Land Degradation and Improvement in Argentina 1. Identification by remote sensing

ZG Bai DL Dent







FOOD AND AGRICULTURE ORGANIZATION OF THE UNITED NATIONS

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Inquiries: C/o Director, ISRIC – World Soil Information PO Box 353 6700 AJ Wageningen The Netherlands Telefax: +31-(0)317-471700 E-Mail: soil.isric@wur.nlT Web: www.isric.org

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 assess the state and trends of land degradation – identifying degrading areas and areas where degradation has been arrested or reversed. In the LADA partner countries, this screening by remote sensing 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 remotely-sensed normalized difference vegetation index (NDVI) or greenness index is used as a proxy indicator of productivity; it may be translated to net primary productivity (NPP). Spatial patterns and temporal trends of NDVI combined with climatic indices 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.
- 3. In Argentina, net primary productivity increased overall during the period of 1981-2003. Areas of decreasing climate-adjusted NPP occupy one third of the country: about half all cropland, including some of the most productive regions, and a quarter of grasslands. The degrading areas suffered an average loss of net primary productivity of 11.4 kgC ha⁻¹ year⁻¹.
- 4. 37 per cent of the population (14.5million out of 39.1million in 2005) live in the degrading areas.
- 5. There is some correlation between land degradation and aridity: 69 per cent of the degrading areas are in the humid regions, 13 per cent in the more restricted dry sub-humid, and 18 per cent in the semi-arid and arid regions.
- 6. Climate-adjusted net primary productivity increased across 16 per cent of the country: over 80 per cent of this land is grassland and scrub.

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

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Abbreviations

CIESIN	Center for International Earth Science Information Network, Colombia University, Palisades, NY
CoV	Coefficient of Variation
CRU TS	Climate Research Unit, Time Series
ENSO	El Niño/Southern Oscillation
FAO	Food and Agriculture Organization of the United Nations
GEF	The Global Environment Facility, Washington DC
GIMMS	The Global Inventory Modelling and Mapping Studies
GLADA	Global Assessment of Land Degradation and Improvement
GLASOD	Global Assessment of Human-Induced Soil Degradation
GPCC	The Global Precipitation Climatology Centre, German Meteorological Service, Offenbach
JRC	European Commission Joint Research Centre, Ispra, Italy
LADA	Land Degradation Assessment in Drylands
Landsat ETM+	NASA Land Resources Satellites, Enhanced Thematic Mapper
LUS	Land Use Systems, FAO
MOD17A3	MODIS 8-Day Net Primary Productivity dataset
MODIS	Moderate Resolution Imaging Spectroradiometer
NASA	National Aeronautics and Space Administration
NDVI	Normalized Difference Vegetation Index
NPP	Net Primary Productivity
RESTREND	Residual Trend of sum NDVI
RUE	Rain-Use Efficiency
SOTER	Soil and Terrain Database
SPOT	Système Pour l'Observation de la Terre
SPSS	Statistical Package for the Social Sciences Software
SRTM	Shuttle Radar Topography Mission
UNCCD	United Nations Convention to Combat Desertification
UNCED	United Nations Conference on Environment and Development
UNEP	United Nations Environment Programme
VASClimO	Variability Analyses of Surface Climate Observations

1 Introduction

Economic development, burgeoning cities and growing rural populations 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 Millennium Goals (UNCED 1992, UNEP 2007).

Quantitative, up-to-date information is needed to support policy development for food and water security, environmental integrity, and economic development. The only harmonized 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. Within the FAO program *Land Degradation Assessment in Drylands*, the *Global Assessment of Land Degradation and Improvement* (GLADA) maps *hot spots* of land degradation and *bright spots* of improvement according to change in net primary productivity (NPP, the rate of removal of carbon dioxide from the atmosphere and its conversion to biomass). In the next phase of the program, hot spots and bright spots will be further characterised in the field by national teams.

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 in studies of 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). However, remote sensing can provide only indicators of land degradation and improvement: a negative trend in greenness does not necessarily mean land degradation, nor does a positive trend necessarily mean land improvement. Greenness depends on several factors including climate (especially fluctuations in rainfall, temperature, sunshine and the length of the growing season), land use and management; changes 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 report, land degradation is identified by a declining trend in *both* NDVI and RUE; presented as RUE-adjusted NDVI, which may be translated to NPP values that are open to economic analysis. Comparable RESTREND values are presented as an additional layer of information. The pattern of land degradation is further explored by comparisons with land cover and land use, and socio-economic data.

2 Context and Method

2.1 GLADA partner country: Argentina

In Argentina, land degradation is severe and widespread, not only in drylands but also in the most productive parts of the country. It threatens food and water security, economic development, and natural resource conservation strategies. Overgrazing has led to the progressive elimination of palatable species from the high plateaux in the north to Patagonia. Woodcutting for timber, firewood, and charcoal has depleted the woodlands; for instance in the Gran Chaco it is now difficult to find good stands of *quebracho* that once grew everywhere. Soil erosion by wind and water plagues both rangeland and cropland; it has been an intractable problem, leading to abandonment of land, for example in NW of the country (UNEP 2007).

Spanish settlement in the 16th and 17th centuries brought woodcutting for mine timbers and fuel, localised overgrazing and cultivation of sloping lands, and consequent soil erosion. However, widespread land degradation dates from the 20th century. Burgeoning population, economic growth and globalisation ill-matched with land tenure systems have combined to put further pressure on the land.

Argentina is one of only 14 countries to have more than 1 million km² of dryland (WRI 2003). Drylands cover two-thirds of the country and support 9 million people - 30 per cent of the population (Naumann and Madariaga 2003, SAyDS 1997). Ranching is the most extensive land use but hardly any pasture improvement has been undertaken.

Extensive cropping has been accompanied by soil erosion by both water and wind. In 1963, an estimated 16 million hectares was affected by wind erosion, most seriously in the dry croplands in central Argentina; the situation has become worse since then although some progress has been made in stabilizing dunes. The most promising development has been the large-scale adoption of conservation tillage, which increases infiltration of rain into the soil compared with conventional ploughing; adoption rates in large farms are now better than 70 per cent although adoption is less on small farms.

Irrigation is economically important but salinization and waterlogging affect much of the irrigated land.

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 the AVHRR radiometer instrument on board US National Oceanic and Atmospheric Administration satellites. The fortnightly images at 8km-spatial resolution are corrected for calibration, view geometry, volcanic aerosols, and other effects not related to actual vegetation change (Tucker and others 2004). 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). GIMMS data from July 1981 to December 2003 were used for this study.

To provide a measure of land degradation and improvement that is open to economic analysis, the GIMMS NDVI time series has 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 interannual 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. It is compiled on the basis of long, quality-controlled station records, gridded at resolution of 0.5° , from 9 343 stations (Beck and others 2005), about 60 in Argentina. For the period up to 2003, rainfall data are supplemented by the GPCC full data re-analysis product (Schneider and others 2008) to provide monthly rainfall values to match 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 also 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 Argentina (Figure 1) and used for preliminary comparison with NPP trends. Likewise, land use data have been derived from *Land use systems of the World* (FAO 2008).



Figure 1. Main land cover types (JRC 2003)

2.2.4 Soil and terrain

An updated soil and terrain database for Argentina at scale at 1:1M has been prepared (Engelen and others 2008). This will be used in the next phase of investigations for analysis of relationships between land degradation, soils and landforms.

2.2.5 Population, urban areas and poverty indices

The 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 data for population and, as proxies for poverty, rates of infant mortality and child underweight status at 2.5 arc-minutes CIESIN 2005) were compared with indices of land degradation.

2.2.6 Aridity index

Turc's aridity index was calculated as the formula P/PET where P is annual precipitation in mm and $PET = P/\sqrt{(0.9 + (P/L)^2)}$ where L = 300 + 25T + 0.05T³ where T is mean annual temperature (Jones 1997). Precipitation was taken from the gridded VASClimO data, mean annual temperature from 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 (beginning October 1 through the following September) 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

Land degradation and improvement are identified by a sequence of analyses of remotely sensed data:

- 1. Simple NDVI indicators: NDVI minimum, maximum, maximum-minimum, mean, sum, standard deviation and coefficient of variation are computed for the period October to the following September, encompassing a complete growing season. Their trends are analysed over the 23-year period of the GIMMS data (Appendix2).
- 2. Annual sum NDVI, representing the aggregated greenness over the biological year, is chosen as the standard proxy for annual biomass productivity. NDVI is translated to net primary productivity (NPP) by correlation with MODIS data; trends are calculated by linear regression.

- 3. To distinguish between declining productivity caused by land degradation and declining productivity caused by rainfall variability, the following procedure was adopted;
 - a. Identify the areas where there is a positive relationship between productivity and rainfall, i.e. where rainfall determines NPP;
 - b. For those areas where rainfall determines productivity, RUE was considered: where productivity declined but RUE increased, declining productivity was attributed to declining rainfall and those areas were masked;
 - c. For the remaining areas with a positive relationship between NDVI and rainfall, and for all areas where there is a negative relationship between NDVI and rainfall (humid and irrigated areas where rainfall does not determine NPP), NDVI trend has been calculated as *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. Residual trends of NDVI (RESTREND);
- 5. Energy-use efficiency the ratio of annual sum NDVI to accumulated temperature;
- 6. Stratification of the landscape according to land cover and land use, aridity index, and calculation of the loss of NPP, e.g. for various land use types or for all degrading areas; urban areas are masked;
- 7. Comparison of indices of land degradation with rural population density and poverty.

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

At the next stage of analysis, areas of land degradation and improvement identified on the basis of NDVI indices will be characterised manually, using 30m-resolution Landsat data, to identify the probable kinds of land degradation, and comparison will be made with updated soil and terrain data. 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 the identified areas of degradation and 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 annual green biomass productivity.

3.1 Trends in biomass productivity

Biomass productivity fluctuates in concert with rainfall. Countrywide, there has been increasing trend in biomass productivity over the period of 1981-2003 (Figure 2, Appendix 2, and Table A1).



Figure 2. Spatially aggregated annual sum NDVI 1981-2003, p<0.01 Years run from 1 October through the following September

Figure 3 maps 23-year mean annual sum NDVI and trends over the period 1981-2003, determined for each pixel by the slope of the linear regression equation. The annual sum NDVI increased across 54 per cent of the country and decreased over 46 per cent. Decrease was most marked in the productive north-eastern regions.



Argentina: multi-year mean annual (October - following

Argentina: change in annual (October - following September) sum NDVI between 1981 and 2003





-2 - -1.5

-1.5 - -1

-1 - -0.5

-0.5 - 0

0 - 0.5

0.5 - 1

1 - 1.5

1.5 - 2

0 or nodata

900 1,200

>2

Argentina: confidence levels of trend in annual (October - following September) sum NDVI between 1981 and 2003

Jal and

150 300

600



Figure 3. Annual sum NDVI 1981-2003: mean (a) and trends (b – percentage change, c – absolute change, d - confidence levels) Years run from 1 October through the following September

3.2 Spatial patterns of biomass and rainfall

Biomass fluctuates according to rainfall, season and stage of growth, and changes in land use, as well as according to land quality. Across most of the country, biomass productivity (represented by sum NDVI in Figure 3a) is clearly related to rainfall (Figure 5a) which has varied significantly, both cyclically (Figure 4) and spatially (Figure 5b, c) over the period. Statistics show a moderate correlation between NDVI and annual rainfall at a pixel level:

NDVI_{ann. sum} =
$$0.00381$$
*Rainfall [mm yr⁻¹] + 1.9273 (r = 0.63, n=52 979) [1]

Error in the regression model [1] is: slope $(0.00381) \pm 0.00004$; intercept $(1.9273) \pm 0.032192$.



Figure 4. Spatially aggregated annual rainfall 1981-2003 Years run from 1 October through the following September

Over the study period, rainfall increased nearly 60 per cent of the country (with an annual rate of 4mm), across Jujuy, Salta, central Neuquén and northern Santa Cruz. At the same time, rainfall decreased over some 40 per cent (average rate of 6.5mm/yr) (Figure 5b and c). Overall, there was slight decreasing trend in annual rainfall (Figure 4).

The correlation between spatially aggregated annual sum NDVI (all pixels) and annual rainfall (all pixels) is low (Figure 6).

Argentina: trends in annual (October - following September) rainfall between 1981 and 2003



а Annual rainfall (mm) (Oct-following Sep) < 100 100 - 300 300 - 600 600 - 900 900 - 1,200 1,200 - 1,500 1,500 - 1,800 1,800 - 2,100 2,100 - 2,400 > 2,400 3780 900 1,200 0 150 300 600

Argentina: confidence levels of trend in annual (October - following September) rainfall between 1981 and 2003



Figure 5. Annual rainfall 1981-2003: spatial pattern (a) and trends (b – percentage change, c – absolute change, d- confidence levels) Years run from 1 October through the following September

Argentina: multi-year mean annual (October - following September) rainfall between 1981 and 2003

N



12

Argentina: changes in annual (October - following September) rainfall between 1981 and 2003





Figure 6.Relationship between annual sum NDVI (all pixels) and annual rainfall
(all pixels), each dot represents one year, p<0.01
Years run from 1 October through the following September

3.3 Rain-use efficiency

The effect of fluctuations in rainfall on biomass productivity may be taken into account by considering rain-use efficiency (RUE), i.e. production per unit of rainfall. RUE may fluctuate dramatically in the short term - often, there is a sharp decline in RUE in a wet year and we may assume that the vegetation, whether cultivated or semi-natural, cannot make immediate use of the additional rain. However, where rainfall is the main limiting factor on biomass productivity, we judge that 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). RUE 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 measurements of net primary productivity, which are not easy to obtain. For Argentina, RUE was calculated as the ratio of annual sum NDVI and station-observed annual rainfall.

Figure 7 shows mean annual RUE and its trend over the period of 1981-2003: RUE is generally higher in the drylands than the humid areas - which generate drainage to streams and groundwater (Figure 7a); over the period 1981-2003, RUE decreased over half of the country and increased over the other half. Confidence levels are assessed by the T-test.

Argentina: trend in annual (October - following





Argentina: confidence of trend in annual (October - following September) rain-use efficiency between 1981 and 2003



Figure 7. Rain-use efficiency 1981-2003: mean (a) and trends (b - percentage change, c - absolute change, d - confidence levels) Years run from 1 October through the following September

Areas of declining RUE include Buenos Aires, Entre Rios, Santa Fe, Cordoba, San Juan, Misiones, eastern La Pampa, eastern Rio Negro, NW La Rioja and SW Catamarca; significantly, several of these are humid, highly productive areas.

3.4 RESTREND

Countrywide, there is a significant negative correlation between RUE and rainfall $(r=-0.53, n=52\ 979)$ and RUE fluctuates from year to year; used in isolation, RUE says as much about rainfall variability as about land degradation. To avoid the correlations between RUE and rainfall and so distinguish land degradation from the effects of rainfall variability, Wessels and others (2007) suggest the alternative use of residual trends (RESTREND).

Following their general procedure, we have correlated for each pixel annual sum NDVI and annual rainfall (with the year running from October 1 through the following September to include the entire growing season). The resulting regression equation represents the statistical association between observed sum NDVI and rainfall (Figure 8a, b); the model predicts sum NDVI according to rainfall. Residuals of sum NDVI (i.e. differences between the observed and predicted sum NDVI) for each pixel were calculated, 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 but the spatial distribution is different from RUE; overall, RESTREND patterns are remarkably close to sum NDVI but of lesser amplitude (Figure 3c), see Section 3.8.



Argentina: residual trend in sum NDVI (October



Argentina: confidence of residual trend in sum NDVI (October - following September) between 1981 and 2003



Figure 8. Residual trend of sum NDVI (RESTREND) 1981-2003

Years run from 1 October through the following September, (a) Correlation coefficient between sum NDVI and annual rainfall; (b) Slope of linear regression between sum NDVI and rainfall; (c), RESTREND; (d) Confidence levels of RESTREND

3.5 Net primary productivity

It is hard to visualise the degree of land degradation and improvement from NDVI values. To estimate their quantitative effects, 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 (at 1km resolution from the year 2000). Figure 9a shows four-year (2000-2003) mean annual MODIS NPP at 1-km resolution; the pattern is similar to the GIMMS annual sum NDVI (Figure 3a) but at 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 resampled to 8km resolution by nearest neighbour assignment; the four-year mean annual sum NDVI over the same period (2000-2003) was then calculated. Correlation between the two data sets is high:

$$NPP_{MOD17} [tonneC ha^{-1} year^{-1}] = 0.9296 * NDVI_{sum} + 0.24898$$
[2]

$$(r^2 = 0.78, n = 51763, P < 0.001)$$

Where NPP_{MOD17} is annual net primary productivity derived from MOD17, NDVI_{sum} is a four-year (2000-2003) mean annual sum NDVI derived from GIMMS. Error in the regression model [2] is: slope (0.9296) \pm 0.00457; intercept (0.25898) \pm 0.0238. The high coefficient of variation (r²) 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 and c; the confidence level (Figure 9d) refers to the T-test (Appendix 1). During the period, NPP increased overall (Table 1).

Table 1. Changes in net primary productivity 1981-2003

	Positive	Negative	Mean
Land area (pixels, %)	53	47	
% NPP change/year (tonneC ha ⁻¹ year ⁻¹)	0.37	0.21	0.10
Δ NPP (kg C ha ⁻¹ year ⁻¹)	12.2	11.5	1.0



Argentina: mean ann. net primary productivity 2000-2003



Argentina: change in ann. net primary productivity 1981-2003

С



Argentina: confidence of trend in net primary productivity 1981-2003

Ν

Figure 9. Net primary productivity 1981-2003: mean (a) and trends (b, % change; c, absolute change; d, confidence level)

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.

Rainfall variability: 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 depicts the negative trend of RUE-adjusted NDVI 1981-2003, which affected one third of the country, mostly in the north-east.



Argentina: proxy assessment of land degradation 1981-2003

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

Quantitative estimation: Figure 11, Table 2 present a pixel-based estimate of the loss of NPP compared with the average over the period 1981-2003.



Argentina: loss of NPP in degrading land 1981-2003

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

	Degrading land (km²)	% territory	% global degrading land	NPP loss (kg C/ha/yr)	Total NPP loss (Tonne C/23yr)
Argentina	902 438	32.6	3.1	11.4	23 556 380
The World	35 058 104	23.5	100	11.8	955 221 419

Comparison between RUE-adjusted NDVI and RESTREND: For Argentina, the two indicators of land degradation show very similar patterns (compare Figures 10 and 8c). Negative RESTREND encompasses a somewhat larger area than negative RUE-adjusted NDVI, see Section 3.9.

Land use change: As with rainfall variability, land use change may generate false alarms about land degradation. 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. Lack of consistent time series data for land use and management precludes a generalised analysis of land use change but this can be undertaken manually for the potential *hot spots* identified in this analysis.

3.7 Land improvement

Land improvement is identified by combination of: 1) a positive trend in sum NDVI for those areas where there is a no correlation between rainfall and NDVI; 2) for areas where NDVI is correlated with rainfall, a positive trend in rain-use efficiency; and 3) a positive trend in energy-use efficiency (Figure 12). Urban areas are masked. These areas account for about 16 per cent of the country. Figure 13 shows the gain in NPP in those areas.





Figure 12. Areas of increasing NPP, RUE and EUE, 1981-2003



Argentina: gain of NPP in improving land 1981-2003

Figure 13. NPP gain in the improving areas 1981-2003

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 involves sealing of the land surface, it is degradation according to our criterion of loss of loss of ecosystem function. The *Global Rural Urban Mapping Project* shows 2 per cent of the country as urban. These areas are masked, which makes only a small difference to the results: a reduction of 1 per cent in degrading land, and a reduction of 0.6 per cent in improving land.

3.9 Comparison of indicators

Countrywide, there is a similar pattern of trend in sum NDVI and RESTREND (Table 3). About 37 per cent of land area shows negative trend of both sum NDVI and RESTREND, 50 per cent shows positive trend of both indicators, 2 per cent shows no change, but 12 per cent gives mixed signals - either positive sum NDVI and negative RESTREND, or vice versa. If we take a negative RUE-adjusted NDVI as the

primary definition of degrading areas, then 92 per cent of the degrading land shows negative trends in both sum NDVI and RESTREND. Taking a positive trend in RUEadjusted NDVI as the primary definition of improving land, then 93 per cent of the improving land shows positive trend in both sum NDVI and RESTREND

Comparing RUE with RESTREND, 27 per cent of the country shows negative trend in both RUE and RESTREND, 38 per cent shows positive trend in both RUE and RESTREND, 2 per cent shows no change , but 33 per cent gives mixed signals - either positive RUE and negative RESTREND, or vice versa. Eighty per cent of the degrading area shows negative trends in both RUE and RESTREND, and almost all of the improving area shows positive trends in both RUE and RESTREND.

Indicators	Total pixel	Negative trend	Positive trend	No change	Mixed
	(%)	(%)	(%)	(%)	(%)
Annual sum NDVI	100	45.6	53.0	1.4	0.0
RESTREND ¹	100	40.2	57.9	1.9	0.0
Sum NDVI N RESTREND	100	37.0	49.6	1.4	12.0
Sum NDVI ${\ensuremath{}}$ RESTREND within LD^2		91.7			
Sum NDVI ${\ensuremath{\bigcap}}$ RESTREND within ${\ensuremath{\text{LI}}}^3$			92.9		
RUE	100	47.4	50.6	1.9	0.0
RUE ∩ RESTREND	100	27.1	37.6	1.9	33.4
RUE î RESTREND within LD		80.2			
RUE î RESTREND within LI			100.0		

Table 3. Comparison of trends in sum NDVI, RUE, RESTREND, and linkage to degrading/improving lands, 1981-2003

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 Association with land cover and land use

Comparing degrading and improving areas with land cover (Table 4): 17 per cent of degrading land is cropland and a further 15 per cent mosaic of cropland with other land covers, so at least half of the arable is affected; 47 per cent of degrading land is scrub and grassland; 19 per cent is forest. Over 80 per cent of the improving land is grassland and scrub; only 4 per cent is cropland with a further 4.5 per cent mosaic of cropland with other land cover.

Comparing degrading areas with global land use systems (Table 5): 30 per cent is agricultural land, 40 per cent is rangeland, and 18 per cent forestry. Most improving land is rangeland, only 9 per cent is agricultural land and 8 per cent is under forestry (Table 6).

Table 4. Degrading and improving land by land cover

Code	Land cover	Total pixels ¹ (TP)	Degrading pixels (DP) ²	DP/TP	DP/TDP ³	Improving pixels (IP)	IP/TP	IP/TIP ⁴
				(%)	(%)		(%)	(%)
1	Tree cover, broadleaved evergreen	137 739	54132	39.3	5.1	12566	9.1	2.3
2	Tree cover, broadleaved deciduous, closed	368 646	140622	38.1	13.4	24901	6.8	4.6
3	Tree cover, broadleaved deciduous, open	24 918	5819	23.4	0.6	4346	17.4	0.8
6	Tree cover, mixed leaf type	3 251	197	6.1	0.02	204	6.3	0.04
7	Tree cover, regularly flooded, fresh water	134	50	37.3	0.005	0	0.0	0.0
8	Tree cover, regularly flooded, saline water	1 629	815	50.0	0.1	0	0.0	0.0
11	Shrub cover, evergreen	10 025	5506	54.9	0.5	934	9.3	0.17
12	Shrub cover, deciduous	588 506	107273	18.2	10.2	178979	30.4	32.8
13	Herbaceous cover,	191 739	74163	38.7	7.0	19086	10.0	3.5
14	Sparse herbaceous or sparse shrub cover	1 202 945	245025	20.4	23.3	236284	19.6	43.3
15	Regularly flooded shrub and/or herbaceous cover	131 211	63610	48.5	6.0	11077	8.4	2.0
16	Cultivated and managed areas	336 955	174775	51.9	16.6	22587	6.7	4.1
17	Mosaic: cropland/tree cover/other natural vegetation	71 525	37317	52.2	3.5	4722	6.6	0.9
18	Mosaic: cropland/shrub and/or grass cover	217 042	118406	54.6	11.3	19578	9.0	3.6
19	Bare areas	154 936	24163	15.6	2.3	10207	6.6	1.9
20	Water bodies	63 724	0	0	0	0	0	0
21	Snow and ice	9 404	0	0	0	0	0	0
22	Artificial surfaces	1 850	186	10.1	0.02	70	3.8	0.01
	Total	3 516 179	1052059		100	545541		100

¹ Pixel size 1x1km, ² Urban extents are excluded, ³ TDP - Total degrading pixels, ⁴ TIP - Total improving pixels

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

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)	2 862	985	34.4	8.0	229	8.0	3.6
2	Forestry - protected areas	243	45	18.5	0.4	24	9.9	0.4
4	Forestry - pastoralism moderate or higher	2 850	1 190	41.8	9.7	230	8.1	3.7
5	Forestry - pastoralism moderate or higher with scattered plantations	10	1	10.0	0.01	1	10.0	0.02
6	Forestry - scattered plantations	35	11	31.4	0.1	2	5.7	0.03
7	Herbaceous - not managed (natural)	1 406	271	19.3	2.2	147	10.5	2.3
8	Herbaceous - protected areas	860	99	11.5	0.8	176	20.5	2.8
9	Herbaceous - extensive pastoralism	12 359	2 573	20.8	21.0	2 499	20.2	39.7
10	Herbaceous - moderately intensive pastoralism	5 293	842	15.9	6.9	1 553	29.3	24.7
11	Herbaceous - intensive pastoralism	2 546	1 135	44.6	9.3	489	19.2	7.8
13	Rain-fed agriculture	835	345	41.3	2.8	52	6.2	0.8
14	Agro-pastoralism - moderately intensive	1 810	705	39.0	5.8	198	10.9	3.1
15	Agro-pastoralism - intensive	4 084	2 516	61.6	20.5	253	6.2	4.0
16	Agro-pastoralism with large-scale irrigation	32	5	15.6	0.04	4	12.5	0.1
17	Agriculture - large scale irrigation (> 25% pixel size)	162	54	33.3	0.4	30	18.5	0.5
18	Agriculture - protected areas	18	4	22.2	0.0	4	22.2	0.1
19	Urban areas	826	323	39.1	2.6	48	5.8	0.8
20	Wetlands - not managed (natural)	1 389	669	48.2	5.5	118	8.5	1.9
21	Wetlands - protected areas	123	47	38.2	0.4	27	22.0	0.4
22	Wetlands - mangroves	11	6	54.5	0.05	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)	544	23	4.2	0.2	43	7.9	0.7

25	Bare areas - protected areas	310	46	14.8	0.4	24	7.7	0.4
26	Bare areas - extensive pastoralism	926	182	19.7	1.5	56	6.0	0.9
27	Bare areas - moderately intensive pastoralism	50	8	16.0	0.1	6	12.0	0.1
28	Water - coastal or not managed (natural)	44	1	2.3	0.01	0	0.0	0.0
29	Water - protected areas	104	13	12.5	0.1	14	13.5	0.2
30	Water - inland Fisheries	520	154	29.6	1.3	63	12.1	1.0
100	Undefined	0	0	0.0	0.0	0	0.0	0.0
	Total	40 252	12 253		100.0	6 290		100.0

¹TDP - total degrading pixels, ²TIP - total improving pixels

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

Land use system	Codes	Total pixels (TP)	Degrading pixels (DP)	DP/TP	DP/TDP ¹	Improving pixels (IP)	IP/TP	IP/TIP ²
		(5'x5')	(5'x5')	(%)	(%)	(5'x 5')	(%)	(%)
Forestry	1-6	6 000	2 232	37.2	18.2	486	8.1	7.7
Rangeland	7-11	22 464	4 920	21.9	40.2	4 864	21.7	77.3
Agricultural land	13-18	6 941	3 629	52.3	29.6	541	7.8	8.6
Urban	19	826	323	39.1	2.6	48	5.8	0.8
Wetlands	20-23	1 523	722	47.4	5.9	145	9.5	2.3
Bare areas	24-27	1 830	259	14.2	2.1	129	7.0	2.1
Water	28-30	668	168	25.1	1.4	77	11.5	1.2
Undefined	0,100	0	0	0.0	0.0	0	0.0	0.0
Total		40 252	12 253		100.0	6 290		100.0

¹TDP - total degrading pixels, ²TIP - total improving pixels

3.10.2 Association with population density

About 37 per cent of the Argentinean population (14.5 million out of 39.1million in 2005) lives in the degrading areas (Figure 14). There is no clear correlation between the degrading areas and rural density ($r^2 = 0.04$) (Figure 15). The improving areas are sparsely populated.



Argentina: population density in the degrading land

Figure 14. Population counts affected by the land degradation



Figure 15. Relationship between population density and land degradation and improvement

3.10.3 Association with aridity

There is no clear association between degrading areas and drylands; there is a weak negative correlation ($r^2 = 0.1$) between land degradation and Turc's aridity index; 69 per cent of degrading area is in the humid regions, 13 per cent in the dry sub-humid, 15 per cent in the semi-arid regions, and 3 per cent in the arid areas.

3.10.4 Association with poverty

Taking infant mortality rate and the percentage of underweight children who are less than five years of age as proxies for poverty, there is no statistical relationship. More rigorous analysis is needed to tease out the underlying biophysical and social and economic variables, which would require more specific geo-located data, e.g. from household surveys.

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.
- 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 GLSAA 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 is defined as a long-term decline in ecosystem function and measured in terms of net primary productivity (NPP); the remotelysensed normalised difference vegetation index (NDVI) is used as a proxy. Climatic variability is taken into account by rain-use efficiency-adjusted NDVI and by residual trends of the rainfall-NDVI relationship (RESTREND), temperature by using energy-use efficiency. Spatial patterns and trends of climate-adjusted NDVI are analysed for the period 981-2003at 8km resolution. NDVI is translated to NPP; land degradation is indicated by a declining trend of climate-adjusted NPP and land improvement by an increasing trend.
- In Argentina, over the period of 1981-2003, NPP increased slightly overall against a background of significant cyclical fluctuations. Degrading areas occupy one third of the country, including large areas of dryland but, also, some of the most productive land: 17 per cent of degrading land is arable and a further 15 per cent in mosaics of arable with other land covers about half of all arable land is degrading; 47 per cent is scrub and grassland; 19 per cent is forest (38 per cent of the forest area). Argentina ranks 8th in the world in terms of its percentage of the global area and 10th in terms of NPP loss.
- About 37 per cent of the Argentinean population (14.5 million out of 39.1 million) live in the degrading areas. Globally Argentina ranks 17th in terms of rural population affected.
- Land improvement is identified across 16 per cent of the country. Over 80 per cent of this area is scrub and grassland, and sparsely populated.
- 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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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 resampled 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 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 combined NPP and RUE index 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).

NDVI indicators	NDVI values			Pixels (%)		% NDVI change/year			Δ NDVI/year		
	min	max	mean	Pos.	Neg.	Pos.	Neg.	mean	Pos.	Neg.	mean
Minimum	0.172	0.346	0.272	58.0	42.0	1.176	0.514	0.475	0.00143	0.00156	0.00017
Maximum	0.430	0.609	0.511	55.2	44.8	0.375	0.304	0.068	0.00149	0.00135	0.00022
Max-Min	0.133	0.379	0.238	50.5	49.5	0.871	0.819	0.031	0.00192	0.00188	0.00004
Mean	0.337	0.441	0.391	53.8	46.2	0.385	0.212	0.098	0.00094	0.00090	0.00009
Sum	4.047	5.290	4.694	53.8	46.2	0.385	0.212	0.098	0.01128	0.01077	0.00111
STD	0.041	0.116	0.075	54.6	45.4	0.893	0.796	0.118	0.00063	0.00056	0.00009
CoV	0.118	0.141	0.179	49.8	50.2	0.919	0.898	0.011	0.00044	0.00147	0.00140

Table A1. Statistics of NDVI indicators*

*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 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** 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 **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** 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** 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.



Argentina: multi-year mean annual (October - following September) minimum NDVI between 1981 and 2003



Argentina: trend in annual (October - following

Argentina: change in annual (October - following September) minimum NDVI between 1981 and 2003



Figure A1. Annual minimum NDVI 1981-2003: mean (a), trends (b - % change, c absolute change, d - confidence levels) Years run from 1 October through the following September

Argentina: confidence levels of trend in annual (October - following September) minimum NDVI 1981-2003

Ν

900 1,200

Argentina: trend in annual (October - following

September) maximum NDVI between 1981 and 2003



Argentina: change in annual (October - following September) maximum NDVI between 1981 and 2003





Argentina: confidence levels of trend in annual (October - following September) maximum NDVI 1981-2003



Figure A2. Annual maximum NDVI 1981-2003: mean (a) and trends (b – % change, c – absolute change, d - confidence levels) Years run from 1 October through the following September



Argentina: multi-year mean annual (October - following September) max-min NDVI between 1981 and 2003

Argentina: change in annual (October - following September) max-min NDVI between 1981 and 2003





Argentina: trend in annual (October - following

Argentina: confidence levels of trend in annual (October - following September) max-min NDVI between 1981 and 2003



Figure A3. Max-min NDVI 1981-2003: mean (a) and trends (b – % change, c – absolute change, d - confidence levels) Years run from 1 October through the following September

Argentina: trend in annual (October - following

September) mean NDVI between 1981 and 2003

b

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Argentina: multi-year mean annual (October - following September) mean NDVI between 1981 and 2003

> % mean NDVI change/yr (Oct - following Sep) < -2.5 -2.5 - -2 -2 - -1.5 -1.5 - -1 -1 - -0.5 -0.5 - 0 0 - 0.5 0.5 - 1 1 - 1.5 1.5 - 2 2 - 2.5 > 2.5 0 or nodata 513 0 150 300 600 900 1,200

Argentina: change in annual (October - following September) mean NDVI between 1981 and 2003



Argentina: confidence levels of trend in annual (October - following September) mean NDVI between 1981 and 2003



Figure A4. Mean NDVI 1981-2003: spatial pattern (a) and trends (b – % change, c – absolute change, d - confidence levels) Years run from 1 October through the following September

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Argentina: change in annual (October - following September) sum NDVI between 1981 and 2003





Argentina: trend in annual (October - following

Argentina: confidence levels of trend in annual (October - following September) sum NDVI between 1981 and 2003



Figure A5. Annual sum NDVI 1981-2003: mean (a) and trends (b – % change, c – absolute change, d - confidence levels) Years run from 1 October through the following September

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Argentina: multi-year mean annual (October - following

September) NDVI standard deviation 1981-2003

Argentina: change in annual (October - following September) NDVI standard deviation 1981-2003

N С A STD NDVI/year (Oct - following Sep) < -0.0025 -0.0025 - -0.002 -0.002 - -0.0015 -0.0015 - -0.001 -0.001 - -0.0005 -0.0005 - 0 0 - 0.0005 0.0005 - 0.001 0.001 - 0.0015 0.0015 - 0.002 0.002 - 0.0025 > 0.0025 0 or nodata 0 150 300 600 900 1,200

Argentina: confidence levels of trend in annual (October - following September) NDVI standard deviation 1981-2003



Figure A6. NDVI standard deviation 1981-2003: mean (a) and trends (b – % change, c – absolute change, d - confidence levels) Years run from 1 October through the following September

Argentina: trend in annual (October - following September) NDVI standard deviation 1981-2003



Argentina: trend in annual (October - following September) NDVI coefficient of variation 1981-2003



Argentina: multi-year mean annual (October - following September) NDVI coefficient of variation 1981-2003



Argentina: change in annual (October - following
September) NDVI coefficient of variation 1981-2003Argentina: confidence levels of trend in annual (October -
following September) NDVI coefficient of variation 1981-2003





Figure A7. NDVI coefficient of variation 1981-2003: mean (a) and trends (b – % change, c – absolute change, d - confidence levels) Years run from 1 October through the following September

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- To undertake applied research on land and water resources.