GLADA Report 1d
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Land Degradation and Improvement in China

1. Identification by remote sensing

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LADA
Land Degradation Assessment in Drylands

ISRIC World Soil Information

FOOD AND AGRICULTURE ORGANIZATION OF THE UNITED NATIONS

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MAIN POINTS

1. **Land degradation is a global environment and development issue.** Up-to-date, quantitative information is needed to support policy and action for food and water security, economic development, environmental integrity and resource conservation. To meet this need, the Global Assessment of Land Degradation and Improvement uses remote sensing to identify degraded areas and areas where degradation has been arrested or reversed. In the LADA program, this screening will be followed up by field investigations to establish the situation on the ground.
2. **Land degradation and improvement is inferred from long-term trends of productivity when other factors that may be responsible (climate, soil, terrain and land use) are accounted for.** The normalized difference vegetation index (NDVI) or greenness index is used as a proxy. Its spatial patterns and temporal trends are analysed for the period 1981-2003 at 8km resolution; land degradation is indicated by a declining trend of climate-adjusted NDVI and land improvement by an increasing trend. NDVI may be translated to net primary productivity
3. **In China, over the period of 1981-2003, net primary productivity increased overall.** However, areas of declining climate-adjusted net primary productivity occupy 23 per cent of the country, mainly in southern China and including highly productive areas. These degrading areas suffered an average loss of NPP of 12 kgC/ha/year.
4. **Twenty one per cent of degrading area is cropland - about 24 per cent of the arable; 40 per cent is forest and 31 per cent is grassland and scrub.** There is no particular correlation between land degradation and drylands: 80 per cent of degrading land is in humid and cold-climate regions, 10 per cent in the dry sub-humid, 5 per cent in the semi-arid, and 5 per cent in arid and hyper-arid regions.
5. **About 35 per cent of the China's population (457 million out of 1317 million) depends on the degrading land.** There is no simple statistical relationship between land degradation and rural population density or poverty.
6. **Eight per cent of the country shows an increase in climate-adjusted net primary productivity over the period 1981-2003, mostly in the north of the country**. 47 per cent of the improving areas is grassland – 10 per cent of the grassland; 25 per cent is arable – 11 per cent of the arable.
7. **Dryland in north China has experienced a thousand years of land degradation.** Many landscapes have now stabilised, but at stubbornly low levels of productivity. **The identified areas of present-day land degradation are in the south and east, driven by unprecedented land use change.**

Key words: land degradation/improvement, remote sensing, NDVI, rain-use efficiency, net primary productivity, land use/cover, China

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Abbreviations

ADB	Asian Development Bank
CIESIN	Center for International Earth Science Information Network, Colombia University, Palisades NY
CoV	Coefficient of Variation
CRU TS	Climate Research Unit, University of East Anglia, Time Series
ENSO	El Niño/Southern Oscillation phenomenon
FAO	Food and Agriculture Organization of the United Nations, Rome
GDP	Gross Domestic Product
GEF	The Global Environment Facility, Washington DC
GIMMS	The Global Inventory Modelling and Mapping Studies, University of Maryland
GLADA	Global Assessment of Land Degradation and Improvement
JRC	European Commission Joint Research Centre, Ispra, Italy
LADA	Land Degradation Assessment in Drylands
Landsat ETM+	Land Resources Satellite, Enhanced Thematic Mapper
LUS	Land Use Systems, FAO
MOD17A3	MODIS 8-Day Net Primary Productivity dataset
MODIS	Moderate Resolution Imaging Spectroradiometer
NDVI	Normalized Difference Vegetation Index
NPP	Net Primary Productivity
PRC	The People's Republic of China
EUE	Energy-Use Efficiency
RESTREND	Residual Trend of sum NDVI
RUE	Rain-Use Efficiency
SFA-PRC	State Forest Administration, PR of China
SOTER	Soil and Terrain database
SPOT	Système Pour l'Observation de la Terre
SRTM	Shuttle Radar Topography Mission
UNCED	United Nations Conference on Environment and Development
UNEP	United Nations Environment Programme, Nairobi, Kenya
VASClimO	Variability Analyses of Surface Climate Observations

1 Introduction

Economic development, burgeoning cities and a growing rural population are driving unprecedented land-use change. In turn, unsustainable land use is driving land degradation: a long-term loss in ecosystem function and productivity that requires progressively greater inputs to repair the situation. Its symptoms include soil erosion, nutrient depletion, salinity, water scarcity, pollution, disruption of biological cycles, and loss of biodiversity. This is a global development and environment issue recognised by the UN Convention to Combat Desertification, the Conventions on Biodiversity and Climatic Change, and the Millennium Goals (UNCED 1992, UNEP 2007).

Quantitative, up-to-date information is needed to support policies for food and water security, environmental integrity, and economic development. The only previous harmonised assessment, the *Global assessment of human-induced soil degradation* (Oldeman and others 1991), is a map of perceptions - the kinds and degree of degradation - not a measure of degradation, and is now out of date. The new *Global Assessment of Land Degradation and Improvement* maps land degradation and improvement according to change in net primary productivity (NPP, the rate of removal of carbon dioxide from the atmosphere and its conversion to biomass).

Satellite measurements of the normalised difference vegetation index (NDVI or greenness index) for the period 1981-2003 are used as a proxy for NPP. NDVI data have been widely used to assess land degradation from the field scale to the global scale (e.g. Tucker and others 1991, Bastin and others 1995, Stoms and Hargrove 2000, Wessels and others 2004, 2007, Singh and others 2006) but remote sensing can only provide indicators of process: loss of greenness does not necessarily mean land degradation, nor does increase necessarily mean land improvement. Greenness depends on several factors including climate, land use and management; its trends may be interpreted as land degradation or improvement only when these other factors are accounted for.

Where productivity is limited by rainfall, rain-use efficiency (RUE, the ratio of NPP to rainfall) accounts for variability of rainfall and, to some extent, local soil and terrain characteristics. RUE is strongly correlated with rainfall; in the short term, it says more about rainfall fluctuation than land degradation but we judge that its long-term trends distinguish between rainfall variability and land degradation. To get around the correlation of RUE with rainfall, Wessels and others (2007) have suggested the alternative use of residual trends of NDVI (RESTREND) – the difference between the observed NDVI and that modelled from the local rainfall-NDVI relationship. In this assessment, land degradation is identified by a declining trend in *both* NDVI and RUE; comparable RESTREND values are presented as an additional layer of information.

The pattern of land degradation is further explored by comparisons with soil and terrain, land cover, and socio-economic data. In the parent FAO program *Land Degradation Assessment in Drylands*, areas identified by this first screening will be validated and characterized in the field by national teams.

2 Context and methods

2.1 GLADA partner country: China

China supports 22 per cent of the world's population on only 6.4 per cent of the global land area; and the greater part of this is dryland - China has only 7.2 per cent of the world's arable. Food and water security, environmental services and continued economic development all depend on sustainable management of the land but China suffers more than most countries in terms of the extent, intensity and economic impact of land degradation, and is the most severely afflicted in terms of the absolute number of people directly affected (Bai and others 2008). The Asian Development Bank (2002) estimated that in 1999 land degradation caused a direct loss of $7.7 billion, 4 per cent of the GDP; indirect loses are estimated at $31 billion. The costs of remediation are hard to quantify but current investment appears to be an order of magnitude smaller than what is needed to arrest degradation.

Berry (2003) cites environmental conditions combined with inappropriate management as drivers of land degradation:

- In south China, soil erosion is exacerbated by high-intensity rains, often associated with typhoons;
- In north China, strong winds in spring blow the loose, dry soil, especially in loess country and degraded grasslands where the vegetation cover has been weakened;
- Extensive hilly and mountainous relief adjoining plains with flood-prone, sediment-laden rivers;
- Deforestation and reckless cultivation of sloping land and drylands without soil conservation measures;
- Neglect of communal conservation practices under the new rural system;
- Mismanagement of groundwater and irrigated land;
- Urban and industrial expansion;
- Reliance on biomass for fuel in rural areas. Over 70 per cent of energy in rural areas is supplied by natural or cultivated biomass (ADB 2002, ADB/GEF 2002, World Bank 2001).

Zhang and others 2007 suggest that undesirable land use/cover changes have not been addressed owing to inadequate policy; for example loss of farmland to agricultural users because of the growing towns and economic developments like industrial parks. The Government has recently initiated several programs to protect the environment.

Underlying pressures include:

- Less and less land per person, driving ever-more-intensive land use;
- Poverty in the most ecologically vulnerable regions;
- Burgeoning urban demands: as living standards rise, there is increasing demand for livestock products;
- Change in farming systems from traditional and conservative to dependence on mechanisation and agrochemicals;
- Top-down application of policies without respect to local conditions;

- Inadequate regulatory environment, management by sectoral goals, and lack of coordination between ministries and between national, regional and local administrations. Even within one sector, such as water or soil, several different agencies may have overlapping responsibilities;
- Inadequate incentives for conservation;
- Under-pricing or perverse incentives in respect of natural resources, especially for irrigation water and land rents (Li 2002, ADB 2002).

In China, degradation has a long history (Zhao 1991). Drylands have attracted most attention (Dregne 2002), especially in North China where livelihoods have always been precarious. However, for many purposes, it is more important to address present-day land degradation in high-potential areas – which have not received the same attention in respect of soil and water conservation. The present assessment, based in consistent data since 1981, distinguishes between the legacy of historical land degradation and land degradation that is taking place now.

2.2 Data

2.2.1 NDVI and net primary productivity

The NDVI data used in this study are produced by the Global Inventory Modelling and Mapping Studies (GIMMS) group from measurements made by AVHRR radiometer on board US National Oceanic and Atmospheric Administration satellites for the period July 1981 to December 2003. The fortnightly images at 8km-spatial resolution are corrected for calibration, view geometry, volcanic aerosols, and other effects not related to vegetation cover (Tucker and others 2004). Their accuracy is proven to be suitable for global and regional environmental assessment and these data are compatible with those from other sensors such as MODIS, SPOT Vegetation, and Landsat ETM+ (Tucker and others 2005, Brown and others 2006).

To provide a measure open to economic analysis, the GIMMS NDVI data have been translated to NPP using MODIS (moderate-resolution imaging spectro-radiometer) data for the overlapping period 2000-2003. MOD17A3 is a dataset of terrestrial gross and net primary productivity, computed at 1-km resolution at an 8-day interval (Heinsch and others 2003, Running and others 2004). Though far from perfect (Plummer 2006), the dataset has been validated in various landscapes (Fensholt and others 2004, 2006, Gebremichael and Barros 2006, Turner and others 2003, 2006); MODIS gross and net primary productivity are related to observed atmospheric CO_2 and the inter-annual variability associated with the ENSO phenomenon, indicating that these data are reliable at the regional scale (Zhao and others 2005, 2006). The translation from NDVI to NPP is approximate.

2.2.2 Climatic data

The VASClimO 1.1 dataset comprises the most complete monthly precipitation data for 1951-2000, compiled on the basis of long, quality-controlled station records, 280 in China, gridded at resolution of 0.5° (Beck and others 2005); monthly rainfall data since January 1981 were used for this analysis, supplemented by the GPCC full re-analysis product (Schneider and others 2008) to produce rainfall values matching the GIMMS NDVI data. Mean annual temperature values from the CRU TS 2.1 dataset (Mitchell and Jones 2005) of monthly, station-observed values also gridded at 0.5° resolution, were used to calculate the aridity index and energy-use efficiency.

2.2.3 Land cover and land use

Land Cover 2000 global land cover data (JRC 2003) have been generalised for China (Figure 1); similarly, *Land use systems of the World* (FAO 2008) have been derived for China and used for preliminary comparison with NPP trends.

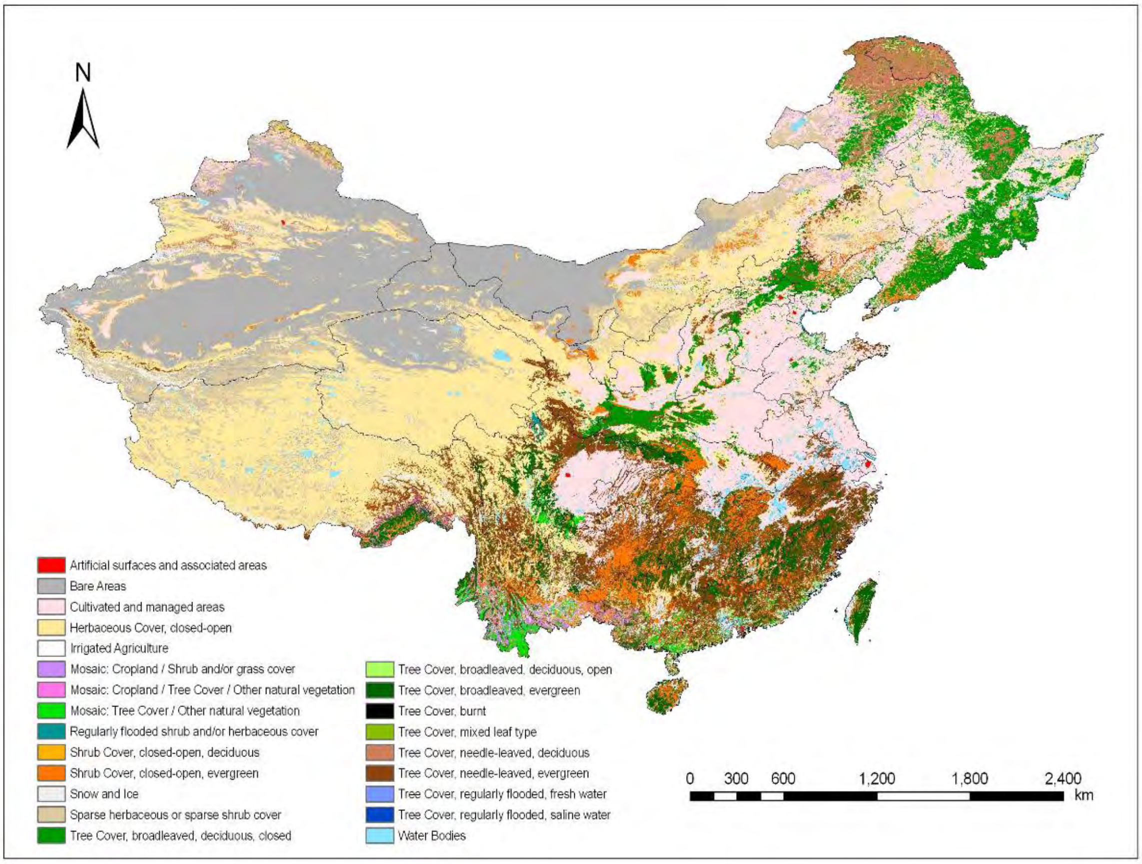

Figure 1. Main land cover types
(JRC 2003)

2.2.4 Soil and terrain

A Soil and Terrain database for China at scale 1:1 M with a consistent minimum dataset of key soil attributes has been prepared for the next stage of this study (Engelen and others 2008).

2.2.5 Population, urban areas and poverty indices

The CIESIN Global Rural-Urban Mapping Project provides data for population and urban extent, gridded at 30 arc-second resolution (CIESIN 2004); for this study, the Urban/Rural Extents dataset is used to mask the urban area. Sub-national rates of infant mortality and child underweight status and the gridded population for 2005 at 2.5 arc-minutes resolution (CIESIN 2005) were compared with indices of land degradation.

2.2.6 Aridity index

Turc's aridity index was calculated as P/PET where P is annual precipitation in mm and $PET = P/\sqrt{(0.9 + (P/L)^2)}$ where L = 300 + 25T + 0.05T^3 where T is mean annual temperature (Jones 1997). Precipitation was taken from the gridded VASClimO data, mean annual temperature from the CRU TS 2.1 data.

2.2.7 RESTREND

Following the general procedure of Wessels and others (2007), correlation between annual sum NDVI and annual rainfall was calculated for each pixel. The regression equation enables prediction of sum NDVI according to rainfall. Residuals of sum NDVI (i.e. differences between the observed and predicted sum NDVI) were calculated and the trend of these residuals was analysed by linear regression.

2.3 Analysis

Areas of land degradation and improvement are identified by a sequence of analyses of the remotely sensed data:

1. Simple NDVI indicators (NDVI minimum, maximum, maximum-minimum, mean, sum, standard deviation and coefficient of variation) are computed for the calendar year. Each of these indicators has biological meaning (Appendix 2).
2. The 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 are calculated by linear regression.
3. 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:
    a. Identifying where there is a positive relationship between NDVI and rainfall, i.e. where rainfall determines productivity;
    b. For those areas where rainfall determines productivity, RUE has been considered: where 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 also for all areas where there is a negative relationship between NDVI and rainfall, i.e. 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.

4. As an additional indicator, the residual trend of sum NDVI (RESTREND) is calculated for all pixels.
5. To take account of the significant lengthening and warming of the growing season at high latitudes and altitudes, energy-use efficiency – ratio of annual sum NDVI to accumulated temperature is calculated and overlaid on RUE-adjusted NDVI to calculate climate-adjusted NDVI.
6. The indices of land degradation and improvement are compared with land cover, land use, aridity, rural population density and indices of poverty.

Details of the analytical methods are given as Appendix 1. Algorithms have been developed that enable these screening analyses to be undertaken automatically.

Relationships with attribute of soil and terrain will be analysed in the next phase of investigations along with manual characterisation of areas of land degradation and improvement, identified on the basis of NDVI indices, using 30m-resolution Landsat data, to identify the probable kinds of land degradation. At the same time, the continuous field of the index of land degradation derived from NDVI and climatic data will enable a statistical examination of other data for which continuous spatial coverage is not available - for instance spot measurements of soil attributes, and other social and economic data that may reflect the drivers of land degradation, provided that these other data are geo-located.

Finally, field examination of *hot spots* of land degradation and bright spots of improvement will be undertaken by national teams within the LADA program.

3 Results

The spatial patterns and temporal trends of several indicators of land degradation and improvement are presented in Appendix 2. The main text deals with interpretation of the annual sum NDVI data, which are taken to represent aggregated green biomass production.

3.1 Trends in biomass productivity

Biomass productivity fluctuates according to rainfall cycles. Countrywide, greenness increased over the period 1981-2003 (Figure 2, Table A1).

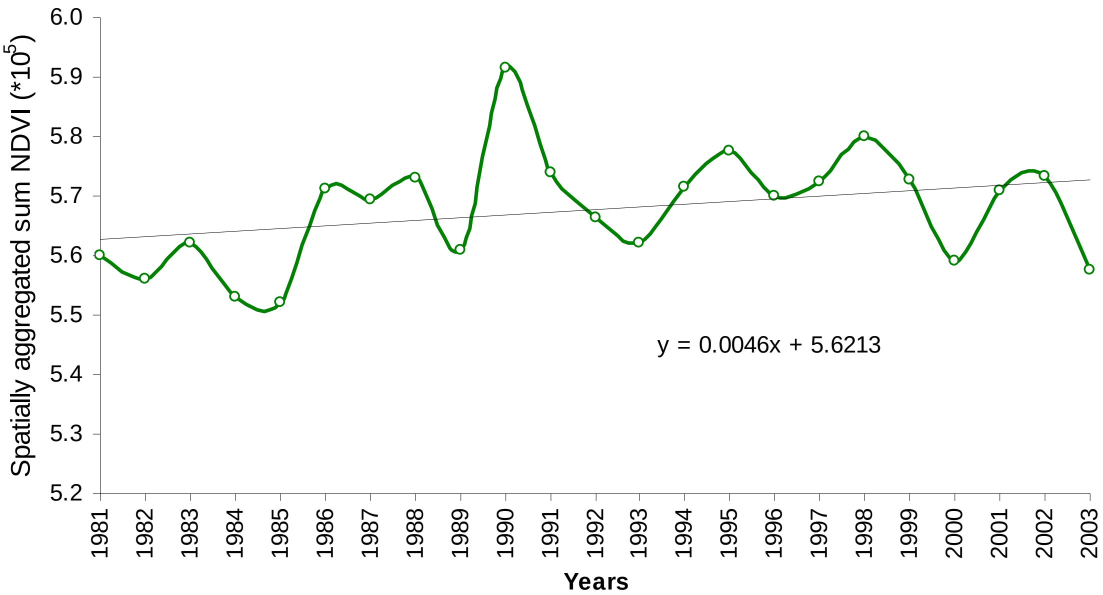

Figure 2. Spatially aggregated annual sum NDVI 1981-2003, $p<0.05$

Figure 3 maps the mean annual sum NDVI and trends over the period 1981-2003, determined for each pixel by the slope of the linear regression equation. Across 49 per cent of the country, greenness increased; over 31 per cent of the country, mostly in the south and north-east, it decreased and 20% remains no change.

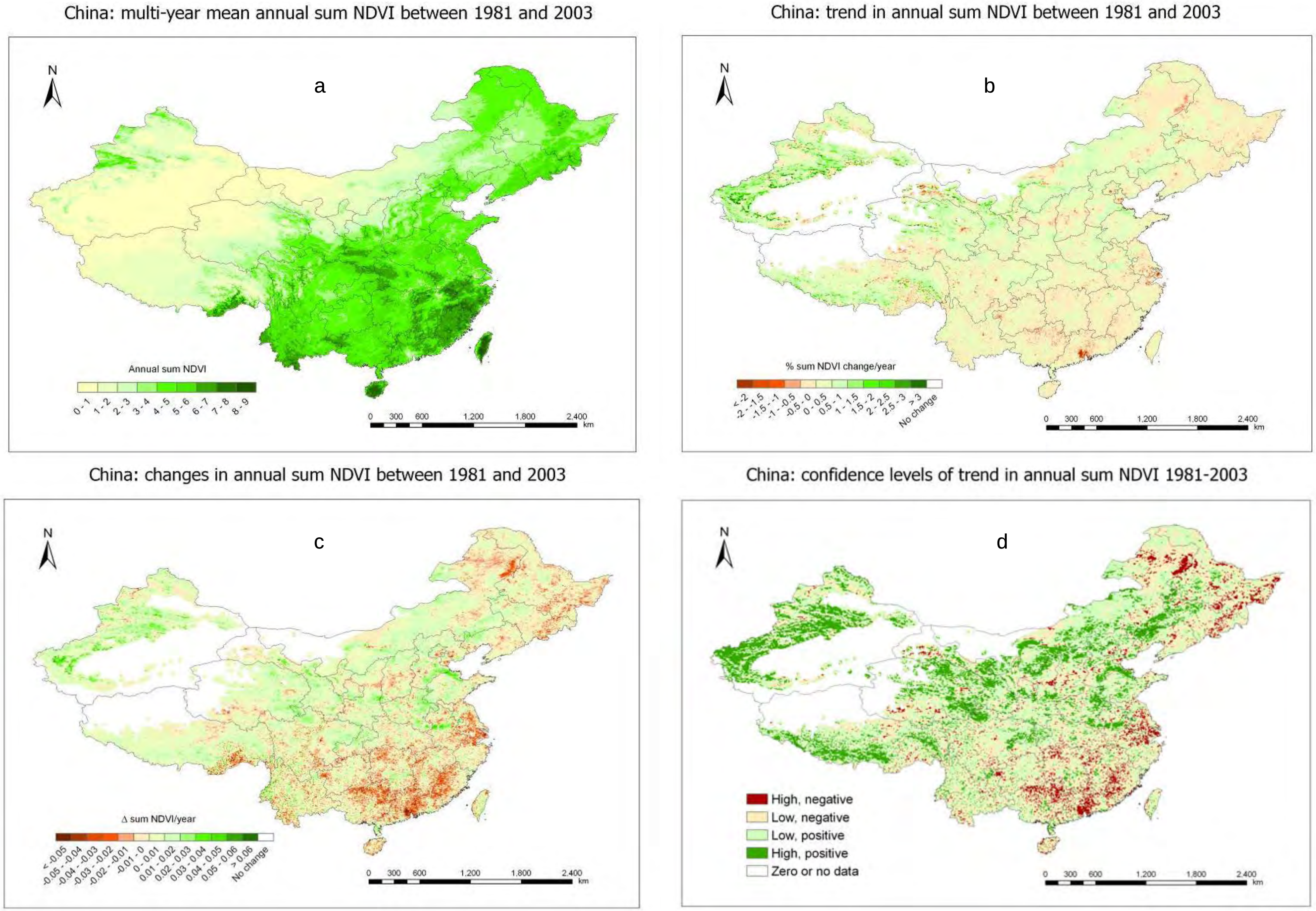

Figure 3. Annual sum NDVI 1981-2003: mean (a) and trends, trends (b – percentage, c – absolute, d - confidence levels)

3.2 Spatial patterns of biomass and rainfall

Biomass fluctuates according to rainfall, stage of growth and changes in land use, as well as land quality. Countrywide, mean annual biomass productivity (represented by sum NDVI in Figure 3a) is related to rainfall (Figure 5a) - which has fluctuated significantly, both cyclically (Figure 4) and spatially (Figure 5b and c).

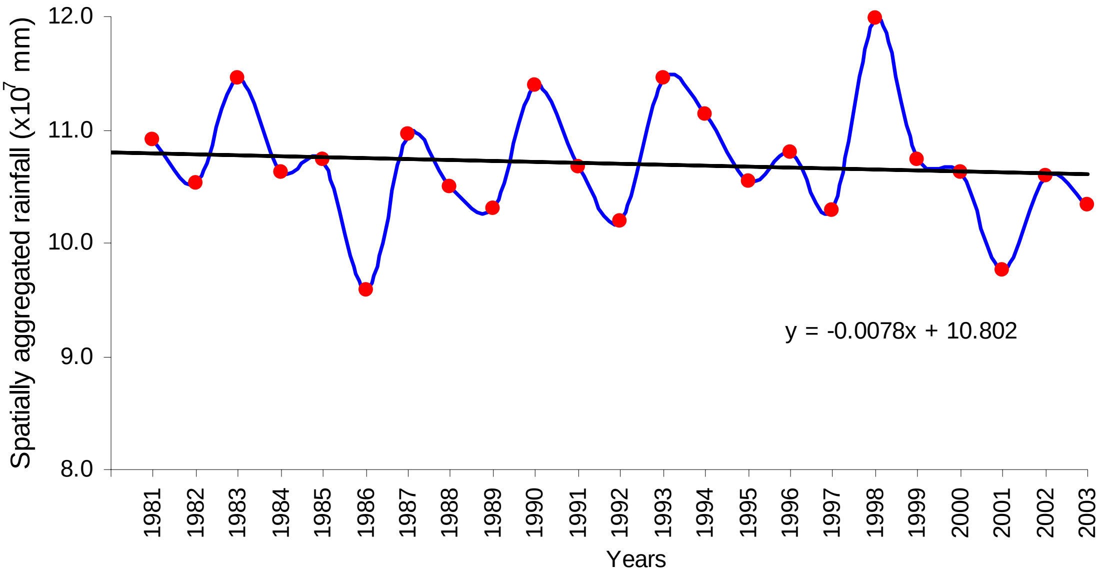

Figure 4. Spatially aggregated annual rainfall 1981-2003

Statistics show a moderate correlation between sum NDVI and annual rainfall:

$$NDVI_{ann.\ sum} = 0.0029 * Rainfall\ [mm\ year^{-1}] + 1.444 \quad [1]$$

(r^2 = 0.54, n=181 357)

The standard error in the regression model [1] is: slope (0.0029) ± $1.2*10^{-5}$; intercept (1.444) ± 0.0092.

Over the period of 1981-2003, rainfall decreased slightly overall (Figure 4); increasing over about half of the country, at an average of 3.2mm/yr, and decreasing over the other half of the country, at 3.9mm/yr (Figure 5b and c). Rainfall decreased in NE China, Shaanxi and Shanxi provinces, most of Inner Mongolia, northern Sichuan, northern Hubei and NW Henan provinces. However, biomass increased overall. The correlation of spatially aggregated rainfall and biomass productivity is weak (Figure 6).

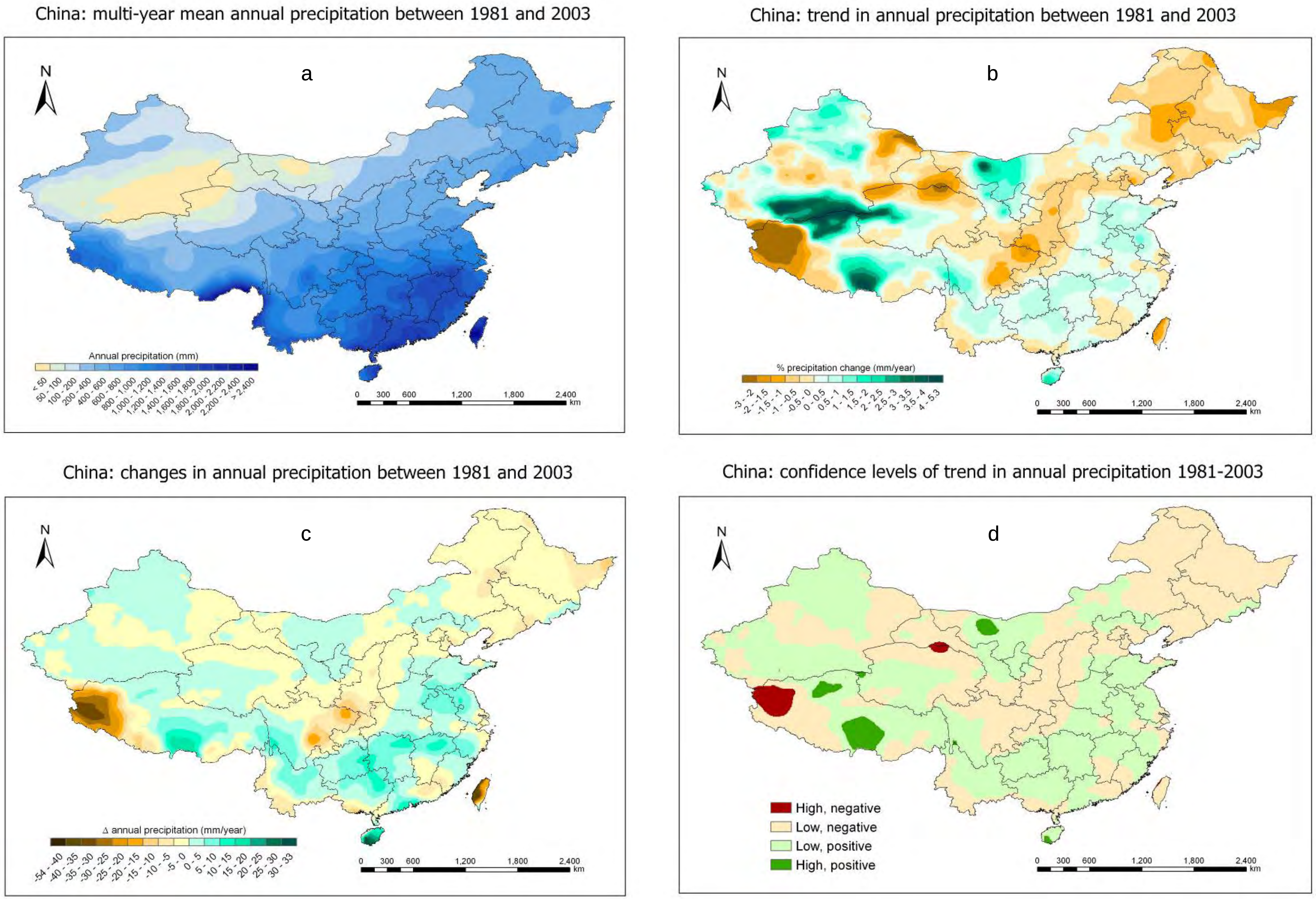

Figure 5. Annual rainfall 1981-2003: mean (a) and trends (b – percentage change, c – absolute change, d - and confidence levels

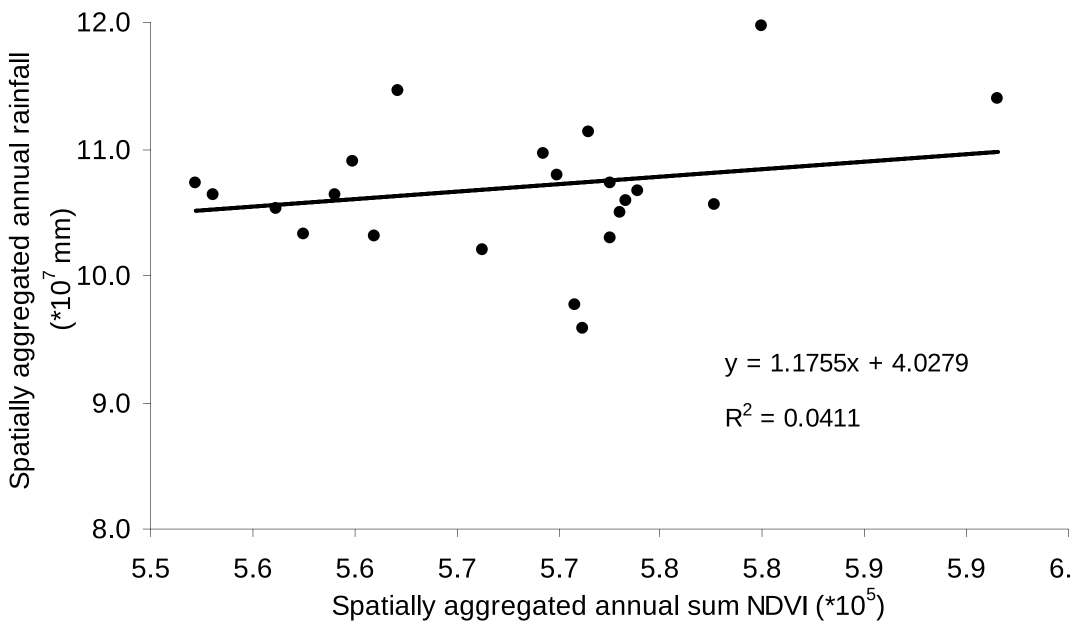

Figure 6. Relationship between annual sum NDVI (all pixels) and annual precipitation (all pixels). Each dot represents one year

3.3 Rain-use efficiency

The effects of rainfall variability on biomass productivity may be accounted by rain-use efficiency (RUE, production per unit of rainfall). RUE may fluctuate wildly in the short term, often it declines sharply when rainfall increases and we assume that the vegetation cannot make full use of the additional rain. However, we judge that, where rainfall is the main constraint on productivity, the long-term trend of RUE is a good indicator of land degradation or improvement (Houérou 1984, 1988, 1989; Snyman 1998; Illius and O'Connor 1999; O'Connor and others 2001). Analysis of the local rainfall–biomass production relationship also accommodates the effects of local variations in slope, soil and vegetation (Justice and others 1991).

In North China and Kenya, Bai and others (2005, 2006) demonstrated that values for RUE calculated from NDVI, *which are easy to obtain*, were comparable with those calculated from field measurements of NPP, which are not easy to obtain. For this analysis, RUE was calculated as the ratio of annual sum NDVI and station-observed annual rainfall.

Figure 7 maps mean annual RUE and its trend over the period 1981-2003. In general, RUE is higher in the drylands than in the humid areas - which generate drainage to streams and groundwater (Figure 7a). Over the period, RUE increased over half of the country, decreased over thirty per cent, and remained substantially unchanged over the remaining twenty per cent. For the country as a whole, RUE increased. Four big regions show a significant decline: adjacent areas of Hunan, Guangxi and Guizhou provinces; central Yunnan and south Sichuan; south central Tibet; and most of Hainan (Figure 7b, c). Confidence levels are assessed by the T-test.

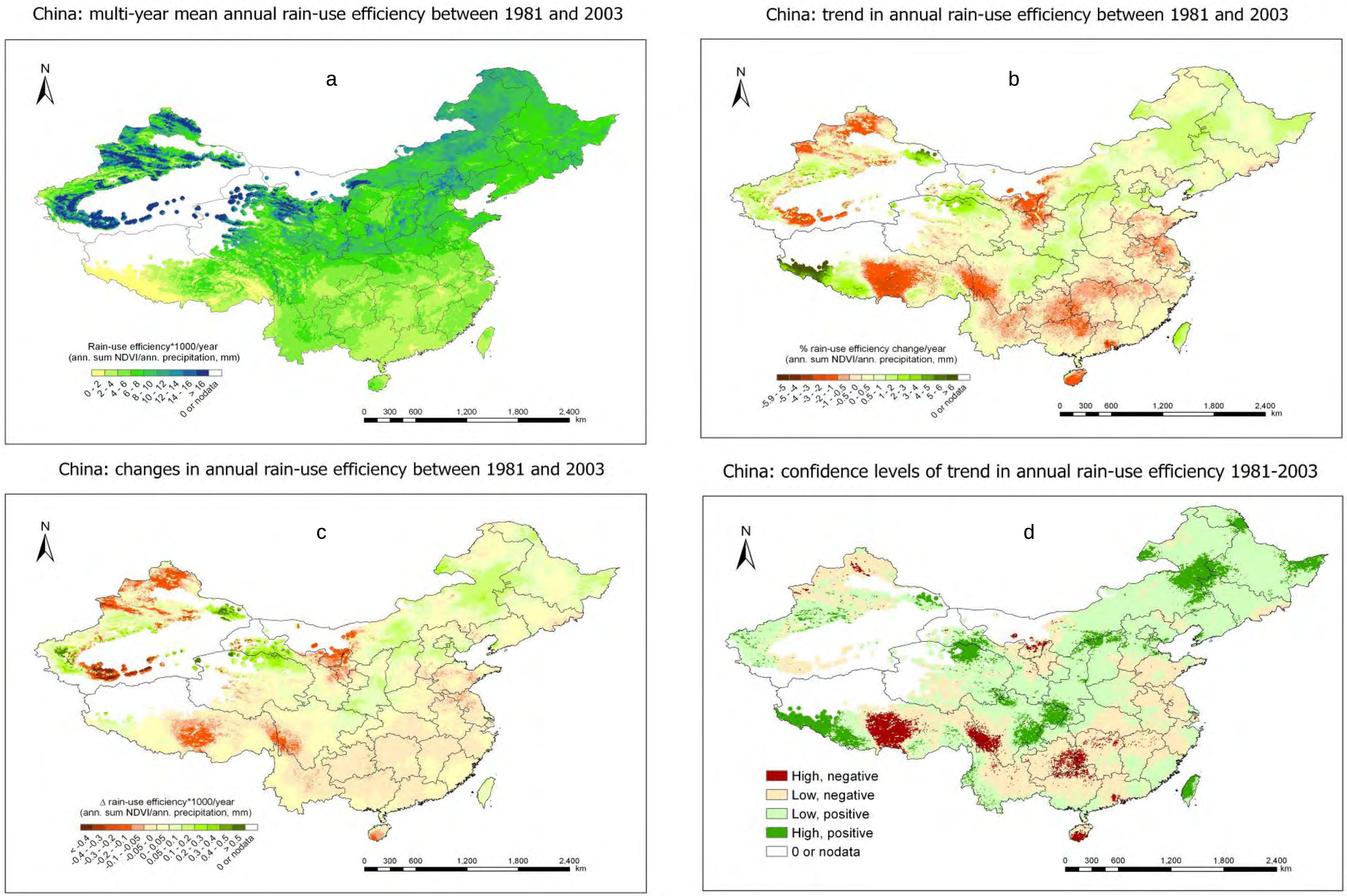

Figure 7. Rain-use efficiency 1981-2003: Mean (a) and trends (b – percentage change, c – absolute change, d - confidence levels)

3.4 RESTREND

Countrywide, there is a significant negative correlation between RUE and rainfall (r=-0.79, n=181 357) so that RUE, in isolation, says as much about rainfall variability as about land degradation.

To get around the correlation between RUE and rainfall, Wessels and others (2007) suggest the alternative use of Residual Trends to distinguish land degradation from the effects of rainfall variability. Following their general procedure, we have correlated annual sum NDVI and annual rainfall for each pixel. The resulting regression equation represents the statistical association between observed sum NDVI and rainfall (Figure 8a, b) and it enables prediction of NDVI according to rainfall. Residuals of sum NDVI (i.e. differences between the observed and predicted value) were calculated for each pixel, and the trend of these residuals (RESTREND) was analysed by linear regression (Figure 8c). T-test confidence levels are shown in Figure 8d.

RESTREND points in the same direction as RUE: a negative RESTREND may indicate land degradation, a positive RESTREND improvement. However, the spatial distribution is different from RUE. Overall, RESTREND patterns are remarkably close to those of sum NDVI but the amplitude of the residuals is less (Figure 3c), cf Section 3.9.

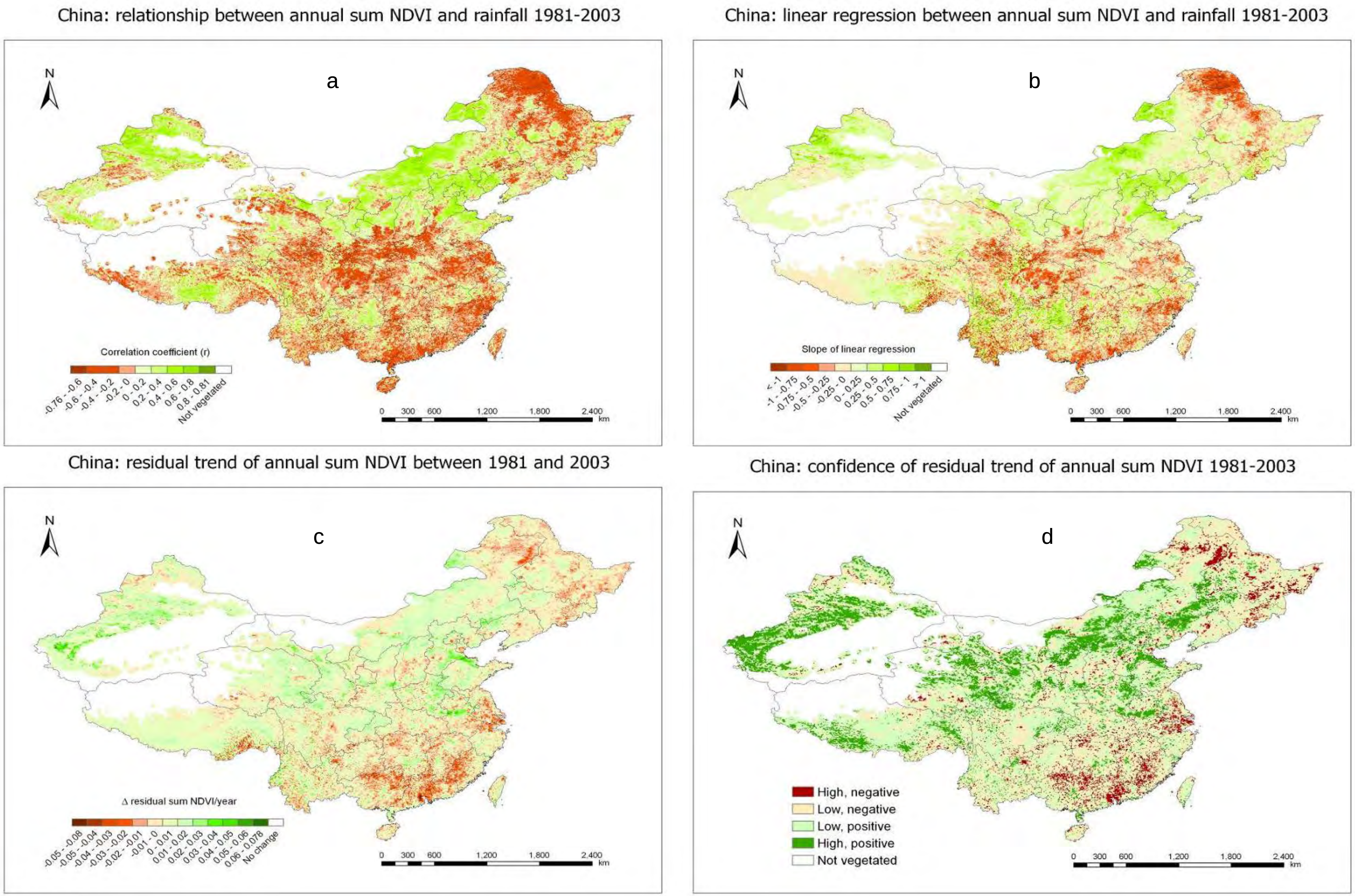

Figure 8. Residual trend of sum NDVI (RESTREND) 1981-2003:
(a) Correlation coefficient between sum NDVI and annual rainfall; (b) Slope of linear regression between sum NDVI and rainfall; (c) RESTREND; (d) Confidence levels

3.5 Net primary productivity

It is hard to visualise the degree of land degradation or improvement from NDVI values or residuals. For a quantitative estimation, NDVI may be translated to net primary productivity (NPP) - the rate at which vegetation fixes CO_2 from the atmosphere less losses through respiration; in other words, biomass productivity - which includes food, fibre and wood.

The most accessible global NPP data are from the MODIS model (available at 1km resolution from the year 2000). Figure 9a shows four-year (2000-2003) mean annual MODIS NPP at 1-km resolution for China; the pattern is similar to the GIMMS annual sum NDVI (Figure 3a) but in finer detail. GIMMS NDVI data were translated to NPP by correlation with MODIS 8-day NPP values for the overlapping period: MODIS four-year annual mean NPP was re-sampled to 8km resolution by nearest-neighbour assignment; the four-year mean annual sum NDVI over the same period (2000-2003) was then calculated:

$$NPP_{MOD17}\ [\text{tonneC ha}^{-1}\ \text{year}^{-1}] = 1.1349 * NDVI_{sum,\ GIMMS} - 1.06927 \qquad [2]$$

(r^2 = 0.67, n = 145 926)

Where NPP_{MOD17} is annual NPP derived from MOD17, $NDVI_{sum}$ is a four-year (2000-2003) mean annual sum NDVI derived from GIMMS.

The standard error in the regression model [2] is: slope (1.1349) ± 0.00401; intercept (-1.06927) ± 0.016208. This is very small. The high coefficient of variation, r^2, indicates that MOD17A3 NPP can be reasonably used to convert the GIMMS NDVI values to NPP.

The percentage and absolute changes in NPP are mapped in Figure 9b, c; the confidence level (Figure 9d) refers to the T-test (Appendix 1). Table 1 shows the estimated changes in NPP in vegetated areas between 1981 and 2003.

Table 1. Changes in net primary productivity 1981-2003

	Positive	*Negative*	*No change*	*Mean*
Land area (pixels, %)	49	31	20	
% NPP change/year [TonneC ha^{-1} $year^{-1}$]	0.28	0.11	0	0.18
Δ NPP [kg C ha^{-1} $year^{-1}$]	4.90	3.19	0	1.71

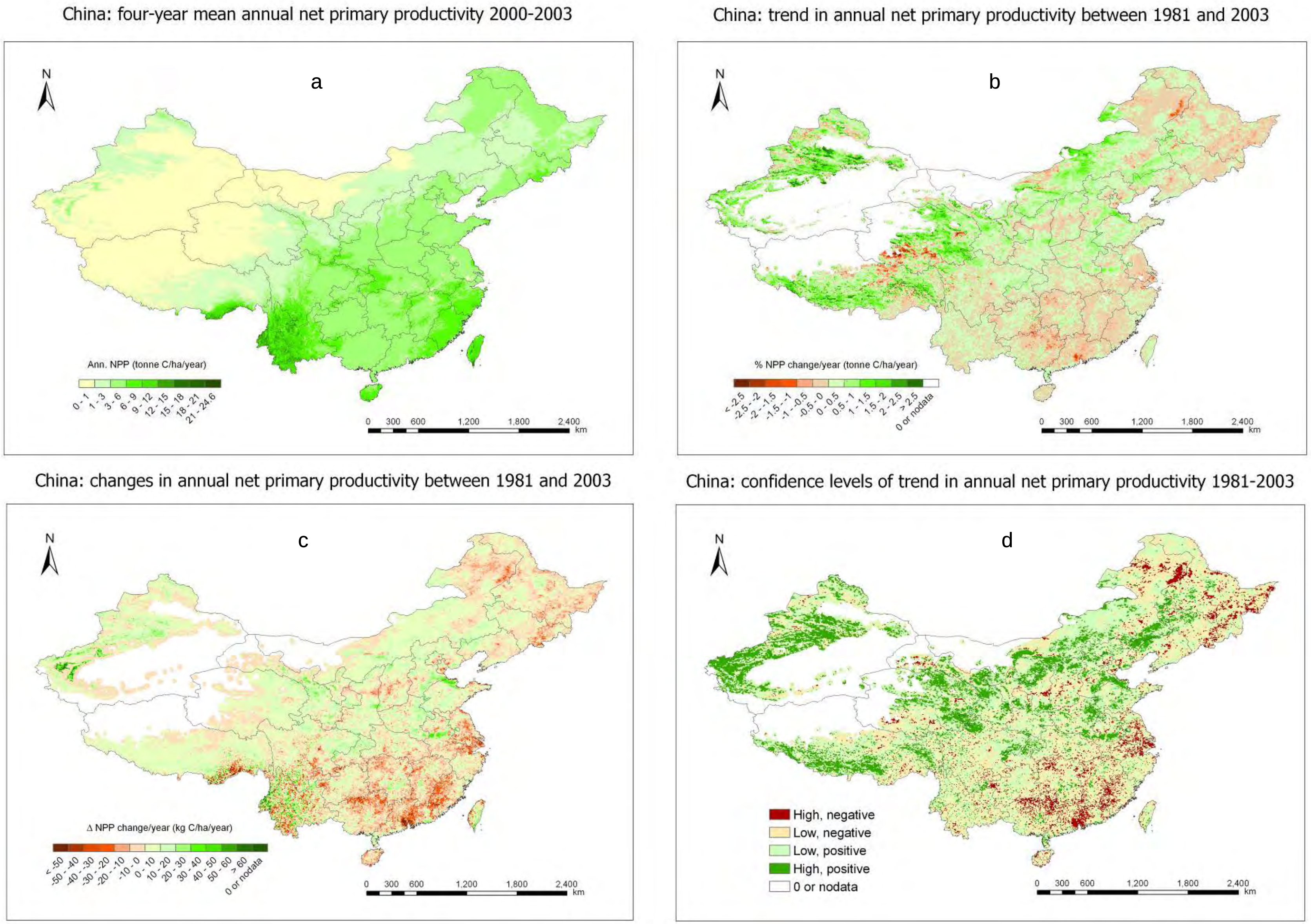

Figure 9. Net primary productivity: mean (a), trends (b, % change; c, absolute change); confidence level (d)

3.6 Land degradation

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 arising from climatic variability and changes in land use and management.

3.6.1 Accounting for rainfall variability

Variability of rainfall has been accounted for using both rain–use efficiency (RUE) and RESTREND. RUE is considered by, first, identifying pixels where there is a positive relationship between productivity and rainfall. For those areas where productivity depends on rainfall *and* where productivity declined but RUE increased, we attribute the decline of productivity to drought. Those areas are masked (urban areas are also masked). NDVI trends are presented for the remaining parts of the country as RUE-adjusted NDVI (Figure 10). Further consideration of energy-use efficiency does not alter this picture.

Twenty three per cent of the country suffered declining RUE-adjusted NDVI, mostly in the higher rainfall areas in the south of the country; land degradation, so defined, is not conspicuous in the drylands in northern China.

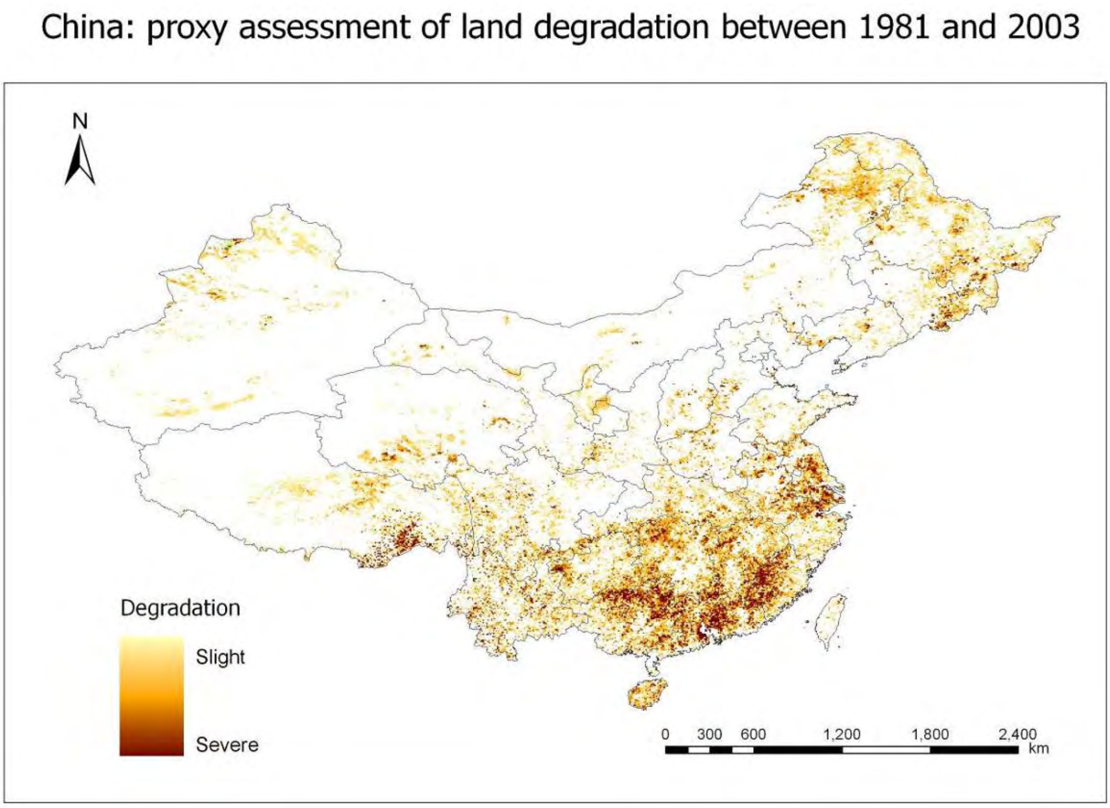

Figure 10. Negative trend in RUE-adjusted annual sum NDVI, 1981-2003

3.6.2 Quantitative estimation

To estimate the decline in productivity in quantitative terms, we have calculated loss of NPP, relative to the 1981-2003 mean using the relationship between GIMMS and MODIS data for the overlapping years 2000-2003 (Figure 11 and Table 2). These are big numbers.

Table 2. China and the world: NPP loss from degrading land 1981-2003

	Degrading land, km^2	*% territory*	*% global degrading land*	*NPP loss, kgC/ha/yr*	*Total NPP loss, tonneC/23-yr*
China	2 193 697	22.9	7.6	11.7	58 840 237
Globe	35 058 104	23.5	100	11.8	955 221 419

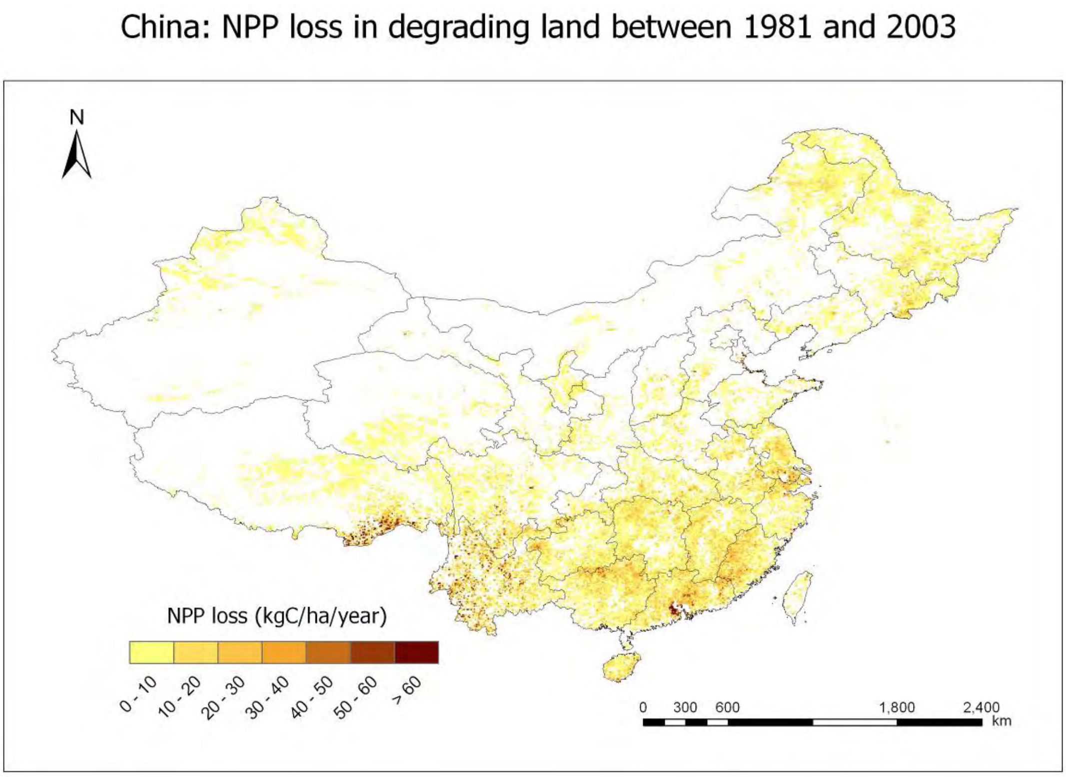

Figure 11. NPP loss in the degrading areas 1981-2003

3.6.3 Land use change

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.

The Ministry of Land Resources has published time-series data on land use for since 1980s (Li 2000) which show that China is experiencing rapid and profound land use changes. From the point of view of the environment, many of these changes are harmful. Based on a sample analysis of Landsat imagery from 1980 to 1999, Liu and others (2000) report striking variations in the degree and rate of land use change: “severe change” (greater than 5 per cent annually) in coastal areas of South China experienced); “fast change” (0.3-1.% annually) in the middle and lower Yangtze basin and east China; “slow change”(0.1-0.3% annually) in N China , the Sichuan Basin and the north east plains, particularly rural areas far from cities; and “very slow change” in the west and north west. It is unlikely to be a coincidence that GLADA measures the mosty severe and extensive land degradation in south andf east of the country, and some land improvement in the north and west.

Systematic interpretation of the GLADA data alongside up-to date time series data for land use and management would surely be a valuable guide for policy development and management.

3.7 Land improvement

Land improvement (Figure 12) is identified by combination of a positive RUE-adjusted NDVI and positive energy-use efficiency. Figure 13 shows the t-test confidence levels.

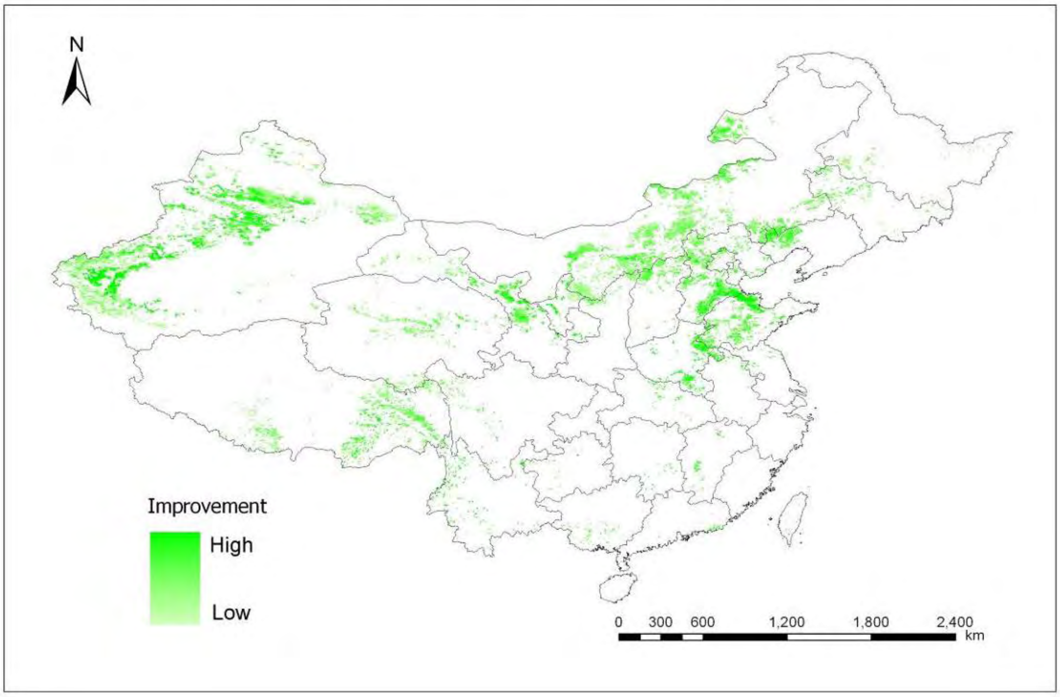

Figure 12. China: areas of positive climate-adjusted NDVI, 1981-2003

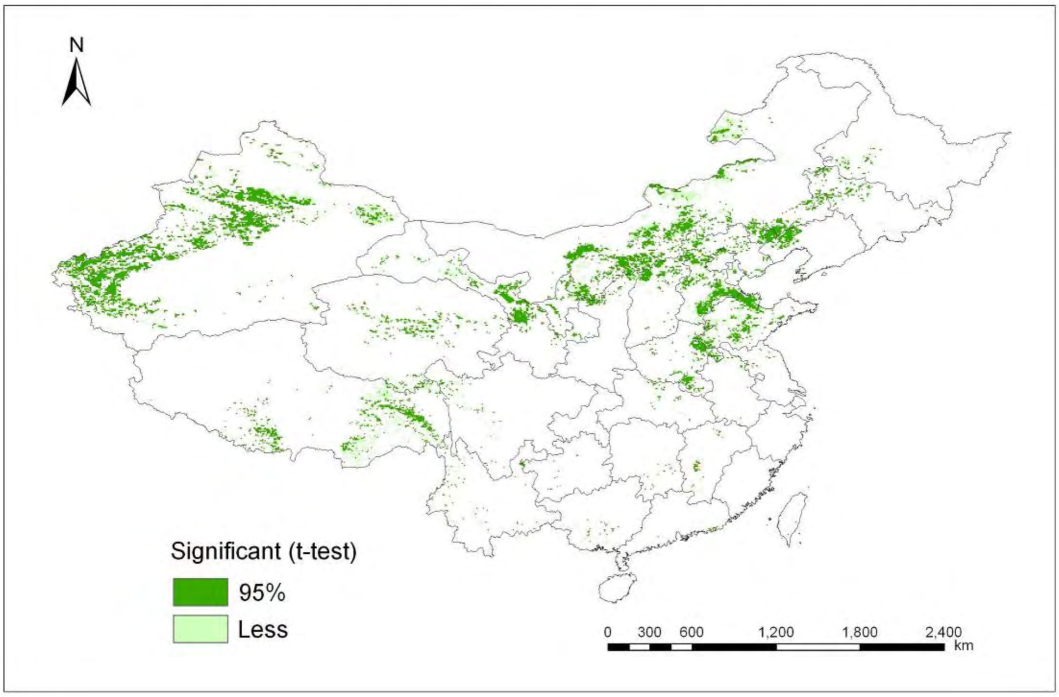

Figure 13. Confidence levels of positive climate-adjusted NDVI, 1981-2003

Improving areas account for about 8 per cent of the country, mostly in northern China: south-east Hebei Province, central Shandong, eastern Henan, parts of central Inner Mongolia and north Shaanxi provinces, the He Xi corridor of Gansu province and extensive areas in west Xinjiang.

Apart from the degrading and improving land (23 per cent and 8 per cent of the country, respectively), non-vegetated land occupies 20 per cent, urban areas about 3 per cent, and the remaining 46 per cent of the country shows no clear trends.

3.8 Urban areas

Whether urbanisation is degradation is arguable. It brings a huge increase in the financial value of the land but, if it which involves sealing of the land surface, it is degradation according to our criterion of partial loss of ecosystem function.

The CIESIN Global Rural Urban Mapping Project shows 2.8 per cent of the land area as urban. This area is masked in the maps, which makes only a small difference to the results: a reduction of 1 per cent in the area of identified degrading land, and a reduction of 0.3 per cent for the improving land.

3.9 Comparison of indicators

Annual sum NDVI, i.e. annually accumulated greenness, is our standard indicator of land degradation and improvement. Rain-use efficiency, RUE-adjusted NDVI and RESTREND are different ways of eliminating false alarms caused by rainfall variability (cf Sections 3.3 and 3.4, respectively).

Countrywide, the patterns of the trends in sum NDVI and RESTREND are almost identical (Table 3): about 30 per cent of land area shows negative change in both sum NDVI and RESTREND, 46 per cent shows positive trend in both indictors, 20 per cent no change and only 4 per cent gives a mixed signal - either positive sum NDVI and negative RESTREND, or vice versa.

If we take negative RUE-adjusted NDVI as the primary definition of degrading areas, then 96 per cent of these areas are also degrading in terms of *both* unadjusted NDVI and RESTREND. Taking a positive trend of RUE-adjusted NDVI as the primary definition of improving land, 99.6 per cent of the area are also positive in terms of *both* unadjusted NDVI and RESTREND.

Comparing RUE with RESTREND, 17 per cent of the land area shows negative trend in both RUE and RESTREND, 35 per cent shows positive trend in both indicators and 20 per cent no change. But we get mixed signals from 28 per cent: either positive RUE and negative RESTREND, or vice versa. If we again take RUE-adjusted NDVI as the primary definition of degrading areas, then 62 per cent shows negative trend in both RUE and RESTREND, and 90 per cent of the improving area shows positive trend in both RUE and RESTREND.

Table 3. Comparison of indicators, 1981-2003

Indicators	*Total pixel*	*Negative trend*	*Positive trend*	*No change*	*Mixed*
	(%)	(%)	(%)	(%)	(%)
Annual sum NDVI	100	31.1	48.8	20.1	0.0
RESTREND[1]	100	32.2	48.0	19.7	0.0
Sum NDVI ∩ RESTREND	100	29.5	46.1	20.2	4.2
Sum NDVI ∩ RESTREND within LD[2]		**96.3**			
Sum NDVI ∩ RESTREND within LI[3]			**99.6**		
RUE	100	29.9	49.9	20.3	0.0
RUE ∩ RESTREND	100	16.8	34.7	20.2	28.3
RUE ∩ RESTREND within LD		**62.4**			
RUE ∩ RESTREND within LI			**89.5**		

[1] Residual trend of sum NDVI; [2] LD - identified improving land; [3] LI - identified degrading land.

3.10 Analysis of degrading and improving areas

3.10.1 Relationship with land use and management

Table 4 compares degrading and improving areas with land cover (Figure 1): 21 per cent of degrading land is arable (codes 16-18, 24 per cent of the arable), 17 per cent is broadleaved forest (codes 1-3), 22 per cent needle-leaved forest (codes 4-5) and 31 per cent is grassland and scrub (codes 11-15). Almost half of the improving area is grassland and scrub (10 per cent of the grassland) and a quarter is arable (11 per cent of the arable). Some credit for the impressive improvement in the north of the country is due to regulations enacted[1] and various national programs to combat land degradation, such the *Three-North shelter belt*, the *Grain for Greening* (grain and cash rewards for returning steep cropland into forest or grassland, Ye and others 2003), *Converting Free-grazing to Meadow*, and *Small-Watershed Management* (SFA-PRC 2006; Liu 2008). Some of these reclaimed areas show up in the mapped areas of land improvement in GLADA and, also, in more detailed local studies (e,g. Xin and others 2008) and, perhaps, in lesser sediment loads in the Yellow and Yangtze rivers.

Comparison of degrading areas with land use systems (Tables 5 and 6) indicates that 39 per cent of degrading land is forestry (about 45 per cent of the forest area, with supposedly protected and natural areas faring no better than the average), 29 per cent is grassland (herbaceous vegetation in the FAO legend, 18 per cent of this unit), 23 per cent is agricultural land (25 per cent of agricultural land) and 5 per cent is bare. 43 per cent of improving land is grassland, 28 per cent is agricultural land and, surprisingly, 19 per cent of the improving land is classified as bare.

1 On Combating Desertification, Grassland Act, Soil and Water Conservation Act, Land Administration Act, State Council circular on Prohibiting collection and sale of wild *facai,* excessive gathering of liquorice and ephedra, etc.

Table 4. Degrading and improving areas by LC 2000 land cover types

Code	Land cover	Total pixels[1] (TP)	Degrading pixels (DP)	DP/TP (%)	DP/TDP[2] (%)	Improving pixels (IP)	IP/TP (%)	IP/TIP[3] (%)
1	Tree cover, broadleaved evergreen	443 913	237 441	53.5	8.6	8 283	1.9	0.8
2	Tree cover, broadleaved deciduous, closed	681 660	229 849	33.7	8.4	24 532	3.6	2.4
3	Tree cover, broadleaved deciduous, open	363	4	1.1	0.0	21	5.8	0.0
4	Tree cover, needle-leaved evergreen	1 035 212	499 406	48.2	18.2	33 302	3.2	3.3
5	Tree cover, needle-leaved deciduous	244 575	103 575	42.3	3.8	4 308	1.8	0.4
6	Tree cover, mixed	15 713	6 274	39.9	0.2	173	1.1	0.0
9	Mosaic: tree cover / other natural vegetation	106 764	51 172	47.9	1.9	3 105	2.9	0.3
10	Tree cover, burnt	944	397	42.1	0.0	0	0.0	0.0
11	Shrub cover, evergreen,	551 446	269 945	49.0	9.8	29 139	5.3	2.9
12	Shrub cover, deciduous	15 702	5 161	32.9	0.2	272	1.7	0.0
13	Herbaceous cover,	3 173 203	508 795	16.0	18.5	320 664	10.1	31.7
14	Sparse herbaceous or sparse shrub cover	760 114	47 057	6.2	1.7	120 505	15.9	11.9
15	Regularly flooded shrub and/or herbaceous cover	59 354	19 344	32.6	0.7	1 591	2.7	0.2
16	Cultivated and managed areas	2 242 026	533 285	23.8	19.4	245 274	10.9	24.2
17	Mosaic: cropland/tree cover/other natural vegetation	27 474	12 945	47.1	0.5	2 393	8.7	0.2
18	Mosaic: cropland / shrub and/or grass cover	103 572	36 629	35.4	1.3	3 826	3.7	0.4
19	Bare	2 262 000	118 541	5.2	4.3	179 971	8.0	17.8
20	Water bodies	172 920	48 551	28.1	1.8	12 649	7.3	1.3
21	Snow and ice	155 485	14 925	9.6	0.5	21 320	13.7	2.1
22	Artificial surfaces	6 936	1731	25.0	0.1	463	6.7	0.0
23	No data	900	0	0.0	0.0	0	0.0	0.0
	Total	12 060 276	2745 027		100.0	1011 791		100.0

[1]Pixel size 1x1km, [2]TDP - total degrading pixels, [3]TIP - total improving pixels

Table 5. Degrading and improving areas by FAO 2008 land use systems

Code	*Land use system*	*Total pixels (TP)*	*Degrading pixels (DP)*	*DP/TP*	*DP/TDP*[1]	*Improving pixels (IP)*	*IP/TP*	*IP/TIP*[2]
		(5'x5')	(5'x5')	(%)	(%)	(5'x5')	(%)	(%)
0	Undefined	0	0	0.0	0.0	0	0.0	0.0
1	Forestry - not managed (natural)	9 643	4 402	45.6	14.0	226	2.3	2.0
2	Forestry - protected areas	1 635	767	46.9	2.4	47	2.9	0.4
4	Forestry - pastoralism moderate or higher	15 228	6 651	43.7	21.1	455	3.0	3.9
5	Forestry - pastoralism moderate or higher with scattered plantations	503	233	46.3	0.7	33	6.6	0.3
6	Forestry - plantations	226	109	48.2	0.3	28	12.4	0.2
7	Herbaceous - not managed (natural)	8 848	1 180	13.3	3.7	710	8.0	6.1
8	Herbaceous - protected areas	11 928	1 382	11.6	4.4	230	1.9	2.0
9	Herbaceous - extensive pastoralism	9 852	2 045	20.8	6.5	1 278	13.0	11.1
10	Herbaceous - moderately intensive pastoralism	5 824	937	16.1	3.0	1 056	18.1	9.1
11	Herbaceous - intensive pastoralism	13 115	3 519	26.8	11.2	1 663	12.7	14.4
13	Rain-fed agriculture (subsistence / commercial)	4 012	984	24.5	3.1	344	8.6	3.0
14	Agro-pastoralism - moderately intensive	2 151	396	18.4	1.3	241	11.2	2.1
15	Agro-pastoralism - intensive	11 657	2 632	22.6	8.3	1 159	9.9	10.0
16	Agro-pastoralism - moderately intensive or higher with large-scale irrigation	7 723	2 129	27.6	6.8	1 254	16.2	10.9
17	Agriculture – large-scale irrigation (> 25% pixel size)	2 009	752	37.4	2.4	182	9.1	1.6
18	Agriculture - protected areas	583	227	38.9	0.7	44	7.5	0.4
19	Urban areas	3 811	1 138	29.9	3.6	259	6.8	2.2
20	Wetlands - not managed (natural)	397	115	29.0	0.4	15	3.8	0.1
21	Wetlands - protected areas	60	11	18.3	0.03	0	0.0	0.0
22	Wetlands - mangroves	0	0	0.0	0.0	0	0.0	0.0
23	Wetlands - agro-pastoralism	0	0	0.0	0.0	0	0.0	0.0

24	Bare areas - not managed (natural)	16 915	635	3.8	2.0	786	4.6	6.8
25	Bare areas - protected	3 240	132	4.1	0.4	89	2.7	0.8
26	Bare areas - extensive pastoralism	5 918	594	10.0	1.9	894	15.1	7.7
27	Bare areas – moderately intensive pastoralism	1 742	210	12.1	0.7	461	26.5	4.0
28	Water - coastal or not managed (natural)	42	5	11.9	0.02	2	4.8	0.02
29	Water - protected areas	409	84	20.5	0.3	12	2.9	0.1
30	Water - inland fisheries	857	261	30.5	0.8	80	9.3	0.7
100	Undefined	2	0	0.0	0.0	0	0.0	0.0
	Total	138 330	31 530		100.0	11 548		100.0

[1]TDP - total degrading pixels; [2]TIP - total improving pixels

Table 6. Degrading/improving lands in the aggregated land use systems

Land use system (LUS)	**Codes**	**Total pixels (TP)** (5'x5')	**Degrading pixels (DP)** (5'x 5')	**DP/TP** (%)	**DP/TDP[1]** (%)	**Improving pixels (IP)** (5'x 5')	**IP/TP** (%)	**IP/TIP[2]** (%)
Forestry	1-6	27 235	12 162	44.7	38.6	789	2.9	6.8
Herbaceous	7-11	49 567	9 063	18.3	28.7	4 937	10.0	42.8
Agricultural land	13-18	28 135	7 120	25.3	22.6	3 224	11.5	27.9
Urban	19	3 811	1 138	29.9	3.6	259	6.8	2.2
Wetlands	20-23	457	126	27.6	0.4	15	3.3	0.1
Bare areas	24-27	27 815	1 571	5.6	5.0	2 230	8.0	19.3
Water	28-30	1 308	350	26.8	1.1	94	7.2	0.8
Undefined	0,100	2	0	0.0	0.0	0	0.0	0.0
Total		138 330	31 530		100.0	11 548		100.0

[1]TDP - total degrading pixels; [2]TIP - total improving pixels

3.10.2 Relationship with population density

About 35 per cent of the China's population (457 million out of 1 317 million) live in the degrading areas (Figure 14). There is no obvious correlation between land degradation and population density (r=0.04).

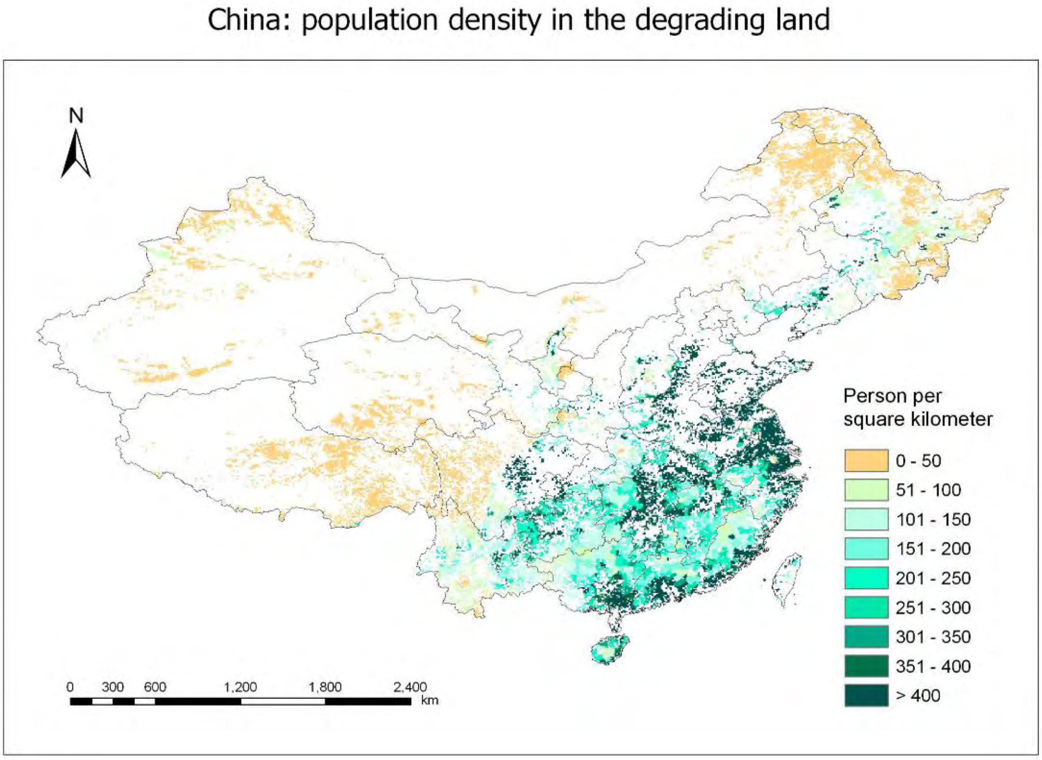

Figure 14. Population counts affected by the land degradation

3.10.3 Association with aridity

There is no correlation between degrading areas and Turc's aridity index (Jones 1997) (r^2 = 0.04); 80 per cent of degrading land is in the humid and cold-climate regions, 5 per cent in the semi-arid, 10 per cent in the dry sub-humid, and 5 per cent in the arid and hyper-arid regions.

3.10.4 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 would require more specific geo-located data.

4 What GLADA can and cannot do

- We have defined land degradation as a long-term loss of ecosystem function and we use net primary productivity (NPP) as an indicator. GLADA is an interpretation off GIMMS time series NDVI data, i.e. a measure of greenness, which is taken as a proxy for NPP. Translation of NDVI is robust but approximate.

- The proxy is several steps removed from recognisable symptoms of land degradation as it is commonly understood - such as soil erosion, salinity or nutrient depletion; the same goes for land improvement. Greenness is determined by several factors and, to interpret it in terms of land degradation and improvement, these other factors must be accounted for – in particular variability of rainfall and temperature and changes I land use and management, Rain-use efficiency (RUE, NPP per unit of rainfall) accounts for rainfall variability and, to some extent, local soil and land characteristics. 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. Taken together, the two indicators may provide a more robust assessment than either used alone. Alternatively, RESTREND points in the same direction: it shows much the same pattern as NDVI though with lesser amplitude. Land use change is not taken into account in this study owing to the lack of consistent time series data.

- Declining NPP, even allowing for climatic variability, may not even be reckoned as land degradation: urban development is generally considered to be *development* – although it generally means a long-term loss of ecosystem function; land use change from forest or grassland to cropland or rangeland is usually associated with a loss of NPP but it may or may not be accompanied by soil erosion, compaction and nutrient depletion, and it may well be profitable and sustainable , depending on management. Similarly, increasing NPP means greater biological production but may reflect, for instance, encroachment of bush or invasive species – which is not land improvement as commonly understood.

- The coarse resolution of the GIMMS data is a limitation: an 8km pixel integrates the signal from a wider surrounding area. Many symptoms of even severe degradation, such as gullies, rarely extend over such a large area; degradation must be severe indeed to be seen against the signal of surrounding unaffected areas.

- In the particular case of loess areas, continued soil loss and consequent river sediment loads is not detected by greenness. There are two issues here: first, historical land degradation - which is not detected by the trend of the last 25 years; secondly, the vegetation of many of these areas has stabilized or even improved, but significant soil loss is still taking place – as we can measure in the sediment loads of the rivers.

- As a quantitative estimate of land degradation, loss of NPP relative to the average trend has been calculated for those areas where both NPP and RUE are declining. This is likely to be a conservative estimate: where NPP is increasing but RUE is declining, some land degradation may have begun that is reducing NPP but is not yet reflected in declining NPP.

- By the same reasoning, RUE should be used alone for early warning of degradation or as a herald of improvement. Where NPP is rising but RUE is declining, some process of degradation may be under way which will remain undetected if we consider only those areas where both indices are declining. The reverse also holds true: we might not recognise promising interventions that increase RUE but have not yet brought about increasing NPP.

- GLADA presents a different picture from previous assessments of land degradation which compounded historical degradation with what is happening now. The data from the last 25 years indicate present trends but tell us nothing about the historical legacy; many degraded areas have become stable landscapes with a stubbornly low level of productivity. For many purposes, it is more important to address present-day degradation; much historical degradation maybe irreversible.

- Remote sensing provides only indicators of biomass productivity. The various kinds of land degradation and improvement are not distinguished; the patterns revealed by remote sensing should be followed up by fieldwork to establish the actual conditions on the ground and results are provisional until validated in the field. This is not straightforward: an 8km pixel cannot be checked by a windscreen survey and a 23-year trend cannot be checked by a snapshot. A rigorous procedure must be followed, as defined in the forthcoming *LADA Field Handbook.* Apart from systematically and consistently characterising the situation on the ground across a range of scales, the field teams may validate the GLADA interpretations by addressing the following questions:

    1. Is the biomass trend indicated by GLADA real?
    2. If so, does it correspond with physical manifestations of land degradation and improvement that are measurable on the ground?
    3. If the answer to either of the above questions is no, what has caused the observed trend?
    4. Is the mismatch a question of timing of observations – where the situation on the ground has subsequently recovered or reverted?

5 Conclusions

Land degradation and improvement have been assessed by remotely sensed indicators of biomass productivity. NDVI, the greenness index, is used as a proxy; it may be translated to net primary productivity. Decreasing and increasing trends may be interpreted as land degradation or improvement, respectively. Biomass depends on several factors. To interpret its trends in terms of land degradation and improvement, these other factors must be accounted for – in particular, variability of rainfall and changes in land use and management. Rain-use efficiency (RUE, NPP per unit of rainfall) accounts for rainfall variability. 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. Taken together, the two indicators may provide a more robust assessment than either used alone. Alternatively, RESTREND points in the same direction; it shows much the same pattern as the sum NDVI.

Land use change is not accounted for in this study for lack of access to consistent time series data. It will be investigated for specific *hot spots* and *bright spots* at the next stage of investigation.

As a quantitative measure of land degradation, loss of NPP relative to the normal trend has been calculated for those areas where *both* NPP and RUE are declining. This is likely to be a conservative estimate: where NPP is increasing but RUE is declining, some process of land degradation may have begun that is reducing NPP but is not yet reflected in a declining NPP trend. By the same reasoning, RUE should be used alone for *early warning* of land degradation, or a herald of improvement. Where NPP is rising but RUE declining, some process of land degradation might be under way that is not yet reflected in declining NPP; it will remain undetected if we consider only those areas where both indices are declining. The reverse also holds true: we might forgo promising interventions that increase RUE but have not yet brought about increasing NPP.

- In China, over the period of 1981-2003, degrading areas (defined as those suffering both decreasing NPP and RUE), occupy 23 per cent of the country, most conspicuously in southern China. Twenty one per cent of degrading land is arable (24 per cent of the total cultivated area), 39 per cent is forest, and 31 per cent is grassland and scrub. There is no correlation between land degradation and aridity: 80 per cent of degrading area is in the humid and cold-climate zones, 5 per cent in the semi-arid, 10 per cent in the dry sub-humid, and 5 per cent in the arid and hyper-arid zones.

- About 35 per cent of the China's population (457 million out of 1 317 million) live in the degrading areas.

- Land improvement (defined by increasing net primary productivity, rain-use efficiency and energy-use efficiency) is identified across 8 per cent of the country, mostly in the north and far west. 47 per cent of the improving land is grassland (about 10 per cent of the total grassland) and 25 per cent is arable.

- This assessment of land degradation and improvement presents a different picture from previous assessments of land degradation which compounded historical land degradation with what is happening now. The data from 1981-2003 indicate current trends but tell us nothing about the historical legacy; there is no doubt that large areas of dryland in the north of the country have suffered severe degradation in the past; although some of these areas now appear to be stable, they are still suffering substantial soil loss. However, GLADA draws 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.

- Remote sensing provides only indicators of trends of biomass productivity. 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.

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References

ADB 2002 *PRC National strategies for soil and water conservation, Final Report.* Asian Development Bank Technical Assistance TA 3548 (Draft)

ADB/GEF 2002 Partnerships on land degradation in dryland systems PRC-GEF project document

Bai ZG & DL Dent 2006 *Global assessment of land degradation and improvement: pilot study in Kenya.* ISRIC Report 2006/01, Wageningen

Bai ZG, DL Dent & ME Schaepman 2005 Quantitative global assessment of land degradation and improvement: pilot study in North China. ISRIC Rept 2005/06, Wageningen

Bai ZG, DL Dent, L Olsson & ME Schaepman 2008 *Global assessment of land degradation and improvement 1. identification by remote sensing.* Rept 2008/1, ISRIC – World Soil Information, Wageningen

Bastin GN, G Pickup & G Pearce 1995 Utility of AVHRR data for land degradation assessment - a case study. *International Journal of Remote Sensing* 16, 651-672

Beck C, J Grieser &d B Rudolf 2005 A new monthly precipitation climatology for the global land areas for the period 1951 to 2000. 181-190 in *Climate Status Report* 2004. German Weather Service, Offenbach

Berry L 2003 *Land degradation in China: its extent and impact* http://lada.virtualcentre.org/eims/download.asp?pub_id=92084 accessed 6September 2007

Brown ME, JE Pinzon, K Didan, JT Morisette & CJ Tucker 2006 Evaluation of the consistency of long-term NDVI time series derived from AVHRR, SPOT-Vegetation, SeaWIFS, MODIS and LandSAT ETM+. *IEEE Transactions on Geoscience and Remote Sensing* 44, 1787-1793

CIESIN 2004 *Global rural-urban mapping project*. Center for International Earth Science Information Network, International Food Policy Research Institute, the World Bank & Centro Internacional de Agricultura Tropical, Columbia University, Palisades NY http://sedac.ciesin.columbia.edu/gpw/ accessed 20 Dec 2006

CIESIN 2005 *Gridded population of the World: future estimates*. Center for International Earth Science Information Network Columbia University; United Nations Food and Agriculture Programme (FAO); and Centro Internacional de Agricultura Tropical (CIAT). Socioeconomic Data and Applications Center, Columbia University, Palisades NY http://sedac.ciesin.columbia.edu/gpw accessed 15 June, 2007.

Dregne HE 2002 Land degradation in the drylands. *Arid Land Research and Management* 16, 99-132

Engelen VWP van, JA Dijkshoorn & JRM Huting 2008 *Global assessment of land degradation and improvement 2. Soil and landform properties for SOTER units*. Rept 2008/02, ISRIC – World Soil Information, Wageningen

FAO 2008 Land use systems of the World. http://www.fao.org/geonetwork/srv/en/metadata.show. Accessed 15 June 2008

Fensholt R, I Sandholt & MS Rasmussen 2004 Evaluation of MODIS LAI, fAPAR and the relation between fAPAR and NDVI in a semi-arid environment using in situ measurements. *Remote Sensing of Environment* 91, 490–507

Fensholt R, I Sandholt, MS Rasmussen, S Stisen & A Diouf 2006 Evaluation of satellite-based primary production modelling in the semi-arid Sahel. *Remote Sensing of Environment* 105, 173-188

Gebremichael M & AP Barros 2006 Evaluation of MODIS gross primary productivity in tropical monsoon regions. *Remote Sensing of Environment* 100, 150–166

Heinsch FA, M Reeves, P Votava & others 2003 *User's guide: GPP and NPP (MOD17A2/A3) products NASA MODIS Land Algorithm Version 20.* University of Montana ftp://ftp.ntsg.umt.edu/pub/MODIS/TERRA/Mosaics accessed 1 Dec 2006

Houérou HN Le 1984 Rain-use efficiency: a unifying concept in arid-land ecology. *Journal of Arid Environments* 7, 213-247

Houérou HN Le 1989 *The grazing land ecosystems of the African Sahel*. Springer-Verlag, Berlin

Houérou HN Le, RL Bingham & W Skerbek 1988 Relationship between the variability of primary production and variability of annual precipitation in world arid lands. *Journal of Arid Environments* 15, 1-18

Illius AW & TG O'Connor 1999 On the relevance of nonequilibrium concepts to arid and semiarid grazing systems. *Ecological Applications* 9, 798–813

Jones JAA 1997 *Global hydrology: processes, resources and environmental management.* Longman, Harlow

JRC 2003 *Global Land Cover 2000 database*. European Commission, Joint Research Centre http://www-gemjrcit/glc2000 accessed 30 Aug 2006

Justice CO, JRG Townshend, EF Vermote & others 2002 An overview of MODIS Land data processing and product status. *Remote Sensing of Environment* 83, 3-15

Li Y 2000 Land resources in China. *China Land Press*. Beijing. 640pp

Li Z 2002 *Survey of the linkage between land degradation and poverty*. ADB Technical Assistance 3548 PRC

Liu J 2008 *Lessons of the Loess Plateau, it's our choice and Earth's hope*. http://www.earthshope.org/Lessons_of_the_Loess_Plateau.html accessed 15 May 2008

Liu JY, Buheaosier 2000 Study on spatial-temporal feature of modern land-use change in China: using remote sensing techniques. *Quaternary Sciences* 20, 229-239

Livezy RE & WY Chen 1983 Statistical field significance and its determination by Monte Carlo techniques. *Monthly Weather Review* 111, 46-59

Mitchell TD and PD Jones 2005 An improved method of constructing a database of monthly climate observations and associated high resolution grids. *International Journal of Climate* 25, 693-712

O'Connor TG, LM Haines & HA Snyman 2001 Influence of precipitation and species composition on phytomass of a semi-arid African grassland. *Journal of Ecology* 89, 850-860

Oldeman LR, RTA Hakkeling & WG Sombroek 1991 *World map of the status of human-induced soil degradation: An explanatory note*, second revised edition ISRIC, Wageningen

Plummer S 2006 On validation of the MODIS gross primary production product. *IEEE Transactions on Geoscience and Remote Sensing* 44, 7, 1936-1938

Running SW, FA Heinsch, M Zhao, M Reeves & H Hashimoto 2004 A continuous satellite-derived measure of global terrestrial production. *Bioscience,* 54, 547-560

Schneider U, T Fuchs, A Meyer-Christoffer & B Rudolf 2008 *Global precipitation analysis products of the GPCC, full data re-analysis product version 4.* Global Precipitation Climatology Centre, Deutscher Wetterdienst, Offenbach ftp://ftp-anon.dwd.de/pub/data/gpcc/html/fulldata_download.html accessed August 8 2008

SFA-PRC 2006 *Combating desertification, our common duty.* State Forest Administration, PR China

Singh D, MSP Meirelles, GA Costa & others 2006 Environmental degradation analysis using NOAA/AVHRR data. *Advances in Space Research* 37, 720-727

Snyman HA 1998 Dynamics and sustainable utilization of rangeland ecosystems in arid and semi-arid climates of southern Africa. *Journal of Arid Environments* 39, 645–666

Stoms DM & WW Hargrove 2000 Potential NDVI as a baseline for monitoring ecosystem functioning. *International Journal of Remote Sensing* 21, 401-407

Tucker CJ, HE Dregne & WW Newcomb 1991 Expansion and contraction of the Sahara Desert from 1980-1990. *Science* 253, 299-301

Tucker CJ, JE Pinzon & ME Brown 2004 *Global Inventory Modeling and Mapping Studies (GIMMS) Satellite Drift Corrected and NOAA-16 incorporated Normalized Difference Vegetation Index (NDVI), Monthly 1981-2002*. University of Maryland

Tucker CJ, JE Pinzon, ME Brown & others 2005 An extended AVHRR 8-km NDVI Dataset compatible with MODIS and SPOT vegetation NDVI data. *International Journal of Remote Sensing* 26, 4485-4498

Turner DP, WD Ritts, WB Cohen & others 2003 Scaling gross primary production (GPP) over boreal and deciduous forest landscapes in support of MODIS GPP product validation. *Remote Sensing of Environment* 88, 256–270

Turner DP, WD Ritts, WB Cohen & others 2006 Evaluation of MODIS NPP and GPP products across multiple biomes. *Remote Sensing of Environment* 102, 282–292

UNCED 1992 Managing fragile ecosystems: combating desertification and drought, Ch 12 *Agenda 21* UN Nations Conference on Environment and Development http://wwwunorg/esa/sustdev/documents/agenda21, accessed 5 Aug 2005

UNEP 2007 *Global Environmental Outlook GEO-4*, UN Environment Programme, Nairobi

Wessels KJ, SD Prince, J Malherbe & others 2007 Can human-induced land degradation be distinguished from the effects of rainfall variability? A case study in South Africa. *Journal of Arid Environments* 68, 271-297

Wessels KJ, SD Prince, PE Frost & D van Zyl 2004 Assessing the effects of human-induced land degradation in the former homelands of northern South Africa with a 1 km AVHRR NDVI time-series. *Remote Sensing of Environment* 91, 47-67

World Bank 2001 *China: air, land & water – environmental priorities for a new millennium.* World Bank, Washington DC

Xin ZB, Xu JX and Zhang W 2008 Spatiotemporal variations of vegetation cover on the Chinese Loess Plateau (1981-2006): impacts of climate change and human activities. *Science in China D: Earth Sciences* 51, 67-78

Ye YQ, Chen GJ and Fan H 2003 Impacts of the “grain for green” project on rural communities in the Upper Min River Basin, Sichuan, China. *Mountain Research and Development* 23, 345-352

Zhang k, Yu Z, Li X Zhou W and Zhang D 2007 Land use change and land degradation in China from 1991 to 2001. *Land degradation & development* 18, 209-219

Zhao M, FA Heinsch, RR Nemani & SW Running 2005 Improvements of the MODIS terrestrial gross and net primary production global data set. *Remote Sensing of Environment* 95, 164-176

Zhao M, SW Running & RR Nemani 2006 Sensitivity of Moderate Resolution Imaging Spectroradiometer (MODIS) terrestrial primary production to the accuracy of meteorological reanalyses. *Journal of Geophysical Research* 111, G01002, doi:10.1029/2004JG000004

Zhao S 1991 Natural hazards and melioration in northwest arid China. *Chinese Journal of Arid Land Research* 11, 3-10

Appendix 1: Analytical methods

Derivation of NDVI indicators

ArcGIS Spatial Analyst, ERDAS IMAGINE and ENVI-IDL were used to calculate NDVI minimum, maximum, maximum-minimum, mean, sum, standard deviation (STD) and coefficient of variation (CoV), as well as climate variables. The fortnightly NDVI data were geo-referenced and averaged to monthly; annual NDVI indicators were derived for each pixel; their temporal trends were determined by linear regression at an annual interval and mapped to depict spatial changes (Appendix 2).

A negative slope of linear regression indicates a decline of green biomass and a positive slope, an increase – except for STD and CoV which indicate trends in variability. The absolute change (Δ in map legends, titled "changes in .....") is the slope of the regression; the relative change (% in map legends, titled "trend in ....") is 100(slope of the regression/multi-year mean).

Monthly grids of rainfall for the period 1981-2002 were geo-referenced and re-sampled to the same spatial resolution as the NDVI (8km) using neighbourhood statistics. Spatial pattern and temporal trend of rainfall and rain-use efficiency (RUE, the ratio of annual NDVI and annual rainfall) for each pixel were determined by regression.

Land degradation was identified by negative trends of both biomass and rain-use efficiency. To distinguish between declining productivity caused by land degradation, and declining productivity due to other factors, rainfall variability has been accounted for by, first, identifying pixels where there is a positive relationship between productivity and rainfall; secondly, for those areas where productivity depends on rainfall, rain-use efficiency has been considered: where productivity declined but RUE increased, we attribute the decline of productivity to declining rainfall and those areas are masked. Land improvement was identified by positive changes in sum NDVI where show positive rain-use efficiency which has a positive correlation between sum NDVI and rainfall and energy-use efficiency. Both were masked by the mapped urban extents.

Statistical tests

The trend analysis assumes that the data are spatially and temporally independent. This was tested by examining autocorrelation coefficients following Livezy and Chen (1983). When the absolute values of the autocorrelation coefficients of lag-1 to lag-3 calculated for a time series consisting of n observations are not larger than the typical critical value corresponding to 5 per cent significance level, i.e., $1.96/\sqrt{n}$, the observations in this time series can be accepted as being independent from each other.

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

$$T = b / se(b)$$

Where *b* is the calculated 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 per cent confidence level; trends were labelled *high* if the *T*-values of the slope exceeded the 0.025 *p*-value of either tail of the distribution; lesser *T*- values were labelled *low*.

In addition, SPSS and MS Excel were employed to analyze trends, correlations and significances of the non-gridded variables.

Associations between land degradation/improvement and other variables

Maps of the negative trend in climate-adjusted NDVI were overlaid on the other maps. Corresponding comparative values were calculated, pixel-by-pixel and a univariate correlation calculated.

Appendix 2: NDVI indicators of the land degradation / improvement

Minimum NDVI: The lowest value that occurs in any one year (annual) - which is usually at the end of the dry season. Variation in minimum NDVI may serve as a baseline for other parameters.

Maximum or peak NDVI: Represents the maximum green biomass. The large spatial variations reflect the diverse landscapes and climate.

Maximum-minimum NDVI: The difference between annual maximum and minimum NDVI reflects annual biomass productivity for areas with one, well-defined growing season but may not be meaningful for areas with bimodal rainfall.

Sum NDVI: The sum of fortnightly NDVI values for the year most nearly aggregates annual biomass productivity.

Standard deviation (STD): NDVI standard deviation is the root mean square deviation of the NDVI time series values (annual) from their arithmetic mean. It is a measure of statistical dispersion, measuring the spread of NDVI values.

Coefficient of variation (CoV): CoV can be used to compare the amount of variation in different sets of sample data. NDVI CoV images were generated by computing for each pixel the standard deviation (STD) of the set of individual NDVI values and dividing this by the mean (M) of these values. This represents the dispersion of NDVI values relative to the mean value.

Temporal trends: The long-term trends of the indicators of biological productivity may be taken as indicators of land degradation (where the trend is declining) or land improvement (where the trend is increasing). A positive change in the value of a pixel-level CoV over time relates to increased dispersion of values, not increasing NDVI; similarly, a negative CoV dispersion – which is the case over nearly the whole country - means decreasing dispersion of NDVI around mean values, not decreasing NDVI.

The patterns and trends of all NDVI indicators for each pixel, determined by the slope of the linear regression equation, are depicted in Figures A1-7; their values are summarised in Table A1. No further analyses were made for these indicators except for the sum NDVI which is discussed in detail in the main text. It is recommended, however, that these maps should be considered in the field investigation - in particular the land use change during the study period (1981-2003).

Table A1. Statistics of NDVI indicators*

NDVI indicators	*NDVI values*			*Pixels (%)*		*% NDVI change/year*			*Δ NDVI/year*		
	min	*max*	*mean*	*Pos.*	*Neg.*	*Pos.*	*Neg.*	*mean*	*Pos.*	*Neg.*	*mean*
Minimum	0.090	0.207	0.154	58.3	41.7	1.113	0.900	0.274	0.0011	0.00104	0.00021
Maximum	0.434	0.991	0.528	44.7	55.3	0.599	0.336	0.082	0.00208	0.0018	-0.00006
Max-Min	0.265	0.487	0.374	42.6	57.4	0.808	0.667	-0.039	0.00223	0.00212	-0.00027
Mean	0.269	0.346	0.309	61.1	38.9	0.405	0.219	0.162	0.00081	0.00072	0.00022
Sum	3.228	4.156	3.711	61.1	38.9	0.405	0.219	0.162	0.00976	0.00864	0.00259
STD	0.089	0.160	0.125	48.6	51.4	0.785	0.654	0.046	0.00072	0.00064	0.00002
CoV	0.296	0.536	0.417	43.9	56.1	0.630	0.704	-0.119	0.00265	0.00241	-0.00019

*In the calculations of the min., max. and mean values of each NDVI indicator, an average value of the all pixels in the vegetated area, defined as areas with net primary productivity greater than 1 g C m^{-2} $year^{-1}$, were calculated. For example, *min.* value of the Maximum NDVI indicator: overlay statistic **minimum** of CELL STATISTIC in ArcMap was performed to extract minimum values of the time series annual Maximum NDVI for each pixel over the period (1981-2003), and the averaged **minimum** value of the maximum NDVI for all pixels was assigned as *min.* for the Maximum NDVI indicator; *max.* value of the Maximum NDVI indicator: overlay statistic **maximum** of CELL STATISTIC in ArcMap was performed to extract maximum values of the time series annual Maximum NDVI for each pixel over the period (1981-2003), and the averaged **maximum** value of the maximum NDVI for all pixels was assigned as *max.* for the Maximum NDVI indicator; *mean* value of the Maximum NDVI indicator: overlay statistic **mean** of CELL STATISTIC in ArcMap was performed to extract mean values of the time series annual Maximum NDVI for each pixel over the period (1981-2003), and the averaged **mean** value of the maximum NDVI for all pixels was assigned as *mean* for the Maximum NDVI indicator.

The rates of the positive and negative pixels were counted from the slope of the regression, i.e., positive slope (pos.) negative slope (neg.).

% NDVI change/year was calculated from the trend maps for each NDVI indicator: positive value (pos.) is the average of the all pixels with a positive trend; negative (neg.) is the average of the all pixels with a negative trend; mean value is the average of the all pixels; Δ NDVI/year is calculated the same as % NDVI change but from the absolute change maps.

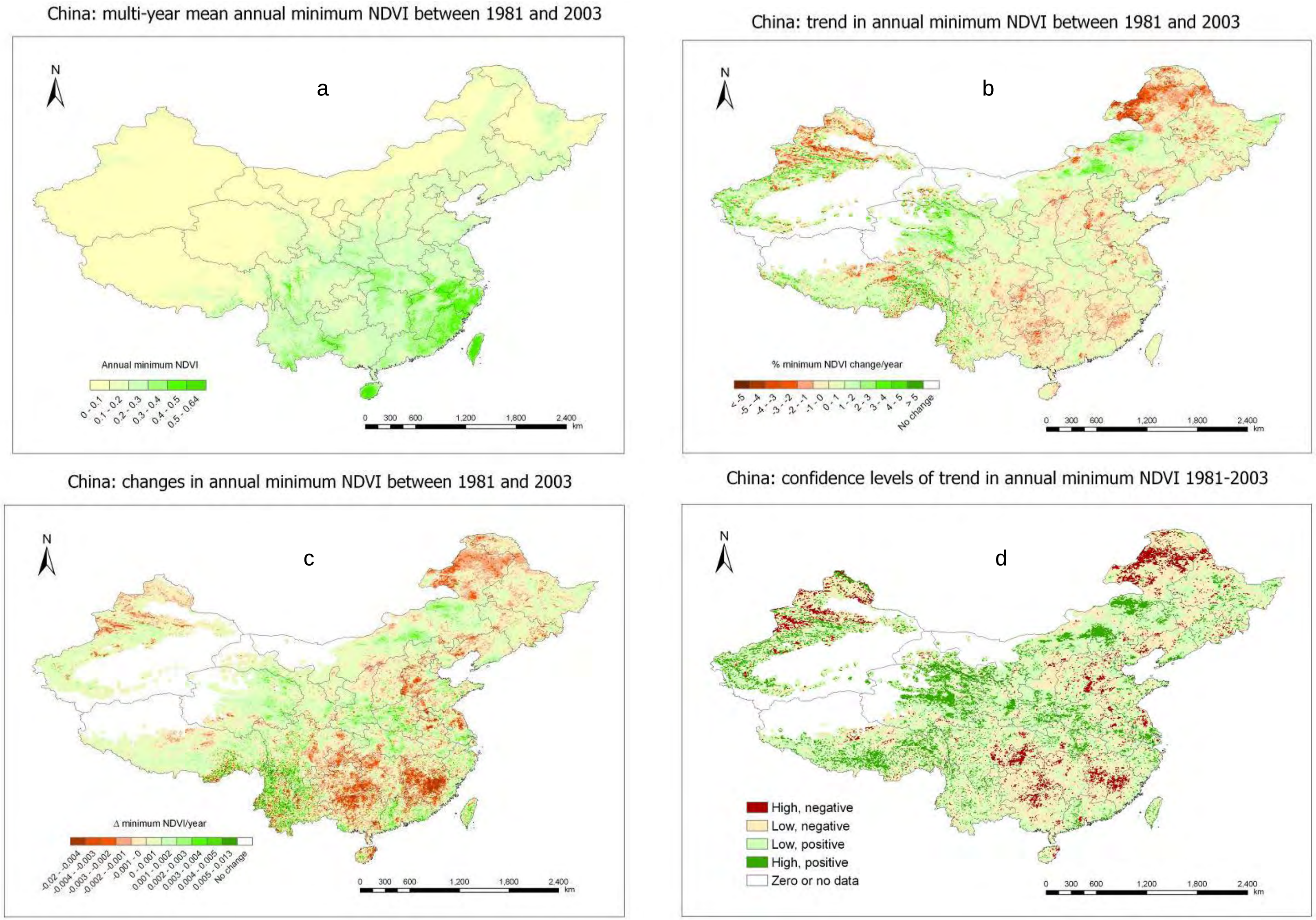

Figure A1. Annual minimum NDVI 1981-2003: mean (a) and trends (b – percentage, c – absolute. d - confidence levels)

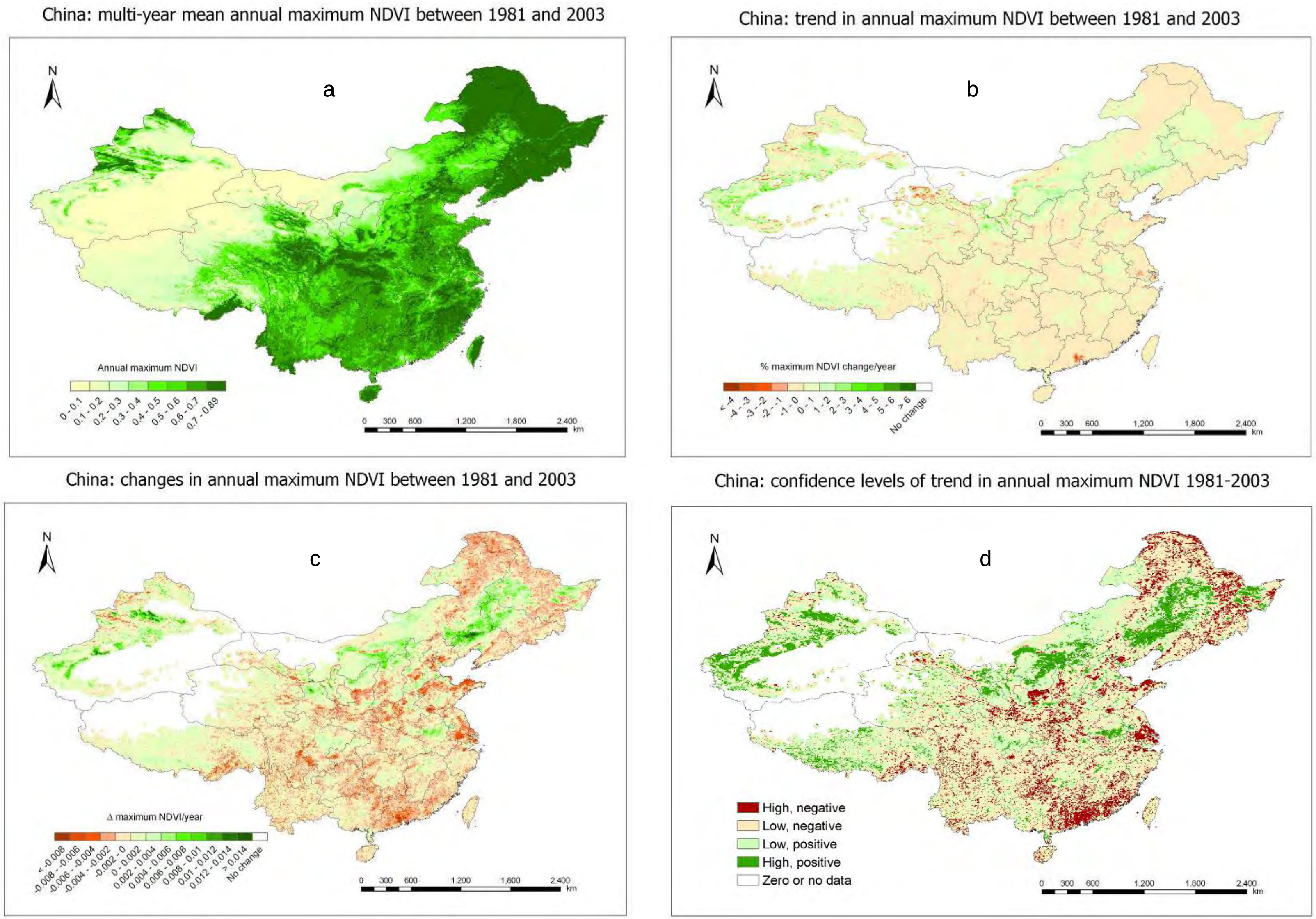

Figure A2. Annual maximum NDVI 1981-2003: mean (a) and trends (b – percentage, c – absolute, d - confidence levels)

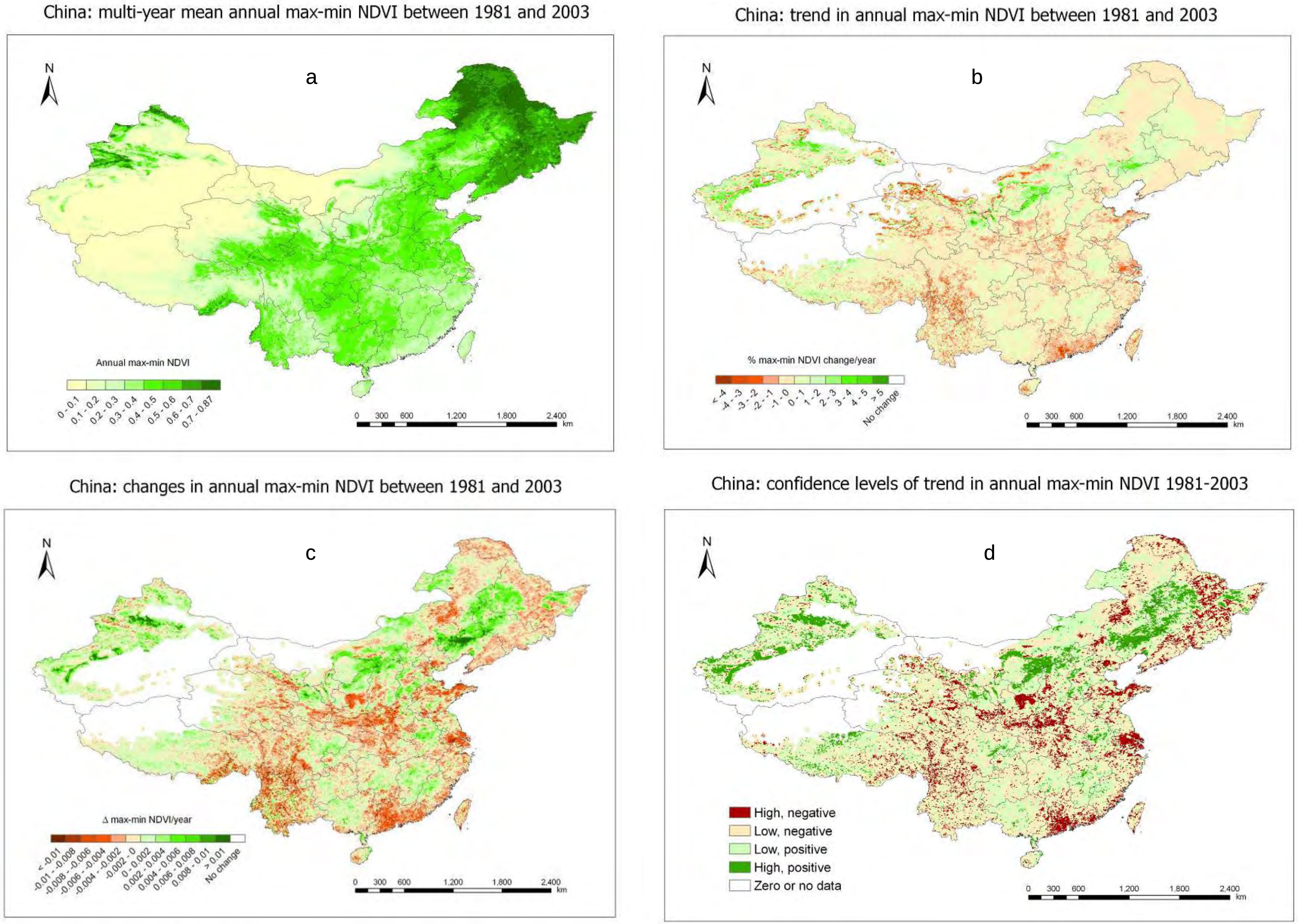

Figure A3. Annual maximum-minimum NDVI 1981-2003: mean (a) and trends (b – percentage, c – absolute, d - confidence levels)

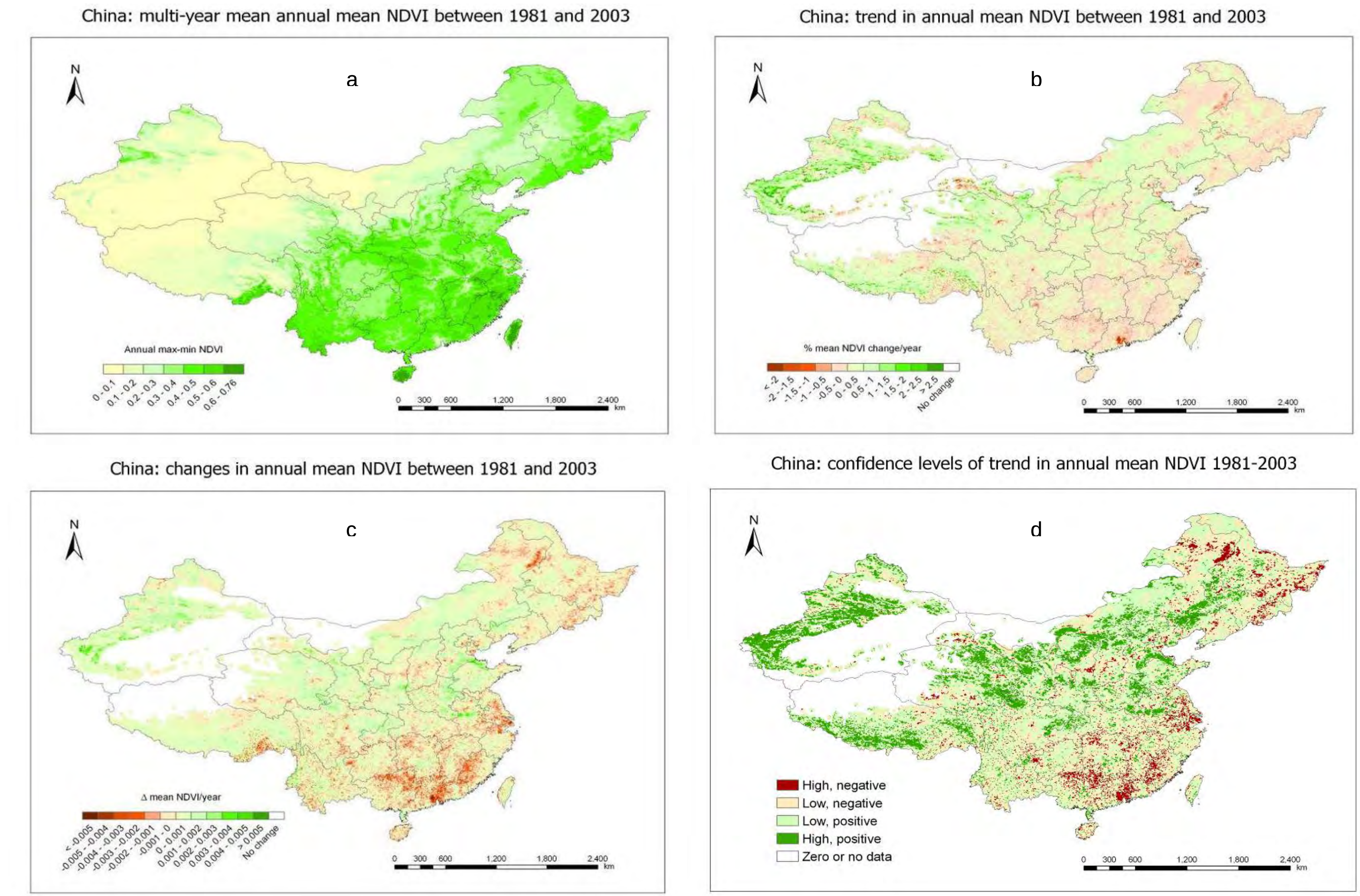

Figure A4. Annual mean NDVI 1981-2003: multi-year mean (a) and trends (b – percentage, c – absolute, d - confidence levels)

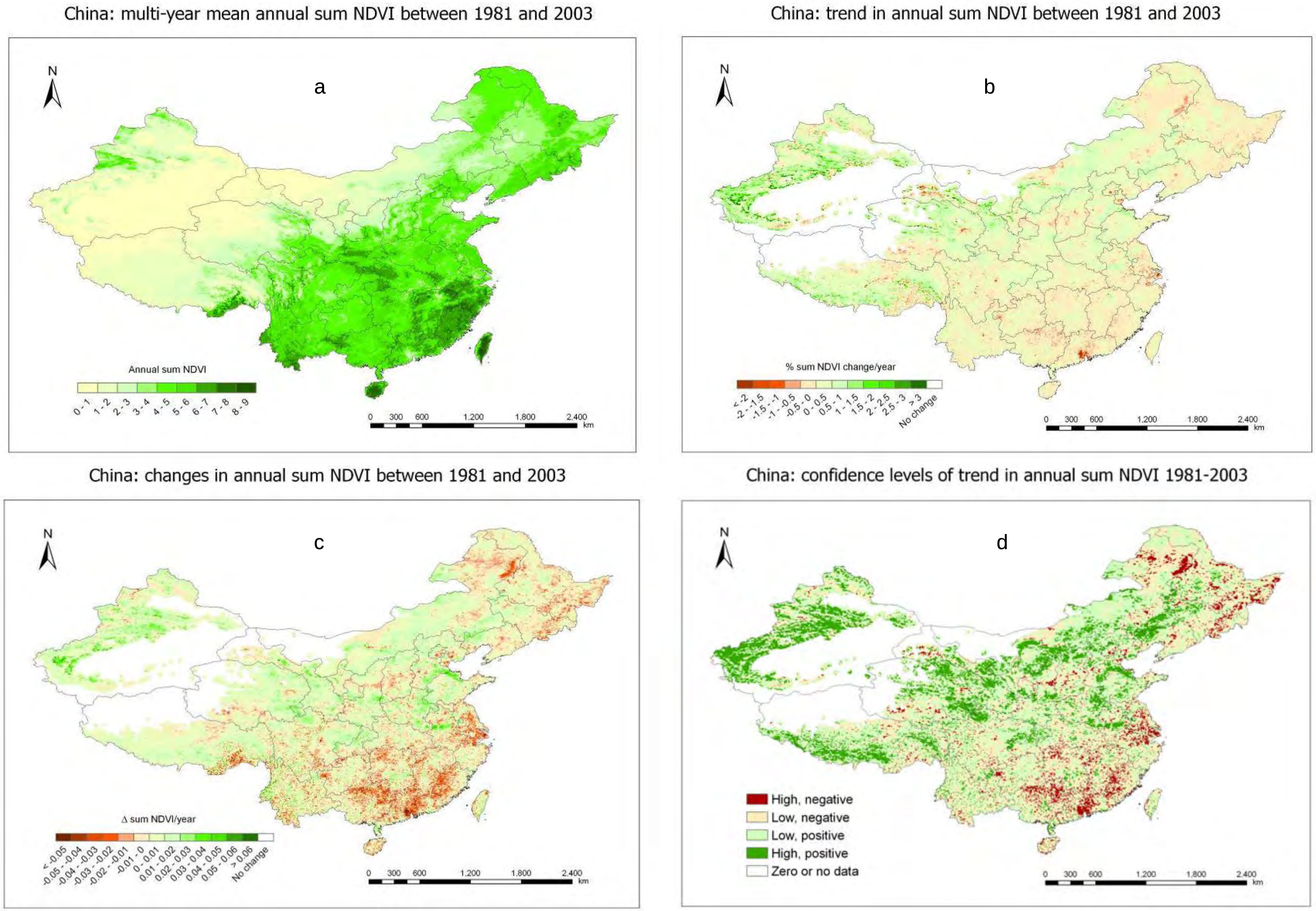

Figure A5. Annual sum NDVI 1981-2003: multi year mean (a) and trends (b – percentage, c – absolute, d – confidence level)

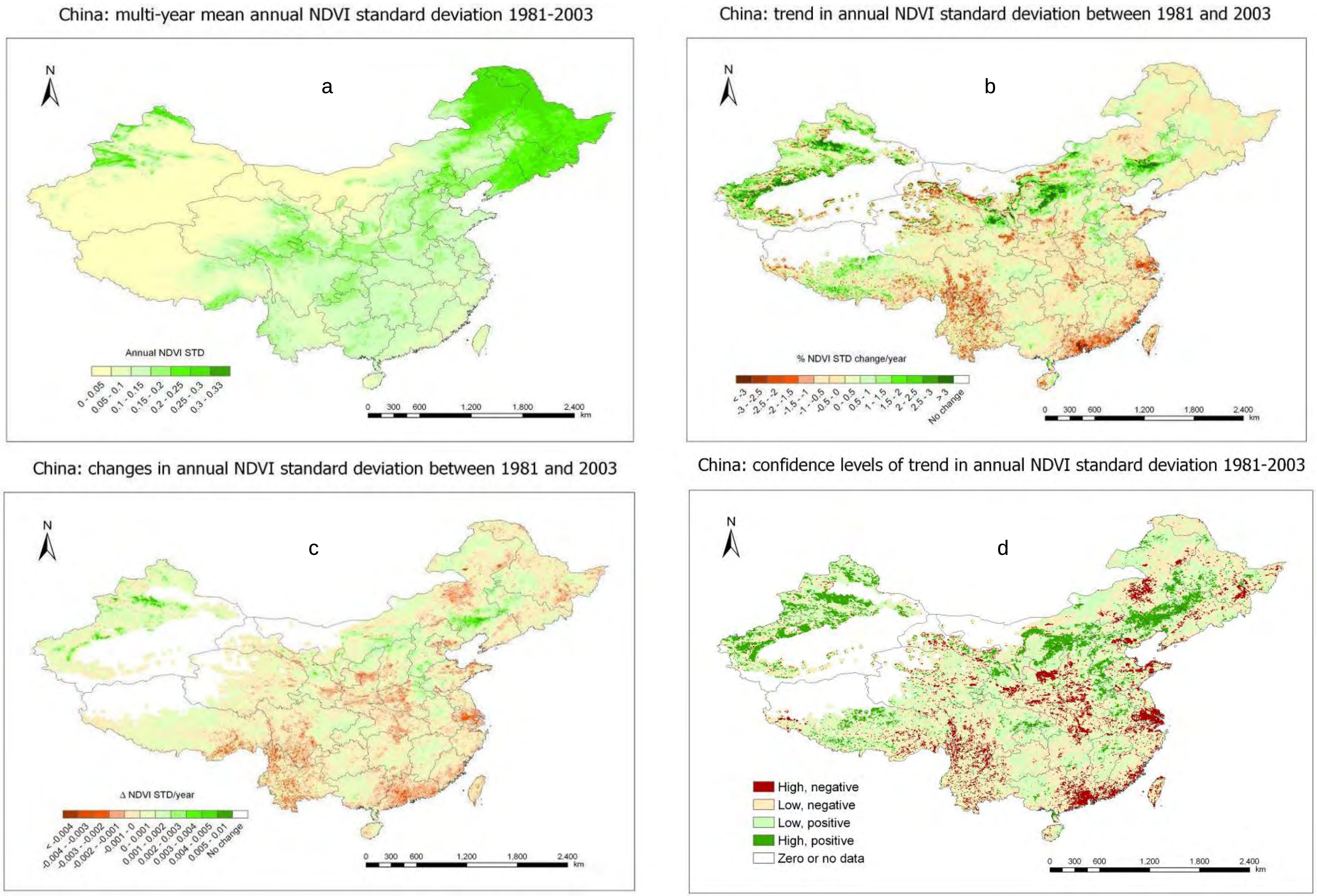

Figure A6. Annual NDVI standard deviation 1981-2003: mean (a) and trends (b – percentage, c – absolute, d - confidence levels)

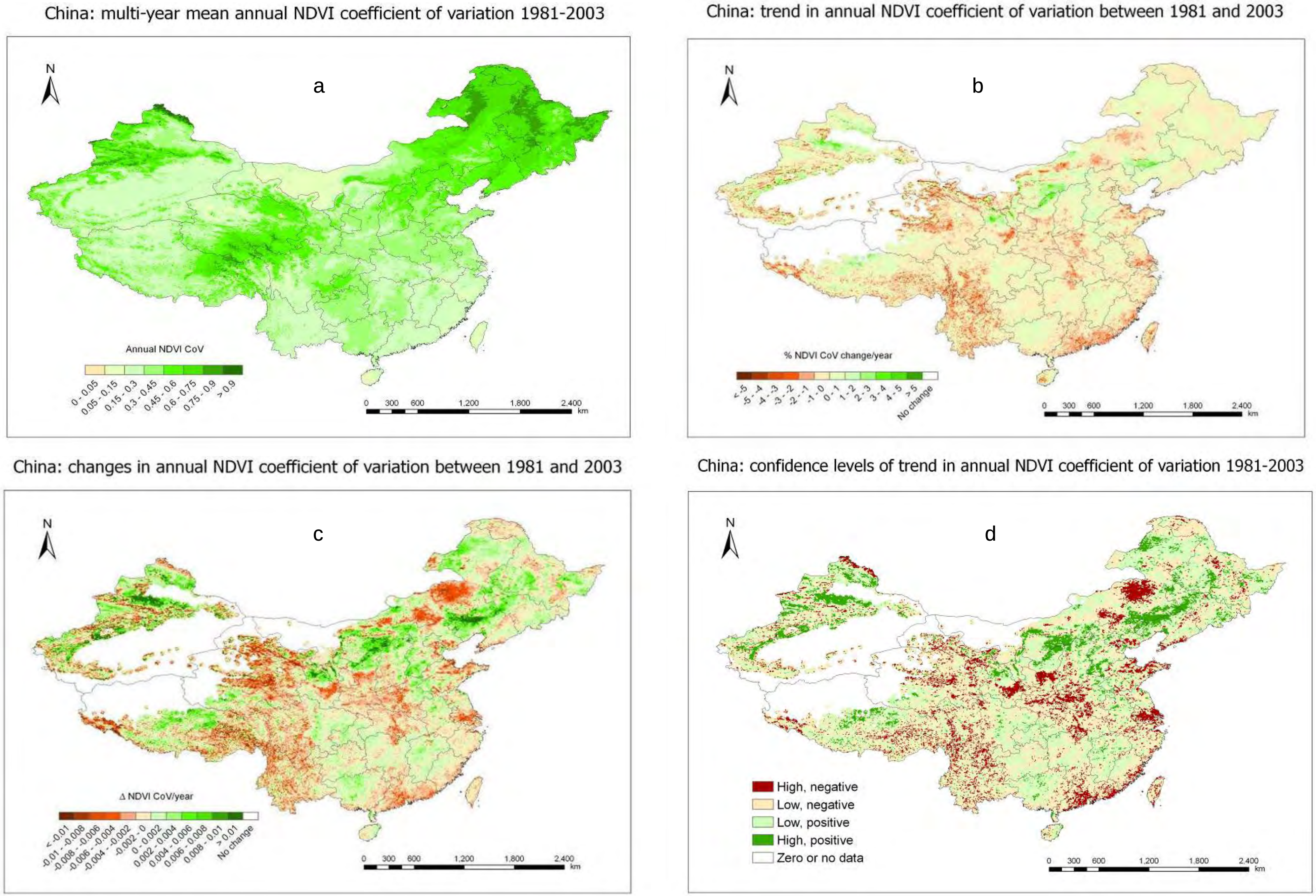

Figure A7. Annual NDVI coefficient of variation 1981-2003: mean (a) and trends (b – percentage, c – absolute, d - confidence levels)

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- *To undertake applied research on land and water resources.*