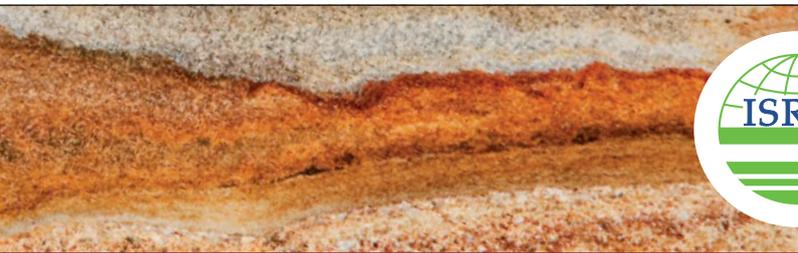


An Update of GLADA - Global Assessment of Land Degradation and Improvement

GLADA Report Update



World Soil Information

ISRIC Report 2010/08



Z.G. Bai, R. de Jong, G.W.J. van Lynden



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Preface

Degradation of soil and land resources has for long been recognized as an important threat to the carrying capacity of the world to sustain human wellbeing and development. Increasingly the importance for sustaining ecosystems services for current and future generations and for a healthy environment is also acknowledged. The society represented through its policies, pressure groups, civil society organisations and private sector is urgently looking for ways to manage world's land resources for which they are requesting simple indicators.

The assessment of the extent and intensity of the degradation and its implications for society and ecosystems appears however to be rather complex. Degradation of land quality has many dimensions, including erosion due to wind and water, salinization due to improper irrigation and drainage, loss of above ground biodiversity that goes hand in hand with the loss of below ground biodiversity and soil organic matter content, depletion of soil nutrients due to unbalanced nutrient management in agricultural production systems. For a degradation assessment, its scope should be properly delineated and the concept clearly defined. Next, for identifying measures to revert degradation, the driving forces causing degradation as well as interventions for rehabilitation should be identified. These again form a complex interaction between natural phenomena, such as storms, earthquakes, variation and long term changes in weather conditions, and socio-economic factors related to human activities like land clearing for extraction of wood or for conversion into agricultural land, overgrazing by cattle as a result of increasing population pressure, but also too intensive use of lands leading to pollution.

Over the past 6 years a large international consortium of international and national institutions led by the FAO and UNEP, and funded by the GEF, have commissioned research to institutions in six pilot countries to assess degradation at national and local scale and to ISRIC to develop a methodology for the global assessment of land degradation. FAO has compiled information into a comprehensive GLADIS methodology for assessing land degradation.

ISRIC had previously developed a qualitative assessment of global degradation (GLASOD) based on expert judgement. The research as summarized in this report has looked for a quantitative method to assess the biophysical components of land degradation, components of which have been described in a series of previous reports and as has been discussed by the groups involved in this consortium.

Above ground biomass can be perceived as an integral measures of below ground activities in the soil and the prevailing climatic conditions. In a World Bank led program to define land quality, biomass production was identified as an integral indicator. Here biomass production was the resultant of soil and weather conditions (Bindraban *et al.*, 1999; 2000). In this current report, the change in biomass has therefore been selected to serve as an indirect indicator for degradation, i.e. a change in the quality of land. Because NDVI, a greenness indicator of the earth surface, is available in a long time series from 1981 to 2006 and correlates well with above ground biomass (Tucker *et al.*, 1985), its change of this period has been used as an indicator for change in biomass and therefore as an indirect indication for land degradation or rehabilitation.

While this methodology has its obvious shortcomings, it does provide insight in long term changes and as such serves its initial purpose as a first step in search of an integral measure for land degradation. So far, the methodology has been corrected for total rainfall. The results reveal some interesting features of “hot” (degradation) and “bright” (rehabilitation) spots worthwhile to analyse further. The validity of the method has yet to be verified by comparison with national observations of degradation and maybe even validated through comparison with on-the ground observations. Moreover, NDVI or biomass assessment has to be related to soil and weather conditions. ISRIC will seek future opportunities to advance the method by linkage to soil and crop models and through verification and validation for which it calls for collaboration.

Prem Bindraban
Director, ISRIC – World Soil Information

Executive summary

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 (GLADA) uses remote sensing to identify degrading areas and areas where degradation has been arrested or reversed. This screening has been investigated within the parent LADA program at global scale (Bai *et al.*, 2008a & b), and country level (Bai & Dent, 2006; Bai, 2007; Bai *et al.*, 2007a-f, Bai & Dent, 2009, Bai *et al.*, 2010).

Links have been established between land degradation and a decline in biomass or vegetation cover, which may be measured in terms of biomass productivity. Since the early 1980s, consistent, remotely sensed global normalized difference vegetation index (NDVI) data, and detailed studies of the relationship between NDVI and leaf area index and net primary productivity (Running & Nemani, 1988; Diallo *et al.*, 1991; Carlson & Ripley, 1997) have prompted the use of NDVI trends as a proxy for land degradation (Wessels *et al.*, 2004, 2007; Metternicht *et al.*, 2010). The difficulty is to discount false alarms raised by other factors, notably fluctuations in rainfall, rising temperatures, atmospheric CO₂ concentration, nitrate precipitation, and land use change, which may not be accompanied by land degradation as commonly understood (Bai *et al.*, 2008a).

The current report is an addendum to the “international” GLADA report (Bai *et al.*, 2008a) summarizing the 'evolution' of the GLADA approach and progress made since then.

- 1. Harmonic Analysis of GIMMS NDVI:** Harmonic Analysis of NDVI Time Series (HANTS) algorithm (Roerink *et al.*, 2000) has been applied in the GIMMS dataset to remove cloud interference and to eliminate the influence of phenological shift between the northern and southern hemispheres. It has solved or, at least, mitigated some limitations of previous work that used yearly-accumulated NDVI data. In this way both land surface phenology and cloud interference are extracted from the same dataset, without using *a priori* information on land cover or cloudiness statistics. With this information, the number of false alarms of land degradation generated by NDVI analysis can be reduced. After applying the HANTS procedure, we found no significant differences with respect to the original method in sparsely overcast areas, including semi-arid regions, but many clouded scenes were removed in more humid areas. It is, however, considered unlikely that averaging to cumulative values will influence the trend analysis, but the explaining power increased because of a larger number of observations.
- 2. Phenological analysis of GIMMS NDVI:** the HANTS procedure eliminates the influence of phenological shift between the northern and southern hemispheres, but does not affect inter-annual phenological shifts from which the applied linear and non-parametric models suffer. The power of the linear model may be overestimated because of serial auto-correlation of the NDVI data, whereby any one value may be influenced by the value of the previous time-period. This means that not all data points may be truly independent as required by linear trend analysis. An alternative non-parametric test has been used: the seasonal Mann-Kendall test with NDVI data normalized by vegetation development stages, which is robust against serial auto-correlation and variations in length or start of growing season. The two approaches measure different things: the linear regression measures annual accumulated photosynthetic activity, the Mann-Kendall model measures the photosynthetic intensity during the growing season. If the test statistic (Kendall's tau) is significantly different from zero, we may conclude that there is a positive ($\tau > 0$) or negative ($\tau < 0$) trend in photosynthetic intensity over time but the index cannot easily be translated to

NPP. However, the revealed changes in photosynthetic intensity provide another indicator on drivers of land degradation.

3. **An update of GLADA dataset from 1981-2003 to 2006** has been made and the updated maps and dataset have been delivered to FAO; the updated maps are presented in the Appendix.
4. **Simplified GLADA approach - Alternative Decision Tree:** an alternative decision tree has been developed to discriminate between climate and human-induced vegetation change through correlation between NDVI and rainfall for each pixel. Six categories of NDVI trends are separated: 1) negative trend, mainly human-induced; 2) negative trend, mainly climate-induced; 3) positive trend, mainly human-induced; 4) positive trend, mainly climate-induced; 5) stable and 6) no significant change. The results indicate that, globally, about half of the areas experienced no significant changes in NDVI, significantly negative change in NDVI mainly due to human activities occurred over 4% of the total area and a negative change mainly due to climate change over another 5%; significant positive change in NDVI mainly due to human activities accounts for some 10% of the area and another 15% is mainly due to climate-related positive NDVI changes during the period 1981-2006. The resulting maps and data have been put in the FAO GLADIS system.
5. **GLADA limitations and suggestions:** GLADA is an interpretation of GIMMS NDVI data, which is taken as a proxy for NPP. The proxy is a coarse indicator of land degradation as commonly understood such as soil erosion, salinity, or nutrient depletion. The same applies to land improvement. Limitations and suggestions about use of NDVI time series data as an indicator of land degradation and improvement have been pointed out.

Keywords: harmonic analysis, Mann-Kendall VDS Model, alternative decision tree, update of GLADA maps, land degradation.

Acronyms

AVHRR	Advanced Very High Resolution Radiometer
Biome-BGC	Terrestrial Ecosystem Process Model: Biome = an area characterized by its flora, fauna, and climate; BGC = BioGeochemical Cycles
CIESIN	Center for International Earth Science Information Network, Columbia University, Palisades, NY
CRU TS	Climate Research Unit, University of East Anglia, Time Series
DEM	Digital Elevation Model
DMA	Delayed Moving Average
EoS	End of Growing Season
EUE	Energy-Use Efficiency
FAO	Food and Agriculture Organization of the United Nations, Rome
f_{PAR}	Fraction of Photosynthetically Active Radiation
GEF	The Global Environment Facility, Washington DC
GIMMS	Global Inventory Modelling and Mapping Studies, University of Maryland
GLADA	Global Assessment of Land Degradation and Improvement
GLADIS	Global Land Degradation Information Systems
GLASOD	Global Assessment of Human-Induced Soil Degradation
GPCP	The Global Precipitation Climatology Centre, German Meteorological Service, Offenbach
HANTS	Harmonic Analyses of NDVI Time-Series
IGBP	International Geosphere-Biosphere Programme
LADA	Land Degradation Assessment in Drylands
LoS	Length of Growing Season
MOD17A3	MODIS 8-Day Net Primary Productivity data set
MODIS	Moderate-Resolution Imaging Spectroradiometer
MVC	Maximum Value Composite
NDVI	Normalized Difference Vegetation Index
NOAA	The National Oceanic and Atmospheric Administration, USA
NPP	Net Primary Productivity
RESTREND	Residual Trend of Sum NDVI
RUE	Rain-Use Efficiency
SPOT VGT	Système Pour l'Observation de la Terre, VEGETATION
SoS	Start of Growing Season
SOTER	Soil and Terrain Database
UNCED	United Nations Conference on Environment and Development
UNEP	United Nations Environment Programme, Nairobi
VDS	Vegetation Development Stages

1 Introduction

Economic development, burgeoning cities and increasing 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 which requires progressively greater inputs to remedy the situation. 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 UN Conventions on Biodiversity and Climatic Change, and the Millennium Goals (UNCED 1992, UNEP 2007).

Quantitative, up-to-date and accurate information is needed to support policy development for food and water security, environmental integrity, and economic development. But land degradation is a contentious field. Crucial questions that must be answered in a scientifically justifiable way include:

1. Is land degradation a global issue or a collection of local problems?
2. Which regions are hardest hit; how hard are they hit?
3. Is it mainly a problem of drylands?
4. Is it mainly associated with farming? Is it related to population pressure - or poverty?

The only harmonized assessment world-wide, the *Global Assessment of Human-induced Soil Degradation (GLASOD)*, was a compilation of expert judgements of the kind and degree of soil degradation, e.g. soil erosion by water or by wind, salinity or nutrient depletion (Oldeman *et al.*, 1991). It was a map of perceptions, not a quantitative measure of land degradation and is now out-of-date; its qualitative judgements have proven hardly replicable, relationships between land degradation and policy-pertinent criteria were unverified – as its authors were the first to point out. Within the FAO program *Land Degradation Assessment in Drylands (LADA)*, the global assessment of land degradation and improvement (GLADA) uses remote sensing to identify areas where significant biological change is happening, indicating possible *hot spots* of land degradation and *bright spots* of land improvement at global scale (Bai *et al.*, 2008a & b), and country level (Bai & Dent, 2006; Bai, 2007; Bai *et al.*, 2007a-f, Bai & Dent, 2009, Bai *et al.*, 2010).

In LADA program, land degradation is defined as reduction in the capacity of the land to provide ecosystem goods and services over a period of time for its beneficiaries. GLADA initially took land degradation as a long-term loss of ecosystem function and measured in terms of changes in net primary productivity (NPP), this, later, has been considered as one important indicator in the FAO GLADIS (Nachtergaele *et al.*, 2010). Satellite measurements of the normalised difference vegetation index (NDVI or greenness index) for the period 1981-2006 are used as a proxy for NPP. NDVI has been widely used in studies of land degradation from the field scale to the global scale (e.g. Tucker *et al.*, 1991, Bastin *et al.*, 1995, Stoms & Hargrove, 2000, Wessels *et al.*, 2004, 2007, Singh *et al.*, 2006).

In a GLADA pilot study in Kenya (Bai & Dent, 2006), hotspots of land degradation were identified by both negative trend in NDVI (surrogate for mean annual biomass productivity) and negative trend of rain-use efficiency, treated equally; followed by linking NDVI to net primary productivity and calculating the changes of biomass production for dominant land use types; stratification of the landscape using land cover and soil and terrain data. Urban and irrigated areas were masked using contemporary global datasets.

The preliminary approach was peer-reviewed in the meeting on mid-term review of GLADA in January 2008 at FAO HQ in Rome, by Paul Vlek (ZEF, Bonn), Steve Prince (University of Maryland) and Assad Anyamba (Goddard

EST) with input from John Latham, Hubert George, Freddy Nachtergaele, Ricardo Biancalani and Stefan Schlingloff (FAO). The following points were agreed upon:

1. Biological productivity has fundamental significance;
2. Most regional assessments of land degradation are based on NDVI; it is a good proxy for biological productivity, measurable, sensitive, enabling detection and measurement of changes in productivity. However, NDVI trends do not directly reflect land degradation or improvement. Degradation and improvement are manifested when other factors that may be responsible for the observed trends have been accounted for (e.g. by simultaneous analyses of rainfall, temperature and changes in land use). The effects of current farm, rangeland and forest management are hard to differentiate from land degradation as commonly understood: soil erosion, nutrient depletion, salinity, water scarcity and disruption of biological cycles;
3. Trends since 1980 do not take into account the effects of previous degradation, although this is reflected in the absolute NDVI values;
4. GIMMS is the best available corrected global data set enabling analysis of NDVI trends since 1981. However, the 8 km fortnightly resolution (effective footprint about 100 km²) and the scale limitations of national and global ancillary data limit its applications to large-area phenomena: regional sustainability, disaster management, carbon management, policy development, monitoring and forecasting ecosystems. The users are thus seen as international, national and regional administrative units;
5. As a translation to a tangible indicator, conversion to NPP is valid; it provides a fair measure for rangeland productivity but it does for instance not translate to grain yields. Findings for low-input smallholder farming may be similar, but this has not been tested here;
6. Response to rainfall, temperature and light intensity varies with vegetation types.

Significant methodological changes were made since the mid-term review of GLADA. These were based on the first round of comments provided by the GLADA partner countries (South Africa, China, Argentina, Senegal, Cuba, Tunisia) and on the in-depth peer review held in Rome in January 2008. Importantly, the previous simple amalgamation of RUE and NDVI was superseded by RUE-adjusted NDVI, where RUE was considered only where there is a positive relationship between rainfall and RUE. In such cases where NDVI declined but RUE did not, the decline in NDVI was attributed to drought and these areas were masked; where both NDVI and RUE declined, the NDVI value was carried forward with other considerations as follows:

1. Urban extents have been masked which makes only a small difference to the global results: 0.53% for the identified degrading land, and 0.19% for the improving land.
2. Irrigated areas have not been masked in the latest version. In earlier versions they were treated differently for the obvious reason that RUE is not an appropriate measure for these areas. However, by separating areas of positive and negative correlation with rainfall, we have effectively separated wetlands, irrigated areas and areas with surplus rainfall (like rainforest) from the areas where RUE is a good measure of degradation and improvement.
3. Rainforest/humid areas have not been masked. We used unadjusted NDVI for areas where RUE is *not* appropriate (like rainforest, wetlands and irrigated areas); we use RUE-adjusted NDVI for those areas where it is suitable, by masking areas where RUE is positive.
4. Land use change is one of the key drivers of the land/vegetation degradation; it would be useful to undertake analysis of NDVI against change in land use and management. However, there are no corresponding time series data for land use or land cover. We have only the inventory of global land cover from GLC2000 (JRC, 2003) and GLOBCOVER (ESA, 2008) and these are hardly comparable, because of different classification schemes. For selected hot-spots in south China, we have analyzed the influence of land cover change on pixel-by-pixel basis (Bai *et al.*, 2010).
5. Relationship with soil and terrain: stratification of identified hot/bright spots with soil and terrain were considered in the country reports and only analyzed for China, as it is not practicable to do this globally. Even at the country level it is clear that degradation is worse on gentle slopes than on steep slopes – because usually the gentle slopes are cultivated and hence deprived of major natural protection.

6. Limitations of a proxy indicator: Loss of biomass is not necessarily synonymous with land degradation as usually understood by scientists; and increase in biomass is not necessarily land improvement as understood by land users – bush encroachment is a case in point.

In the mid-term review of GLADA, it was agreed to introduce residual trend of sum NDVI (RESTREND) as *an additional layer of information*. Comparison of the results of RESTREND and RUE-adjusted NDVI shows little difference between them: globally, 96.2% of the identified degrading land by negative RUE-adjusted NDVI also shows negative RESTREND; 99.9% of the land identified as improving by climate-adjusted NDVI shows a positive RESTREND.

We prefer the RUE-adjusted NDVI value as principal indicator because:

- a. It is a simpler concept; both the greenness index and RUE are already well established and easy to understand;
- b. The resulting measure of the RUE-adjusted NDVI approach is NDVI. NDVI can be translated into NPP, which can be subjected to economic analysis;
- c. On the other hand, RESTREND is a more abstruse statistical concept and is one modelled step further removed from the raw data;
- d. RESTREND is not amenable to economic evaluation;
- e. RESTREND does not seem to give us a better answer.

The caveats about use of NDVI time series data as an indicator of land degradation and improvement have been flagged including inherent issues of cloudiness and what GLADA can and cannot show (Bai *et al.*, 2008a).

Analyses for individual countries were checked by the national partner countries, comments and suggestions were given; response was provided directly to partners and by Dent *et al.* (2009). However, from the comments and feedback it appeared that a common understanding of the reporting framework was still lacking. What is measured and shown on maps is essentially trends in the NDVI proxy for biomass over the study period, from which net primary productivity is estimated. The issue is that it is impossible to verify or disprove by spot field observations an effect measured at a nominal pixel scale of 8 km. A more fundamental issue is that decline in biomass productivity has biological meaning *of itself* - a decline in biomass production is an aggregation of declining ecosystem function and leads to a decrease in carbon sequestration and stock (an essential ecosystem service).

This report summarizes the evolution of the GLADA approach, progress made since the study provided in the previous report (Bai *et al.*, 2008a), an alternative decision tree, recommendations and conclusions.

2 Enhancement of GIMMS NDVI analysis

2.1 Harmonic analysis of GIMMS NDVI

The GIMMS NDVI dataset (Version G, Pinzon *et al.*, 2007) has been used in the GLADA analysis. It consists of 26 years of NDVI data from 1981 through 2006, summarized fortnightly at 8 km resolution. It was derived from daily 4 km global area coverage (GAC) data from a suite of NOAA satellites (Tucker *et al.*, 2005), applying the maximum-value-composite (MVC) technique to remove bias caused by atmospheric conditions (Holben, 1986). However, MVC is not an atmospheric-correction method and some uncertainty remains, especially in hazy and cloudy conditions (Nagol *et al.*, 2009). Doubts were casted by national partners on the effect of cloud cover on NDVI derivation in China. To remove any residual cloud effects or other outliers, we therefore include harmonic analysis as an enhancement to the GIMMS NDVI data. Besides that cloudiness is eliminated, this procedure provides smoothed NDVI curves, which are useful for determination of phenological parameters. Orbital decay and changes in NOAA satellites affect AVHRR data but processed NDVI data have been found to be free of trends introduced from these effects (Kaufmann *et al.*, 2000).

2.1.1 Method

The basis of harmonic analysis is that seasonal effects in vegetation can be described using a limited number of low frequency sine or cosine functions with different phases, frequencies and amplitudes (Verhoef *et al.*, 1996). A specific application of this technique is the Harmonic Analysis of NDVI Time-Series (HANTS) algorithm (Verhoef *et al.*, 1996, Roerink *et al.*, 2000, de Wit, 2004), of which the IDL-ENVI implementation (Wit & Su 2005) was used. The HANTS algorithm has been used in two ways: first, long-term seasonal trends were determined for each pixel using the full GIMMS dataset; secondly, each year was analyzed separately. Differences between the two filtered results were considered to be NDVI anomalies. Figure 1 indicates the HANTS flowchart (Jong de *et al.*, 2009).

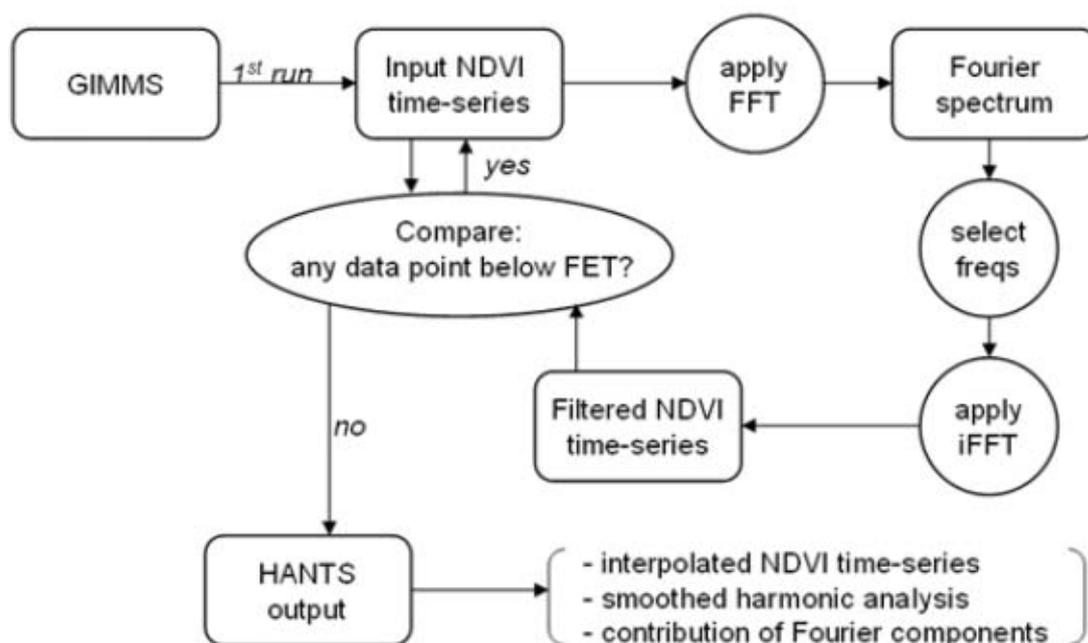


Figure 1
Flowchart of harmonic analysis of NDVI time-series.

Table 1 lists the parameters used for analysis of both the full dataset and each year separately.

Table 1
Parameters used in HANTS analysis.

	Single year	Full GIMMS (26 years)
Number of data points	26	624
Fourier frequencies	0, 1, 2, 3	0, 26, 52, 78
Fit error tolerance (FET)	0.1	0.1
Maximum iterations (i_{MAX})	6	12
Minimum retained data points	16	416

HANTS uses a Fourier analysis but complements this with a detection of outliers which are flagged and replaced in an iterative approach. The configuration of the algorithm determines the sensitivity for outliers and which frequencies are used to model the seasonal pattern. We included the frequencies representing one up to three growing cycles for each year. One and two cycles are common and in certain cases, for instance specific harvesting practices, three growing seasons occur. For illustration, Figure 2 shows a management regime in India which has three cropping stages; the left image shows the NDVI trend (green = positive; brown = negative).

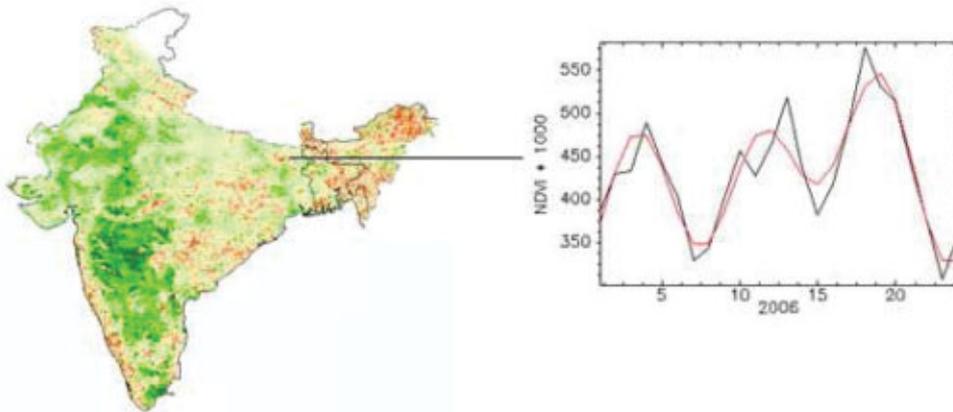


Figure 2

Harmonic analysis of GIMMS NDVI in India. Left: NDVI trend derived using GLADA method, right: example of HANTS-smoothed NDVI curve (black = original NDVI data, red = harmonic representation).

2.1.2 Results and discussion

The number of data points that have been flagged and replaced by HANTS is indicative for the extent to which the data at that location is affected by cloudiness (Figure 3). This can be helpful information for interpretation of the trends and the quality of the trend analysis.

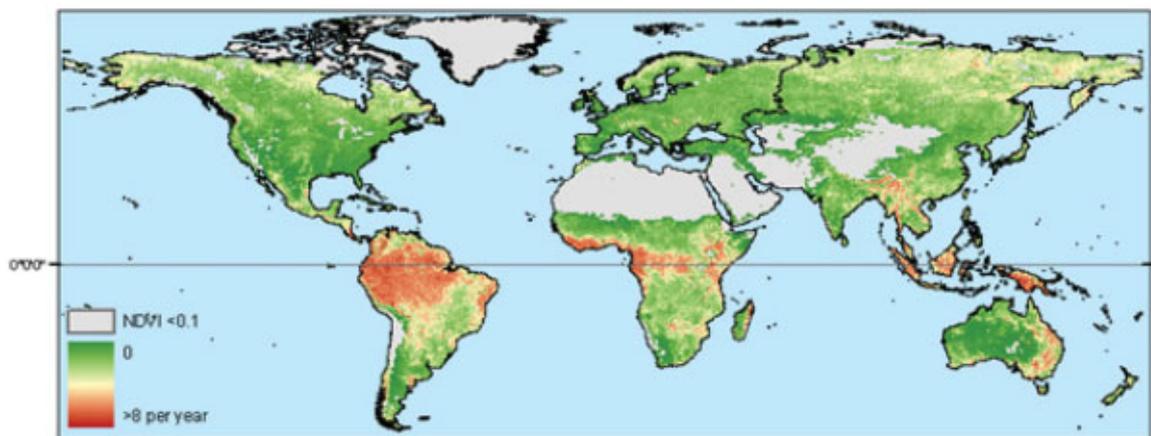


Figure 3

Number of outliers per year detected by the HANTS procedure. In the tropics cloudiness is most persistent and in tundra regions partial snow cover causes outliers.

To evaluate the effects of HANTS results, the CRU 3.0 monthly time series cloudiness data is used to produce a cloud cover map and to compare with removal of cloud effects on NDVI using HANTS. CRU TS 3.0, created by the Climate Research Unit of the University of East Anglia, UK, comprises monthly grids of meteorological station-observed data from for the period of 1901-2006 covering the global land surface at 0.5° resolution (Mitchell & Jones 2005). The classes of persistent cloud coverage in Figure 4 show a spatial distribution similar to the high number of outliers in Figure 3. This illustrates that the HANTS procedure is effective in removing remaining cloudiness from the GIMMS data.

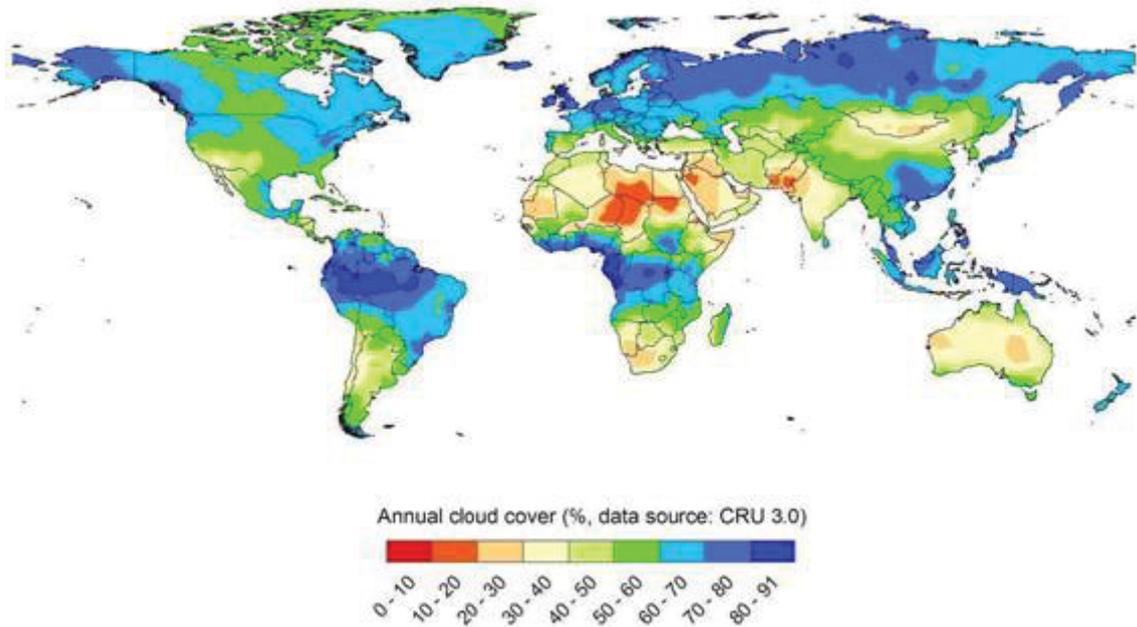


Figure 4
 Multi-year mean annual cloud cover, 1981-2006.

2.1.3 Main findings

The harmonic analysis refines the input data used in the GLADA approach. It has not only solved or mitigated some limitations of previous work that used only yearly-accumulated NDVI data. Thereby, both land surface phenology and cloud interference can be extracted from the same dataset, without using *a priori* information on land cover or cloudiness statistics. With this information, the number of false alarms of land degradation generated by NDVI analysis can be reduced.

The harmonised GIMMS NDVI time series and Fourier Components were used in the subsequent analysis. The removal of residual cloud effects from the 1981-2006 GIMMS dataset by HANTS harmonic analysis had little effect on trends or areas affected (Figure 5).

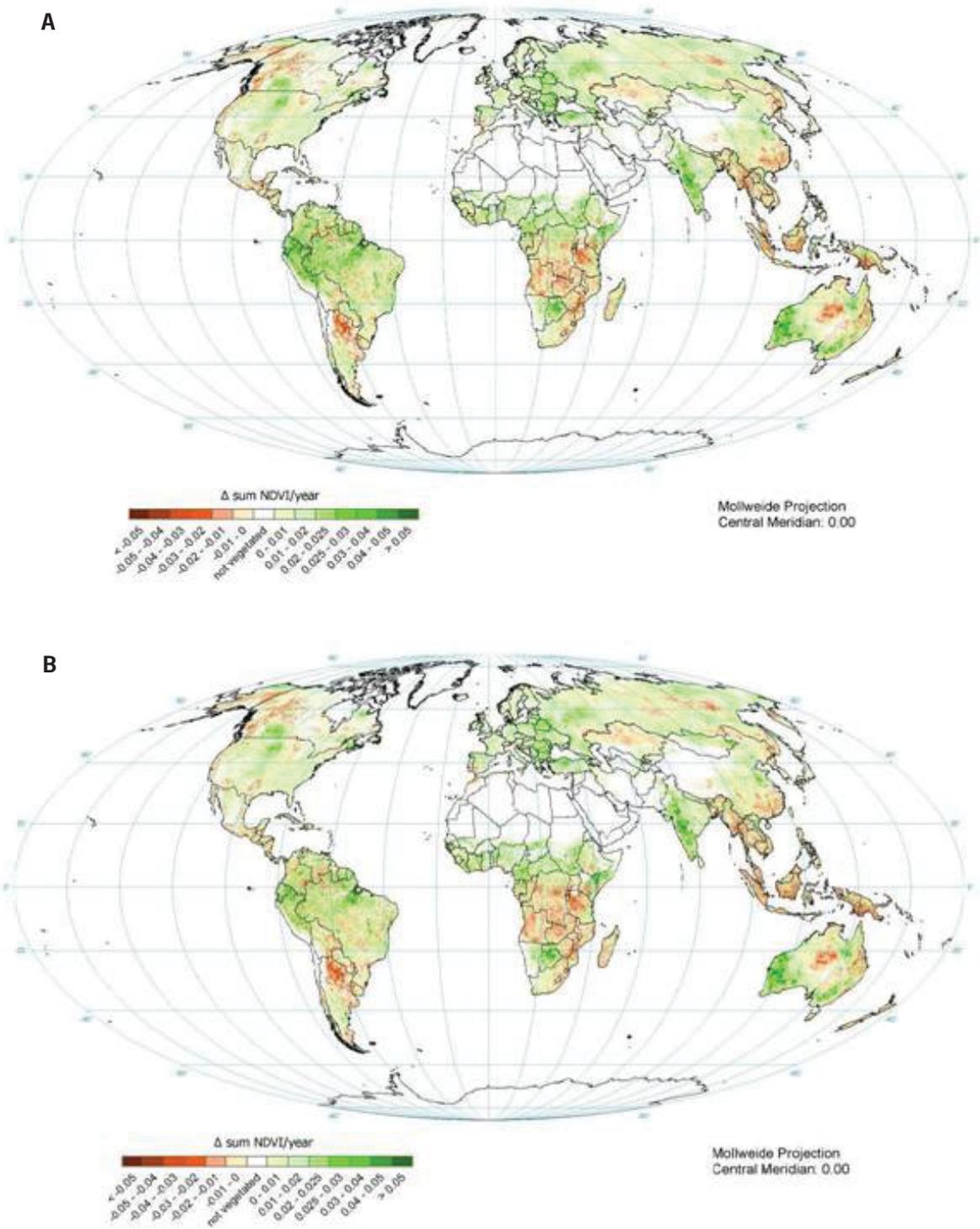


Figure 5
 Comparison of the non-harmonised (A) and harmonised (B) GIMMS NDVI trends.

2.2 Phenological analysis of GIMMS NDVI

2.2.1 Introduction

The GLADA approach uses a linear model with annual cumulative NDVI to estimate trends. At the global scale, comparison of NDVI values by calendar date is inadequate – due to phenological shifts and variation in length of growing season. However, it is difficult to extract phenological measures using a generalized method. There is valuable information in the seasonal shape of the NDVI curves that may be analyzed and also the power of the linear model may be overestimated because of serial auto-correlation of the NDVI data, whereby any one value may be influenced by the value of the previous time-period. This means that all the data points may not be truly independent - as required for linear trend analysis.

The HANTS procedure eliminates the influence of phenological shift between the northern and southern hemispheres, but does not affect inter-annual phenological shifts from which the linear model, especially, the seasonal Mann-Kendall model suffers. We apply non-parametric trend tests to the GIMMS NDVI dataset (1981-2006) as an alternative to reducing the temporal resolution (de Jong *et al.*, 2010). Two tested approaches are: 1) a linear model applied to *de-seasonalized* data (*i.e.* NDVI residuals after the seasonal component has been removed); 2) a non-parametric model applied to data in which phenological cycles are adjusted to the same start and length of growing season. Long-term and annual harmonic analyses were used to filter cloudiness and seasonality, and to derive phenological measures that take account of inter-annual variations in phenology.

2.2.2 Method

Various approaches have been described to derive the start of the growing season (SoS) from NDVI time-series: half-maximum (White *et al.*, 1997), 10% amplitude (Jönsson & Eklundh, 2002), inflection point (Moulin *et al.*, 1997), maximum curvature (Zhang *et al.*, 2003), delayed moving average (DMA) and forward-looking moving average (Reed *et al.*, 2003). Following White *et al.* (2009), we used the first derivative of the HANTS-smoothed NDVI profile where SoS is defined as the maximum of the first derivative (maximum NDVI increase) and the end of growing season (EoS) is defined as the first point in time after SoS where the NDVI value drops below the value at the start of the growing season. Between SoS and EoS, 10 equally spaced vegetation development stages (VDS) were then defined. For each growing season, the 12 $NDVI_{ds}$ values (SoS, EoS + 10 development stages) were calculated using the harmonic model and were subsequently used as input for the non-parametric seasonal Mann-Kendall (SMK) model. The test is based on Kendall's rank correlation coefficient (τ) ranging from -1 to 1 (Kendall, 1938). The null hypothesis H_0 is that the samples are randomly ordered, versus the alternative hypothesis H_A of a monotonic trend in one or more seasons (Hirsch & Slack, 1984). H_0 is tested two-sided against H_A and rejected when Kendall's tau (τ) of NDVI versus time is significantly different from zero ($\alpha = 0.1$). We then conclude that there *is* a monotonic trend in NDVI over time: a *greening trend* if $\tau > 0$ and a *browning trend* if $\tau < 0$. Figure 6 illustrates how the vegetation development stages were calculated.

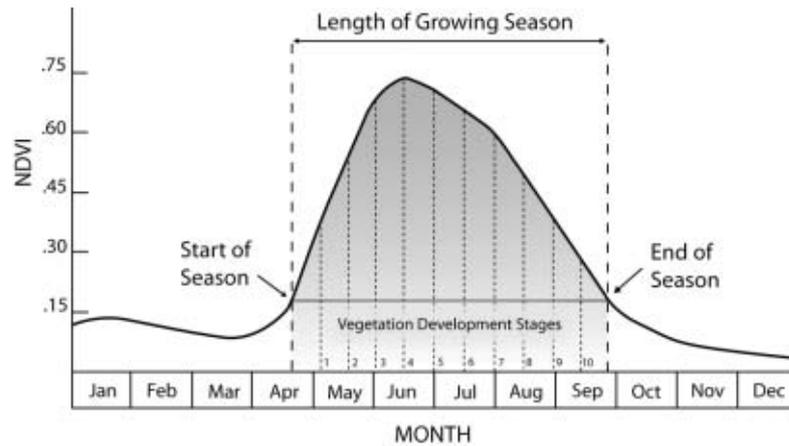


Figure 6
Example of single growing season and related phenological measures.

2.2.3 Results and discussion

In Figure 7a, green and red colours indicate significant trends ($\alpha = 0.1$), where green indicates a positive trend and red a negative trend, and areas with little or no vegetation (yearly average NDVI < 0.1) are masked. Overall, greening predominates, especially in the Northern Hemisphere and most notably in the boreal forests, eastern Europe, Asia Minor, the Sahel, and western India. In the southern hemisphere, greening is apparent in Western Australia and Botswana; and browning in the tropical Africa and Indonesia/Oceania and in northern Argentina.

The linear model slopes detected by anomalies between long-term and yearly harmonic fits using fortnightly NDVI values are very close to the linear trend analysis of yearly cumulative values (Bai *et al.*, 2008a). On average, the absolute difference in trend is < 0.001 units/year and never as much as 0.01 units/year - which supports the contention that reducing the temporal resolution to yearly values and the choice of annual break-point does not affect the trend slopes (Dent *et al.* 2009). However, the explaining power decreases with a decreasing number of observations. All models agree on a greening trend in western India, the Sahel and parts of Asia Minor, Canada, northern China and Western Australia.

The map of Kendall's τ scores from the VDS model (Figure 7b) identifies the same areas of distinct greening with absolute Kendall τ values around 0.3. Results from the VDS model can be interpreted in combination with the trend in length of growing season (LoS) because greening can be caused either by a longer growing season or by a higher rate of production. The former effect is not captured by this method because the data were adjusted for changes in length of growing season; the analysis is a measure of productivity within a growing season (changes in *photosynthetic intensity* or *rate of production*) rather than of the total yearly productivity (changes in *integrated production*) (Jong de *et al.*, 2010).

Prominent regional greening trends identified by several other studies were confirmed but the models were inconsistent in areas with weak trends. The linear model using data corrected for seasonality showed similar trend slopes to those described in previous work using linear models on yearly mean values. The non-parametric models demonstrated the significant influence of variations in phenology; accounting for these variations should yield more robust trend analyses and better understanding of vegetation trends.

In the analysis of GLADA for China (Bai and Dent, 2009), it was concluded that land degradation is most conspicuous in the rapidly-developing, humid south, rather than in the dry lands of the north and west where

major reclamation initiatives have concentrated. Both the linear model and the VDS model support this conclusion and a study using GIMMS and SPOT VGT in the Loess Plateau region found a similar relationship between rainfall and land degradation (Xin *et al.*, 2008). The spatial pattern of correlation between NDVI and time (1981 onwards) is best reproduced by using the VDS model.

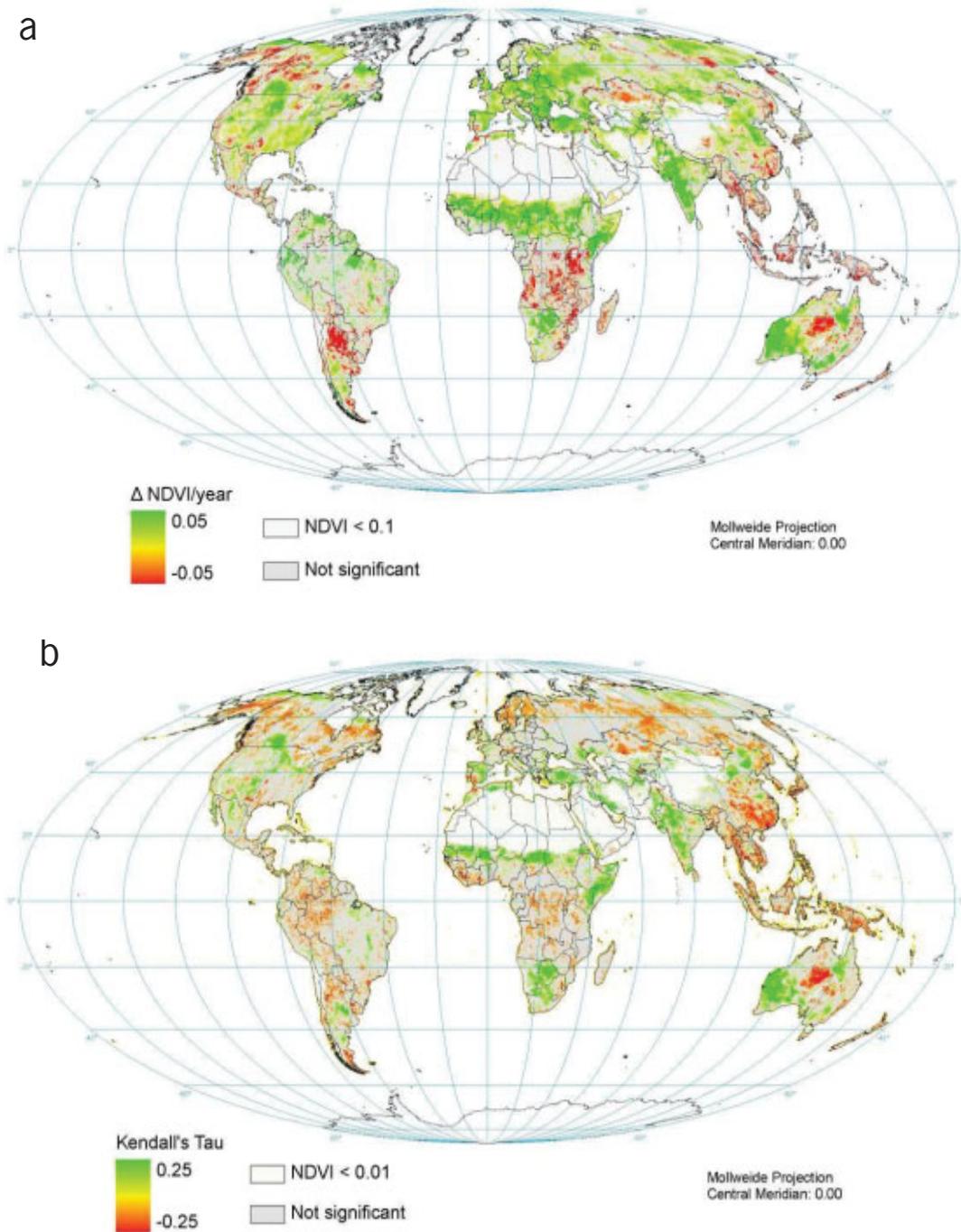


Figure 7

a: Trend in NDVI based on linear model of NDVI anomalies (1981-2006). b: Kendall's tau from seasonal Mann-Kendall model on data adjusted by vegetation development stage (VDS). In both cases trends were assessed for significance using analysis of variance. Weak trends ($\alpha=0.1$) have been masked.

Summarizing the results by (IGBP) biomes shows that the linear model approach indicates overall greening in all biomes except deciduous needle-leaved forest (Figure 8). The photosynthetic intensity trend is opposite to the trend in LoS in all biomes, except shrub lands and savannas, where greening is likely induced by longer thermal growing seasons. The VDS model indicates a decrease in photosynthetic intensity in all forest types, which is counterbalanced by an overall increase in LoS. This might indicate that vegetation growth is no longer limited by temperature, but by other limiting factors such as depletion of soil water or nutrients; the strongest indication of this phenomenon is in the Scandinavian boreal forest (Figure 7).

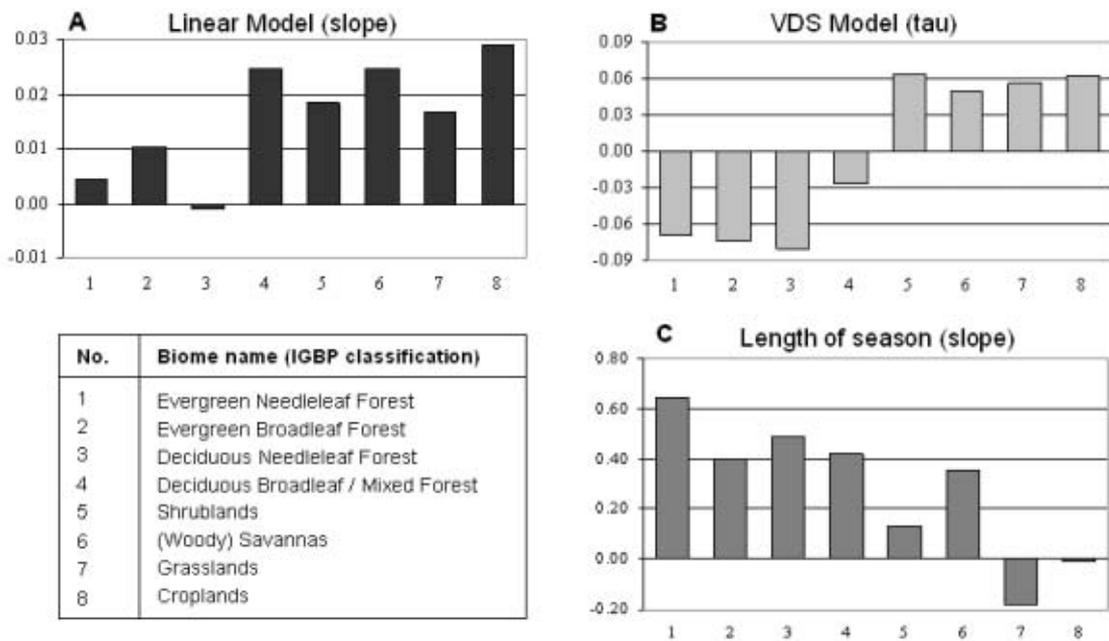


Figure 8

Statistics based on selected IGBP biomes. (A) Slope linear model, (B) Kendall's tau of vegetation development stage (VDS) model, (C) Slope linear model length of season (LoS). Some IGBP biomes have been merged based on similar responses. Biomes which are not shown are: urban, snow and ice, barren / sparsely vegetated, permanent wetlands and water bodies.

2.2.4 Main findings

Linear model trends derived from anomalies between long-term and yearly harmonic fits were hardly different from the original GLADA approach. It is therefore considered unlikely that averaging to cumulative values influences the trend analysis. However, the explaining power decreases with a decreasing number of observations. The non-parametric model demonstrated the significant influence of variations in phenology. The two analyses do not measure the same thing: the linear regression measures *annual accumulated photosynthetic activity*, the Mann-Kendall model measures the *photosynthetic intensity of the growing season*. If the Kendall's tau value is significantly different from zero, we may conclude that there is a positive ($\tau > 0$) or negative ($\tau < 0$) trend in photosynthetic intensity over time but the index cannot easily be translated to NPP.

2.3 Update of GLADA dataset to 2006

A new GIMMS dataset from 1981 to 2006 has been corrected and reconstructed; this harmonised GIMMS NDVI time series was used to update the GLADA data to 2006 and for the subsequent analysis in chapter 3. Corresponding precipitation data have also been updated to match the NDVI time period. The removal of residual cloud effects from the 1981-2006 GIMMS dataset by harmonic analysis made almost no difference to trends or areas affected. A series of updated maps is attached in Appendix.

3 Simplified GLADA approach - an alternative decision tree

The GLADA method using remotely sensed NDVI time series can be seen as providing one indicator of land degradation, but not as a comprehensive tool to assess the actual status of land degradation. Therefore an alternative decision tree was developed to demonstrate the importance of taking into account precipitation and the vegetation response when trying to analyze changes in vegetation cover. Figure 9 shows the alternative decision tree to discriminate between climate and human-induced vegetation change.

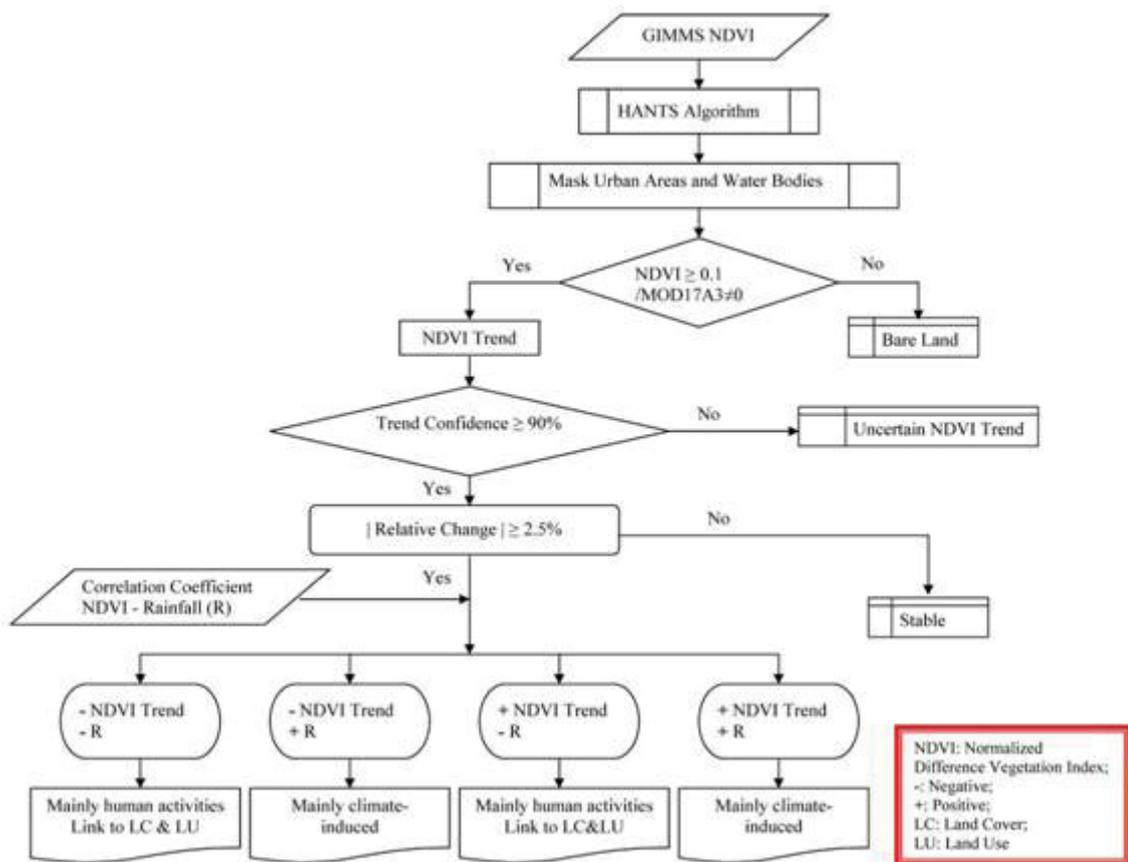


Figure 9
Flow chart for the GLADA alternative decision tree.

3.1 Data and methods

NDVI data: The harmonised GIMMS NDVI time series 1981-2006.

Precipitation: The Global Precipitation Climatology Centre (GPCC) provides monthly precipitation data compiled from long, quality-controlled station records, gridded at resolution of 0.5° (Schneider *et al.*, 2008).

It is the most complete precipitation dataset for 1951-2006. Monthly rainfall from 1981-2006 is used to correlate with the GIMMS NDVI over the period of 1981-2006 at pixel level.

Urban areas: Global Rural-urban mapping project: urban/rural extents. Center for International Earth Science Information Network (CIESIN, 2004), Columbia University, Palisades NY.

Bare land: MOD17A3 (Collection 5.1) is used to distinguish the bare land where MOD17A3 equals zero. MOD17A3 C5.1 is a dataset of terrestrial gross and net primary productivity, computed at 1 km resolution at an 8-day interval (Heinsch *et al.*, 2003, Running *et al.*, 2004, Zhao *et al.*, 2005). Though far from perfect (Plummer, 2006), MODIS has been validated in various landscapes (Fensholt *et al.*, 2004, 2006, Gebremichael & Barros, 2006, Turner *et al.*, 2003, 2006).

Open Water: GLOBCOVER Land Cover v2.2 database (ESA, 2008).

Linear regression models were used to determine trends in NDVI, statistically significant changes in NDVI are set as 90% by Student's *t* test. Correlation coefficient (R) between NDVI and rainfall were calculated for each pixel ($p < 0.1$).

Percentage change equals $100 * (Y_{26} - Y_1) / Y_1$, where Y_{26} is the calculated NDVI from the linear trend equation for the year 26; Y_1 is the calculated NDVI from the linear trend equation for the year 1. A relative change smaller than 2.5% is considered to be indicative for "Stable" land .

3.2 Results

Correlation of NDVI with climate change, in particular, precipitation could discriminate between climate and human-induced vegetation change. We assume the following relationships:

1. Negative trend in NDVI and negative R, 90% confidence: mainly human-induced;
2. Negative trend in NDVI and positive R, 90% confidence: mainly climate-induced;
3. Positive trend in NDVI and negative R, 90% confidence: mainly human-induced;
4. Positive trend in NDVI and positive R, 90% confidence: mainly climate-induced;
5. Stable: relative change $< 2.5\%$ /26-year, 90% confidence;
6. No significant change in NDVI: significance of NDVI change below 90%.

The results indicate that during the period 1981-2006, globally, about half of the area experienced no significant changes in NDVI; significant negative change in NDVI mainly due to human activities can be allocated to 4% and mainly due to climate change to another 5% of the total area; mainly human activities accounts for significant positive change in NDVI in some 10% of the area and mainly climate-affected positive change for another 15% (Table 2 and Figure 10).

Table 2

Statistics of greenness evolution.

Classes	Proportion (%)
No data	0.3
Non significant trend (<90% confidence)	52.2
Negative greenness trend due mainly to human intervention	3.8
Negative greenness trend due mainly to climate	4.7
Positive greenness trend due mainly to human intervention	9.6
Positive greenness trend due mainly to climate	14.7
Stable greenness evolution (<2.5% change)	0.1
Open water	0.9
Urban areas	0.7
Bare areas	13.0
Total	100.0

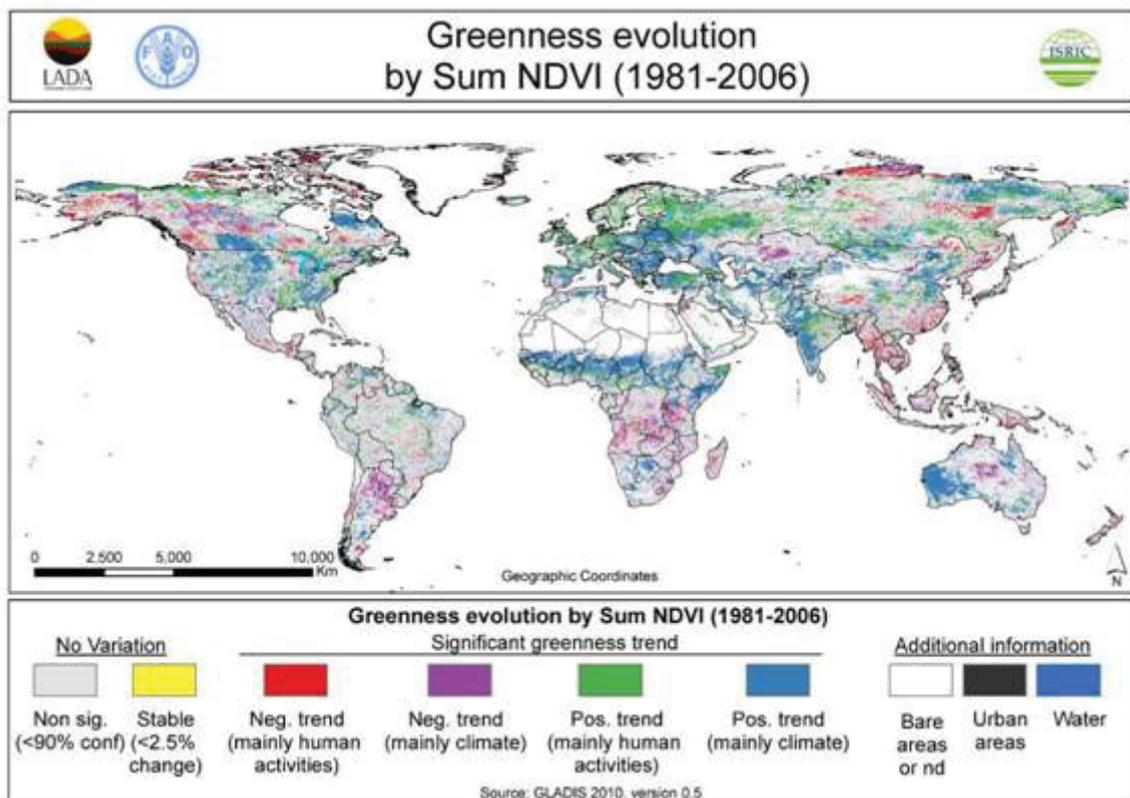


Figure 10

Greenness evolution by sum NDVI 1981-2006.

The same approach but with annual accumulation of the NDVI from October to next September were calculated and mapped for South Africa (Figure 11).

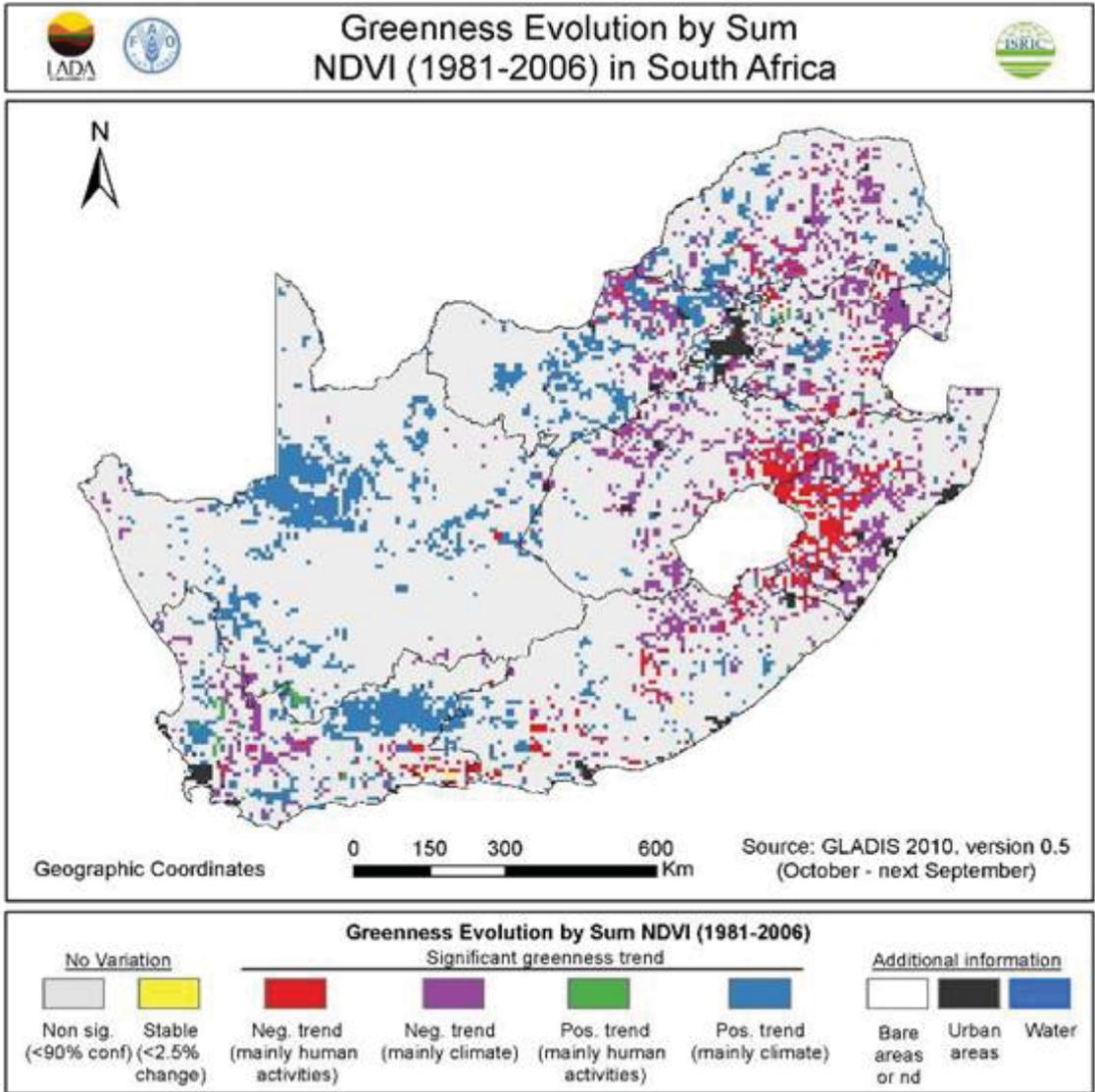


Figure 11
Greenness evolution by sum NDVI 1981-2006 in South Africa.

4 Limitations and recommendations

GLADA is an interpretation of GIMMS NDVI data, which is taken as a proxy for NPP. The NPP is perceived as an integral measure of below ground activities in the soil and the prevailing climatic conditions (Bindraban *et al.*, 1999; 2000). We consider the proxy to be a coarse, indirect indicator of land degradation as commonly understood such as soil erosion, salinity, or nutrient depletion. The same applies to land improvement. Any particular trend in NDVI may mean something very different in Central Africa from a quantitatively similar trend in South China or South Africa – both in terms of the kind of land degradation and the underlying causes.

A declining trend of NPP, even allowing for climatic variability, may not even always be reckoned as land degradation: urban expansion is generally considered to be development, although it results in a loss of some ecosystem functions; land use change from forest or grassland to cropland of lesser biological productivity may or may not be accompanied by soil erosion, compaction and nutrient depletion and it may well be sustainable and profitable, depending on management. Similarly, an increasing trend of NPP means greater biological production but may reflect, for instance, bush encroachment in rangeland or cropland, which is not land improvement as commonly understood.

Land use change is clearly a major driver of change in NPP. However, we have not been able to make allowance for land use change in the same way as for rainfall and temperature because available data are not compatible with the GIMMS data. Only one case study has been carried out in the Zhejiang Province of South China (Bai *et al.*, 2010).

The 8 km resolution of the GIMMS data is a limitation in two senses. First, an 8 km pixel integrates the signal from a wider surrounding area. Many symptoms of even very severe land degradation, such as gullies, rarely extend over such a large area; they must be severe indeed to be seen against the signal of the surrounding unaffected areas. More detailed analysis is possible for those areas that have higher resolution time series data, such as South Africa (Wessels *et al.*, 2004). Secondly, an 8 km pixel or even a 1 km pixel cannot be validated by a windscreen survey; and a 26-year trend cannot be validated by a single snapshot. As already mentioned, the lack of consistent time series data on land use prevents a general accounting of land use change in the global assessment.

Some inherent limitations of the NDVI data have already been flagged or eliminated: saturation of the NDVI signal by dense vegetation - leading to a lack of precision for forest mapping; interference by cloud in perennially cloudy areas; and the scant rainfall observations in many parts of the world.

1. GIMMS dataset continues to be developed and further updates are possible; so does the GPCC precipitation data; this will enable updating of the GLADA. With time-series becoming longer, the occurrence of trend breaks needs to be accounted for in the future.
2. As an indicator of land degradation and improvement, fraction of photosynthetically active radiation (f_{PAR}) is preferred to NDVI – in its own right as a direct measurement of an important biophysical parameter, and to derive NPP either from MODIS or SPOT imagery. Data are available from the year 2000 and at 1 km resolution rather than the 8 km resolution of GIMMS. Looking ahead, these data would be preferred for monitoring and early warning;
3. Rather than using sometimes-sparse station-observed data, rainfall data modelled from earth-observation satellite data are now available at the same level of precision as f_{PAR} .
4. Cloud interference may be minimised by calculating trends for longer time steps, up to five years rather than annual, but this entails loss of precision.

GLADA used only a fraction of the information available in the GIMMS data:

- We have used simple linear regression of the 26-year GIMMS period to analyse the trends of NDVI and NDVI derivatives. It is possible to use power functions and separate, say successive 10-year periods;
- Visualization can be greatly improved by three-dimensional overlays of the NDVI/NPP trend surfaces over topography in combination with other data layers;
- Comparison of the present situation with potential biological productivity *without* human-induced land use change – the Garden of Eden scenario – modelled from climatic, soils and topographic data using, e.g. the BIOME-BGC model (Thornton *et al.*, 2005), will enable separation of the last 26 years of land degradation from the historical legacy.

For China, individual areas of hotspots and bright spots, identified on the basis of NDVI indicators, have been characterised by DEM, land use and soils and terrain data. Within individual soil and terrain (SOTER) units, a more refined analysis has been performed by modelling the relationships between rainfall, temperature and NDVI for the whole SOTER unit, then calculating the deviation for individual pixels. This makes allowance for soil and terrain and lessens the bias of the rainfall-NDVI model imposed by that pixel's deviations from the general trend.

Time series of high resolution imagery, e.g. 30m-resolution Landsat scenes, can be used to identify land use change and the probable types of land degradation causing changes in biomass at a very regional scale. The LADA national assessment, using the WOCAT/LADA mapping method based on expert opinion and other existing knowledge, will provide valuable additional information about degradation and improvement in the LADA pilot countries. Finally, field examination of the identified areas of degradation and improvement should be undertaken by national teams within the wider LADA program. Apart from systematically and consistently characterising the situation on the ground across a range of scales, the field teams should address the following questions:

1. Is the biomass trend indicated by GLADA real?
2. If so, does it correspond with physical manifestations of land degradation or improvement that are measurable on the ground?
3. In the case of a negative answer to either of the preceding questions, what has caused the observed NPP trend? For instance, is it a question of timing of observations - where the situation on the ground has recovered?

Relationship between NPP loss and total organic carbon stock should be investigated.

More work should be done in terms of quantitative assessment of biophysical and also social-economic information using a human-centred and watershed-based approach. Consideration of socio-economic data in the assessment of land degradation could help reveal the main drivers of land degradation. However difficulties are expected to arise due to incompatibilities of scale and time. Socio-economic aspects can be presented using decision matrices or decision trees.

5 Conclusions

GLADA is an interpretation of GIMMS NDVI using biophysical trend analysis and climatic data. As such, it is not an update of GLASOD, which was based on expert opinion. GLADA provides a biophysical indicator of land degradation but results cannot be directly related to known soil degradation problems such as erosion or salinization; it considers NPP decline as an indicator of land degradation or improvement in terms of carbon sequestered in above-ground biomass.

The removal of residual cloud effects from the 1981-2006 GIMMS dataset by HANTS harmonic analysis made almost no difference to trends or areas affected, but many clouded scenes were removed in more humid areas.

Linear model trends derived from anomalies between long-term and yearly harmonic fits were similar to those reported for the original GLADA approach. It is therefore considered unlikely that averaging to cumulative values greatly influences the trend analysis. However, the explaining power decreased with a decreasing number of observations. The non-parametric model demonstrated the significant influence of variations in phenology. The two analyses do not measure the same phenomenon. The linear regression is a measure for annual accumulated photosynthetic activity, while the Mann-Kendall model provides a measure for the photosynthetic intensity during the growing season, which might serve as another indicator for land degradation, as a possible decline might be caused by exhaustion of the soil.

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Appendix 1 Updated GLADA maps

Note: The numbers of the figures correspond to those in the report: Bai ZG, DL Dent, L Olsson & ME Schaepman 2008a. *Global assessment of land degradation and improvement. 1. Identification by remote sensing*. Report 2008/01, ISRIC – World Soil Information, Wageningen. LADA technical Report no. 12. The maps inserted in the main text of the report derived from annual sum NDVI, the aggregate of greenness over the growing season as the standard surrogate for annual biomass productivity, have been illustrated and interpreted. The other NDVI indicators (NDVI minimum, maximum, maximum-minimum, mean, standard deviation and coefficient of variation) were derived as well because each of those indicators has biological meaning, the description of the each indicator was given and mapped in appendix but not interpreted further.

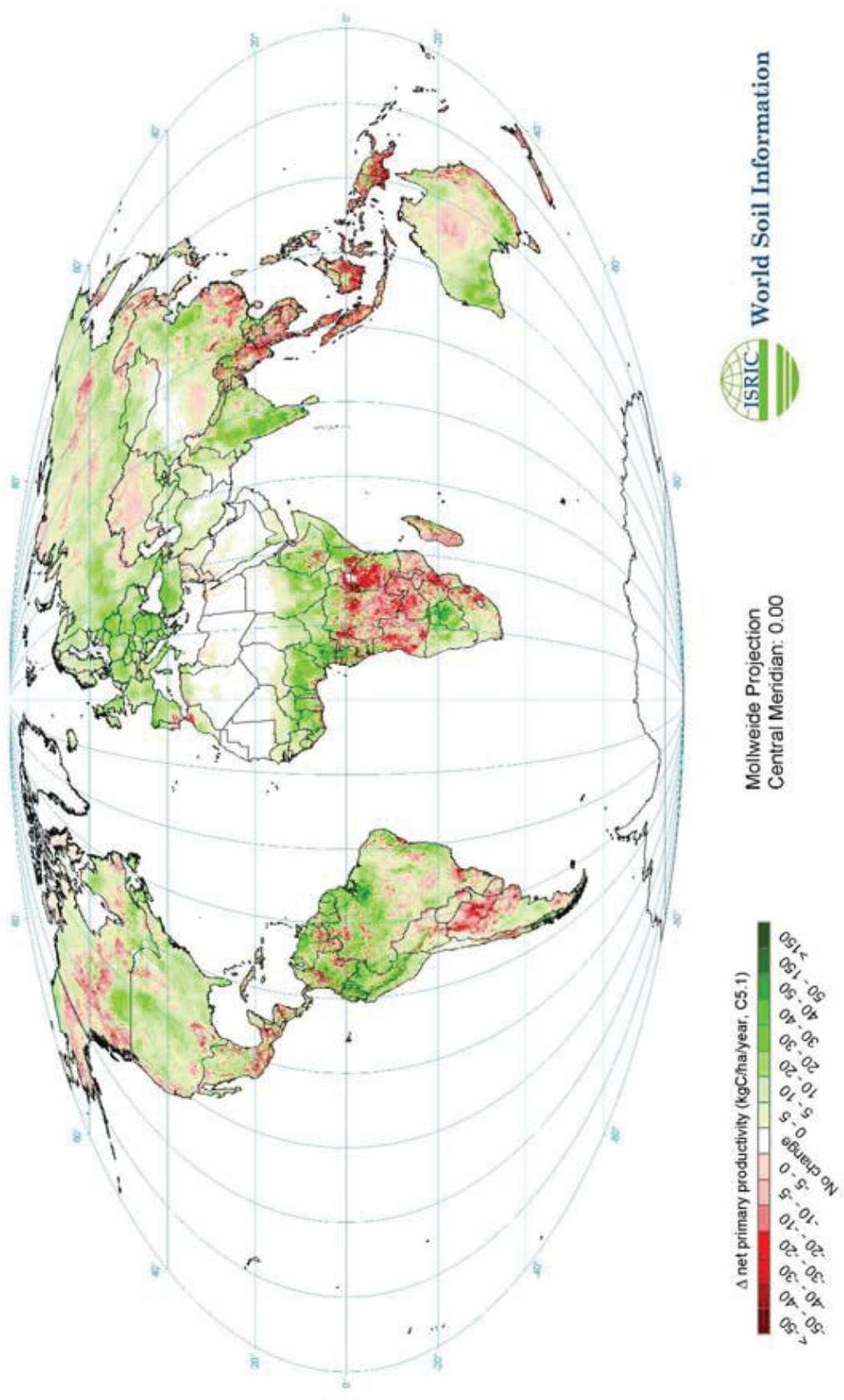


Figure 2
Global change in net primary productivity between 1981 and 2006.

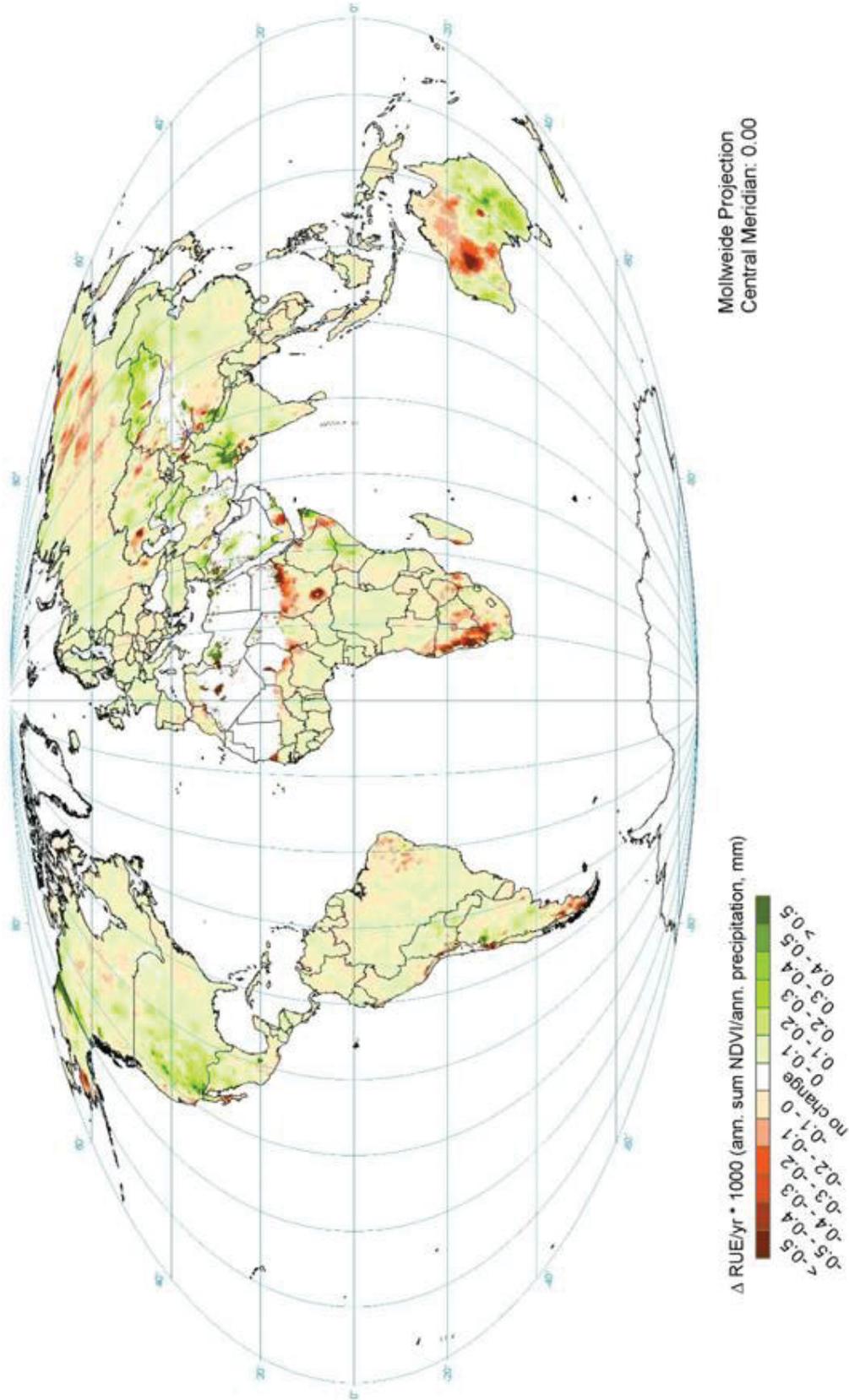


Figure 3
 Global change in rain-use efficiency between 1981 and 2006.

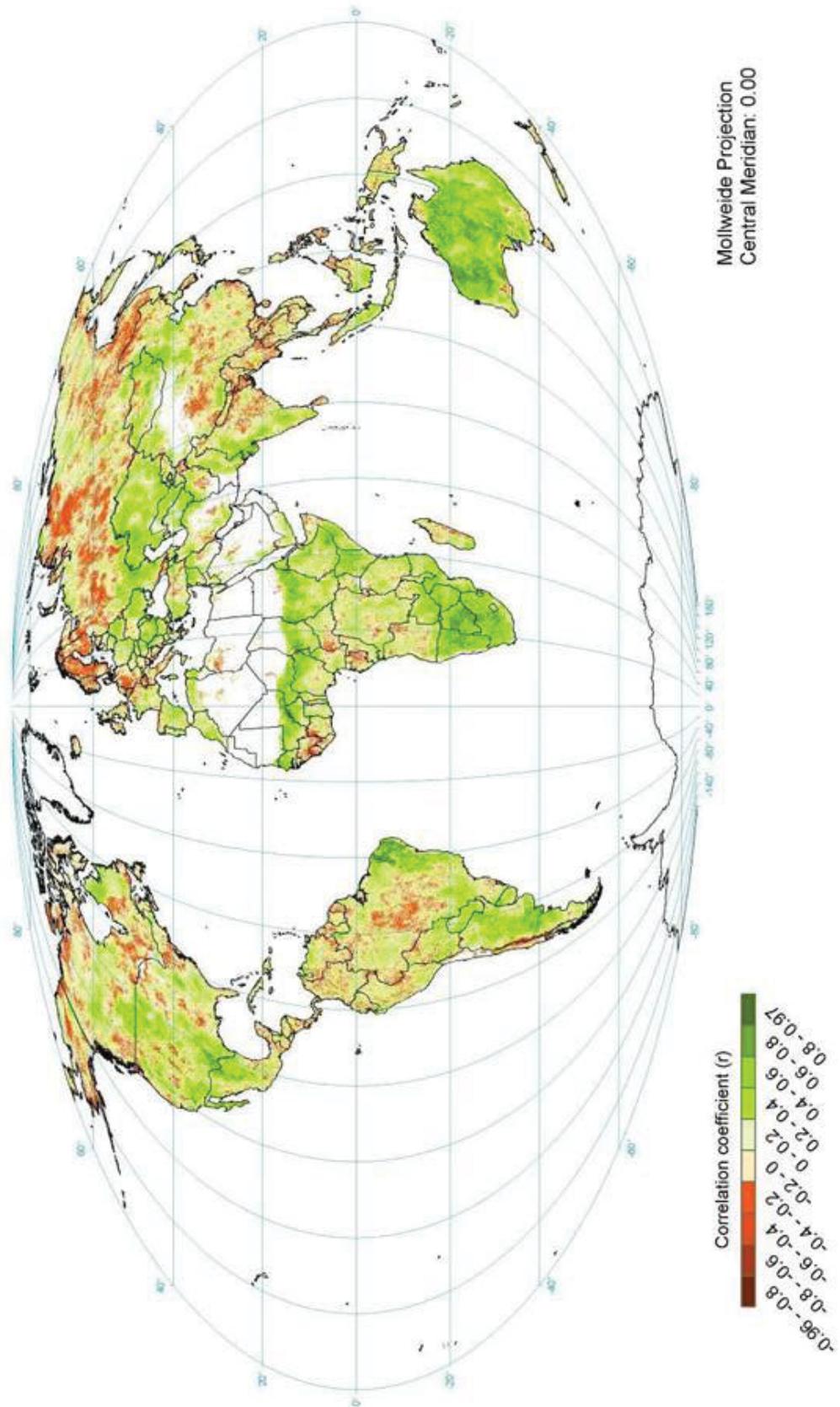


Figure 4
Global correlation between annual sum NDVI and rainfall 1981-2006.

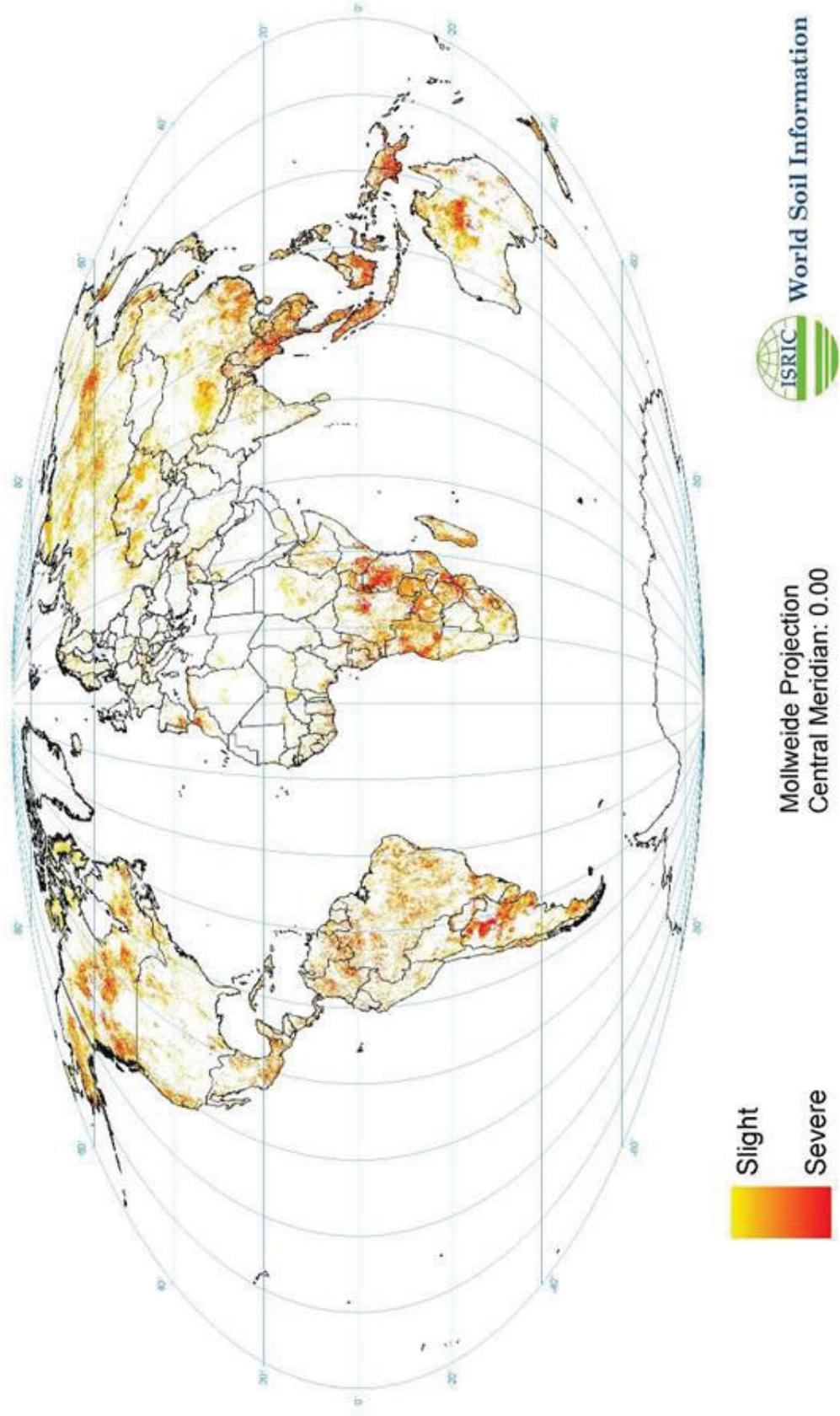


Figure 5
Global negative trend of RUE-adjusted NDVI, 1981-2006.

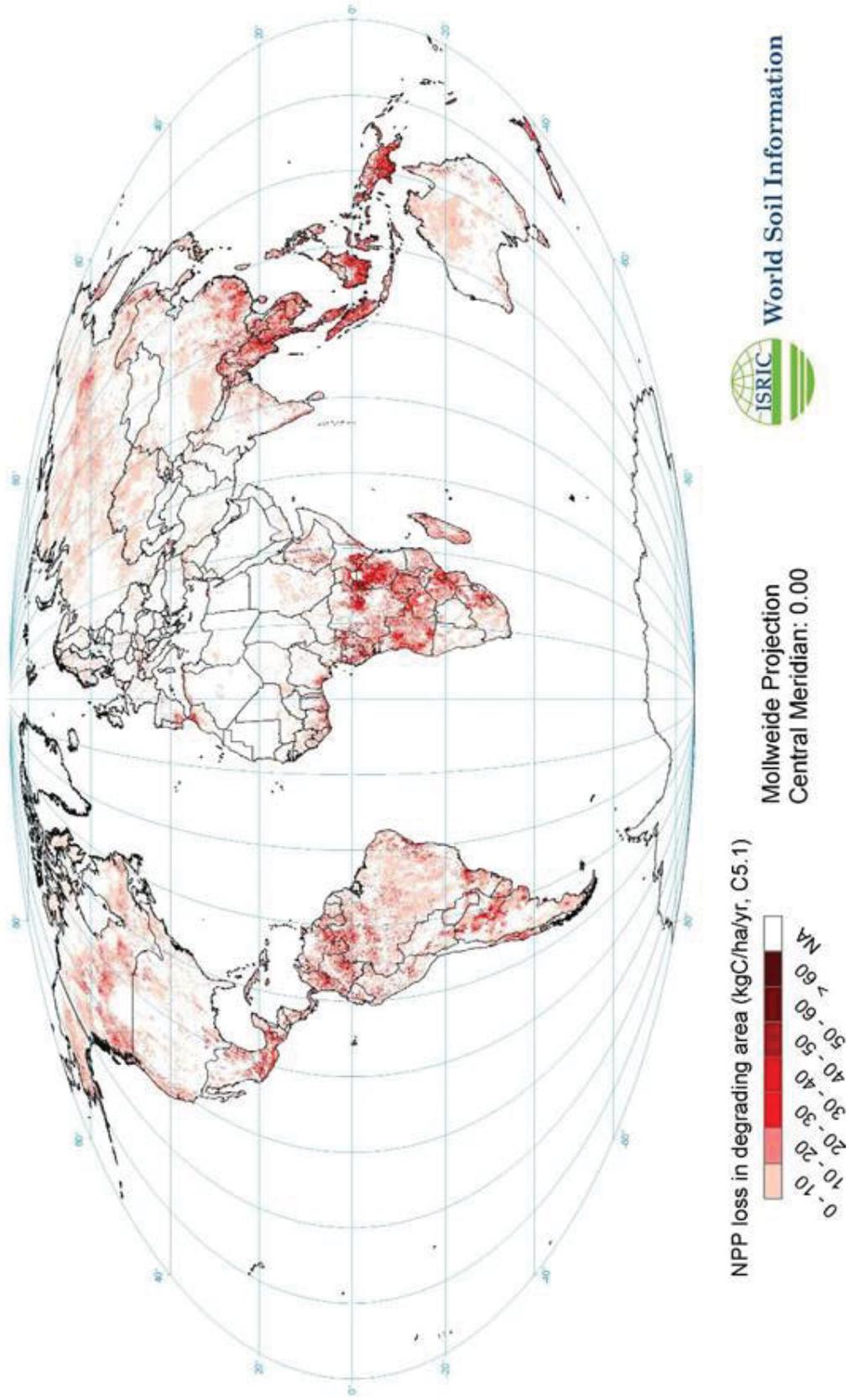


Figure 6
Global loss of net primary productivity in the degrading areas, 1981-2006.

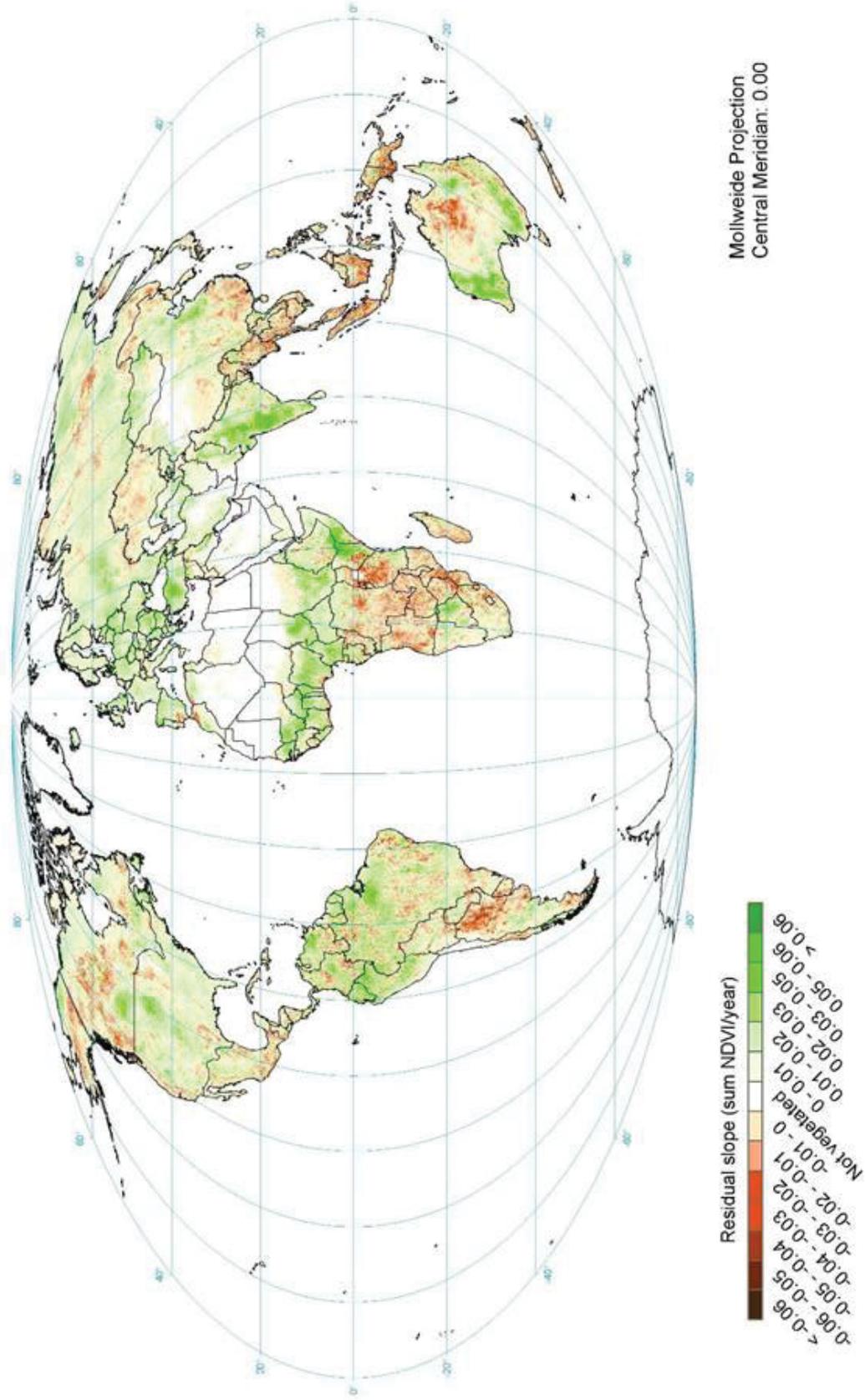


Figure 7
Global residual trend of annual sum NDVI (RESTREND), 1981-2006.

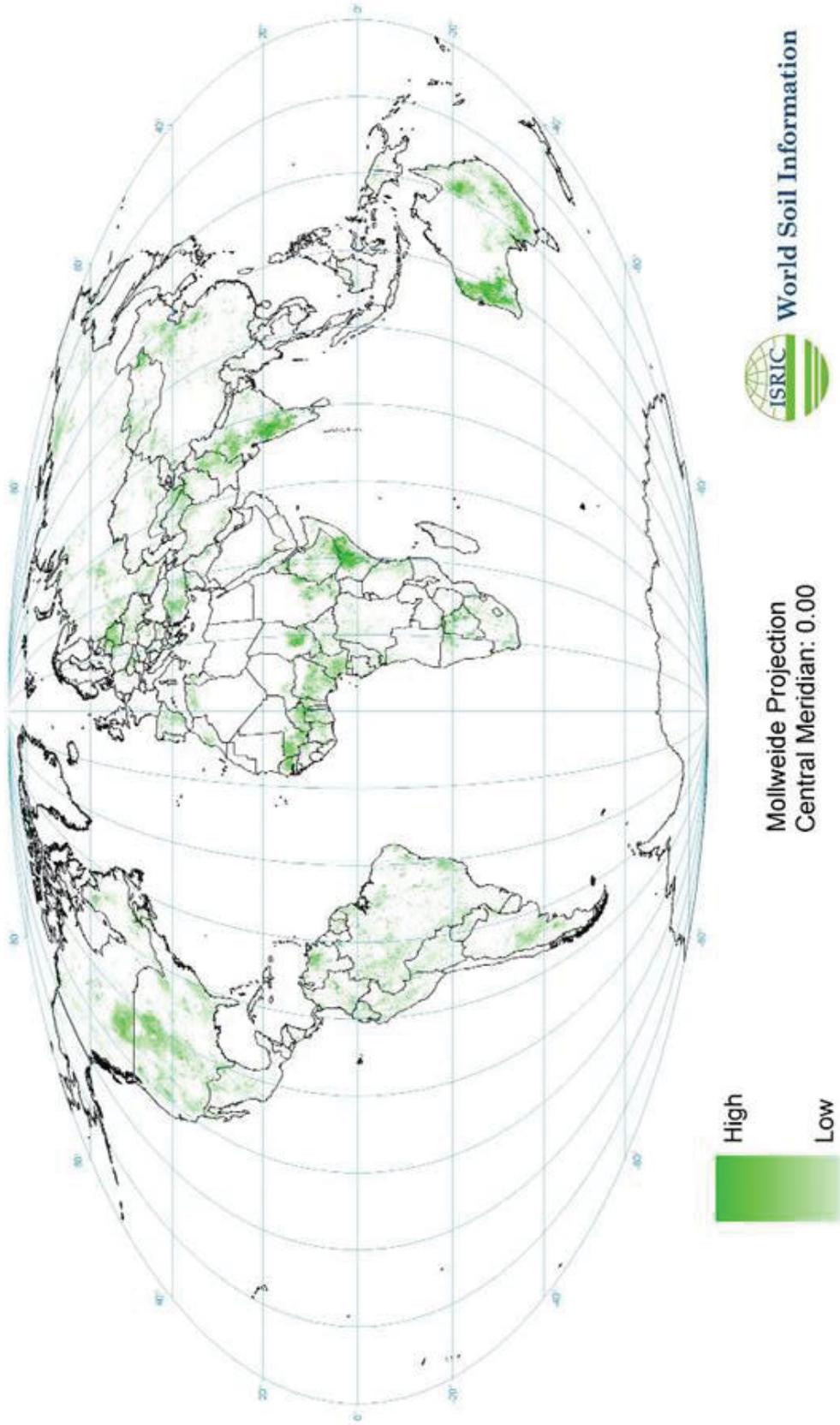


Figure 10
Global positive trend of climate-adjusted NDVI, 1981-2006.

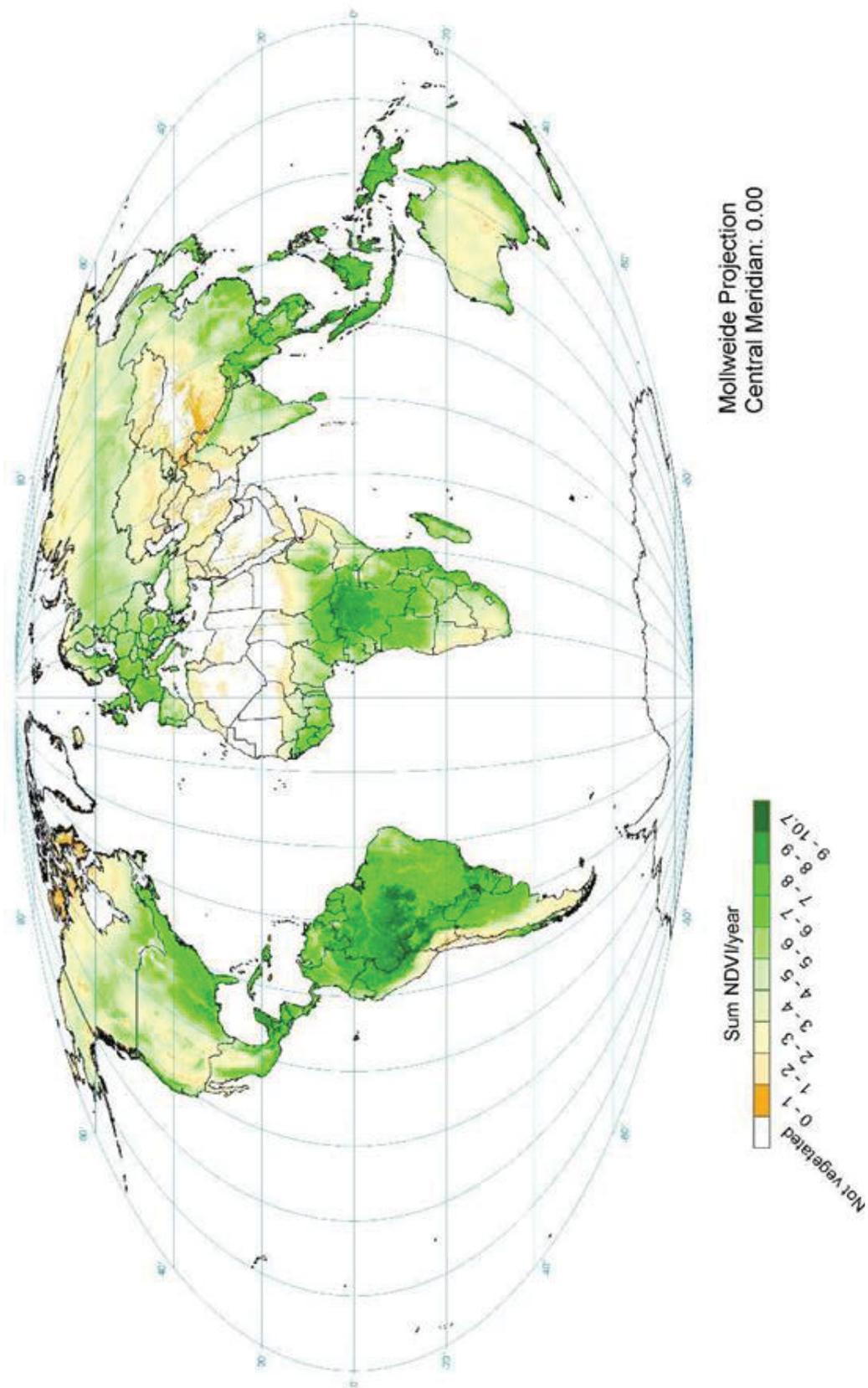


Figure S5a
Global multi-year mean annual sum NDVI, 1981-2006.

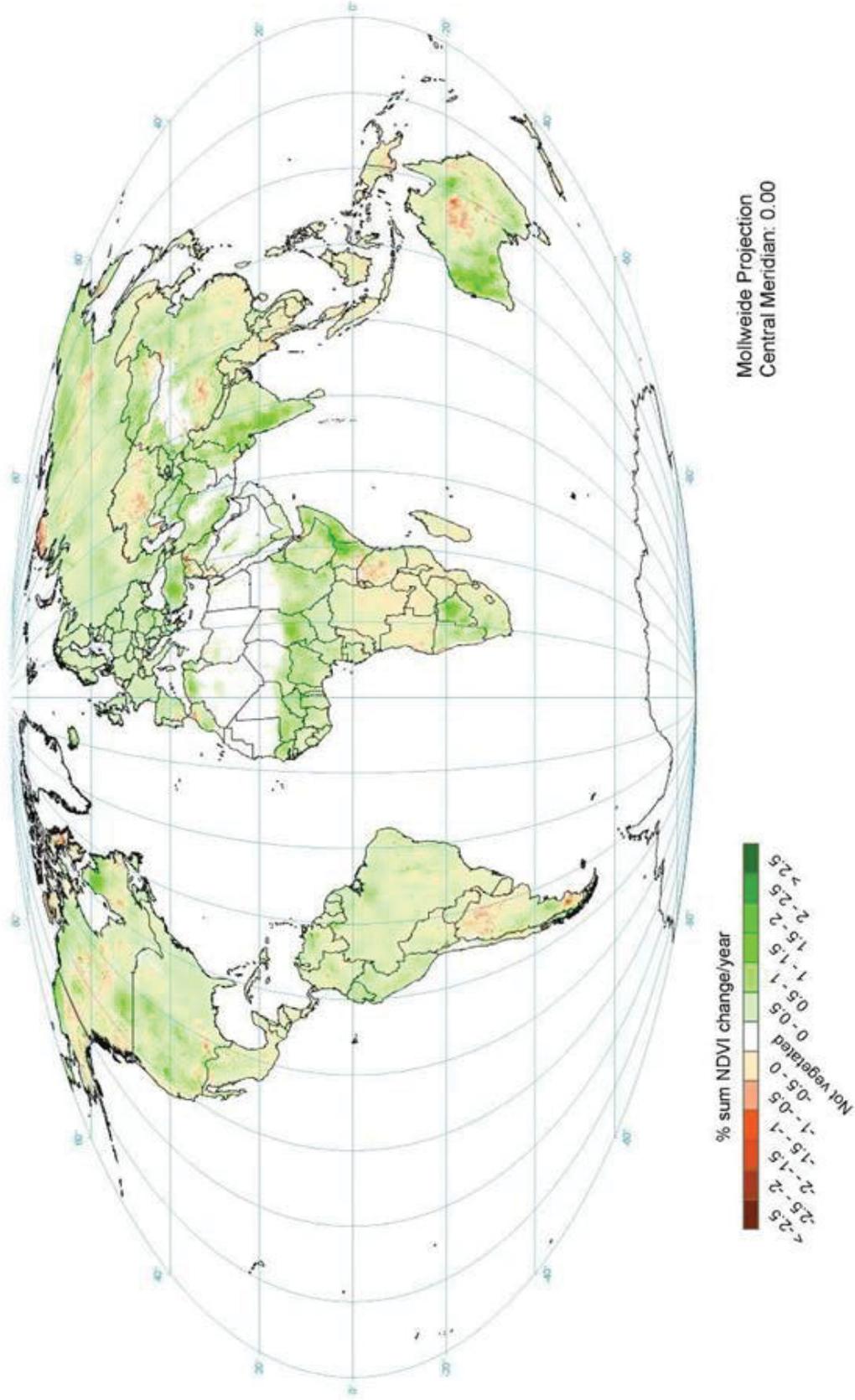


Figure S5b
Global trend in annual sum NDVI, 1981-2006.

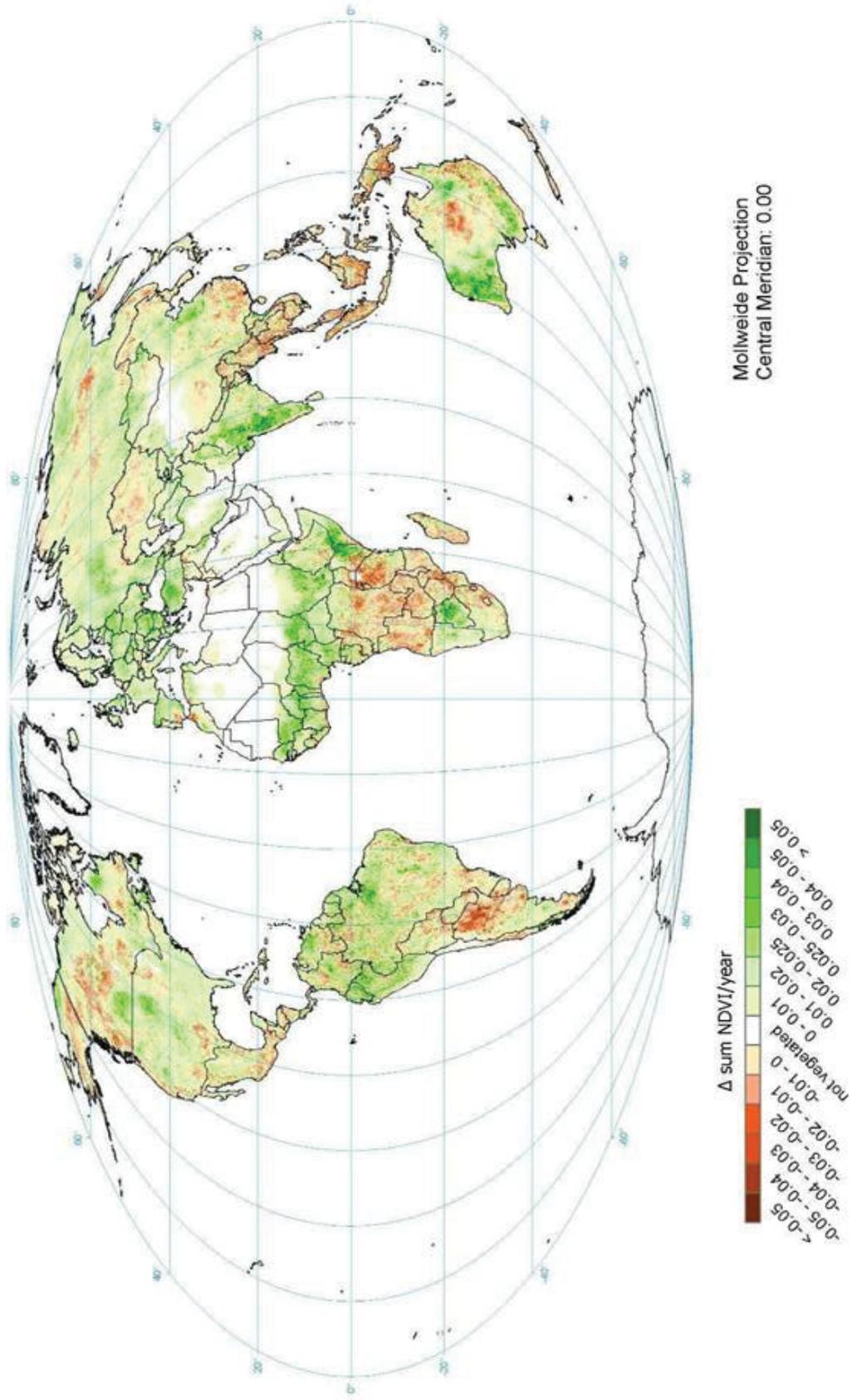


Figure S5c
 Global change in annual sum NDVI, 1981-2006.

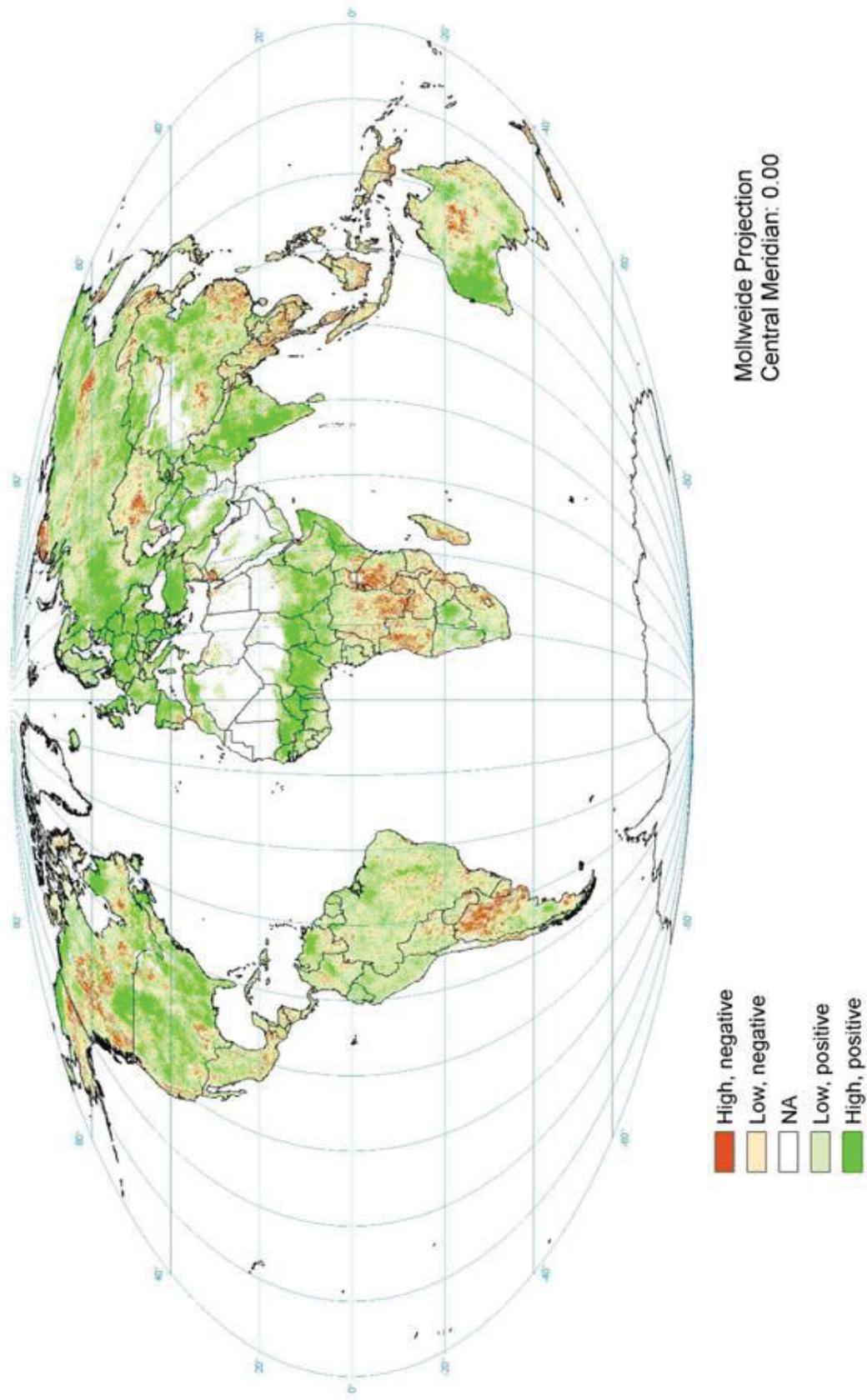


Figure S5d
Global confidence of annual sum NDVI trend, 1981-2006.

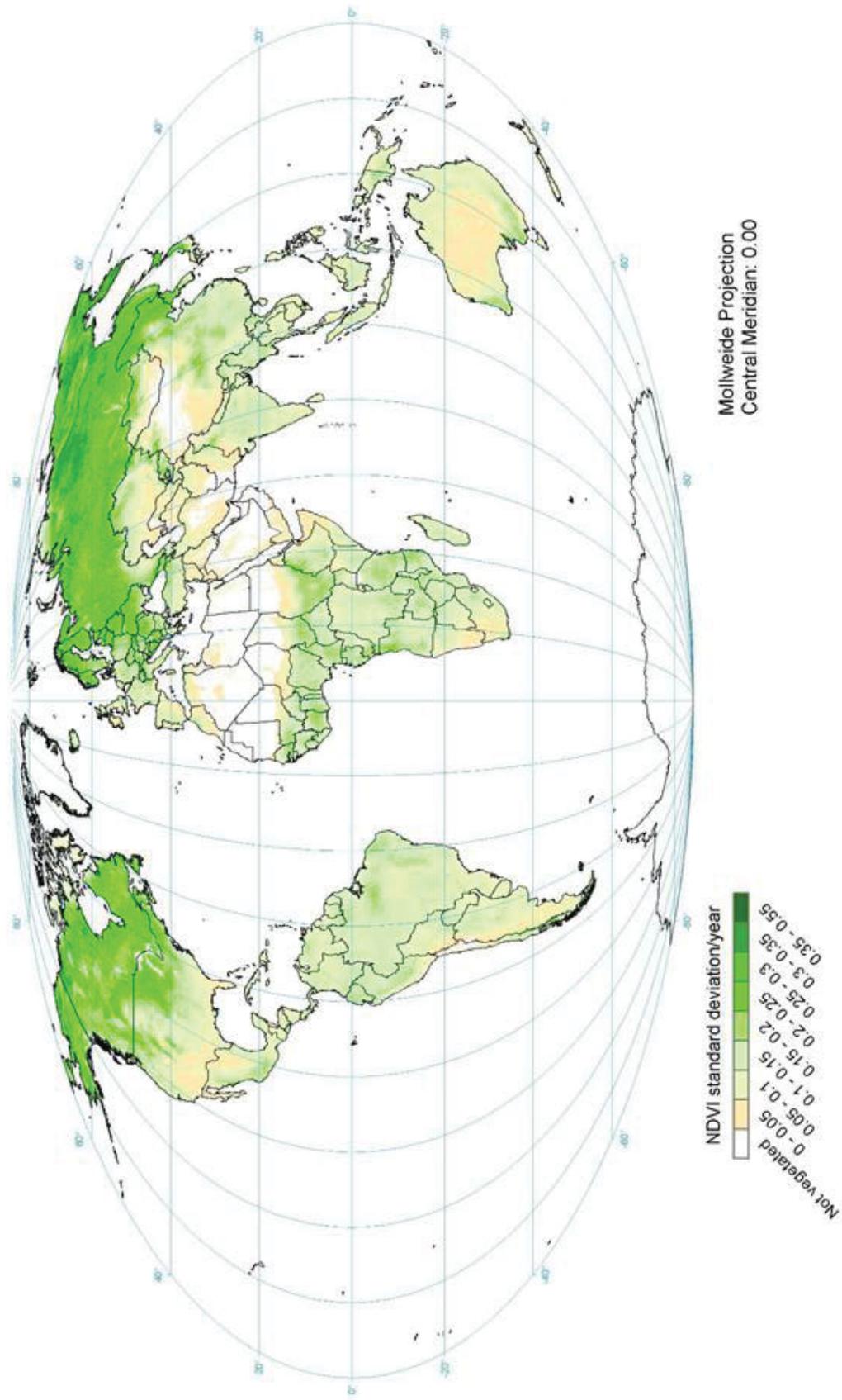


Figure S6a
Global multiyear mean NDVI standard deviation, 1981-2006.

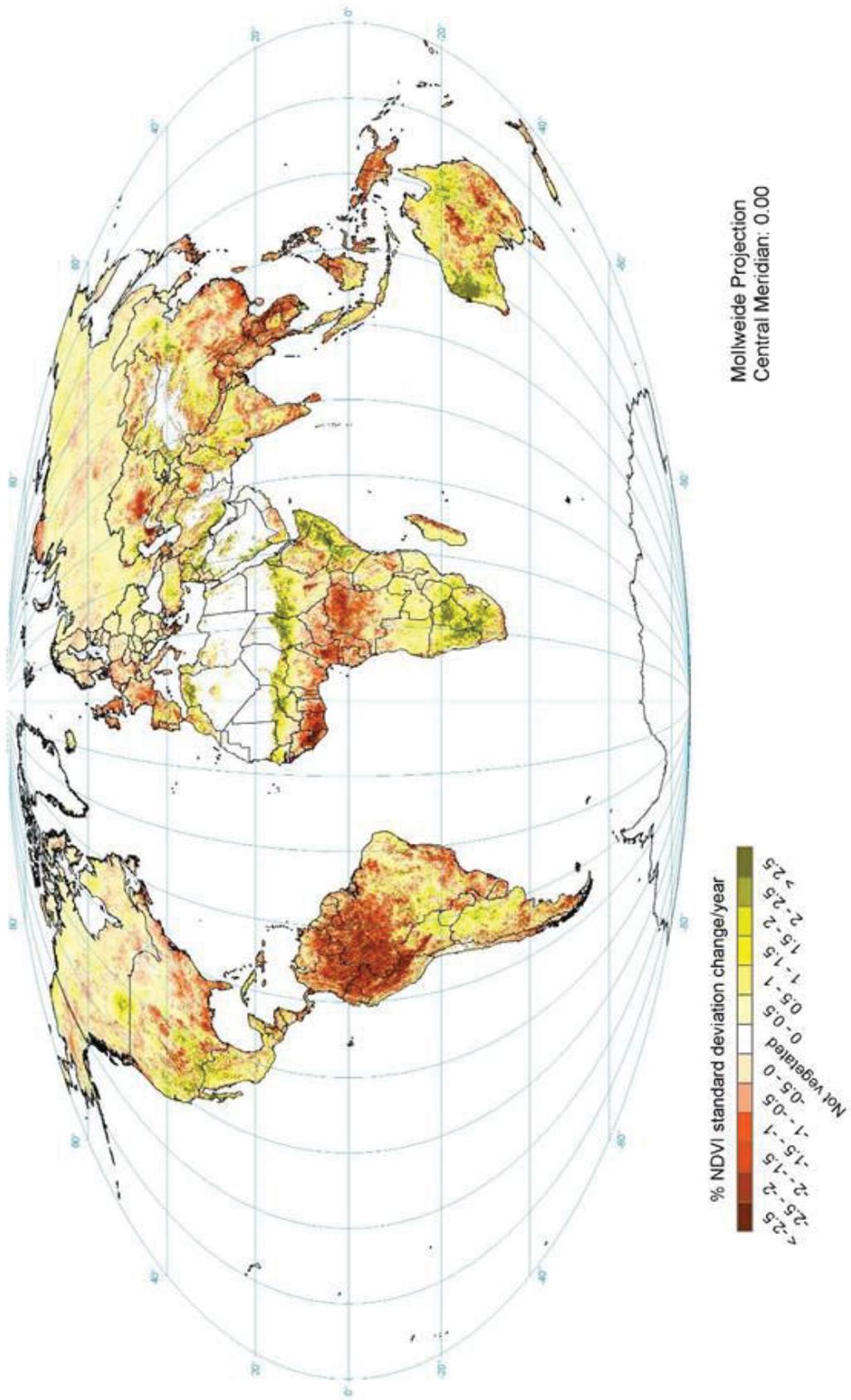


Figure S6b
Global trend in annual NDVI standard deviation, 1981-2006.

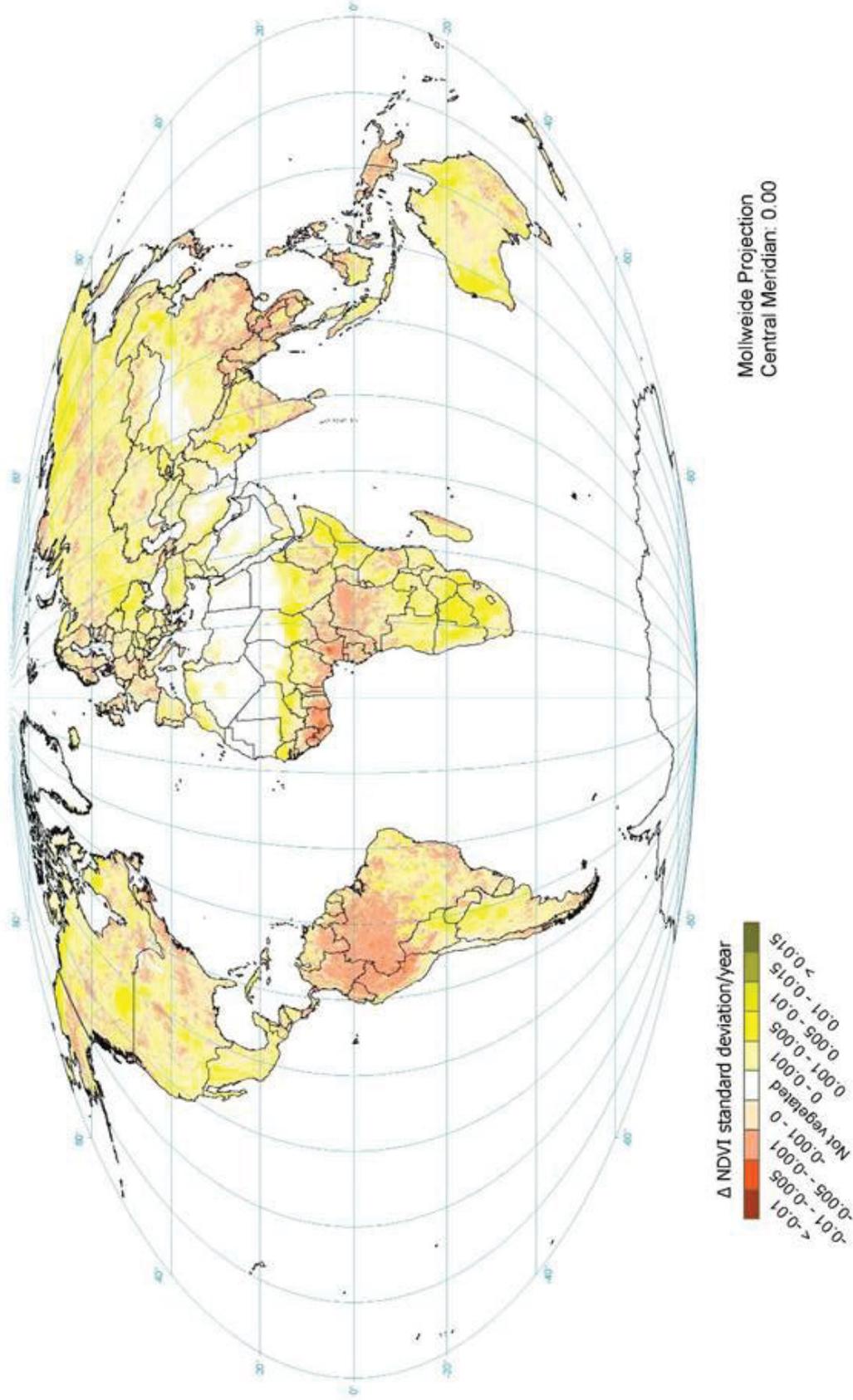


Figure S6c
 Global change in annual NDVI standard deviation, 1981-2006.

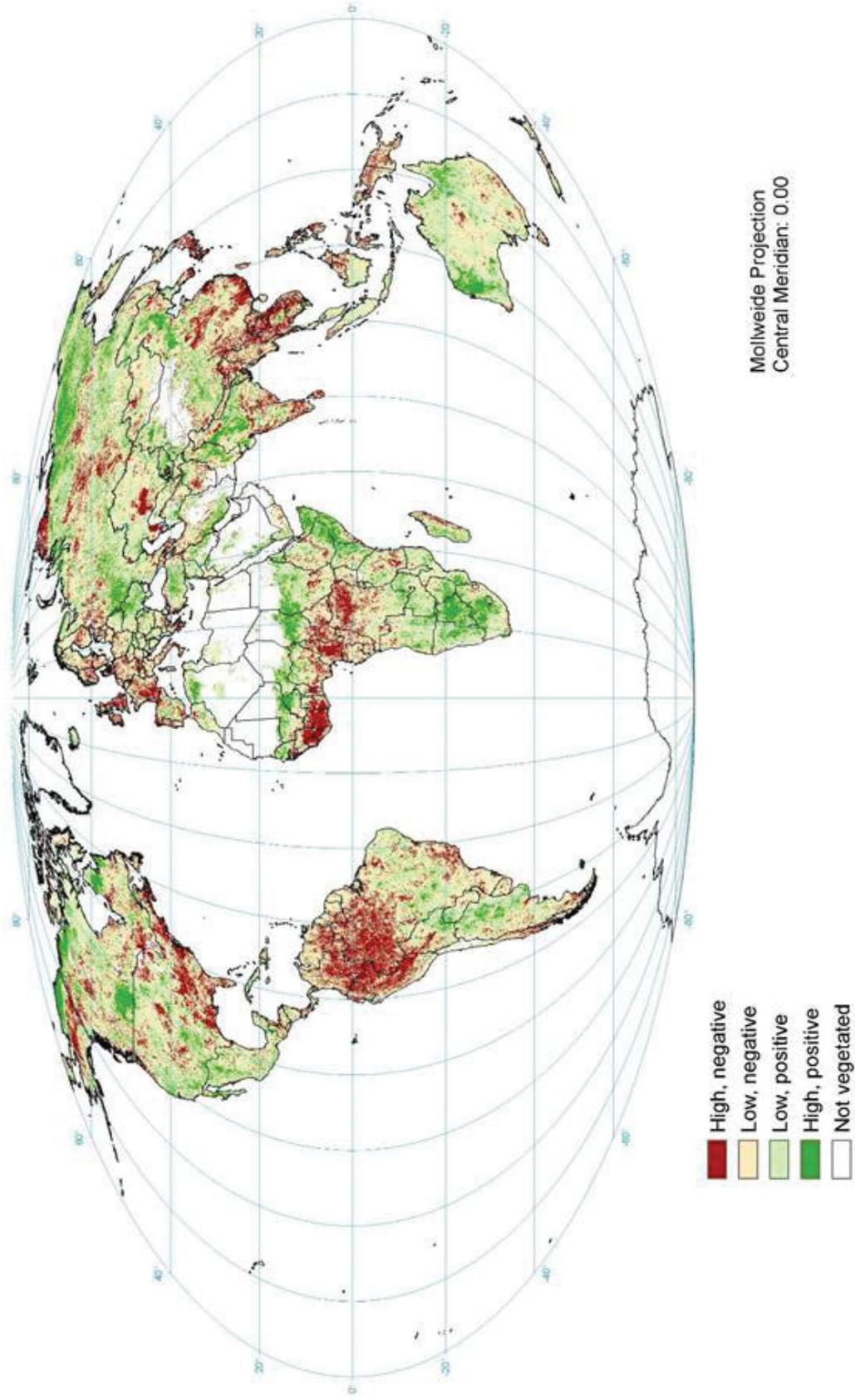


Figure S6d
Global confidence of trend in annual NDVI standard deviation, 1981-2006.

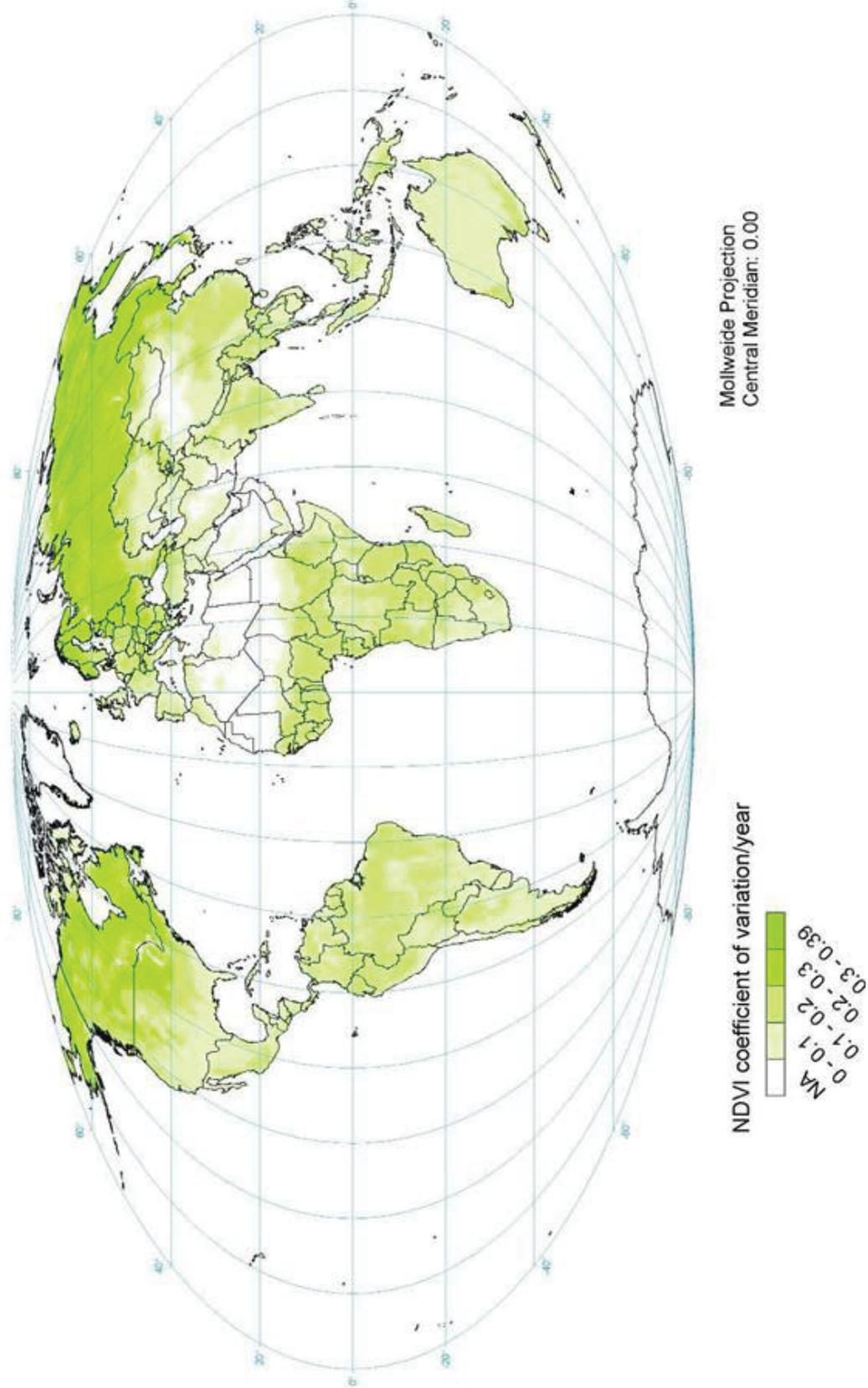


Figure S7a
Global multiyear mean annual NDVI coefficient of variation, 1981-2006.

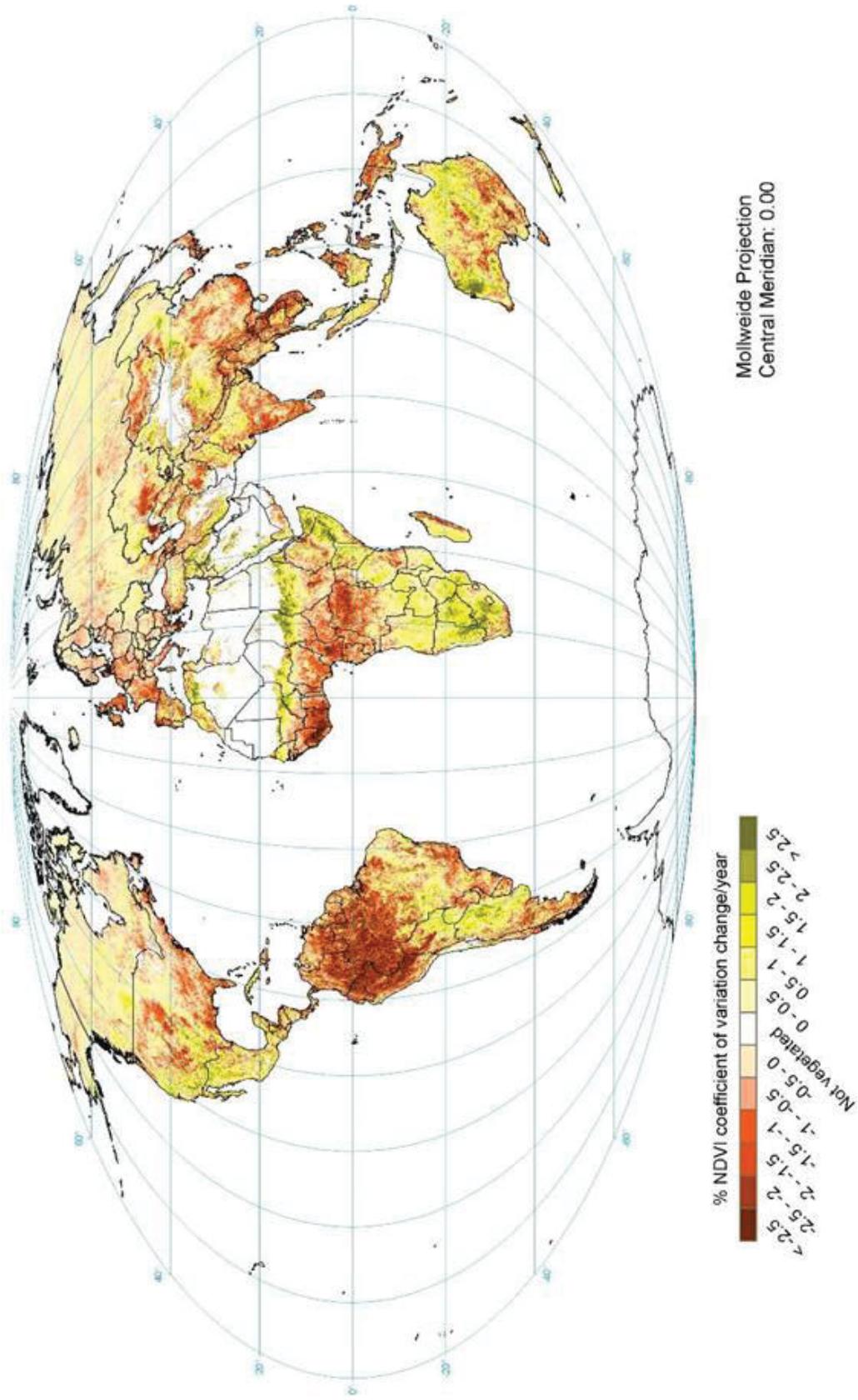


Figure S7b
Global trend in annual NDVI coefficient of variation, 1981-2006.

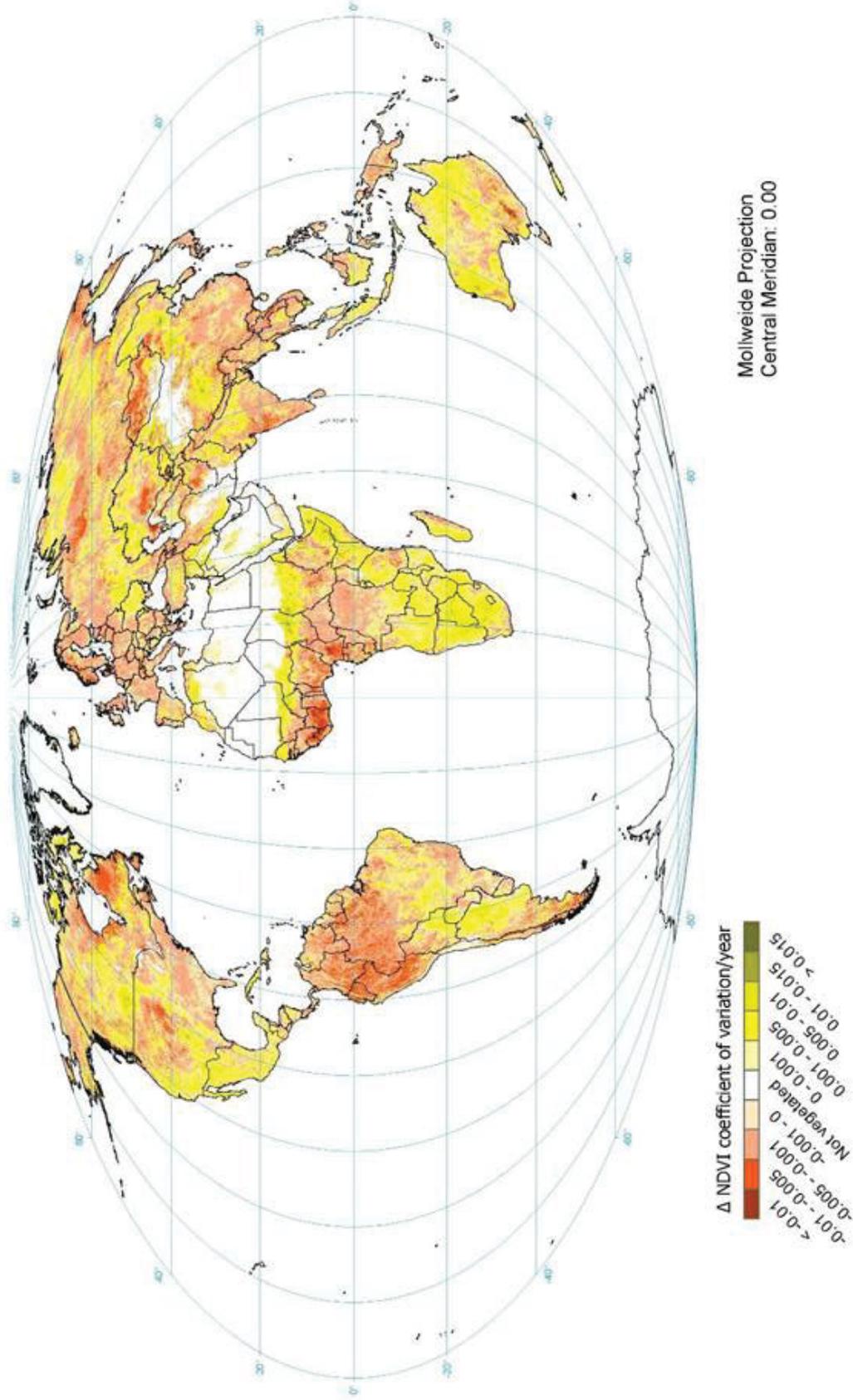


Figure S7c
 Global changes in annual NDVI coefficient of variation, 1981-2006.

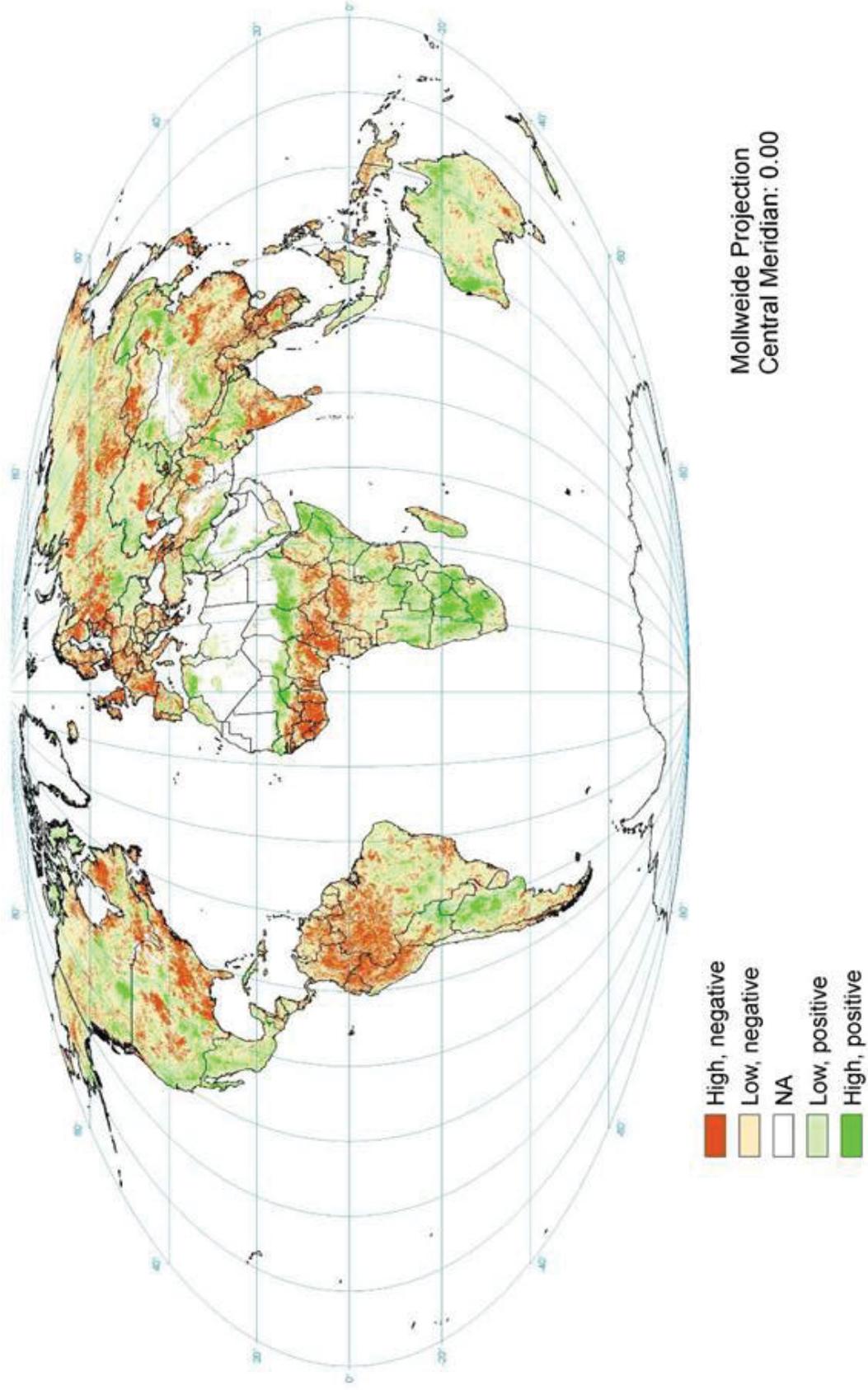


Figure S7d
Global confidence of trend in annual NDVI coefficient of variation, 1981-2006.



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