Land Degradation Neutrality: Productivity Indictor & Remote Sensing Challenges

David Fargey

1. Introduction

Sustainable development goal (SDG) 15.3 adopted by the UN General Assembly in 2015:

"By 2030, combat desertification, restore degraded land and soil, including land affected by desertification, drought and floods, and strive to achieve a land degradation-neutral world."[9]

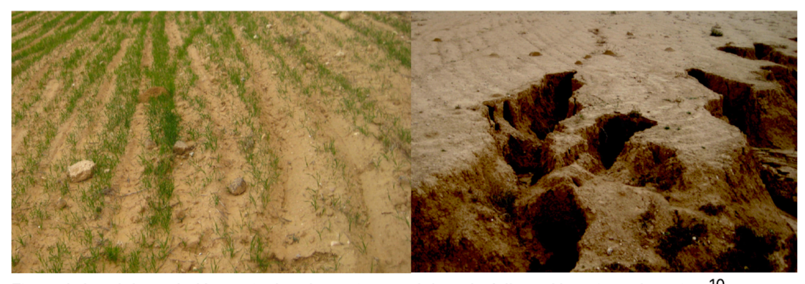

Figure 1. Land degraded by agricultural practices and drought followed by rain and erosion.[10]

Status and change in land productivity measured by net primary production (NPP; see Fig 2.) was one of three indicators adopted for monitoring SDG 15.3.[11]

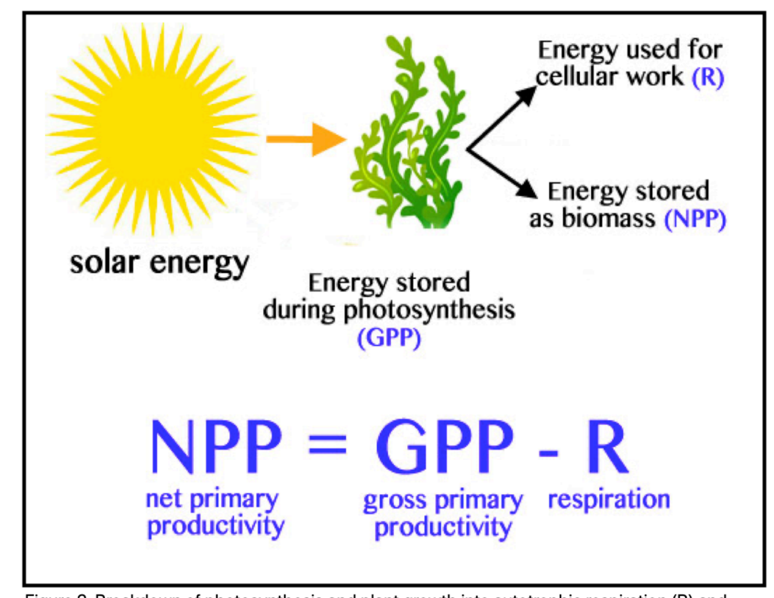

Figure 2. Breakdown of photosynthesis and plant growth into autotrophic respiration (R) and biomass (NPP). Source: http://www.bio.miami.edu/dana/330/330F19_18.html

Satellite remote sensing methods have been recommended for tracking NPP[12] (see Fig. 3)

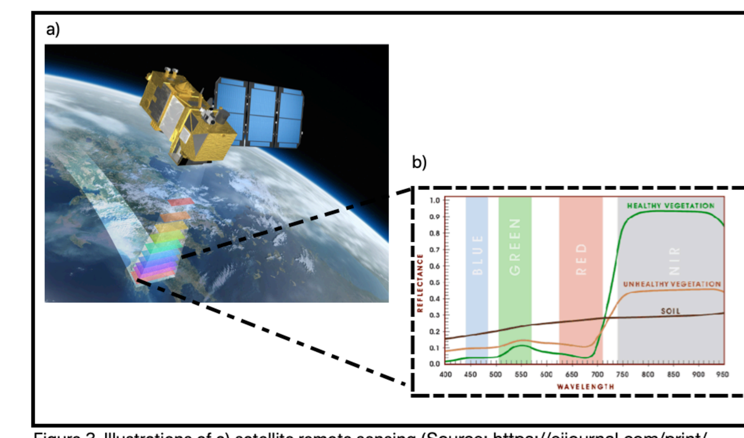

Figure 3. Illustrations of a) satellite remote sensing (Source: https://eijournal.com/print/industry-update/industry-updates-3) and b) the spectral signature derived from remote sensing data for healthy vegetation, unhealthy vegetation, and soil (Sources: Source: https://support.dronedeploy.com/docs/camera-filters-for-ndvi-mapping-1

Guidance on methods for monitoring productivity recognizes the value of the validation of satellite observations but indicates that it is "not essential."[12]

2. Methods & Challenges

The normalized difference vegetation index (NDVI) is derived from satellite imagery and is related to biomass and NPP[2,4,6,7,13] (see Fig.4)

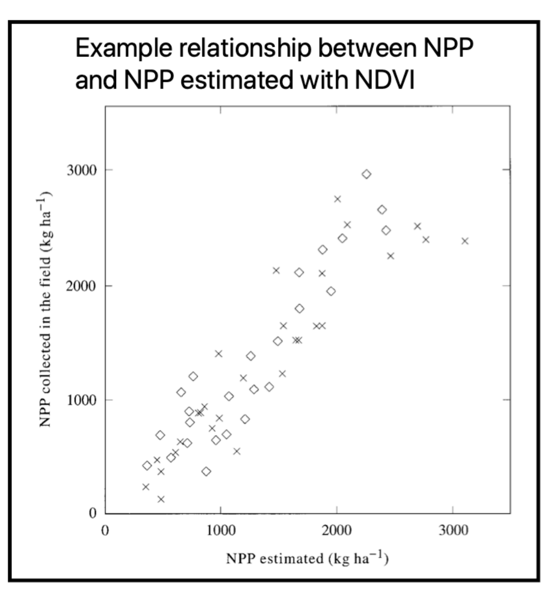

Figure 4. Plot of NPP collected in the field vs NPP estimated from a multiple linear regression model in Senegal with the variables: NDVI integral, percentage tree cover, and the mean surface temperature. NPP in 1990 (squares) and 1991 (crosses).[8]

Challenging to distinguish between anthropogenic and non-anthropogenic contributions to land degradation with remote sensing imagery.[5,15]

Non-degraded areas for establishing baseline productivity can be difficult if not impossible to identify and statistical approaches can underestimate productivity.[5]

Satellite measurements of productivity are based on absorbed photosynthetically-active solar radiation, but it is difficult to accurately account for variations due to additional plant physiological or ecological factors (see Fig. 5).[5]

Unknown limits of various land-cover productivity may lead to misclassification.[5]

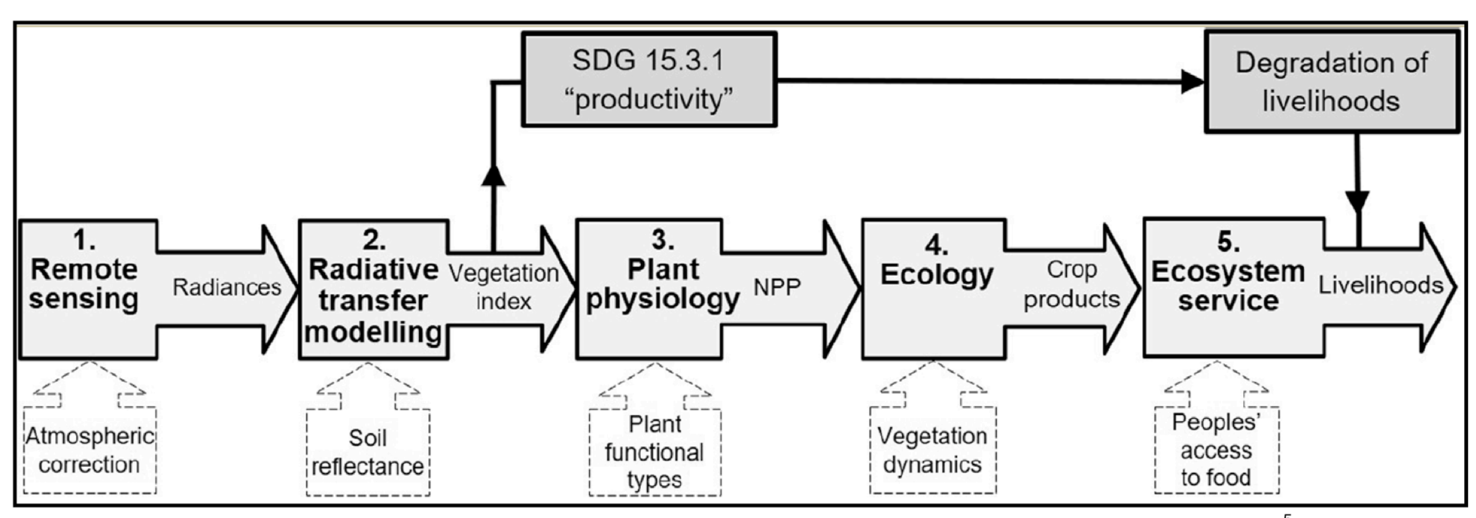

Figure 5. The logical sequence of stages between (1) remotely-sensing measurements and (5) degradation of ecosystem services- illustrated using provision of food.[5]

Invasive species can have higher rates of productivity than native species.[5]

Agricultural lands can be highly productive while contributing to land degradation.[15]

Forest and agricultural lands can show a negative productivity trend due to land management practices(see Fig. 6).[14]

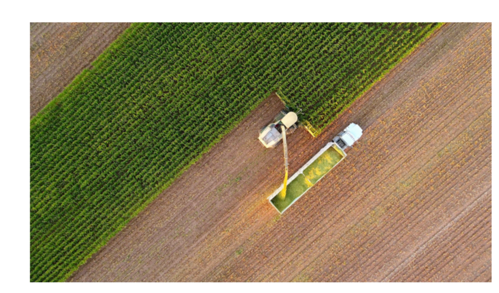

Figure 6. Agricultural field being harvested. Lands will be identified as highly productive before harvest and minimally productive after using NDVI. Source: https://blog.orbcomm.com/iot-agriculture-harvest-monitoring-maximizing-crop-value-productivity/

Land degradation can occur at finer scales than can be detected with the relatively coarse spatial resolution of satellite imagery.[1]

3. Case Study[3]

Comparison study of differences between expert knowledge and remote sensing methods evaluating land degradation and productivity in the Puna Region, Argentina (see Fig. 7).

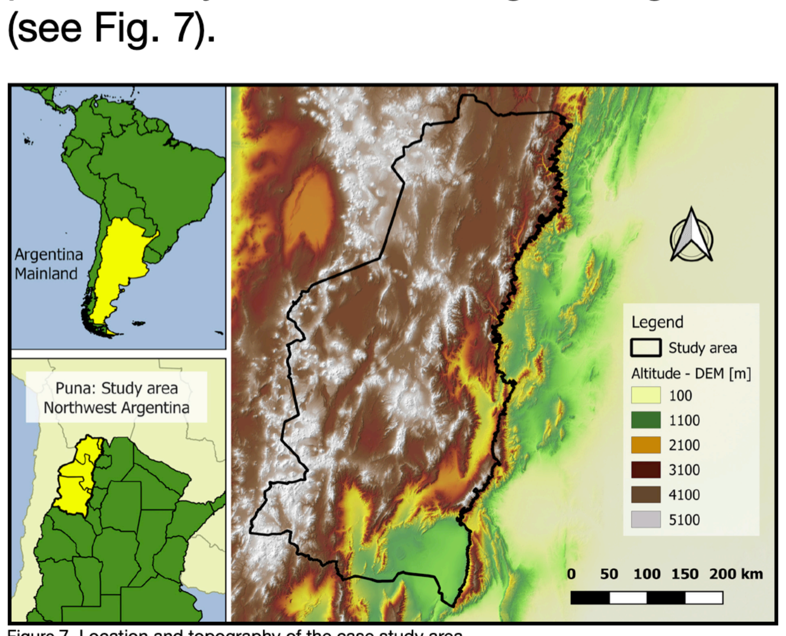

Figure 7. Location and topography of the case study area.

Table 1. Land use for each land use system unit.

LUS	Land use
1	Transhumance
2	Lake shores livestock rearing
3	Irrigated lands
4	Extensive livestock rearing
5	Extensive livestock rearing
6	NA
7	Extensive livestock rearing
8	Extensive livestock rearing
9	NA
10	Irrigated lands
11	Extensive livestock rearing
12	Extensive livestock rearing
13	NA
14	NA
15	Intensive mining
16	Intensive mining
17	Extensive livestock rearing
18	Extensive livestock rearing

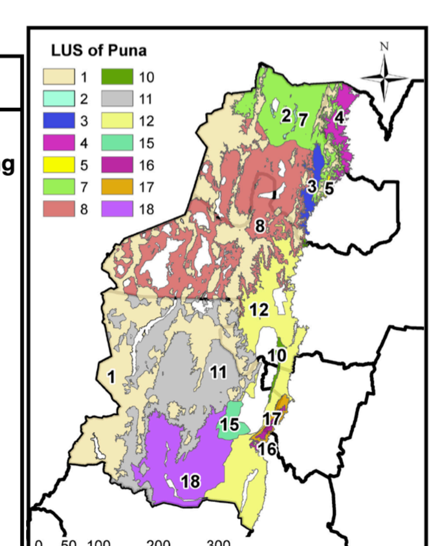

Figure 8. LUS units obtained from participatory mapping during the expert assessment in the Puna region of Argentina.

Areas are delineated into land use systems (LUS) based on land cover and land use (see Table 1 and Fig. 8).

Expert knowledge indicated degradation trends, satellite derived NDVI indicated increased productivity trends (see Fig. 9).

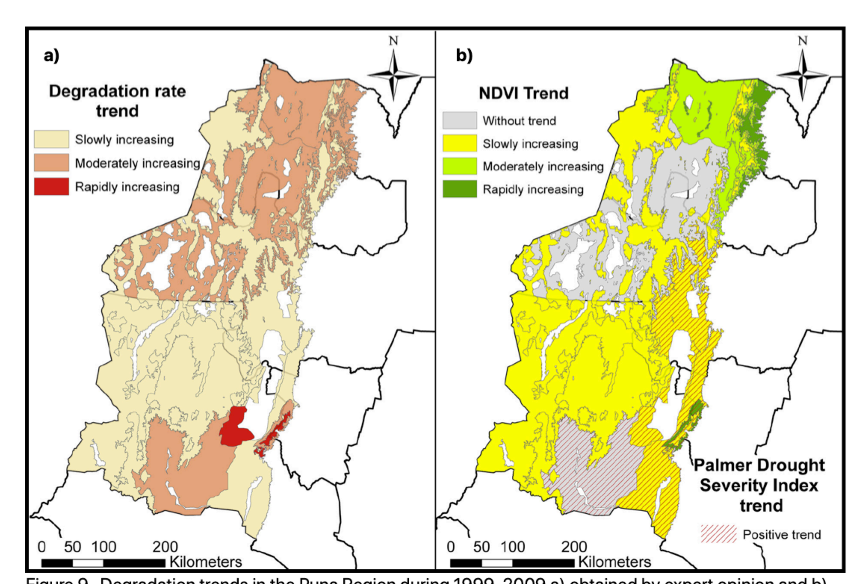

Figure 9. Degradation trends in the Puna Region during 1999-2009 a) obtained by expert opinion and b) NDVI and PDSI trends at the LUS level for the same period.

Difference for LUS 17 can be explained by positive Palmer Drought Severity Index (PDSI) trends (i.e. increased humidity).

Difference for LUS 4 can be explained by changes in agricultural practices, i.e. land degradation and increased productivity.

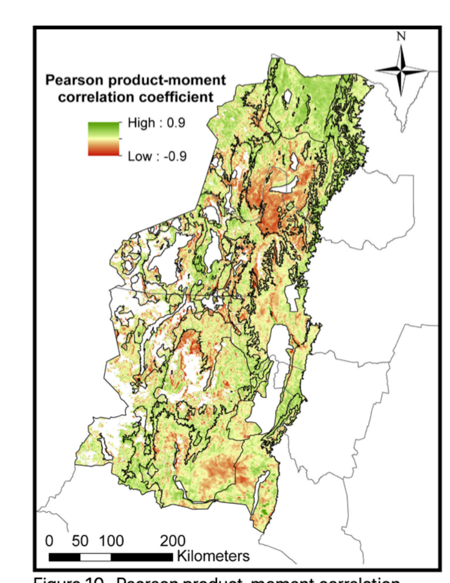

Figure 10. Pearson product-moment correlation coefficient of the NDVI deseasonalized time series of the 1999-2009 period in the Puna Region. Positive and high coefficients (green) indicate NDVI positive trends whereas negative ones (red) indicate the opposite.

When LUS polygons are disaggregated into satellite pixels (1 pixel = 1km^2), trends reported by expert knowledge become apparent (see Figs. 9-10).

Degradation reported in LUS polygons may also be biased by expert knowledge focused on subareas within each polygon.

4. Discussion

True land degradation neutrality requires a level of monitoring that is difficult to accomplish. Land degradation neutrality is a framework that aims to increase land rehabilitation, decrease degradation rates, and limit new degradation.

Rate of change is not well accounted for in the productivity indicator (see Table 2.), and faster rates of degradation may outpace land-rehabilitation rates.

Table 2. Lookup table for determining pixel degradation for productivity indicator. Y is degraded and N is not degraded. "Performance" is based on baseline comparison.[12]

Class	Trajectory	State	Performance	Degraded
1	Y	Y	Y	Y
2	Y	Y	N	Y
3	Y	N	Y	Y
4	Y	N	N	Y
5	N	Y	Y	Y
6	N	Y	N	N
7	N	N	Y	N
8	N	N	N	N

Some of the remote sensing limits monitoring productivity are offset by the land cover/ land use change indicator (see Fig. 11) and the soil organic carbon indicator included in the SDG 15.3 monitoring guidelines; if one indicator provides evidence of degradation, the area is classified as undergoing degradation or as being in a degraded state.[13]

Original Class / Final Class: IPCC Class	Forest Land	Grassland	Cropland	Wetlands	Settlements	Other Land
Forest Land	Stable	Vegetation loss	Deforestation	Inundation	Deforestation	Vegetation loss
Grassland	Afforestation	Stable	Agricultural expansion	Inundation	Urban expansion	Vegetation loss
Cropland	Afforestation	Withdrawal of Agriculture	Stable	Inundation	Urban expansion	Vegetation loss
Wetlands	Woody Encroachment	Wetland drainage	Wetland drainage	Stable	Wetland drainage	Wetland drainage
Settlements	Afforestation	Vegetation establishment	Agricultural expansion	Wetland establishment	Stable	Withdrawal of Settlements
Other Land	Afforestation	Vegetation establishment	Agricultural expansion	Wetland establishment	Urban expansion	Stable

Figure 11. Graphical summary of the land cover/land use change matrix. Major land cover processes (flows) are identified and boxes are colour coded as improvement (green), stable (blue) or degraded (red).[12]

5. Conclusion

Satellite remote sensing provides a means of monitoring national or regional areas but does not comprehensively capture all attributes of land degradation.

Supplementary methods and validation methods provide information complementing remote sensing data.

Biases due to the geographical limitations of expert knowledge for large areas of land are possible; disaggregated remote sensing data can support these assessment and monitoring methods.

6. References

1. Cowie, A. L., Orr, B.J., Castillo Sanchez, V.M., Chasek, P., Crossman, N.D., Erlewein, A., Louwagie, G., Maron, M., Metternicht, G.I., Minelli, S., Tengberg, A.E., Walter, S., & Welton, S. (2018). Land in balance: The scientific conceptual framework for Land Degradation Neutrality. *Environmental Science & Policy, 79*, 25-35.

2. Field, C. B., Randerson, J.T., & Malmström, C.M. (1995). Global net primary production: Combining ecology and remote sensing. *Remote Sensing of Environment, 51*(1), 74-88.

3. García, C.L., Teich, I., Gonzalez-Roglich, M., Kindgard, A.F., Ravelo, A.C., & Liniger, H. (2019). Land degradation assessment in the Argentinean Puna: Comparing expert knowledge with satellite-derived information. *Environmental Science & Policy, 91,* 70-80.

4. Jensen, J.R. (2007). *Remote sensing of the environment: An earth resource perspective* (2nd ed). Pearson Prentice Hall.

5. Prince, S. D. (2019). Challenges for remote sensing of the Sustainable Development Goal SDG 15.3.1 productivity indicator. *Remote Sensing of Environment, 234*, 111428.

6. Prince, S.D., & Goward, S.N. (1995). Global primary production: A remote sensing approach. *Journal of Beogeography, 22*(4/5), 815.

7. Purkis, S.J., & Klemas, V. (2011). *Remote sensing and global environmental change.* Wiley-Blackwell.

8. Rasmussen, M.S. (1998). Developing simple, operational, consistent NDVI-vegetation models by applying environmental and climatic information: Part I. Assessment of net primary production. *International Journal of Remote Sensing, 19*(1), 97-117.

9. Rosa, W. (Ed.). (2017) *Transforming Our World: The 2030 Agenda for Sustainable Development.* Springer Publishing Company.

10. Safriel, U. (2017). Land Degradation Neutrality (LDN) in drylands and beyond - where has it come from and where does it go. *Silva Fennica, 51*(1B).

11. Sims, N.C., England, J.R., Newnham, G.J., Alexander, S., Green, C., Minelli, S., & Held, A. (2019). Developing good practice guidance for estimating land degradation in the context of the United Nations Sustainable Development Goals. *Environmental Science & Policy, 92,* 349-355.

12. Sims, N.C., Green, C., Newham, G.J., England, J.R., Held, A., Wulder, M.A., Herold, M., Cox, S.J.D., Huete, A.R., Kumar, L., Viscarra-Rossel, R.A., Roxburgh, S.H., & McKenzie, N.J. (2017). *Good practice guidence SDG indicator 15.3.1: Proportion of land that is degraded over total land area.*

13. Vlek, P.L.G., Le, Q.B., & Tamene, L. (2010). Assessment of land degradation, its possible causes and threat to food security in Sub-Saharan Africa. In R. Lal & B.A. Stewart (Eds.), *Food security and soil quality* (pp. 57-86). CRC Press.

14. Wessels, K.J. (2009). Letter to the Editor. *Soil Use and Management, 25*(1), 91-92.

15. Yengoh, G.T., Dent, D., Olsson, L., Tengberg, A.E., & Tucker, C.J. (2015). Limits to the Use of NDVI in Land Degradation Assessment. In G.T. Yengoh, D. Dent, L. Olsson, A.E. Tengberg, & C.J. Tucker III (Eds.), *Use of the Normalized Difference Vegetation Index (NDVI) to Assess Land Degradation at Multiple Scales* (pp. 27-30). Springer International Publishing