were significant in the estimated regression models, clearly indicating the additional value of the market influence index to the more traditional accessibility indicators.

There is a close relationship between population density and all market influence indices (figure 5). Is this just an artifact of the similar inputs used to map these variables, or is there a good theoretical reason for this strong relationship? Theory would indicate the latter. Markets emerge in space as a function of population density, with low densities capable of feeding themselves without markets and having less labor and consumptive demand to offer the marketplace, while higher densities would increase the need for, support for, and advantages of the marketplace. However, at the same time the results indicate that not all regions with high population densities evolve into strong markets. Examples of regions with high population densities and low values of the market influence index are Nigeria, Ethiopia and the rural areas of Southern Asia (e.g. large parts of Bangladesh). Many of such landscapes with high population densities rely on subsistence farming and have poorly developed markets. Moreover, integration of the rural hinterland into the market economy strongly depends on infrastructural conditions. It is especially these aspects that are captured in our new indices, together with patterns depending more on market forces than on population patterns, especially for the market access and influence indices, which were derived independent of population data.

Accessibility and economic development are also related to other geographic factors such as terrain and climate. The provision of infrastructure is significantly correlated with geography, particularly for poorer countries, probably because the costs and benefits of infrastructure vary with geography. This implies that the impact of infrastructure on economic growth may depend on geography and that geographical considerations should be taken into account when analyzing these effects (Canning and Pedroni 2008, Krugman 1999). Although such relations have been explored by several authors (Nordhaus 2006) it is obvious that large regional deviations occur. Therefore, the inclusion of data on the spatial distribution of socioeconomic conditions in global environmental change studies will remain essential. The high spatial resolution indicator datasets presented in this letter can potentially make an important contribution to global change assessments and models by addressing one of the most important dimensions of human–environment processes: the marketplace.

4.3. Limitations

As in any global analysis, data available for use in our analysis are subject to the inconsistencies and other limitations of international socioeconomic data collections (Verburg *et al* 2011). Publicly available road data in most regions are outdated and major extensions have been made to the road system in recent years, perhaps most notably in China. Also, the level of detail of road maps is inconsistent between nations, leading to further bias.

Our use of an arbitrary cut-off for city size does not necessarily reflect the relative strength and global importance of their markets. Some cities with less than 750 000 inhabitants are important international markets and are disregarded in this analysis. Also the selection of ports does not fully account for the type of commodities shipped in the port. Finally, the weight given to respectively large and smaller market locations was arbitrarily chosen similar to the distance decay coefficient of the Gaussian function of the accessibility index. Although all choices were discussed at various workshops and accounted for literature and observations, it is clear that for different regions such values might best be chosen differently. In this study it was decided to derive a consistent global measure. A sensitivity analysis on these underlying assumptions reveals that although locally the patterns may change the overall global pattern in the market influence index remains the same. When sub-national data on GDP become more easily available for a larger range of countries (preferably all of them), it will become possible to specify the strength of regional markets in more detail based on sub-national GDP levels (Nordhaus and Chen 2009).

In a world where large amounts of money are spent to monitor global biophysical variables from space, it is remarkable that there is no international effort or institution in place to annually obtain and share globally consistent, high spatial resolution, socioeconomic data such as sub-national GDP, demographics, and road data. Global environmental changes are increasingly driven by the dynamics and spatial patterning of market forces. Given appropriate data, the simple and straightforward indicators presented here would make it possible to assess changes in market influence on local environments as rapidly as infrastructure and GDP data could become available. Under a more advanced regime of global socioeconomic data gathering and distribution, these maps could be used to monitor changes in the global patterns of market influence on global environmental change.

4.4. Applications

The three different market indices developed in this letter represent three different aspects of market influence on land use decisions. Choice of an optimal market index or indices for a specific application will therefore depend on the purpose of the analysis. The market access index is the simplest measure, indicating only the degree to which market access time and the relative scale of markets (large cities versus towns) produces the global patterns of market influence, independent of total population size or wealth. This index is therefore the best measure for applications in which the fixed infrastructure of the marketplace is the main interest (density of market locations and transportation infrastructure). The market influence index expands on this infrastructural effect by also incorporating the effects of regional and national variations in economic power expressed by GDP, making this index the most useful for investigating the more dynamic and development-related effects of the marketplace, but without adjusting for variations in population size. The market density index is the most comprehensive measure, taking into account variations in market infrastructure, national economic power, and population size, potentially offering the most useful indicator of the overall influence of the marketplace on land use decisions. However, in studies that intend to consider variations in population density as an independent variable, the Market density index should be avoided because it already includes population density, making Market influence index the better choice.

Our results also highlight the large differences between urban and rural regions worldwide. Many global databases on social and economic characteristics disregard urban/rural differences by presenting national level GDP as a fixed influence across nations. The new indicators we present offer the first spatially explicit global approximation of the distribution of economic assets and influence within and across nations. The large spatial variations observable in these maps are in themselves drivers of a wide assortment of global change processes (Grau and Aide 2008, Mcdonald *et al* 2009, Thurow and Kilman 2009). As a result, these new datasets and indices are the first step toward providing a high spatial resolution global overview of regional and local disparities in economic development.

Sanderson *et al* (2002) mapped a human impact indicator (human footprint), and Ellis and Ramankutty (2008) mapped the global patterns sustained direct human interaction with terrestrial ecosystems (anthromes) using empirical analyses of existing global data. These global assessments of human influence on local environments are mere descriptions; unable to fully explain or predict the causes of these global patterns in the environmental changes driven by human activity. Human interactions with local environments depend heavily on the state of local economic development and the level of local interaction with domestic and global markets (Meyfroidt and Lambin 2009, Rudel *et al* 2005). It is therefore essential that market influence be incorporated in future efforts to map and classify anthromes and other more dynamic and robust global representations of human interactions with the environment that drive global environmental change.

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