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Scale dependency of biocapacity and the fallacy of unsustainable development

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ABSTRACT

Area-based information obtained from remote sensing and aerial photography is often used in studies on ecological footprint and sustainability, especially in calculating biocapacity. Given the importance of the modifiable areal unit problem (MAUP; i.e. the scale dependency of area-based information), a comprehensive understanding of how the changes of biocapacity across scales (i.e. the resolution of data) is pivotal for regional sustainable development. Here, we present case studies on the effect of spatial scales on the biocapacity estimated for two typical river basin and watershed in Northwest China. The analysis demonstrated that the area sizes of major land covers and subsequently biocapacity showed strong signals of scale dependency, with minor land covers in the region shrinking while major land covers expanding when using large-grain (low resolution) data. The relationship between land cover sizes and their change ratio across scales was shown to follow a logarithm function. The biocapacity estimated at 10 × 10 km resolution is 10% lower than the one estimated at 1 × 1 km resolution, casting doubts on many regional and global studies which often rely on coarse scale datasets. Our results not only suggest that fine-scale biocapacity estimates can be extrapolated from coarse-scale ones according to the specific scale-dependent patterns of land covers, but also serve as a reminder that conclusions of regional and global un-sustainability derived from low-resolution datasets could be a fallacy due to the MAUP.

1. Introduction

Since the concept of sustainable development was put forward (WCED, 1987), it has become an ideal development mode and a common policy goal. To date, many indicators have been developed to assess the status of sustainable development, such as the life cycle assessment (Robèrt et al., 2002), human development index by the UNDP (1990), barometer of sustainability (IUCN/IDRC, 1995), index of sustainable economic welfare (Daly and Cobb, 1989), environmental pressure indicator (EU, 1999), genuine progress indicator (Cobb et al., 1995), sustainable technology development (Weaver et al., 2000), environmental sustainability index (Siche et al., 2008) and ecological footprint (EF; Rees, 1992; Wackernagel and Rees, 1996). Among these large numbers of indicators of sustainable development, the EF methodology has gain popularity due to its compatibility with the data format commonly derived from economic and social surveys.

The EF for a particular population is defined as the total area of productive land and water ecosystems required to produce sufficient resources and assimilate wastes (Rees, 1992). Rees and Wackernagel (1994) further consider EF as the appropriated carrying capacity (i.e. human demand on nature) and biocapacity (BC) as the locally available carrying capacity of the ecosystem for generating resources and absorbing wastes. EF and BC, thus, represent the demand on and the supply from a regional ecosystem, respectively (Galli et al., 2007). As both EF and BC are measured in the same unit (the global hectare: gha), it is straightforward to calculate regional ecological budget as surplus and deficit (Rees, 1992). To this end, an ecological surplus (BC > EF) has been proposed as a minimum criterion for sustainability (Kitzes et al., 2009).

The EF framework, including both the concepts of EF and BC, are highly operable and easy to understand by the public and policy makers, with the data required accessible from government yearbooks. To date, EF has been applied at a variety of spatial scales, from municipality/provincial level (Solís-Guzmán et al., 2013) to national/global extents (Galli et al., 2012), covering all aspects of socioeconomic sectors, such as industry (Herva et al., 2012), education (Gottlieb et al., 2012), agriculture (Kissinger, 2013; Cerutti

Abbreviations: BC, Biocapacity; EF, Ecological Footprint; GIS, Geographic Information System; IDRC, The International Development Research Centre; IUCN, The World Conservation Union; JRW, Jinghe River Watershed; MAUP, Modifiable Areal Unit Problem; SRB, Shiyang River Basin; UNDP, United Nations Development Programme; WCED, World Commission on Environment and Development.

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et al., 2013; Samuel-Fitwi et al., 2012), tourism (Castellani and Sala, 2012) and waste management (Herva and Roca, 2013).

As a continuously developing field the EF methodology has been widely criticized and mended. For instance, it has been considered a static indicator of weak sustainability as no dynamics and bounds are imposed on the level of ecosystem services and their demands. This has been partially solved by time series analysis and extrapolation. To project the future trend of regional sustainability, Haberl et al. (2001) calculated annual Austrian EF from 1926 to 1995. Senbel et al. (2003) examined the effects of consumption, ecological productivity and material efficiency on the ecological budget of North America over this century. Yue et al. (2006) used two quantitative indices (change rate and scissors difference) and depicted the long-term trend of EF and BC from 1991 to 2015 in the Gansu Province of China. Moore et al. (2012) used a Footprint Scenario Calculator to convert projected consumption and emission quantities and forecasted the trend of annual ecological budget up to 2050 (also see other examples from Niccolucci et al., 2012; Kuzyk, 2012; Vačkář, 2012).

The EF methodology has been rapidly developed in the last decade. To list a few, Bicknell et al. (1998) proposed an input–output framework for assessing the footprint of trading. Venetoulis and Talberth (2008) also improved the calculation of equivalence and yield factors – two weights assigned to each type of land cover for calculating the EF – by introducing the concept of net primary productivity into the EF framework. The calculation of EF has been standardized by the Global Footprint Network (2009). Siche et al. (2010) further combined energy analysis with ecological budget analysis and suggested to include low productivity land types in the calculation of biocapacity. Recently, Shao et al. (2012) proposed a modified exergetic indicator as a supplementary to conventional EF methodology.

As conventional EF methodology ignores management actions and policies, it only provides limited support to decision-making. The introduction of spatial features, with the help of the geographic information system (GIS), has largely released the EF methodology from this constraint (Mayer, 2008). For instance, to address the low accuracy and the lack of spatial heterogeneity of the conventional EF method, Yue et al. (2006, 2011) and Moran et al. (2009) introduced the remote sensing and GIS into the EF methodology, promoting the spatial analysis of EF and BC. We here focus on the scale dependency of BC when evaluated using GIS-based information and examine how such scale dependency affects the regional ecological budget and subsequently the fallacy of unsustainable development.

To calculate the biocapacity of a region, one first needs to estimate the available areas of biologically productive land and water. Specifically, this biologically productive area can be divided into six main categories (cropland, grazing land, fishing land, forest, built-up area and barren land; Chang and Xiong, 2005), and the sizes of these six land covers can then be either retracted from government agencies or increasingly calculated using remote sensing images with the aid of GIS (Wackernagel and Yount, 2000). However, in doing so, we often neglect an important issue that is associated with any spatial or area-based information – the scale dependency of spatial features (specifically here, the area sizes of different land covers). Evidently, the shape and size of different land covers are sensitive to the spatial scale (i.e. the resolution) of the maps as most landscape features are scale dependent and have self-similar, fractal structures (Mandelbrot, 1973). This scale dependency has been known in geography as the modifiable areal unit problem (MAUP; Openshaw, 1984) and is well recognized in spatial ecology (e.g. Kunin, 1998; Wu et al., 2000; Hui and McGeoch, 2008; Hui et al., 2006, 2010). Since the area-based information has been widely implemented for estimating the sizes of different land covers and therefore the BC (e.g. Hansson and Wackernagel, 1999; Wackernagel and Yount, 2000; Yue et al., 2006, 2011), it is important to assess how the BC estimated will be affected by the resolution of the available data and whether this scale dependency will change our perception on regional sustainability.

To this end, we chose two typical river basins in Northwest China (Jinghe River Watershed and Shiyang River Basin) and calculated the biocapacity at different spatial scales based on remote sensing data. This allowed us to further examine whether the conclusion of ecological deficit or surplus of the study areas depends on the resolution of the available data. In brief, we aim to capture the general patterns of this scale dependency of different land cover sizes and biocapacity, and further use the patterns captured to remedy the potential flawed conclusion of unsustainable development in many large-scale studies.

2. Materials and methods

2.1. Study areas

The Jinghe River Watershed (JRW; Fig. 1A) is a mountainous watershed located in the Midwest Loess Plateau (between 106°14′–108°42′E and 34°46′–37°19′N), covering an area of 44,983 km^2. The JRW has a typical temperate continental climate, with an annual average temperature of 8 °C and an annual precipitation of 350–600 mm. The main land categories are grassland (48%) and farmland (40%), with more than 80% of the northern watershed degraded severely from soil erosion. The Shiyang River Basin (SRB; Fig. 1B) is located in the transition zone of the Qinghai-Tibet Plateau to the Alashan Plateau (between 101°41′–104°16′E and 36°29′–39°27′N), covering an area of 41,600 km^2. The SRB has a temperate continental arid climate, with an annual average temperature of 7.2 °C and an annual precipitation of 60–610 mm. Most areas are covered by the barren land desert (48%). The nearest part of JRW and SRB are 22 km apart, and both areas have relatively equal size but distinct climates, topographies and vegetations (Liu and Wan, 2010; Zhao et al., 2011), ideal for comparing the scale dependences of BCs.

2.2. Data analysis and calculation

Following Rees (1992) and Rees and Wackernagel (1994), we calculated the biocapacity (BC) according to the available area of biologically productive land and water as follows:

$$BC = \sum_i A_i \times YF_i \times EQF_i \quad (1)$$

where A_i is the biologically productive area of land cover category i; YF_i is the yield factor of land category i and is calculated annually as the ratio of the local yield of a generic product to the global average yield of the same product (Zhang et al., 2001). The yield factor converts local biologically productive land into unites of global average productivity and thus facilitates comparisons across regions (Bastianoni et al., 2012). EQF_i represents the equivalence factor of land cover category i and is a scaling factor needed for converting a specific land use type into a universal unit of biologically productive area (gha) (Bastianoni et al., 2012). Equivalence factor is also calculated each year as the ratio of the global average productivity of a specific land type to the average productivity of all biologically productive land on the earth (Zhang et al., 2001). For JRW and SRB, the yield factors were estimated by comparing the average yield of the two watersheds with the global yield of different land covers. The equivalence factors were estimated using the data of the global yield of different land covers in specific years. The biocapacity of barren land was assigned to be zero in the calculation due to its extremely low productivity (i.e. the yield and equivalence factors of the barren land were zero; Table 1).

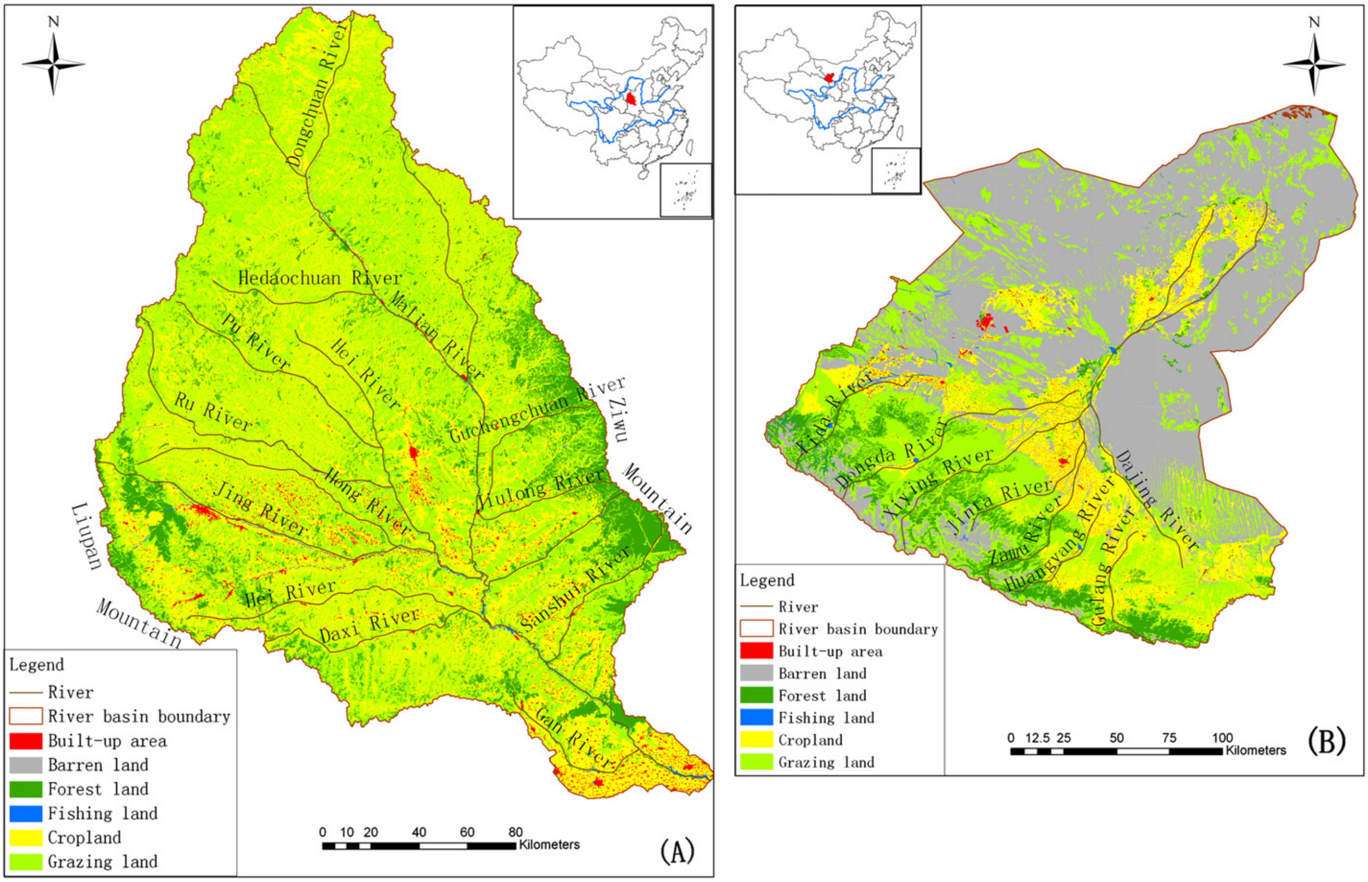

Fig. 1. Land covers of Jinghe River Watershed (A) and Shiyang River Basin (B).

Here, we analysed the 2008 land use/cover map of the JRW and the 1977 land use/cover map of the SRB, with a nominal resolution of 30 m at the scale of 1:100,000. The maps were generated from Landsat-TM images provided by the Environmental and Ecological Science Data Center for Western China. The 30 m-resolution maps were transferred into maps at eight coarser resolutions (specifically, 60, 120, 240, 480, 960, 1920, 3840 and 7680 m in linear dimension). This was done by using *Resample* module in ArcGIS 9.3 (ESRI). Through editing the property sheet of the land cover map, we obtained the area sizes of each land cover type at different resolutions. All social statistics used to estimate the yield and equivalent factors were taken from provincial and regional yearbooks and the Yearbook of the Food and Agriculture Organization of the United Nations in 1977 and 2008.

The biocapacity of the study areas was then calculated using equation (1). Patterns of the scale-dependency of biocapacity for these two regions were then interpolated from the BC calculated at these eight resolutions. To demonstrate the effect of land use changes on the BC, we further conducted a sensitivity analysis, assessing the average effect of 1‰, 5‰ and 1%, land use change on the total BC estimated from 10^6 runs of a Monte Carlo simulation, based on the 30 m resolution maps. The local sensitivity of a particular land cover type on the biocapacity was also estimated by the derivative of the BC with respect to the specific land cover size in equation (1) (Cariboni et al., 2007).

Table 1
Yield factors (YF) and equivalence factors (EQF) in Jinghe River Watershed (JRW) and Shiyang River Basin (SRB).

	YF-JRW	EQF-1977	YF-SRB	EQF-2008
Grazing land	0.39	0.54	0.43	0.49
Cropland	2.02	2.68	2.25	2.41
Forest	0.91	1.14	0.79	1.32
Built-up area	1.75	2.68	1.94	2.41
Fishing land	1.00	0.22	0.62	0.35
Barren land	0	0	0	0

3. Results

The major land covers of these two regions showed a clear scale-dependency (Fig. 2 and Table 2). Specifically, in JRW the size of grassland increased significantly but the sizes of cropland and forestry declined when using low resolution maps; in SRB the sizes of grassland and forestry declined significantly but the size of barren land increased when using low resolution maps (Table 2). Land covers with low proportions in the region showed insignificant changes with the spatial scales (Table 2), while the scale-dependency of the major land covers exhibited a clear two-segment form, with the transition scale around 240 to 480 m in linear dimension (about the resolution of 0.1 km^2; Fig. 2).

The change ratio of land cover sizes, defined as the ratio of the land cover size at the resolution of 7680 $\times$ 7680 m to the size at the resolution of 30 $\times$ 30 m, was clearly correlated with the land cover size (presented at the resolution of 30 $\times$ 30 m) (logarithmic land cover size vs. the changer ratio: $r = 0.849$, $P < 0.001$; Fig. 3). This indicates an overall pattern of 'the rich get richer' that dominant land cover types in a region will increase their sizes at coarser scales (i.e. at lower resolutions; change ratio > 1), while land covers with relatively smaller sizes become even smaller at coarser scales (change ratio < 1).

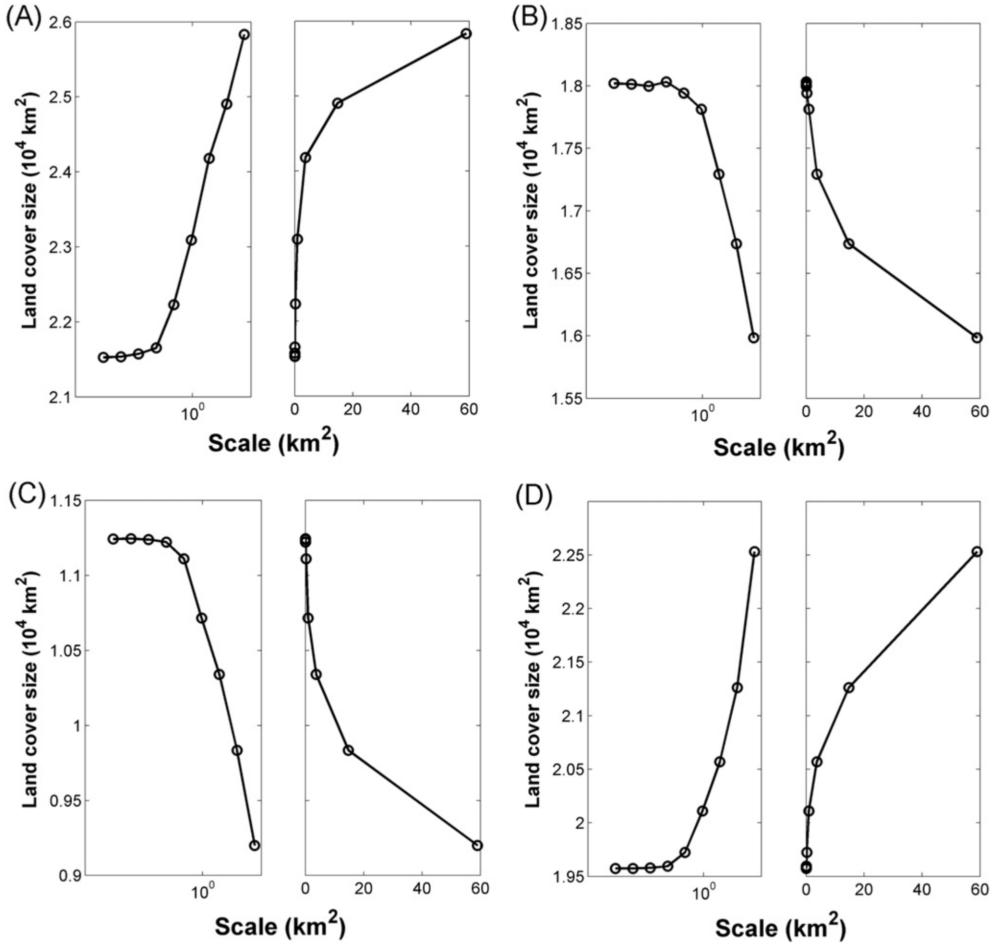

Fig. 2. Scale dependencies of major land covers in Jinghe River Watershed (A: Grazing land [grassland]; B: Cropland) and Shiyang River Basin (C: Grazing land [grassland]; D: Barren land [desert]).

The biocapacity of these two regions showed significant scale-dependency (Fig. 4). In JRW, the BC declined from 9.69×10^6 gha at the 30×30 m resolution to 8.45×10^6 gha at the 7680×7680 m resolution, a 13% drop (Fig. 4A). In SRB, the BC first increased from

Table 2
Scale dependency of land cover sizes and biocapacity in Jinghe River Watershed (JRW) and Shiyang River Basin (SRB), including the percentage (%) of different land covers at 30 m linear resolution, Pearson's *r*, the slope of linear regression (with scales as the independent variable) and *t*-test of the linear trend from 8 different scales of $2^i \times 30$ m ($i = 1$–8).

	%	*r*	Slope	*t*	*P*
JRW:					
Grazing land	47.9	0.793	67.320	3.441	0.011
Cropland	40.1	−0.914	−34.360	−5.977	0.001
Forest	10.1	−0.766	−31.189	−3.152	0.016
Built-up area	1.5	−0.631	−9.637	−2.154	0.068
Fishing land	0.4	−0.572	−2.603	−1.846	0.107
Barren land	<0.1	−0.442	−0.017	−1.303	0.234
Biocapacity		−0.851	−0.020	−4.286	0.004
SRB:					
Grazing land	27.3	−0.874	−33.060	−4.750	0.002
Cropland	16.7	0.409	4.144	1.186	0.274
Forest	7.1	−0.917	−13.413	−6.065	0.001
Built-up area	0.8	−0.469	−3.253	−1.403	0.203
Fishing land	0.4	−0.621	−2.294	−2.095	0.074
Barren land	47.6	0.855	37.210	4.364	0.003
Biocapacity		−0.681	−0.002	−2.462	0.043

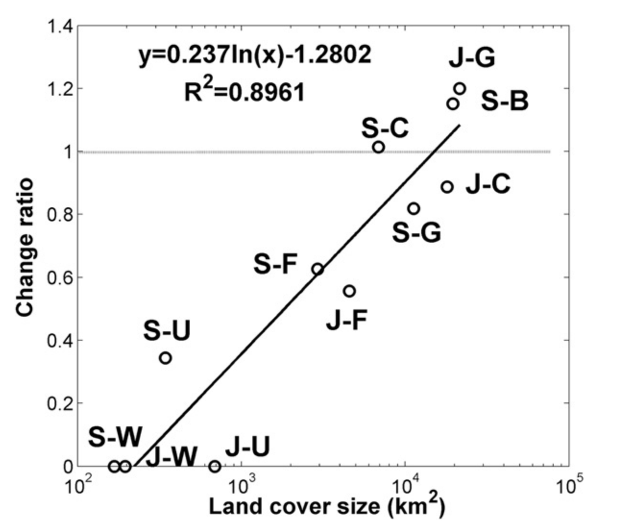

Fig. 3. The relationship between the change ratio and the logarithmic land cover size. Each point indicates one category of the six land cover in the two study areas; the first alphabet (J or S) indicates Jinghe River Watershed or Shiyang River Basin, and the second alphabet (G, C, F, U, W and B) represents the category of land cover (grazing land, cropland, forest, built-up area, waterbody (fishing land) and barren land, respectively).

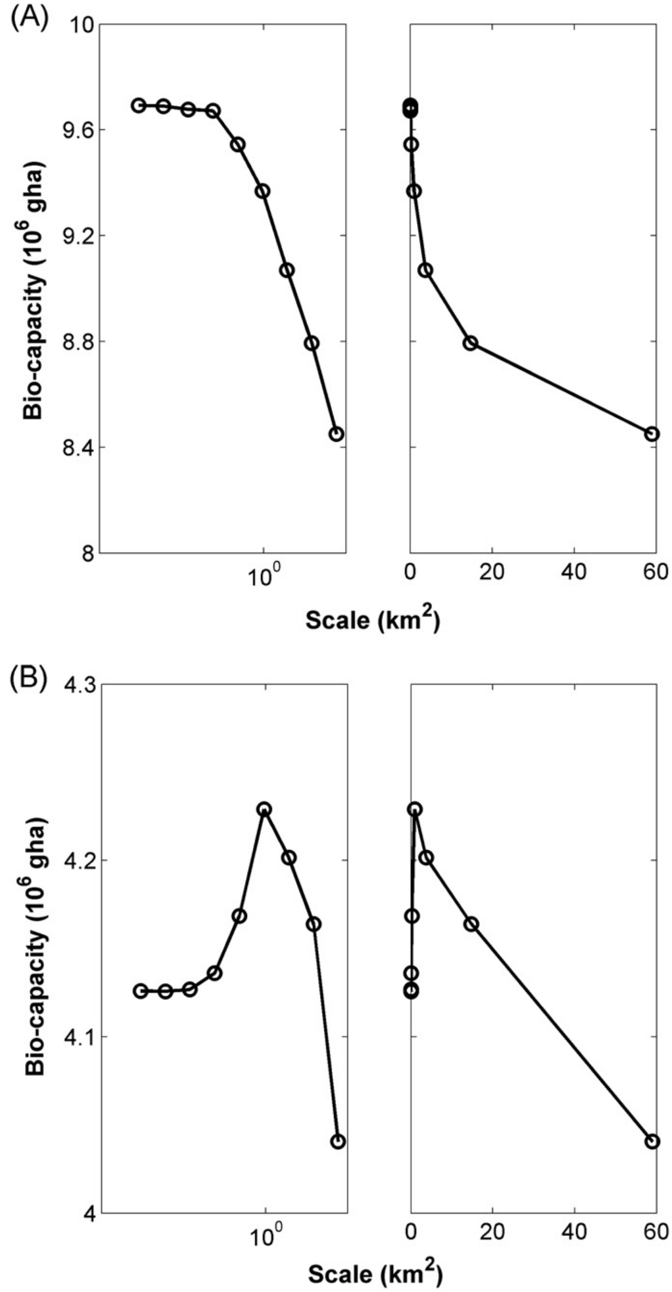

Fig. 4. The scale dependency of the biocapacity in Jinghe River Watershed (JRW; A) and Shiyang River Basin (SRB; B). At 9 different resolutions ($2^i \times 30$ m, where $i = 0$–8), the biocapacities in JRW are 9.69, 9.69, 9.68, 9.67, 9.55, 9.37, 9.07, 8.79 and 8.45×10^6 gha, respectively, and are 4.13, 4.13, 4.13, 4.14, 4.17, 4.23, 4.20, 4.16 and 4.04×10^6 gha in SRB.

4.13×10^6 gha at the 30×30 m resolution to 4.23×10^6 gha at the 960×960 m resolution and then declined to 4.04×10^6 gha at the 7680×7680 m resolution (Fig. 4B). The biocapacities of these two regions can be further extrapolated to even coarser or finer scales. This can be done either by projecting different land cover sizes from adjacent scales and then recalculate the BC according to Equation (1), or directly projecting from the scaling pattern of biocapacity (Fig. 4). Consistent with their scaling patterns (Fig. 4), the biocapacities stabilize at finer scales (higher resolutions, e.g. 15×15 m or 7.5×7.5 m) and the estimates literally do not change. In contrast, biocapacities keep declining at coarser scales (lower resolution, e.g. 8.15×10^6 gha in JRW and 3.87×10^6 gha in SRB at the resolution of 15.36×15.36 km). The rates of decline of BC with the decline of resolution were 13,200 gha/km^2 in JRW and 3100 gha/km^2 in SRB, a rate of 1‰ decline of BC per km^2 increase of the resolution; that is, biocapacity estimated at the 1×1 km resolution can decline by 10% when calculated using a coarser map at 10×10 km resolution.

Evidently, the derivative of the biocapacity for each land cover type is the product of its yield and equivalence factors, and therefore we have the local sensitivities of different land use types from high to low being, respectively, cropland, built-up area, forest, fishing land, grazing land, barren land are following (with the same order for both JRW and SRB). By using the Monte Carlo Simulation, the results showed that the average change of the total BC after 1‰, 5‰, and 1% change of total land cover sizes was $-0.035 \pm 0.11\%$ (the percentage of mean BC change $\pm$ standard deviation), $-0.21 \pm 0.53\%$, $-0.55 \pm 1.05\%$ in JRW and -0.003 ± 2.4‰, $-0.03 \pm 1.23\%$, $-0.12 \pm 2.45\%$ in SRB, respectively, showing negligible effects of minor land cover changes on the regional biocapacity.

4. Discussion

Although the GIS-based method for calculating BC emphasizes the spatial heterogeneity in regional sustainable analysis (Wood, 2003; Yue et al., 2011), it suffers from the scale dependency of its estimates. We here explored the effect of the spatial resolution of land cover maps on the estimated biocapacities for two typical river basins. Results showed that the biocapacity and the major land cover sizes were indeed scale dependent, and the land cover sizes were also in line with the "the rich get richer" pattern. The trends of BC from fine to coarse resolutions are clear and are essential for evaluating, extrapolating and comparing biocapacities across regions. As the biocapacity demand in these two river basins have been previously estimated (1.123×10^7 gha for JRW in 2008 and 1.05×10^6 gha for SRB in 1977) (Yue et al., 2011), the ecological deficit in JRW will be exaggerated from 1.54×10^6 gha at 30 m resolution to 2.78×10^6 gha at 7680 m resolution, and the ecological surplus in SRB will also decline from 3.08×10^6 gha to 2.99×10^6 gha. Therefore, coarse-scale maps will shift the perception of regional sustainability towards unsustainable development. These results are important for the following reasons.

Firstly, while many studies have compared the reliability of biocapacity estimates obtained from different methods, the GIS-based calculation of biocapacity using remote sensing data of land cover has been proved to be time-efficient and often results in high resolution information when compared with methods using only social statistic data (Chang and Xiong, 2005; Yue et al., 2011). However, the number of studies with the biocapacity calculated using GIS and remote sensing data is still low. To this end, studies in landscape ecology have revealed that models and measures are often subject to the spatial scales of the particular study, and conclusions from these studies are not likely to apply to other spatial scales (Jelinski and Wu, 1996; Wu et al., 2000). Therefore, the scale dependency of biocapacity and its specific scaling pattern could help us to better compare biocapacity across regions and extrapolate across scales. Using the typical global land cover map derived from MODIS (moderate-resolution imaging spectroradiometer) data and AVHRR (Advanced Very High Resolution Radiometer) data at the resolutions of from 250 m to 1 km, we could underestimate the global sustainability. Although it is reasonable to stimulate public awareness, we might not need 1.5 earths in 2007 for sustainable development as predicted from the living planet report (WWF, 2010).

Secondly, our results are a reminder that biocapacity is an area-based indicator (Rees, 1992; Rees and Wackernagel, 1994) and thus has its scale-dependent nature. Land cover sizes are important components of the biocapacity estimate (Equation (1)). Our results not only highlighted the scale dependency of the major land cover sizes (Table 2 and Fig. 2) but also the different patterns of scale dependency for different land cover categories (Fig. 4), as summarized by the overall pattern of "the rich get richer" (Fig. 3). Since area-based information is often obtained from remote sensing, aerial photography and field surveys with a specific underlying spatial scale in the data, caution should be applied in interpreting the results and conclusions of these sorts of studies, especially when the scale of the study is not explicitly provided (which is often the case). Following the cross-scale method proposed by Kunin (1998), Wilson et al. (2004) and Hui (2009), biocapacity should be estimated from different spatial scales and then extrapolated to appropriate scales for further use or comparison. Moreover, Hui et al. (2006) has shown that more scattered and fragmented land cover will experience a stronger scale effect and thus a higher change ratio, supported by the sensitivity test. As highly productive lands are rare and also scattered in the region, they are more scale sensitive, and subsequently the biocapacities will be underestimated at coarse scales. For this reason, regional planning should strive to reduce the degree of fragmentation of highly productive lands, coordinate their spatial configuration, and optimize productivity and system resilience.

Finally, social-economic sustainability is not a static issue but a multi-dimensional one. Given the spatial heterogeneity and complexity of biocapacity (Bagliani et al., 2008; Yue et al., 2011), policies for environmental protection and sustainable development that aim to reduce degradation of ecosystems should also be spatially explicit (Yue et al., 2011). However, considering the inadequacy of single-criterion approaches to environmental impact assessment and sustainable development analysis (Ulgiati et al., 2006), the further integration of the EF methodology with other methods could be fruitful. For example, the method for calculating yield and equivalence factors can be potentially improved by incorporating the net primary productivity using the normalized difference vegetation index (Venetoulis and Talberth, 2008). In return, accurate estimation of a spatially and temporally explicit biocapacity can further facilitate the identification of movers and drivers of changes in regional and global eco-social systems. Specifically, the long-term Grain for Green Project has been implemented in both regions to convert farmland to grasslands and forests. This inevitably reduces the cover of highly productive land and thus biocapacity of the region. However, doing so also largely reduces water demand in the region and changes barren land into moderately productive grassland cover, which improves the suitability in long run. Future works need to examine the temporal dynamics of EF, BC and its scale dependency, as well as their relationships with other potential drivers of change (e.g. climate change and long-term land policy).

5. Conclusions

Sustainable development is a desired policy goal at the global scale (WCED, 1987). On the one hand, with BC a preferred indicator of the service level of regional ecosystems (Arrow et al., 1995; Yue et al., 2006), the comparison of EF and BC has been widely accepted for interpreting the sustainability of regional social-economic development (Chang and Xiong, 2005; Wackernagel and Galli, 2007; Bagliani et al., 2008; Siche et al., 2010; Pereira and Ortega, 2012; Yue et al., 2011). On the other hand, the application of GIS and remote sensing data in the EF methodology is to address the requirement for a spatially explicit assessment of regional sustainability (Wood, 2003; Chang and Xiong, 2005). It is therefore important to have a comprehensive understanding of how the area-based land use/cover sizes and BC are affected by the resolution of data. Using coarse-scale data is likely to underestimate the biocapacity of a region and thus reaches a false result of unsustainability. It is only by fully appreciating and utilizing the scale dependencies of land covers and biocapacities that we can have a robust picture of the regional ecological budget and sustainability.

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