Recent Land Degradation and Improvement in China

Land degradation is a global development and environment issue that afflicts China more than most countries in terms of the extent, economic impact, and number of people affected. Up-to-date, quantitative information is needed to support policy and action for food and water security, economic development, and environmental integrity. Data for a defined, recent period enable us to distinguish the legacy of historical land degradation from what is happening now. We define land degradation as long-term decline in ecosystem function and productivity and measure it by remote sensing of the normalized difference vegetation index (NDVI), the greenness index. NDVI may be translated to net primary productivity (NPP). Deviation from the norm serves as a proxy assessment of land degradation and improvement—if other factors that may be responsible are taken into account. These other factors include climate, which may be assessed by rain-use efficiency and energy-use efficiency. Analysis of the 23-year Global Inventory Modeling and Mapping Studies (GIMMS) NDVI data reveals that, in China over the period 1981–2003, NPP increased overall, but areas of declining climate-adjusted NPP comprise 23% of the country, mainly in south China. About 35% of China’s population (457 million out of 1 317 million) depend on the degrading land. Degrading areas suffered a loss of NPP of 12 kgC ha\(^{-1}\) y\(^{-1}\), amounting to almost 60 million tC not fixed from the atmosphere; loss of soil organic carbon from these areas is likely to be orders of magnitude greater. There is no correlation between land degradation and dry lands; it is more of an issue in cropland and forest: 21% of degrading land is cropland and 40% is forest, 24% of the arable and 44% of the forest, respectively. There is no simple statistical relationship between land degradation and rural population density or poverty. Most identified land degradation is in the south and east, driven by unprecedented land-use change.

INTRODUCTION

Economic development, burgeoning cities, and growing rural populations are driving unprecedented land-use change. In turn, unsustainable land use is driving land degradation: soil erosion, nutrient depletion, salinity, water scarcity, pollution, disruption of biological cycles, and loss of biodiversity. This is a global development and environmental issue, recognized by the UN Convention to Combat Desertification and the Conventions on Biodiversity and Climatic Change (1, 2), yet there is no authoritative measure of land degradation. The only harmonized assessment, the Global Assessment of Human-Induced Soil Degradation (3), is a map of perceptions—the kinds and degree of degradation—not a measure of degradation. Its expert judgments have proven inconsistent and hardly reproducible; relationships between land degradation and policy-sensitive criteria were unverified (4); and it is now out of date. To meet the need for quantitative, up-to-date information, the Global Assessment of Land Degradation and Improvement (GLADA) uses remote sensing to assess the state and trends of land degradation, identifying hot spots of land degradation and bright spots where degradation has been arrested or reversed. Within the parent Food and Agriculture Organization program, land degradation assessment in drylands, hot spots, and bright spots will be investigated in the field by national teams to establish the conditions on the ground.

Land degradation is a long-term loss in ecosystem function and productivity from which the land cannot recover unaided, requiring progressively greater inputs to repair the damage. It can be measured by change in net primary productivity (NPP), the rate of removal of carbon dioxide from the atmosphere and its conversion to biomass; deviation from the local norm may be taken as a measure of land degradation or improvement. As a proxy, satellite measurements of the normalized difference vegetation index (NDVI), the difference between reflected near-infrared and visible wavebands divided by the sum of these two wavebands, has been used in studies of land degradation from the field scale to national and global scales (5–10).

China has 22% of the world’s population but only 7.2% of the world’s arable land. Sustainable land management is critical for continued development, but China suffers more than most countries in terms of the extent and economic impact of land degradation, and it tops other countries in terms of the absolute number of people affected (11). It is estimated that, in 1999, land degradation caused a direct loss of USD 7.7 billion (4% of GDP); indirect losses are estimated at USD 31 billion. The cost of remediation is hard to quantify, but current investment appears to be an order of magnitude smaller than the size of the problem (12).

Land degradation has a long history in China. Dry lands, especially in North China, have attracted the most attention (13, 14), but productivity in dry lands declines from a low base; livelihoods in these areas are always precarious. The highly productive areas in south China have been relatively neglected, although, for many purposes, it is more important to address current land degradation in high-potential areas.

Consistent time-series data for a defined, recent period enable us to distinguish the legacy of historical land degradation from what is happening now. This study applies the methods developed in a global study (11) to China, making use of NDVI data for 1981–2003.

METHODS

Data

NDVI. The Global Inventory Modeling and Mapping Studies (GIMMS) dataset comprises radiometer data collected by US National Oceanic and Atmospheric Administration satellites. The fortnightly images at 8-km-spatial resolution are corrected for calibration, view geometry, volcanic aerosols, and other effects not related to actual vegetation change (15). They are compatible with data from MODIS, SPOT Vegetation, and Landsat ETM+ (16). GIMMS data from July 1981 to December 2003 were used for this study.

NPP. GIMMS NDVI data have been translated to NPP using moderate-resolution imaging spectroradiometer (MODIS) data (MOD17A3) for the overlapping period 2000–2003. MOD17A3 is a dataset of terrestrial gross and net primary productivity.
primary productivity at 1-km resolution and an 8-day interval (17). The dataset has been validated in various landscapes (18–22). We have estimated NPP by correlation with MODIS 8-day NPP values. The MODIS four-year mean annual NPP was resampled into 8-km resolution by nearest-neighbor assignment, and the four-year mean annual sum NDVI over the same period (2000–2003) was calculated:

$$\text{NPP}_{\text{MOD17}} [\text{TC ha}^{-1} \cdot \text{y}^{-1}] = 1.135 \times \text{NDVI}_{\text{sum,GIMMS}} - 1.069$$ \hspace{1cm} (Eq. 1)

where NPP$_{\text{MOD17}}$ is four-year mean annual net primary productivity derived from MOD17, and NDVI$_{\text{sum}}$ is a four-year (2000–2003) mean annual sum NDVI derived from GIMMS. Standard error in the regression model (Eq. 1) is slope (1.135) $\pm$ 0.004, and the intercept (-1.069) $\pm$ 0.016.

The high correlation coefficient indicates that MOD17A3 NPP can be used to convert the GIMMS NDVI values to NPP, and the trend in NDVI over the period 1981–2003 can be employed to calculate loss of biomass production over the period. The conversion is approximate.

**Climatic Data.** The VASClimO 1.1 dataset comprises monthly precipitation 1951–2000, compiled on the basis of long, quality-controlled station records, gridded at resolution of 0.5°, interpolated from 9343 stations, 280 in China (23); monthly rainfall data since January 1981 were used for this analysis, supplemented by the GPCC Full Re-analysis Product (24) to produce rainfall values matching the GIMMS NDVI data for calculation of rain-use efficiency (RUE). Mean temperatures from the CRU TS 2.1 dataset (25) of monthly, station-observed data, also at 0.5° resolution, were used to calculate aridity index and energy-use efficiency.

**Land Cover and Land Use.** GLC 2000 land cover data (26) have been generalized for China (Fig. 1); similarly, land use has been abstracted from Land Use Systems of the World (27) for comparison with NPP trends.

**Urban Extent and Population.** The CIESIN Global Rural-Urban Mapping Project provides data for population and urban extent, gridded at 30 arc-second resolution; the Urban/Rural Extents dataset is used to mask the urban area; subnational rates of infant mortality and rates of child underweight status and the gridded population of the world for 2005, at 2.5 arc-minutes resolution, were compared with the index of land degradation (28, 29).

**Aridity.** Aridity index was calculated as $P/PET$, where $P$ is annual precipitation in millimeters and potential evapotranspiration:

$$PET = P/\sqrt{(0.9 + (P/L)^2)}.$$  

where $L = 300 + 25T + 0.05T^3$, where $T$ is mean annual temperature in degrees Celsius (30).

**Analysis**

Degradation areas are identified by a sequence of analyses of the remotely sensed data:

1. Annual sum NDVI, the annual aggregate of greenness, is chosen as the standard proxy for annual biomass productivity. NDVI is translated to NPP by correlation with MODIS NPP data; trends were determined by linear regression. The trend analyses were tested for temporal and spatial independence following Livezy and Chen (31).

   - The $T$-test was used to arrange the slope values in classes showing strong or weak positive or negative trends:

   $$T = \frac{b}{se(b)}$$

   where $b$ is the estimated slope of the regression line between the observation values and time and $se(b)$ represents the standard error of $b$. The class boundaries were defined for 95% confidence level; trends were labeled high if the $T$-values of the slope exceeded the 0.025 p-value of either tail of the distribution; lesser $T$-values were labeled low.

2. To distinguish between declining productivity caused by land degradation and declining productivity caused by other factors, false alarms must be eliminated. Rainfall variability and irrigation have been accounted for by the following:

   - Identifying where there is a positive relationship between NDVI and rainfall, that is, where rainfall determines productivity.
   - Where rainfall determines productivity, RUE has been considered: when NDVI declined but RUE increased,
we may attribute declining productivity to declining rainfall; those areas are masked (urban areas are also masked).

c) For the remaining areas with a positive relationship between NDVI and rainfall but declining RUE, and for all areas where there is a negative relationship between NDVI and rainfall, that is, where rainfall does not determine productivity, NDVI trend has been calculated; this is called RUE-adjusted NDVI.

d) Land degradation is indicated by a negative trend in RUE-adjusted NDVI and may be quantified as RUE-adjusted NPP.

iii) Improving areas were indicated by a positive trend in both RUE-adjusted NDVI and energy-use efficiency, that is, climate-adjusted NDVI.

iv) The indices of land degradation are compared with land cover, land use, aridity, rural population density, and indices of poverty.

RESULTS

Trends in Biomass Productivity

The annual sum NDVI represents annually accumulated greenness or biomass productivity, which fluctuates according to rainfall cycles. Countrywide there has been an increasing trend over the study period (Fig. 2).

Figure 3 maps the mean annual sum NDVI and trends over the period 1981–2003. There was an increasing trend across 49% of the country, a decreasing trend across 31%, mostly in the south and northeast, and 20% remains unchanged.

Spatial Patterns of Biomass and Rainfall

Biomass fluctuates according to rainfall, stage of growth, and changes in land use, as well as land quality. In China biomass productivity (represented by sum NDVI in Fig. 3a) is related to rainfall (Fig. 4a), which has fluctuated significantly, both cyclically (Fig. 2) and spatially (Fig. 4b).

Statistics show a moderate correlation between NDVI and annual rainfall ($r = 0.74$). Over the period 1981–2003, rainfall decreased overall. It increased across about half of the country, at an average of about 3 mm y$^{-1}$, and decreased across the other half of the country at about 4 mm y$^{-1}$. However, biomass increased overall (Fig. 2). In south China there is a surplus of rain, bringing frequent floods, whereas in the north and west, production is constrained by shortage of rain. Also, productivity depends on other factors, such as soil, terrain, and management. Therefore, the correlation of spatially aggregated rainfall and biomass productivity is weak ($r = 0.17$).

Rain-Use Efficiency

Rain-use efficiency (RUE), production per unit of rainfall, takes account of rainfall variability. It may fluctuate wildly in the short term, but, for those areas where rainfall is limiting productivity, we judge that the long-term trend is a good indicator of land degradation (32–35). For this analysis, RUE was calculated as the ratio between annual sum NDVI and annual rainfall on a yearly time step. Figure 5 maps the RUE trends over the period 1981–2003: RUE increased across half of the country, decreased across 30%, and remained substantially unchanged across 20%. Four regions show a significant declining trend: adjacent areas of Hunan, Guangxi, and Guizhou provinces; central Yunnan and south Sichuan; south central Tibet; and most of Hainan (Fig. 5b). Confidence levels are assessed by the $T$-test (Fig. 5c).
Energy-Use Efficiency

Energy-use efficiency (EUE) is calculated as NDVI divided by accumulated monthly temperature on an annual time step. This takes account of increasing temperatures and length of the growing season. Consideration of EUE makes no difference to the interpretation of degrading areas but does significantly affect the interpretation if improving areas.

Net Primary Productivity

As ratios, neither NDVI, RUE, nor EUE is open to economic analysis. To yield a more tangible measure, NDVI may be translated to net primary productivity (NPP). Figure 6a shows four-year (2000–2003) mean annual MODIS NPP at 1-km resolution; the pattern is similar to that represented by GIMMS annual sum NDVI (Fig. 3a) but shows finer detail. Figure 6b depicts changes in NPP derived from the GIMMS data. During the period NPP increased overall.

Land Degradation and Improvement

Land degradation means a loss of NPP, but a decrease in NPP is not necessarily land degradation. To distinguish between declining productivity caused by land degradation and decline due to other factors, it is necessary to eliminate false alarms. To account for variability of rainfall, we first identified areas where there is a positive relationship between productivity and rainfall. For areas where productivity depends on rainfall and where productivity declined but RUE increased, we attribute the decline of productivity to drought. NDVI trends are presented for the remaining parts of the country as RUE-adjusted NDVI (Fig. 7a).

Degrading areas, so defined, comprise 23% of the country, mostly in the higher-rainfall areas in the south. Land degradation is not conspicuous in the dry lands in north and west China. Figure 7b depicts the conspicuously smaller areas with a positive climate-adjusted NDVI, that is, incorporating EUE.
For the degrading areas, the loss of NPP relative to the 1981–2003 mean is estimated using the relationship between GIMMS and MODIS data for the overlapping years 2000–2003 (Table 1). These are large numbers, but the loss of soil organic carbon through land degradation is likely to be orders of magnitude greater.

Analysis of Land Degradation and Improvement

Relationship with Land Cover and Land Use. Comparing the degrading areas with land cover (Fig. 1) shows that 21% of degrading land is arable, 39% is forest, and 31% is scrub and grassland (Table 2). Comparison of degrading areas with land-use systems (Table 3) indicates that, again, 39% of degrading land is under forestry; this amounts to 45% of the forest area; supposedly protected and natural areas fare no better than the average. Twenty-nine percent of the degrading area is rangeland (herbaceous vegetation in the FAO key), 18% of this unit. Twenty-three percent of the degrading land is agricultural land, 25% of this category; 5% is bare. Of the improving land, 43% is rangeland, 28% is agricultural land, and, more surprisingly, 19% of the improving land is classified as bare.

Whether urbanization is degradation or improvement is arguable. It brings a huge increase in the capital value of land, but, if it involves sealing of the land surface, it is degradation by our criterion of partial loss of ecosystem function. Masking the urban areas makes only a small difference to the results: a reduction of 1% in the area of identified degrading land, and a reduction of 0.3% for the improving land.

The Ministry of Land Resources has published data on land use since the 1980s that show that China is experiencing rapid and profound land-use change (36). Based on a sample analysis of Landsat imagery from 1980 to 1999, Liu et. al. (37) report striking contrasts in the degree and rate of land-use change: severe change (greater than 5% annually) in coastal areas of South China; fast change (0.3–1% annually) in the middle and lower Yangtze basin and east China; slow change (0.1–0.3% annually) in north China, the Sichuan basin, and the northeast plains, particularly rural areas; and very slow change in the west and northwest. GLADA measures the most severe and extensive land degradation in south and east of the country; this is unlikely to be a coincidence.

However, land-use change may generate false alarms about land degradation. For instance, conversion of forest or grassland to cropland or pasture will usually result in an immediate reduction in NDVI (and NPP) but may well be profitable and sustainable, depending on management. Likewise, increasing NPP means greater biological production but may reflect encroachment of bush or invasive species—which is not land improvement as it is commonly understood.

Relationship with Population Density. Some 35% of the China’s population (457 million out of 1 317 million) live in the degrading areas. There is no obvious correlation between land degradation and population density ($r = 0.04$).

Association with Aridity. There is no correlation between degrading areas and Turc’s aridity index ($r = 0.06$). Eighty
percent of degrading land is in the humid and cold-climate regions, 10% in the dry subhumid, 5% in the semi-arid, and 5% in the arid and hyper-arid regions.

Relationship with Poverty. Taking infant mortality rate and the percentage of underweight children under five years of age as proxies for poverty, there is no simple correlation between degrading areas and poverty. A more rigorous analysis is needed to tease out the underlying biophysical and social and economic variables; this could be done using more specific data from, for example, household surveys.

CONCLUSIONS

NDVI, the greenness index, has been used as a proxy for land degradation and improvement. Decreasing or increasing trends may be interpreted as land degradation or improvement, but other factors that may be responsible must be accounted for. Rain-use efficiency accounts for rainfall variability, and we assume that, where NPP is limited by rainfall, a declining trend in RUE indicates land degradation. Where rainfall is not limiting, NPP is the best indicator available. Considered together, the two indicators may provide a more robust assessment than either used alone. We have not accounted for land-use change owing to lack of access to consistent time series data, but the correlation is obvious and should be fully investigated.

As a quantitative measure of land degradation, loss of NPP has been calculated.

- Degradation areas occupy 23% of the country, most conspicuously in southern China. Twenty-one percent of degrading land is arable (24% of the cultivated area), 39% is forest, and 31% is grassland and scrub.
- There is no correlation between land degradation and aridity: 80% of degrading areas is in the humid and cold-climate zones, 10% in the dry subhumid, 5% in the semi-arid, and 5% in the arid and hyper-arid zones.
- About 35% of the China’s population (457 million out of 1.317 million) live in the degrading areas.
- Land improvement is identified across only 8% of the country, mostly in the north and far west; 47% of the improving land is rangeland (about 10% of the total rangeland), and 25% is arable.
- This assessment presents a different picture from previous studies that compounded historical land degradation with what is happening now. Improvement has not previously been assessed in a globally consistent way. The data from 1981–2003 indicate recent trends but tell us nothing about the historical legacy.
- There is no doubt that large areas of dry land in the north of the country have suffered severe degradation in the past. According to our analysis, many of these areas are now stable or even improving. The focal areas of some of the major land reclamation initiatives in the northern dry lands appear as improving areas. But they are still suffering substantial soil loss, as may be seen from the decreasing but still very high sediment loads of the rivers.
- We draw attention to the current and severe land degradation across much of the red soil area in the rapidly developing south and east of the country.

### Table 2. Degrading areas by land cover types.

<table>
<thead>
<tr>
<th>Code</th>
<th>Land cover</th>
<th>Total pixels (TP)</th>
<th>Degrading pixels (DP)</th>
<th>DP/TP (%)</th>
<th>DP/TDP (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Tree cover, broadleaved evergreen</td>
<td>443 913</td>
<td>237 441</td>
<td>53.5</td>
<td>8.6</td>
</tr>
<tr>
<td>2</td>
<td>Tree cover, broadleaved deciduous, closed</td>
<td>681 660</td>
<td>229 849</td>
<td>33.7</td>
<td>8.4</td>
</tr>
<tr>
<td>3</td>
<td>Tree cover, broadleaved deciduous, open</td>
<td>363</td>
<td>4</td>
<td>1.1</td>
<td>0.0</td>
</tr>
<tr>
<td>4</td>
<td>Tree cover, needle-leaved evergreen</td>
<td>1 035 212</td>
<td>499 406</td>
<td>48.2</td>
<td>18.2</td>
</tr>
<tr>
<td>5</td>
<td>Tree cover, needle-leaved deciduous</td>
<td>244 575</td>
<td>103 575</td>
<td>42.3</td>
<td>3.8</td>
</tr>
<tr>
<td>6</td>
<td>Tree cover, mixed</td>
<td>15 713</td>
<td>6274</td>
<td>39.9</td>
<td>0.2</td>
</tr>
<tr>
<td>9</td>
<td>Mosaic: tree cover/other natural vegetation</td>
<td>106 764</td>
<td>51 172</td>
<td>47.9</td>
<td>1.9</td>
</tr>
<tr>
<td>10</td>
<td>Tree cover, burnt</td>
<td>944</td>
<td>397</td>
<td>42.1</td>
<td>0.0</td>
</tr>
<tr>
<td>11</td>
<td>Shrub cover, evergreen</td>
<td>551 446</td>
<td>269 945</td>
<td>49.0</td>
<td>9.8</td>
</tr>
<tr>
<td>12</td>
<td>Shrub cover, deciduous</td>
<td>15 702</td>
<td>5161</td>
<td>32.9</td>
<td>0.2</td>
</tr>
<tr>
<td>13</td>
<td>Herbaceous cover</td>
<td>3 173 203</td>
<td>508 795</td>
<td>16.0</td>
<td>18.5</td>
</tr>
<tr>
<td>14</td>
<td>Sparse herbaceous or sparse shrub cover</td>
<td>760 114</td>
<td>47 057</td>
<td>6.2</td>
<td>1.7</td>
</tr>
<tr>
<td>15</td>
<td>Regularly flooded shrub and/or herbaceous cover</td>
<td>59 354</td>
<td>19 344</td>
<td>32.6</td>
<td>0.7</td>
</tr>
<tr>
<td>16</td>
<td>Cultivated and managed areas</td>
<td>2 242 026</td>
<td>533 285</td>
<td>23.8</td>
<td>19.4</td>
</tr>
<tr>
<td>17</td>
<td>Mosaic: cropland/tree cover/other natural vegetation</td>
<td>27 474</td>
<td>12 945</td>
<td>47.1</td>
<td>0.5</td>
</tr>
<tr>
<td>18</td>
<td>Mosaic: cropland/shrub and/or grass cover</td>
<td>103 572</td>
<td>36 629</td>
<td>35.4</td>
<td>1.3</td>
</tr>
<tr>
<td>19</td>
<td>Bare</td>
<td>2 262 000</td>
<td>118 541</td>
<td>5.2</td>
<td>4.3</td>
</tr>
<tr>
<td>20</td>
<td>Water bodies</td>
<td>172 920</td>
<td>48 551</td>
<td>28.1</td>
<td>1.8</td>
</tr>
<tr>
<td>21</td>
<td>Snow and ice</td>
<td>155 485</td>
<td>14 925</td>
<td>9.6</td>
<td>0.5</td>
</tr>
<tr>
<td>22</td>
<td>Artificial surfaces</td>
<td>6036</td>
<td>1731</td>
<td>25.0</td>
<td>0.1</td>
</tr>
<tr>
<td>23</td>
<td>No data</td>
<td>900</td>
<td>0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>12 060 276</td>
<td>2 745 027</td>
<td>100.0</td>
<td></td>
</tr>
</tbody>
</table>

1 Pixel size: 1 × 1 km, 2 Urban extents are excluded. 3 TDP = total degrading pixels.

### Table 3. Degrading lands in the aggregated land-use systems.

<table>
<thead>
<tr>
<th>Land-use system</th>
<th>Total pixels (TP) (5 × 5)</th>
<th>Degrading pixels (DP) (5 × 5)</th>
<th>DP/TP (%)</th>
<th>DP/TDP (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forestry</td>
<td>27 235</td>
<td>12 162</td>
<td>44.7</td>
<td>38.6</td>
</tr>
<tr>
<td>Rangeland</td>
<td>49 567</td>
<td>9063</td>
<td>18.3</td>
<td>28.7</td>
</tr>
<tr>
<td>Agricultural land</td>
<td>28 135</td>
<td>7120</td>
<td>25.3</td>
<td>22.6</td>
</tr>
<tr>
<td>Urban</td>
<td>3811</td>
<td>1138</td>
<td>29.9</td>
<td>3.6</td>
</tr>
<tr>
<td>Wetlands</td>
<td>457</td>
<td>126</td>
<td>27.6</td>
<td>0.4</td>
</tr>
<tr>
<td>Bare ground</td>
<td>27 815</td>
<td>1571</td>
<td>5.6</td>
<td>5.0</td>
</tr>
<tr>
<td>Water</td>
<td>1308</td>
<td>350</td>
<td>26.8</td>
<td>1.1</td>
</tr>
<tr>
<td>Undefined</td>
<td>2</td>
<td>0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Total</td>
<td>138 330</td>
<td>31 530</td>
<td>100.0</td>
<td></td>
</tr>
</tbody>
</table>

1 TDP = total degrading pixels.
Remote sensing can only provide indicators of degradation and improvement. The various kinds of land degradation and improvement are not distinguished; the patterns derived from remote sensing should be followed up by fieldwork to establish the actual conditions on the ground.

References and Notes


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