

# Convergence of Dynamic Vegetation Net Productivity Responses to Precipitation Variability from 10 Years of MODIS EVI

G. Ponce<sup>1,\*</sup>, S. Moran<sup>2</sup>, A. Huete<sup>3,1</sup>, C. Bresloff<sup>4</sup>, T. Huxman<sup>4</sup>, D. Bosch<sup>5</sup>, J. Bradford<sup>6</sup>, A. Buda<sup>7</sup>, S. Gunter<sup>8</sup>, H. McNab<sup>9</sup>, M. McClaran<sup>10</sup>, D. Peters<sup>11</sup>, J. Sadler<sup>12</sup>, M. Seyfried<sup>13</sup>, P. Starks<sup>14</sup>, D. Sutherland Montoya<sup>15</sup>, and T. Heartsill<sup>16</sup>

<sup>1</sup>University of Arizona Soil, Water & Environmental Science, <sup>2</sup>USDA ARS Southwest Watershed Research, <sup>3</sup>University of Technology Sydney, Plant Functional Biology and Climate Change, <sup>4</sup>University of Arizona Ecology & Evolutionary Biology, <sup>5</sup>USDA ARS Southeast Watershed Research Laboratory, <sup>6</sup>USFS Northern Research Station, Grand Rapids MN, <sup>7</sup>USDA ARS Pasture & Watershed Mgmt Research Unit, <sup>8</sup>USDA ARS Southern Plains Range Research Station, <sup>9</sup>USDA Forest Service NC, <sup>10</sup>University of Arizona School of Natural Resources and the Environment, <sup>11</sup>USDA ARS Jornada Experimental Range, <sup>12</sup>USDA-ARS Cropping Systems & Water Quality Research Unit, Columbia MO, <sup>13</sup>USDA Northwest Watershed Research Center, <sup>14</sup>USDA ARS Grazing Lands Research Laboratory, <sup>15</sup>USDA Forest Service Pacific Southwest Research Station, <sup>16</sup>USDA-FS International Institute of Tropical Forestry

**Abstract - According to Global Climate Models (GCMs) the occurrence of extreme events of precipitation will be more frequent in the future. Therefore, important challenges arise regarding climate variability, which are mainly related to the understanding of ecosystem responses to changes in precipitation patterns. Previous studies have found that Above-ground Net Primary Productivity (ANPP) was positively related to increases in annual precipitation and this relation may converge across biomes during dry years. One challenge in studying this ecosystem response at the continental scale is the lack of ANPP field measurements over extended areas. In this study, the MODIS EVI was utilized as a surrogate for ANPP and combined with precipitation datasets from twelve different experimental sites across the United States over a 10-year period. Results from this analysis confirmed that integrated-EVI for different biomes converged toward common precipitation use efficiency during water-limited periods and may be a viable surrogate for ANPP measurements for further ecological research.**

**Keywords:** ANPP, iEVI, MODIS, precipitation.

## 1. INTRODUCTION

One of the main components in the carbon cycle is Net Primary Production (NPP), which is defined as the annual biomass increment of both above- and below-ground components after accounting for autotrophic respiration (Saugier and Mooney, 2001). For several years, ecologists have been widely interested in studying NPP across different biomes and scales by using traditional (Lieth, 1973) and modeling approaches supported by remote sensing (Field et al., 1995; Paruelo et al., 1997; Running et al., 2004). This interest on NPP relies on its influence over other ecosystem processes. Consequently, important challenges arise regarding climate variability, which are mainly related to the understanding of ecosystem responses to changes in precipitation patterns and how to assess the impact across diverse biomes.

As part of this assessment process, previous studies report that Above-ground Net Primary Productivity (ANPP) is positively related to greater Mean Annual Precipitation (MAP) (Lieth, 1973; Knapp and Smith, 2001; Huxman et al., 2004).

One of the major challenges in studying this ecosystem response at the continental scale is the lack of ANPP field measurements over extended areas with suitable temporal variability (Clark et al., 2001). Therefore, the capability of translating spectral data into biological estimations with Vegetation Indexes (VIs) represents a key factor in the use of satellite data to estimate values of variables like ANPP across larger areas and over extended periods of time. The Normalized Difference Vegetation Index (NDVI) has been used extensively to monitor vegetation from satellite by using information from the red (high absorption) and near-Infrared wavelengths (high reflectance) (Tucker, 1979).

In previous research (Box et al., 1989; Paruelo et al., 1997; Fang et al., 2001) the NDVI as an estimator of productivity exhibited strong relationships (NDVI-Productivity) with a higher variability in both wet and dry regions. One of the first efforts in using an integration of NDVI was presented in a study by Goward et al. (1985) where they integrated 3-week composites of NDVI ( $\Sigma$ NDVI) and concluded that annually integrated patterns of NDVI measurements corresponded to known continental patterns of NPP. The accuracy of satellite data as estimator of biological parameters represents a key step in increasing the use and value of satellite information (Paruelo et al., 1997). Therefore, it is necessary that models and techniques using remote sensing data continue to improve through experimentation. As Knapp and Smith (2001) suggested in their response to Fang et al. (2001) regarding the use of NDVI to quantify NPP, where they clarify that it is important that the use of NDVI demonstrate that the inter-annual variability of the vegetation index (NDVI) is sensitive enough to detect changes in NPP across a range of biomes.

The Enhanced Vegetation Index (EVI) has been widely used for environmental studies. It was developed to optimize the vegetation signal with improved sensitivity in high biomass regions and improved vegetation monitoring through a decoupling of the canopy background signal and a reduction in atmosphere influences (Huete, 1988; Liu and Huete, 1995). The aim of this study was to test the suitability of the Enhanced Vegetation Index (EVI) as a surrogate for NPP by analyzing the convergence in dry years across different precipitation regimes.

## 2. DATA AND METHODS

### 2.1 Precipitation data

\* Corresponding author. University of Arizona Soil, Water, & Environmental Science. E-mail address: [geponce@email.arizona.edu](mailto:geponce@email.arizona.edu)

The stations involved in this project were selected from the available network of experimental watersheds across the conterminous United States (Fig. 1).

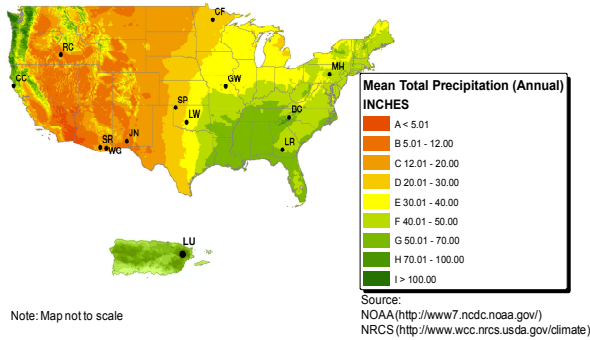


Figure 1. Stations and mean total precipitation across the conterminous United States. See table A.

These sites were reviewed by Moran et al. (2008) as part of a study on the Long-Term Data Collection at USDA for studies in ecohydrology making emphasis on the importance of long-term datasets, spanning more than 20 years, as well as the need for data records across a wide range of ecosystems.

Table A. Locations of the experimental watersheds. The geographic coordinates correspond to the centroid of an homogenous land cover type for at least an area of 2x2 km and MAP from 2000-2009.

Site	Code	MAP (mm)	Latitude	Longitude
Caspar Creek	CC	1108.9	39.337	-123.748
Southern Plains	SP	611.7	36.614	-99.576
Little Washita	LW	744.7	34.918	-97.956
Reynolds Creek	RC	249.2	43.146	-116.736
Walnut Gulch	WG	278.3	31.736	-109.937
Santa Rita Range	SR	318.6	31.846	-110.839
Goodwater Creek	GW	1050.9	39.270	-92.121
Little River	LR	1079.6	31.537	-83.626
Jornada	JN	242.5	32.588	-106.844
Mahantango	MH	1129.6	40.730	-76.591
Bent Creek	BC	1299.2	35.500	-82.624
CutFoot	CF	629.1	47.426	-94.014
Luquillo	LU	3678.9	18.313	-65.742

Precipitation data sets were provided by scientists responsible for data collection and research at each one of the stations. Our main goal in the selection of these stations was to obtain reliable precipitation data with a representative homogenous vegetation type in at least 2x2 km.

## 2. 2 MODIS EVI data set

The satellite product used for this work was MODIS EVI (MOD13Q1) with 16-day and 250-m temporal and spatial resolutions, respectively. By using the coordinates (centroid) of each station, it was possible to acquire the corresponding MODIS tiles of the MOD13Q1 product for the 10-year period (2000-2009). A 9x9 pixel (~2.25x2.25km area) window size from EVI product was used, where each pixel represented ~250m on the ground. We obtained 23 image-files per year from 2000 through 2009 for a total of 230 files for each one of the 13 locations. We applied a quality assurance (QA) control

scheme for each pixel in order to select only those pixels that met our criteria (no mixed-clouds, low-average aerosols, only land).

## 2.3 Time series analysis

For MODIS EVI time series analysis we used the TimeSat package (Jönsson and Eklundh, 2004). The main goal in using TimeSat was to standardize the gap-filling and smoothing of the time series data and obtain the start/end of the growing season, to enable us to acquire more accurate results of the iEVI (Integrated-EVI) values. One of the main features we used from this package was the Savitzky-Golay filtering algorithm (Golay and Savitzky, 1964). The main advantage of this method is that it tends to preserve features of the distribution such as relative maxima, minima and width, which are usually 'flattened' by other adjacent averaging techniques (Jönsson and Eklundh, 2004). It replaces each data value  $y_i$ ,  $i=1, \dots, n$  by a linear combination of nearby values in a window.

$$\sum_{j=-n}^n c_j y_{i+j} \quad (1)$$

where the weights are  $c_j = 1/(2n + 1)$ , and the data value  $y_i$  is replaced by the average of the values in the window. For each data value  $y_i$ ,  $i = 1, 2, \dots, n$  a quadratic polynomial is fitted as  $f(t) = c_1 + c_2 t + c_3 t^2$  to all  $2n+1$  points in the moving window and replace the value  $y_i$  with the value of the polynomial at position  $t_i$  (Jönsson and Eklundh, 2004). Thus, for our purpose this capability was important because we used the integrated portion of EVI signature extracted from the growing season of each year, as our surrogated NPP, which is during this period of time where usually satellites get more atmospheric interference, mainly because of rainfall events. In Fig. 2 we illustrate the components of the resulting smoothed time series from TimeSat.

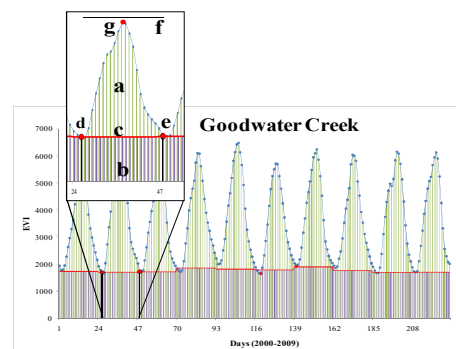


Figure 2. An example of the output obtained from TimeSat. (a) Small integral, (b) large integral, (c) base value, (d) Start of season, (e) end of season, (f) length of season, (g) amplitude.

For the case of the evergreen sites (CC, MH, BC, LR, and LU) where there is no dormant season and productivity occurs the whole year, we integrated the EVI over the entire year. Using TimeSat, we turned off the start/end of season parameters by choosing values close to 0 for the values of season start/stop.

### 3. RESULTS

In this work we tested the use of MODIS EVI dataset as a proxy for ANPP measurements by analyzing responses to precipitation variability. The comparison of totals and mean annuals is commonly applied by using linear regression models (Fang et al., 2001; Knapp and Smith, 2001) to evaluate across-sites and gradients studies. Since ecological implications in relation to the sensitivity of ecosystems to climate variability along with other environmental resources have been extensively reported, we tested the significance of our results on some of the approaches used by Knapp and Smith (2001) for testing interannual variability as well as those used in Huxman et al. (2004) to show the convergence of ecosystems on water-limited conditions using the relationship of MAP and ANPP. The Fig. 3 (a) shows the mean values of the integrated EVI and (b) the MAP (Mean Annual Precipitation) with the standard error (+SE) for the low, medium, and high precipitation regimes of the 13 sites used in this study.

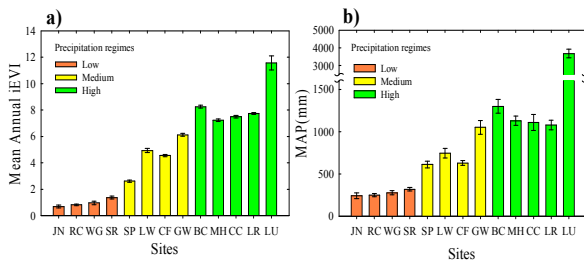


Figure 3. Mean annual values (2000-2009) for each site at low, medium, and high precipitation regime with  $\pm$ SE. (a) Mean annual integrated EVI, (b) Mean Annual Precipitation (MAP).

In Fig. 4, the annual values of precipitation and iEVI across all sites are fitted into an exponential rise to maximum model, identifying the precipitation regimes along with the higher productivity values as similarly reported by Huxman et al. (2004) at the more mesic sites, where the lowest and even negative slopes occurred. We compared the results across sites and years from the fitted model and a regression coefficient of  $r^2=0.85$  ( $P<0.0001$ ) was obtained.

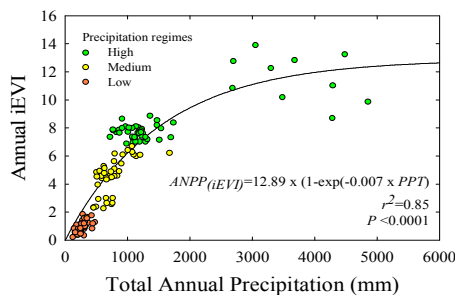


Figure 4. Exponential rise to maximum model between annual integrated EVI values and total annual precipitation of all the sites used in this study.

Our next step was the use of average annuals as presented in several studies where ANPP – PPT relationship has been studied (Paruelo et al., 1997; Knapp and Smith, 2001; Huxman

et al., 2004; Bai et al., 2008). By plotting average annuals from EVI and PPT our results strongly agree with those presented by Knapp and Smith (2001) where their cross-site study demonstrated that at continental scales, ANPP was strongly correlated with mean annual precipitation as is similarly shown in Fig 5 (a) ( $r^2=0.74$ ). Fig. 5 (b) shows the relationship between the magnitude of iEVI pulses (maxima) and declines (minima) for all the sites, with very similar results presented by Knapp and Smith (2001).

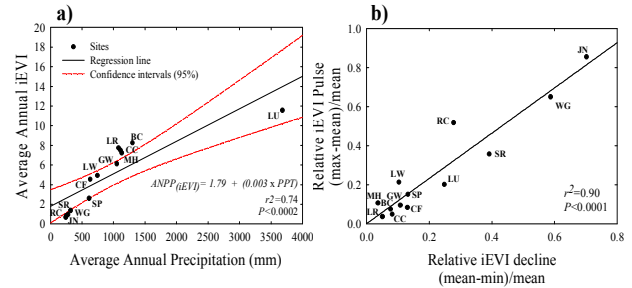


Figure 5. (a) Relationship between average annual precipitation and average annual integrated EVI, and (b) EVI pulses (maxima) and declines (minima) for the 13 sites.

In addition, we compared the minima values of precipitation (driest year) for each one of the sites and correlated them with values of EVI in order to compare with the results from Huxman et al. (2004) to determine if the convergence in those periods with water-limited conditions prevailed. Using the same approach, a linear regression over the driest years was obtained and is depicted in Fig. 6 (a), the results show a good correlation ( $r^2=0.6$ ) for the convergence of driest years, however, in (b) when the Luquillo site is excluded, our correlation coefficient is  $r^2=0.94$  ( $P<0.0001$ ).

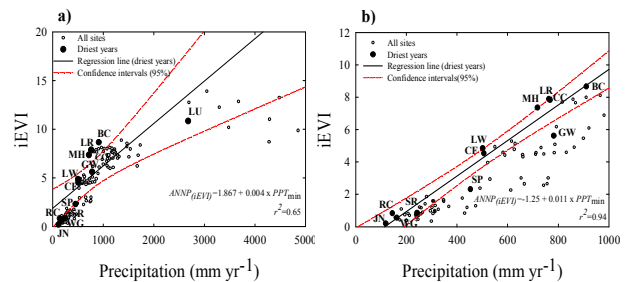


Figure 6. Linear regressions (bold line) of the closed circles, corresponding to the minima in precipitation of each site. (a) the regression over the driest year for each of the 13 sites, (b) the regression over the minima excluding Luquillo watershed.

The convergence of the vegetation productivity exhibited over the driest periods of time across this multi-site experiment strongly supports the methodology of using EVI as a surrogate for estimation of ANPP followed in this work.

### 4. DISCUSSION AND CONCLUSION

Research in ecosystems monitoring using remote sensing data has increased in the recent years because of the high demand for spatial and temporal measurements that can produce inputs for climate modeling. For this study, the use of integrated EVI

values as a proxy for ANPP measurements was the main goal. The results from our analysis lead us to continue in a similar path, where the estimation of a biophysical variable like ANPP can be strongly supported by the use of satellite data. According to Weltzin et al. (2003) there is a need for alternative approaches that can be used to extrapolate the results of isolated experiments that includes those cross-site comparisons or gradient studies. Thus, values of iEVI allowed us to test this extensively studied relationship between ANPP and precipitation across different biomes as an important step in finding new ways to derive ANPP estimations using satellite data.

As part of our approach, in Fig. 6 (a-b), the convergence across sites during the driest years is depicted using the results from this study. However, it is important to consider the issues related with the high variability found in the tropical forest site (LU), Fig. 6 (a), which can lead to dispersion of the model. The methods used to test our results were taken from previous research (Fang et al., 2001; Knapp and Smith, 2001; Huxman et al., 2004) where direct-field measurements of ANPP were used. Our results support hypotheses stated by Knapp and Smith (2001) and Huxman et al. (2004), the use of EVI integrated provide a real opportunity to continue exploring across biomes and at different spatio-temporal scales.

The main limitation found in our approach for the use of remote sensing data sets is the lack of good quality measurements mainly because of atmospheric interferences, mainly in those wet regions as the tropics, as we tested for the Luquillo site. Therefore, in order to counteract this constraint and be able to follow a similar methodology as the one presented in this study, it will be necessary to make emphasis in the time series processing in order to produce relevant estimations of the iEVI values without any bias or dispersion induced by noise in the time series data.

## 5. REFERENCES

- Bai, Y., J. Wu, Q. Xing, Q. Pan, J. Huang, D. Yang, and X. Han. 2008. Primary production and rain use efficiency across a precipitation gradient on the Mongolia plateau. *Ecology*. 89(8): 2140-2153.
- Box, E.O., B.N. Holben, and V. Kalb. 1989. Accuracy of the AVHRR vegetation index as a predictor of biomass, primary productivity and net CO<sub>2</sub> flux. *Vegetatio*. 80(2): 71-89.
- Clark, D.A., S. Brown, D.W. Kicklighter, J.Q. Chambers, J.R. Thomlinson, J. Ni, and E.A. Holland. 2001. Net primary production in tropical forests: an evaluation and synthesis of existing field data. *Ecological Applications*. 11(2): 371-384.
- Fang, J., S. Piao, Z. Tang, C. Peng, and W. Ji. 2001. Interannual variability in net primary production and precipitation. *Science*. 293(5536): 1723.
- Field, C.B., J.T. Randerson, and C.M. Malmström. 1995. Global net primary production: Combining ecology and remote sensing. *Remote Sensing of Environment*. 51(1): 74-88.
- Golay, M.J.E., and Savitzky. 1964. Smoothing and differentiation of data by simplified least squares procedures. *Analytical Chemistry*. 36(8): 1627-1639.
- Goward, S.N., C.J. Tucker, and D.G. Dye. 1985. North American vegetation patterns observed with the NOAA-7 advanced very high resolution radiometer. *Vegetatio*. 64(1): 3-14.
- Huete, A. 1988. A soil-adjusted vegetation index (SAVI). *Remote Sensing of Environment*. 25(3): 295-309.
- Huxman, T.E., M.D. Smith, P.A. Fay, A.K. Knapp, M.R. Shaw, M.E. Loik, S.D. Smith, D.T. Tissue, J.C. Zak, J.F. Weltzin, W.T. Pockman, O.E. Sala, B.M. Haddad, J. Harte, G.W. Koch, S. Schwinning, E.E. Small, and D.G. Williams. 2004. Convergence across biomes to a common rain-use efficiency. *Nature*. 429(6992): 651-654.
- Jönsson, P., and L. Eklundh. 2004. TIMESAT--a program for analyzing time-series of satellite sensor data. *Computers & Geosciences*. 30(8): 833-845.
- Knapp, A.K., and M.D. Smith. 2001. Variation among biomes in temporal dynamics of aboveground primary production. *Science*. 291(5503): 481-484.
- Lieth, H. 1973. Primary production: Terrestrial ecosystems. *Hum. Ecol.* 1(4): 303-332.
- Liu, H.Q., and A. Huete. 1995. A feedback based modification of the NDVI to minimize canopy background and atmospheric noise. *Geoscience and Remote Sensing, IEEE Transactions on*. 33(2): 457-465.
- Moran, M.S., D.P.C. Peters, M.P. McClaran, M.H. Nichols, and M.B. Adams. 2008. Long-term data collection at USDA experimental sites for studies of ecohydrology. *Ecohydrology*. 1(4): 377-393.
- Paruelo, J.M., H.E. Epstein, W.K. Lauenroth, and I.C. Burke. 1997. ANPP Estimates from NDVI for the Central Grassland Region of the United States. *Ecology*. 78(3): 953-958.
- Running, S.W., R.R. Nemani, F.A. Heinsch, M. Zhao, M. Reeves, and H. Hashimoto. 2004. A continuous satellite-derived measure of global terrestrial primary production. *BioScience*. 54(6): 547.
- Saugier, B., and H.A. Mooney. 2001. Terrestrial global productivity, pp. 1-27. Academic Press, San Diego
- Tucker, C.J. 1979. Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sensing of Environment*. 8(2): 127-150.
- Weltzin, J.F., M.E. Loik, S. Schwinning, D.G. Williams, P.A. Fay, B.M. Haddad, J. Harte, T.E. Huxman, A.K. Knapp, G. Lin, W.T. Pockman, M.R. Shaw, E.E. Small, M.D. Smith, S.D. Smith, D.T. Tissue, and J.C. Zak. 2003. Assessing the response of terrestrial ecosystems to potential changes in precipitation. *BioScience*. 53(10): 941-952.