MAPPING LAND PRODUCTIVITY DYNAMICS: detecting critical trajectories of global land transformations

All life on Earth depends on the conversion and fixation of solar energy in the form of organic carbon compounds. On land, this process is driven by the photosynthesis of plants that form the terrestrial vegetation cover and the resulting output is typically referred to as land productivity, which can be quantified in terms of Net Primary Production (NPP). All other organisms (e.g., humans, other species of animal, bacteria, fungi) depend directly and indirectly on this primary production for their health and well-being.

Globally, humans appropriate a constantly increasing proportion of this NPP, affecting the structure and functioning of ecosystems, and which in many cases exceeds their natural variability and dynamics.\(^1\) Hence, land productivity is an essential variable for detecting and monitoring active land transformations typically associated with land degradation processes. It can be expressed as an equivalent of terrestrial NPP per unit of area and time, and reflects the overall capacity of land to support biodiversity and provide ecosystem services. Changes in land productivity are the result of environmental conditions and/or land use and management that impacts the quantity and quality of terrestrial ecosystem services. A persistent decline in land productivity points to the long-term alteration in the health and productive capacity of the land, the basis for economic growth and sustainable livelihoods.

Against this background, trends in land productivity has been adopted by the United Nations Convention to Combat Desertification (UNCCD) as one of three biophysical progress indicators\(^2\) for mandatory reporting and is proposed as a sub-indicator for the global indicator to monitor progress towards achieving Sustainable Development Goal (SDG) target 15.3 on land degradation neutrality (LDN).\(^3\)
Basic principles of monitoring land productivity at the global level

The state of the Earth's vegetative cover and its development over time is a generally accepted representation of land productivity and its dynamics, reflecting integrated ecological conditions and the impact of natural and predominantly anthropogenic environmental change.

The global monitoring of land productivity typically relies on the multi-temporal and thematic evaluation of long-term time series of remotely-sensed vegetation indices, computed from continuous spectral measurements of photosynthetic activity. The provision of the time series of suitable vegetation indices and partly of model-derived gross and net primary production (GPP, NPP) is operationally addressed by existing national and international Earth Observation Systems, closely cooperating within international frameworks such as the intergovernmental Group on Earth Observation (GEO) in implementing Global Earth Observation System of Systems (GEOSS).

A substantial body of peer-reviewed research clearly underpins the use of these indices for studying vegetation dynamics at global, continental and sub-continental scales. There is empirical evidence that these data are highly correlated with biophysically meaningful vegetation characteristics, such as photosynthetic capacity and primary production that are closely related to typical global land surface changes associated with the processes of land degradation and recovery.\(^5\)

The use of continuous time series of global vegetation data, primarily in the form of a Normalized Difference Vegetation Index (NDVI), developed rapidly in the early 1990s. Since then, the data processing and techniques for their analyses have improved significantly. Techniques for data quality screening, geometric correction, calibration between sensors, atmospheric and solar zenith corrections, cloud screening, and data compositing have resulted in several databases of global NDVI data of high quality that are freely accessible over the Internet. Currently, the spatial resolution of these datasets range from coarse (8 to 1 km) to medium (250 m) resolution.\(^5\)

Although NDVI is the most commonly used vegetation index, other indices have been proposed and used for global and regional scale studies, such as two variants of the Enhanced Vegetation Index (EVI),\(^6\) the Soil Adjusted Vegetation Index (SAVI),\(^7\) and the model derived FAPAR (Fraction of Absorbed Photosynthetically Active Radiation).\(^8\) Although some of these indices have been reported to perform better than NDVI under some specific vegetation conditions, e.g., SAVI for sparse vegetation cover or FAPAR for sparse and very dense canopies, they require additional adjustment factors or model inputs for their derivation which are not always reliably measured and depend on empirical estimates. An up-to-date review and comparison of the various vegetation indices can be found in Yengoh et. al., 2015.\(^9\)

Despite its well-understood limitations, NDVI is currently considered the most independent and robust option for the global analyses of land productivity, offering the longest consolidated time series and a broad range of operational data sets at different spatial scales. Over the last few decades, extensive research has demonstrated the strong relationship between NDVI and primary productivity as shown in Figure 1.

**Figure 1: Comparison between integrated gross primary production from 12 flux towers and integrated NDVI from MODIS Terra, for the respective growing seasons where the flux towers were situated. This demonstrates the strong relationship between NDVI and primary production which is directly related to chlorophyll abundance and energy absorption.**\(^{10,11}\)
Thus, the use of NDVI time series is consistent with the demand to use a metric that can provide equivalents of primary productivity. However, in the context of combating desertification and implementing LDN within the UNCCD and SDG frameworks, approaches to assessing land degradation with global satellite data require the ability to disaggregate information from national scales to sub-national administrative and landscape units (e.g., watersheds) in order to be policy relevant. This is essential as all measures to halt and reverse land degradation have to be addressed at the national or sub-national level fully considering the local context and conditions.

The challenge is how to express land productivity changes directly in physical units of GPP or NPP at the subnational and local levels. Comprehensive, spatially-distributed, direct ground measurements of GPP/NPP are not feasible. Current satellite based products, such as the MODIS NPP or the COPERNICUS DMP (Dry Matter Productivity), though delivered at 1 km sampling, are modelled with very coarse resolution inputs of radiation and climate variables (typically 5 to 10 km) which, when disaggregated to the sub-national level, do not reflect the characteristic vegetation heterogeneity at landscape level. More advanced techniques using chlorophyll fluorescence measurements have only recently started with spatial resolutions of 10 km or more.

Consequently, in terms of maturity and “operational readiness”, the estimation of primary productivity state and changes at national and local scales (at resolutions of 250 m to 1 km) with remote sensing inputs, in the form of time integrated vegetation indices as proxies for primary productivity, are the most realistic option for routine use at this time.

Time series processing for land degradation assessments: rationale and strategies

The use of productivity change in land degradation monitoring is aligned in many respects with the principles of ecosystem resilience theory. In this context, a central concept is the system’s ability to cope with and recover from disturbance and stress, which can be described and analysed following trajectories of a hysteresis curve as outlined in Figure 2.17

This implies that land productivity changes cannot be assessed just on the basis of comparing land productivity values expressed in units of primary production (GPP, NPP) for single reference years or averages of a few years centred around them. To be meaningful, approaches must be based on multi-temporal change and trend analysis which are continuously repeated in defined time steps using an extended time series.

In addition, it should be understood that the analyses of trends and changes in land productivity is a methodology to detect areas with persistent and active declines in primary productivity pointing to on-going land degradation rather than areas which have already undergone degradation processes and have reached a new equilibrium from which they do not further degrade within the observation period in the time series used. This is confirmed by studies which paired and monitored non-degraded and degraded areas in South Africa for 16 growing seasons; while both types of land were exposed to identical rainfall regimes, the degraded areas were not less stable or resilient than non-degraded areas.18

Figure 2: Schematic trajectory of a hysteresis curve. With increasing pressure, productivity declines to reach point B until the stress is reduced. When stress is reduced, productivity increases again. A fully resilient system (green curve) will go back to its original state (A), thus oscillating between stages A and B. If the system has decreased resilience (red curve) it will only return to lower productivity at point C and possibly reach a new equilibrium at a lower productivity level. The resilience of the system (R) is related to the distance between A and C.
In view of this, the term “land productivity dynamics” (LPD) used in the 3rd edition of the World Atlas of Desertification (WAD) produced by the Joint Research Centre of the European Commission highlights that the primary productivity of a land system, even in stable conditions, is not a steady state but usually highly variable between different years/vegetation growth cycles. This is a function of natural or human-induced (e.g., sustainable land management) adaptation to the considerable natural variability of environmental conditions. Hence a land system’s primary productivity assumes a dynamic equilibrium rather than a linear continuum.

The LPD maps used in the 3rd edition of the WAD do not provide a numerical measure of land productivity per se but depict the persistent trajectory of land productivity dynamics during the 15 year observation period of the available remote sensing time series. It provides 5 qualitative classes of persistent land productivity trajectories during the available time window from 1999 to 2013 where classes do not directly correspond to a quantitative measure (e.g., t/ha of NPP or GPP) of lost or gained biomass productivity. The 5 classes, as described in Tables 1 and 2, are rather a qualitative combined measure of the intensity and persistence of negative or positive trends and changes in the photo-synthetically active vegetation cover over the observed period. The main elements of the LPD data set processing chain leading to the 5 classes in the image data are summarised below.
Pre-processing

Input: SPOT-VGT daily coverage
- geometric correction
- spectral and radiometric calibrations to top of atmosphere reflectance (ToA)
- pixel masking (land- water- snow delineation, cloud and cloud shadow detection)
- atmospheric correction (includes correction for the absorbing and scattering effects of atmospheric gases, in particular ozone, oxygen and water vapour, of the scattering of air molecules, of absorption and scattering due to aerosol particles) and correction of directional effects.
- NDVI derivation and extraction of 10 days NDVI composite images (3 per month)
  i.e., a total of 540 observations in the time series.

Classification

Main steps:
- For all 15 years, aggregation of the 36 annual NDVI observations to an annual productivity proxy metric i.e., integral NDVI over the main seasonal growth cycle, in case of pronounced ecosystem seasonality, or integrated yearly NDVI in the absence of pronounced seasonality. (see Figure 3)
- Calculation of linear trend of the z-score normalized time series of aggregated NDVI values over the 15 years and parallel calculation of the net change over the same period by applying the Multi Temporal Image Differencing (MTID) method. Combination of the two variables trend and change with 4 variants possible (+trend/+change; +trend/-change; -trend/+change; -trend/-change), (see Figure 4, Step 1)
- Iso-data class levelling and differencing of the average productivity in the initial and final 3 years of the time series, resulting in a productivity class change layer. (see Figure 4, Step 2 and Step 3)
- Logical matrix combination of the latter two layers to an integrated class layer and conclusive aggregation to the final 5 classes (see Figure 5 Global LPD map), applying weighting functions derived from Local Net Scaling (LNS) (see Figure 4, Step 4) applied to the last 5 years average values of the annual productivity metric within an Ecosystem Functional Units

Legend description

The five classes of productivity trends are described as combinations of the above mentioned steps as follows:
1. Declining trend: where negative trend, negative MTID change, LNS performance below median
2. Early/moderate signs of decline: negative trend, negative MTID change, LNS performance above median
3. Stable, but stressed: combinations of contradicting signs of negative trend and positive MTID change, LNS performance below median
4. Stable, not stressed: positive trend, positive MTID change + LNS performance below median or positive trend, negative MTID
5. Increasing trend: positive trend, positive MTID change, LNS above median

Table 1: Processing steps for land productivity dynamics mapping

<table>
<thead>
<tr>
<th>Sensor</th>
<th>SPOT-VGT21</th>
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Figure 3: Phenological parameters derived from remote sensing time series for each year 1999 to 2013 from 1 km SPOT VEGETATION data (36 observations/year)

- S1: seasonal integral (b+e+g)
- CF: cyclic fraction (g)
- PF: permanent fraction (d+e+f)
- SER: seasonal exceeding residual integral (d+f)
- MPI: minimum-minimum permanent integral (a+b+c)
- SPI: seasonal permanent integral (b+e)
- SRI: seasonal residual integral (e+g)
Figure 4: Illustration of the sequence of the 4 main intermediate processing steps as outlined in Table 1, applied to full time series of 15 annual phenological aggregates (1999 to 2013), see also Figure 3 and resulting in final LPD map shown in Figure 5.

**Step 1: Steadiness** (1999 - 2013)

- Strong negative ECD
- Moderate negative ECD
- Moderate positive ECD
- Strong positive ECD

**Step 2: Initial standing biomass** (1999-2001)

- Low
- Medium
- High

**Step 3: Standing biomass at change** (1999-2001 vs 2011-2013)

- No change
- Change for 1 class
- Change for 2 and more classes
- Mixed?

**Step 4: Local net scaling** (performance of last 5 years)

- LS ≥ 50%
- LS < 50%
The thematic evaluation of the resulting LPD map (see Figure 5) is further analyzed in light of available information on land cover/land use and as a second step contextualized with environmental change processes that coincide with potential drivers of land degradation following the WAD conceptual “convergence of evidence” framework.

To accommodate the complex interactions and dynamics that trigger land cover/use change, the WAD relies on the concept of convergence of evidence: when multiple sources of evidence are in agreement, strong conclusions can be drawn even when none of the individual sources of evidence is significant on its own. Convergence maps are compiled by combining global datasets on key processes using a reference period of 15-20 years.

Combinations are made without prior assumptions in the absence of exact knowledge of land change processes at variable locations. Patterns indicate areas where substantial stress on land resources is to be expected.

The LPD map shows that declining land productivity is a global phenomenon with considerable differences between continents and regions. Even more distinct variations in LPD class distributions are evident at the continental level when they are disaggregated by key land cover/land use types. While excluding land areas with no significant vegetal primary productivity, i.e., hyper-arid, arctic and very-high altitude mountain regions, it is apparent that indications of decreasing land system productive capacity can be observed on all continents.

<table>
<thead>
<tr>
<th>Class Value</th>
<th>Description</th>
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<tbody>
<tr>
<td>1</td>
<td>Persistent decline in productivity</td>
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<tr>
<td>2</td>
<td>Persistent moderate decline in productivity</td>
</tr>
<tr>
<td>3</td>
<td>Stable, but stressed; persistent strong inter-annual productivity variations</td>
</tr>
<tr>
<td>4</td>
<td>Stable productivity</td>
</tr>
<tr>
<td>5</td>
<td>Persistent increase in productivity</td>
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</tbody>
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Table 2: Five classes of land productivity dynamics

Figure 5: Global Land Productivity Dynamics map 1999 to 2013 showing 5 classes of persistent land productivity trajectories during the observation period. Decreasing productivity trend classes do not per se indicate land degradation or increasing trends recovery. For further evaluation with the aim of identifying critical land degradation zones, an analytical convergence of evidence framework using additional thematic information is required as outlined in the following sections.

Key

- Declining
- Moderate decline
- Stressed
- Stable
- Increasing

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Referring to the observation period from 1999 to 2013, approximately 20.4% of the Earth’s vegetated land surface shows persistent declining trends in land productivity. However, the level to which the different continents are affected by persistent productivity decline (classes 1 and 2) or a signal of instability or stress in the land’s productive capacity (class 3) varies significantly (see Figure 6). Africa, Australia and South America are affected to an extent that is greater than the global average, with declining or stressed areas at approximately 22% for Africa, 37% for Australia and 27% for South America. Asia with 14%, Europe with 12% and Northern America with 18% declining or unstable land productivity dynamics are below the global average. Further differentiation of the extent and significance of land productivity changes become possible by further stratified analyses of LPD class distributions for example as function of land cover/land use information as briefly demonstrated in Chapter 4 of this Outlook.

**Validation of LPD classes against other data sets**

The validation of LPD classes is not a trivial task as typically there is no directly comparable field data on land productivity change. Nevertheless, the validation of LPD classes in terms of plausibility testing against the land cover change detected by the European Space Agency’s Climate Change Initiative Land Cover (CCI LC) data set and locally against multi-temporal high resolution data in Google Earth has been performed. A preliminary statistical validation of LPD classes was performed against mapped land cover changes between the CCI LC epochs 2000 and 2010, taking into consideration the full range of mapped CCI LC classes, not only the 6 IPCC land cover/use classes. The area of CCI LC mapped land cover change globally covers approximately 246,067 km².

For a number of critical land cover transitions, cross correlation between the expected LPD class distributions in relation to observed changes were investigated and further verification is ongoing. For example, transitions from semi-natural land cover classes with tree cover to bare/sparsely vegetated areas are expected to feature predominantly in LPD classes 1 to 3, but less so in LPD classes 4 and 5. This highlights a somewhat different picture than the overall global LPD class distribution where classes 4 and 5 account for the vast majority accounting for roughly 80% of all pixels.

This example is illustrated in Figure 8 a) and b) where a high level of correspondence between declining land productivity and independently mapped loss of vegetation cover, expressed as land cover class change, provides evidence of the plausibility and relative accuracy of the LPD class distribution. The inverse case is shown with transitions from semi-natural tree covers to irrigated crops (Figure 8 c), one of the limited cases where high input and intensive agriculture may exceed the natural potential of primary productivity. For other land cover transitions, the correlation is less clear at global level (e.g., conversion from evergreen broadleaf forest to cropland) but initial steps towards more refined

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**Figure 6: Global and continental area percentages affected by persistent declining or unstable land productivity dynamics during the observation period 1999 to 2013.**

**Key**

<table>
<thead>
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<th>Declining and moderate decline combined</th>
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<tr>
<td>Stressed</td>
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Figure 7: Global distribution of areas with CCI LC mapped land cover change between 2000 and 2010. Area extents are exaggerated in order to be visible at the scale presented.

Figure 8: Distribution of LPD classes within areas transitioning from a) forest to bare/sparsely vegetated land, b) forest to shrub land and c) forest to irrigated crop.

and spatially disaggregated verification at regional to national levels indicate clearer and more plausible relationships between LPD classes and transition from semi-natural land cover to cropland. Results of this more refined validation process will be made available and presented in the 3rd edition of the WAD.

The vast majority of LPD classes indicating a clear and persistent change of land productivity fall into areas where no mapped information of land cover change is available. Therefore, local verification using Google Earth multi-temporal high-resolution images is recommended as a quick option for verifying land productivity changes. The LPD geo-tiff class images can be easily downloaded from Google Earth and interactively investigated against changes visible in the underlying high-resolution image database. During the UNCCD’s first LDN pilot phase 2014/2015, it was shown that in many cases declining productivity classes were due to urban and infrastructure expansion (e.g., dam construction, mine openings) which acted as a driver of localized land productivity losses affecting ecosystem functioning in their wider surroundings.
CONCLUSION

The 5 classes of the LPD data set integrate – over a 15 years observation period from 1999 to 2013 – information on the direction, intensity and persistence of trends and changes in above-ground biomass generated by photosynthetically active vegetation cover, widely equivalent to GPP of the global land surface.

Within one pixel (1 km²), low-resolution imagery may typically assemble a considerable amount of vegetation heterogeneity, and above-ground biomass production is not to be equated with crop production. Consequently, it must be clearly understood and communicated that ‘land productivity’ in the context of the LPD dataset strictly refers to the overall above-ground vegetation biomass productivity. This is not conceptually the same as, nor necessarily directly related to, agricultural income per area unit or ‘land productivity’ as used in conventional agricultural terminology.

Furthermore, it has to be understood that the 5 LPD classes provided are not associated to specific levels of above-ground biomass production or specific biomass quantities lost or gained during the observation period. Each class characterizes mainly the overall direction, relative change intensity, and persistence of GPP, independently of the actual level of vegetation abundance or land cover type. This means each LPD class can appear in any type of land cover and at any level of vegetation density. Nevertheless, the quantitative information on biomass productivity levels is contained in the input NDVI time series data and used in the processing chain as outlined in Table 1.

Given that the global time series of daily observations of vegetation indices, such as the NDVI (or others), are continuously updated for each subsequent monitoring phase, the extended NDVI time series will be used to produce the LPD classes but with longer time series as input. Thus, LPD class changes between the baseline period and the follow-up monitoring phases will indicate changes in land productivity trajectories. The next LPD release will extend the existing product to the period 1999 to 2016. In parallel it is proposed to address land productivity monitoring with numerical values of change rather than with ‘qualitative classes’ of the LPD by providing information on percentage change in land productivity between the baseline and each subsequent monitoring year. A GPP proxy could be expressed as an average of time-integrated NDVI over a 3 to 5 year window centered on the baseline year and the monitoring reference years.

In terms of maturity and “operational readiness,” the estimation of GPP at national and sub-national levels (at spatial resolution between 1000 to 250m), the use of remote sensing inputs in the form of vegetation indexes, that reflect green vegetation cover dynamics and spatial heterogeneity at these scales, are currently the most practical for routine use. Extension of the LPD approach to 30m resolution for specific areas using available Landsat archives and new data sources (e.g., Copernicus Sentinel) is only 5 to 10 years away.
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