A new radiation index predicts the gross primary production of diverse terrestrial ecosystems

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Abstract

Solar radiation is the primary energy source that drives the physical and biochemical processes and determines the gross primary production (GPP) of an ecosystem. Even though the relationship between solar radiation and GPP is acknowledged, no radiation index (RI) has been developed to estimate GPP. Using data consisting of a total of 267 site-years obtained from 54 flux sites of diverse ecosystems, we introduced a RI that showed a strong linear relationship with GPP. Importantly, the estimation of GPP using the RI is independent of ecosystem types, making it a simple and universal method to estimate the productivity of any terrestrial ecosystems. The results from this study demonstrated the reliable performance of the RI in estimating GPP and its potential application in upscaling and prediction.

INTRODUCTION

Gross primary productivity (GPP) is the rate at which solar energy is utilised by plants to capture the greenhouse gas carbon dioxide (CO_2) in the atmosphere. Knowledge of GPP in diverse terrestrial ecosystems is critical for quantifying the feedbacks of natural ecosystems to climate change and predicting future climatic changes (IPCC, 2013; Falkowski et al., 2000; Campbell et al., 2017; Quere et al., 2000).

Eddy covariance (EC) flux towers provide continuous and integrated measurements of net ecosystem CO_2 exchange from which the ecosystem GPP can be estimated (Baldocchi et al., 2001; Baldocchi, 2003; Reichstein et al., 2005). Currently, over 900 flux sites across the globe employ the EC technique to study carbon cycling in various ecosystems, and much of this data can be found on the FLUXNET database (fluxdata.org). Although the number of sites with an EC system has been rapidly increasing in recent decades, the monitored sites still account for only a small fraction of the global ecosystems. This is largely due to: (1) the relatively small footprint area of EC (i.e. usually within a radius of 1 km) and (2) the lack of accessibility in many remote areas. Therefore, there is a need for approaches that estimate GPP over extensive areas without EC systems.

Process-based ecological models simulate GPP depending on environmental variables that constrain plant photosynthesis (such as solar radiation, temperature, precipitation, nutrient limits, etc.) and plant-specific parameters (such as the maximum photosynthetic rate). However, these models tend to be complex and need many parameters when compared with empirical models (Loarie et al., 2011; Gustafson, 2013; Gitelson et al., 2016; Jiang & Ryu, 2016; Lin et al., 2020). The different parameterisations used in these models often result in large differences in their estimated carbon dynamics (Cramer & Field, 1999; Lin et al., 2017; Running et al., 2000).

Net radiation, which is the balance of total radiation input/output for an ecosystem, indicates the energy that is retained within the system over a given time period. In theory, the energy retained is partially converted into heat that is transmitted throughout the system with the rest being mostly fixed by plants through photosynthesis (Running et al., 2004; Wu et al., 2010; Xiao et al., 2010). Therefore, we hypothesised that a radiation index (RI) that reflects the proportion of radiation energy fixed through photosynthesis is indicative of GPP. To test this hypothesis, we developed an RI based on the radiation balance and investigated its relationship with GPP at different temporal scales using EC data from 54 sites of diverse terrestrial ecosystems. Due to the easy access of radiation data globally through satellite-based remote-sensing products (Monteith, 1972; Heinsch et al., 2003; Sjöström et al., 2013; Xin et al., 2015), this radiation-based approach would be an important alternative for GPP estimation, upscaling and prediction and has the potential to be implemented globally.

METHODS

Radiation index

In this study, we formularised an RI based on different radiation components as follows:

$\mathrm{RI} = \frac{R_n - I}{\mathrm{DSR}}$, (1)

$R_n = (DSR + DLR) - (USR + ULR)$, (2)

$I = ULR - DLR$, (3)

where Rn is the net radiation which indicates the net energy balance of an ecosystem and$I$ the effective radiation which reflects the net heat transmissions within a system through long-wave radiations (Law et al., 2000; Turner et al., 2003; Verma et al., 2014). In theory, the difference between Rn and I can be indicative of the radiation that is absorbed by an ecosystem through photosynthesis. DSR is the downwelling short-wave radiation, also known as global radiation, which is included to normalise Rn and I so that the RI could be applicable in different seasons and regions with variable radiation inputs into a system. DLR, USR and ULR are the downwelling long-wave radiation and upwelling short- and long-wave radiation, respectively (Figure 1).

Study sites and data

We obtained the gap-filled 30-min data, including the four components of radiation (DSR, USR, DLR, ULR; W[?]m^{-2}) and GPP (g[?]C[?]m^{-2}[?]time^{-1}), of 54 sites with EC flux towers from FLUXNET (https://fluxnet.org), OZflux (http://www.ozflux.org.au) and ChinaFlux (http://www.chinaflux.org/) (Figure 2; Table S1). The dataset consists of a total of 267 site-years and covers a wide range of vegetation types, including tropical rainforests, subtropical evergreen forests, temperate deciduous forests, coniferous forests, shrub lands, savannas and grasslands, across North America, Europe, Asia and Australia. Each ecosystem type includes at least three sites in different regions to ensure its regional representativeness (Table S1). The instrumentation information of each site is also outlined in Table S1.

Statistics

In order to show the results of different ecosystem types, we selected a representative site for each ecosystem type. Significant differences between mean values were tested using one-way ANOVA. All data processing and statistical analyses were conducted using the Statistical Analysis System (SPSS 22.0 Software, SPSS Inc. 2013, IBM, Armonk, NY, USA).

RESULTS

Variations of Rn/DSR and I/DSR

Figure 3 shows the seasonal variations of Rn /DSR and I /DSR for seven sites representing each of the seven ecosystem types studied. The variations of Rn /DSR were negatively correlated with the$I$ /DSR. In the tropical and subtropical forests, Rn /DSR was higher than I /DSR over the entire year. By contrast, for other ecosystems that are associated with a strong seasonality, Rn /DSR became lower than I /DSR in the winter or non-growing seasons. Accordingly, the difference between Rn /DSR and I /DSR, which is the RI, varied among the different sites with the greatest seen in the tropical rainforest and smallest in the grassland.

Relationship between the RI and GPP at monthly and daily scales

The monthly GPP showed positive relationships with the RI in all the ecosystems. The correlations were significant ($p < 0.05$) in most of the sites except for the tropical rainforest (MY_PSO), where the correlation was weak ($R^2 = 0.15$, $p = 0.07$) (Figure 4). Besides the tropical rainforest site, the RI explained 73–88% of the GPP variance at the monthly scale, with the greatest explanatory degree presented in the subtropical evergreen forest.

The daily variations of the GPP and RI at the selected sites also showed significant correlations ($p < 0.05$), except in the tropical rainforest (MY_PSO) (Figure 5). Besides the tropical rainforest, the explanatory degrees of RI were between 40% and 71%, which were lower compared with those at the monthly scale.

Relationship between the RI and GPP at the annual scale across all sites

A strong linear relationship was observed between the annual GPP and RI across all 267 site-years (Figure 6). The RI explained 85% of the variance in the annual GPP.

DISCUSSION

Advantages of the RI

This study introduces a new index based on radiation balance to estimate GPP of terrestrial ecosystems of diverse vegetation types. By implementing a simple linear regression equation, RI is a universal index that provides satisfactory estimations of GPP, especially at the annual scale, regardless of the ecosystem types. This approach can be an alternative to the expensive conventional EC method, especially in places where implementation of EC system is not possible. The index also has great potential to be used for GPP upscaling and prediction at the global scale, which needs further evaluations.

The GPP estimation using process-based and empirical models requires complex inputs from meteorological and vegetation observations in addition to remote-sensing data (Huete et al., 2008; Harris & Dash, 2011; Ma et al., 2014; Zhang et al., 2016; Sims et al., 2006, 2008; Jiang & Ryu, 2016; Wonsick et al., 2014). The required data in these models were often not available at a sufficient temporal or spatial scale (Sims et al., 2008; Zhang & Zhao, 2014). For example, inputs of the vegetation photosynthesis model (VPM) include both leaf chlorophyll content and chlorophyll-level fraction of absorbed photosynthetically active radiation (FPARchl) across various terrestrial biomes over time. However, obtaining extensive field measurements of chlorophyll content at different levels is a challenging task (Zhang et al., 2016). Any uncertainty associated with the observations (e.g. sample size) will be propagated throughout the model simulation and will affect the final estimation. By contrast, the RI approach requires only radiation variables as inputs, which can be reliably measured *in situ* using a net radiometer (Prince, 1991; Gower et al., 1999; Xiao et al., 2005; Tang et al., 2015) or acquired from satellite-based remote-sensing products (Zhou et al., 2007; Bonan, 2008; Jackson et al., 2008; Kosugi et al., 2008; Pitman et al., 2011). Therefore, the simplicity of RI makes it an approach with a great potential for wide implementation.

Ecological significance of the RI

Forests generally absorb more solar radiation than grasslands or shrub lands, resulting in a lower albedo at the surface. In particular, tropical rainforests, with high canopy wetness and darker leaves, have a canopy albedo as low as 0–5% (Yanagi & Costa, 2011). This explains the high ratio of Rn to DSR found in tropical rainforests compared with other ecosystems (Figure 3). At the same time, forests generally have high evapotranspiration rates and maintain a relatively cooler canopy surface temperature as compared with the ambient temperature (Helliker & Richter, 2008; Rotenberg & Yakir, 2010; Arora & Montenegro, 2011; Lee et al., 2011; Lawrence & Vandecar, 2014). Therefore, the amount of long-wave radiation transmitted from this cooler canopy surface (ULR) is low. On the other hand, due to the high air temperature, the DLR is high in tropical rainforests, resulting in an overall decrease in the effective radiation (i.e. ULR-DLR) (Figure 3). Hence, the large difference between Rn /DSR and I /DSR throughout the season, as shown in the tropical rainforest in Malaysia (MY_PSO; Figure 3), is likely a result of the combination of high photosynthesis and evapotranspiration. The opposite can be applied to ecosystems like grasslands, where low net radiation and high ULR are present, resulting in smaller RI values (Figure 3).

In this study, by analysing different radiation components measured at the surfaces of various ecosystems, we sought to understand the quantity of radiative energy retained in the ecosystem as a proxy to estimate GPP. Garbulsky et al. (2010) suggested that the global GPP is controlled by climatic constraints which depend on the specific ecosystem type. In this study, we demonstrated that the relationship between RI and GPP is independent of the ecosystem type, suggesting that the RI is a universal variable that depicts the productivity of an ecosystem through the overarching radiation properties without needlessly considering the complex biophysical processes in ecosystems with varying climate and vegetation.

UNCERTAINTIES

Uncertainties are associated with all observations, including radiation measurements. For example, vegetation heterogeneity can lead to non-uniform radiation interception, and global radiation measurements made under direct sunlight were found to be lower (about 10%) than those above the canopy (Tuzet et al., 1997). On the other hand, radiometer readings are greatly influenced by weather. For example, water droplets on sensors can absorb long-wave radiation, resulting in large deviations in long-wave radiation readings during rain or dewfall events (Michel et al., 2008). This explains the relatively weak relationship between RI and GPP at the daily scale. However, these sensor-induced deviations are much less significant at the annual scale, making the annual estimations of GPP more reliable.

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REFERENCES

Arora, V.K. & Montenegro, A. (2011). Small temperature benefits provided by realistic afforestation efforts. *Nat. Geos.* , 4, 514-518.

Baldocchi, D., Falge, E., Gu, L., Olson, R., Hollinger, D., Running, S. *et al.* (2001). Fluxnet: a new tool to study the temporal and spatial variability of ecosystem-scale carbon dioxide,water vapor, and energy flux densities. *B. Am.Meteorol. Soc.* , 82, 2415-2434.

Baldocchi, D.D. (2003). Assessing the eddy covariance technique for evaluating carbon dioxide exchange rates of ecosystems: past, present and future. *Glob. Chang. Biol.* , 9, 479-492.

Bonan, G.B. (2008). Forests and climate change: forcings, feedbacks, and the climate benefits of forests. *Science* , 320, 1444-1449.

Campbell, J.E., Berry, J.A., Seibt, U., Smith, S.J., Montzka, S.A., Launois, T. *et al.* (2017). Large historical growth in global terrestrial gross primary production. *Nature* , 544, 84-87.

Cramer, W. & Field, C.B. (1999). Comparing global models of terrestrial net primary productivity (NPP): introduction. *Glob. Chang. Biol.* , 5, 1-15.

Falkowski, P., Scholes, R.J., Boyle, E., Canadell, J., Canfield, D., Elser, J. *et al.* (2000). The global carbon cycle: a test of our knoledge of earth as a system. *Science* , 290, 291-296.

Garbulsky, M.R., Penuelas, J., Papale, D., Ardo, J., Goulden, M.L., Kiely, G. *et al.* (2010). Patterns and controls of the variability of radiation use efficiency and primary productivity across terrestrial ecosystems. *Global Ecol. Biogeogr.* , 19, 253-267.

Gitelson, A.A., Peng, Y., Vina, A., Arkebauer, T. & Schepers, J.S. (2016). Efficiency of chlorophyll in gross primary productivity: A proof of concept and application in crops. *J. Plant. Physiol.* , 201, 101-110.

Gower, S.T., Kucharik, C.J. & Norman, J.M. (1999). Direct and indirect estimation of leaf area index, fAPAR, and net primary production of terrestrial ecosystems. *Remote Sens. Environ.* , 70, 29-51.

Gustafson, E.J. (2013). When relationships estimated in the past cannot be used to predict the future: using mechanistic models to predict landscape ecological dynamics in a changing world. *Landscape Ecol.* , 28, 1429-1437.

Harris, A. & Dash, J. (2011). A new approach for estimating northern peatland gross primary productivity using a satellite-sensor-derived chlorophyll index. *J. Geophys. Res. Biogeosci.* , 116.

Heinsch, F.A., Reeves, M., Votava, P., Kang, S., Milesi, C., Zhao, M.*et al.* (2003). User's guide GPP and NPP (MOD17A2/A3) products NASA MODIS land algorithm. *Version* , 2, 666-684.

Helliker, B.R. & Richter, S.L. (2008). Subtropical to boreal convergence of tree-leaf temperatures. *Nature* , 454, 511-514.

Huete, A.R., Restrepo-Coupe, N., Ratana, P., Didan, K., Saleska, S.R., Ichii, K. *et al.* (2008). Multiple site tower flux and remote sensing comparisons of tropical forest dynamics in Monsoon Asia.*Agr. Forest Meteorol.* , 148, 748-760.

IPCC. (2013). Climate change 2013: The physical science basis. Cambridge University Press, Cambridge.

Jackson, R.B., Randerson, J.T., Canadell, J.G., Anderson, R.G., Avissar, R., Baldocchi, D.D. *et al.* (2008). Protecting climate with forests. *Environ. Res. Lett.* , 3, 1748-9326.

Jiang, C. & Ryu, Y. (2016). Multi-scale evaluation of global gross primary productivity and evapotranspiration products derived from Breathing Earth System Simulator (BESS). *Remote Sens. Environ.* , 186, 528-547.

Kosugi, Y., Takanashi, S., Ohkubo, S., Matsuo, N., Tani, M., Mitani, T.*et al.* (2008). CO_2 exchange of a tropical rainforest at Pasoh in Peninsular Malaysia. *Agr. Forest Meteorol.* , 148, 439-452.

Law, B.E., Waring, R.H., Anthoni, P.M. & Aber, J.D. (2000). Measurements of gross and net ecosystem productivity and water vapour exchange of a Pinus ponderosa ecosystem, and an evaluation of two generalized models. *Glob. Chang Biol.* , 6, 155-168.

Lawrence, D. & Vandecar, K. (2014). Effects of tropical deforestation on climate and agriculture. *Nat. Clim. Change* , 5, 27-36.

Le Quere, C. *et al.* (2018). Global carbon budget 2018.*Earth Syst. Data.* , 10, 2141-2194.

Lee, X., Goulden, M.L., Hollinger, D.Y., Barr, A., Black, T.A., Bohrer, G. *et al.* (2011). Observed increase in local cooling effect of deforestation at higher latitudes. *Nature* , 479, 384-387.

Lin, H., Chen, Y., Zhang, H., Fu, P., Fan, Z. & Watling, J. (2017). Stronger cooling effects of transpiration and leaf physical traits of plants from a hot dry habitat than from a hot wet habitat. *Funct. Ecol.* , 31, 2202-2211.

Lin, H., Tu, C., Fang, J., Gioli, B., Loubet, B., Gruening, C., *et al.* 2020. Forests buffer thermal fluctuation better than non-forests.*Agr. Forest Meteorol.* , 288–289.

Loarie, S.R., Lobell, D.B., Asner, G.P., Mu, Q. & Field, C.B. (2011). Direct impacts on local climate of sugar-cane expansion in Brazil.*Nat. Clim. Change* , 1, 105-109.

Ma, X., Huete, A., Yu, Q., Restrepo-Coupe, N., Beringer, J., Hutley, L.B. *et al.* (2014). Parameterization of an ecosystem light-use-efficiency model for predicting savanna GPP using MODIS EVI.*Remote Sens. Environ.* , 154, 253-271.

Michel, D., Philipona, R., Ruckstuhl, C., Vogt, R. & Vuilleumier, L. (2008). Performance and uncertainty of CNR1 net radiometers during a one-year field comparison. *J. Atmos. Ocean. Tech.* , 25, 442-451.

Monteith, J.L. (1972). Solar radiation and productivity in tropical ecosystems. *J. Appl Ecol.* , 9, 747-766.

Pitman, A.J., Avila, F.B., Abramowitz, G., Wang, Y.P., Phipps, S.J. & de Noblet-Ducoudre, N. (2011). Importance of background climate in determining impact of land-cover change on regional climate. *Nat. Clim. Change* , 1, 472-475.

Prince, S.D. (1991). A model of regional primary production for use with coarse resolution satellite data. *Int. J. Remote. Sens.* , 12, 1313-1330.

Reichstein, M., Falge, E., Baldocchi, D., Papale, D., Aubinet, M., Berbigier, P. *et al.* (2005). On the separation of net ecosystem exchange into assimilation and ecosystem respiration: review and improved algorithm. *Glob. Chang. Biol.* , 11, 1424-1439.

Rotenberg, E. & Yakir, D. (2010). Contribution of semi-arid forests to the climate system. *Science* , 327, 451-454.

Running, S.W., Thornton, P.E., Nemani, R. & Glassy, J.M. (2000). Global terrestrial gross and net primary productivity from the earth observing system. Methods in ecosystem science. (Sala, O.E., Jackson, R.B., Mooney, H.A. and Howarth, R.W. editors.). Springer-Verlag, New York, USA, pp. 44-57.

Running, S.W., Nemani, R.R., Heinsch, F.A., Maosheng Zhao, Reeves, M. & Hashimoto, H. (2004). A continuous satellite-derived measure of global terrestrial primary production. *Bioscience* , 54, 547-560.

Sims, D., Rahman, A., Cordova, V., Elmasri, B., Baldocchi, D., Bolstad, P. *et al.* (2008). A new model of gross primary productivity for North American ecosystems based solely on the enhanced vegetation index and land surface temperature from MODIS. *Remote Sens. Environ.* , 112, 1633-1646.

Sims, D.A., Rahman, A.F., Cordova, V.D., El-Masri, B.Z., Baldocchi, D.D., Flanagan, L.B. *et al.* (2006). On the use of MODIS EVI to assess gross primary productivity of North American ecosystems. *J. Geophys. Res. Atmos.* , 111, 1-16.

Sjostrom, M., Zhao, M., Archibald, S., Arneth, A., Cappelaere, B., Falk, U. *et al.* (2013). Evaluation of MODIS gross primary productivity for Africa using eddy covariance data. *Remote Sens. Environ.* , 131, 275-286.

Tang, X., Li, H., Huang, N., Li, X., Xu, X., Ding, Z. *et al.*(2015). A comprehensive assessment of MODIS-derived GPP for forest ecosystems using the site-level FLUXNET database. *Environ. Earth. Sci.* , 74, 5907-5918.

Turner, D.P., Urbanski, S., Bremer, D., Wofsy, S.C., Meyers, T., Gower, S.T. *et al.* (2003). A cross-biome comparison of daily light use efficiency for gross primary production. *Glob. Chang. Biol.* , 9, 383-395.

Tuzet, A., Castell, J.F., Perrier, A. & Zurfluh, O. (1997). Flux heterogeneity and evapotranspiration partitioning in a sparse canopy: the fallow savanna. *J. Hydrol.* , 188-189, 482-493.

Verma, M., Friedl, M.A., Richardson, A.D., Kiely, G., Cescatti, A., Law, B.E. *et al.* (2014). Remote sensing of annual terrestrial gross primary productivity from MODIS: an assessment using the FLUXNET La Thuile data set. *Biogeosciences* , 11, 2185-2200.

Wonsick, M.M. & Pinker, R.T. (2014). The radiative environment of the Tibetan Plateau. *Internat. J. Climatol.,* 34(7), 2153-2162.

Wu, C., Munger, J.W., Niu, Z. & Kuang, D. (2010). Comparison of multiple models for estimating gross primary production using MODIS and eddy covariance data in Harvard Forest. *Remote Sens. Environ.* , 114, 2925-2939.

Xiao, J., Zhuang, Q., Law, B.E., Chen, J., Baldocchi, D.D., Cook, D.R.*et al.* (2010). A continuous measure of gross primary production for the conterminous United States derived from MODIS and AmeriFlux data. *Remote Sens. Environ.* , 114, 576-591.

Xiao, X., Zhang, Q., Hollinger, D., Aber, J. & III, B.M. (2005). Modeling gross primary production of an evergreen needleleaf forest using MODIS and climate data. *Ecol. Appl.* , 15, 954-969.

Xin, Q., Broich, M., Suyker, A.E., Yu, L. & Gong, P. (2015). Multi-scale evaluation of light use efficiency in MODIS gross primary productivity for croplands in the Midwestern United States. *Agr. Forest Meteorol.* , 201, 111-119.

Yanagi, S.N.M. & Costa, M.H. (2011). Simulations of tropical rainforest albedo: is canopy wetness important? *Annals of the Brazilian Academy of Sciences* , 83, 1171-1180.

Zhang, Y., Xiao, X., Jin, C., Dong, J., Zhou, S., Wagle, P. *et al.* (2016). Consistency between sun-induced chlorophyll fluorescence and gross primary production of vegetation in North America.*Remote Sens. Environ.* , 183, 154-169.

Zhang, Y. & Zhao, W. (2014). Effects of variability in land surface characteristics on the summer radiation budget across desert-oasis region in Northwestern China. *Theor. Appl. Climatol.* , 119, 771-780.

Zhou, L., Dickinson, R.E., Tian, Y., Vose, R.S. & Dai, Y. (2007). Impact of vegetation removal and soil aridation on diurnal temperature range in a semiarid region: Application to the Sahel. *Proc. Nat. Acad. Sci. USA.* , 104, 17937-17942.

Figures

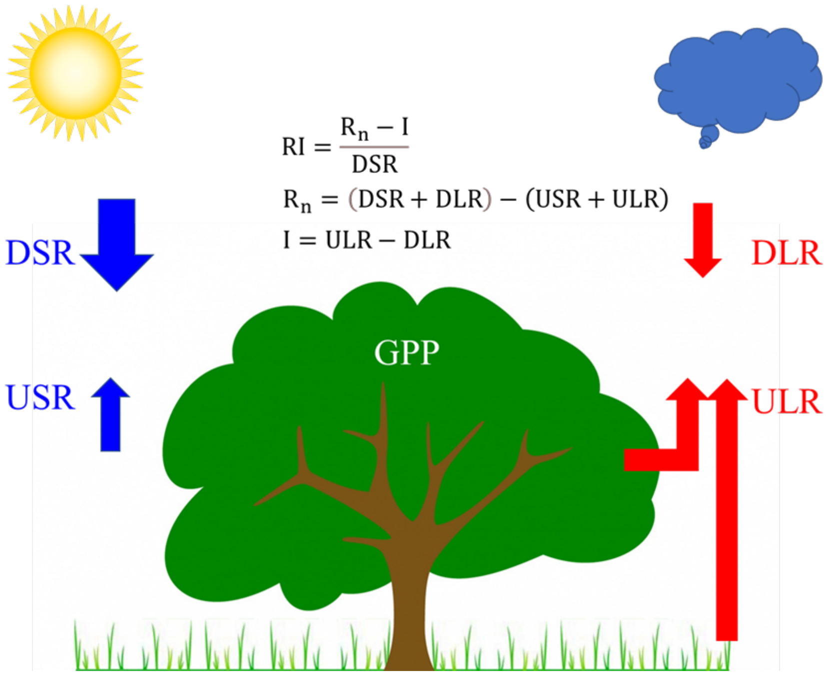

Figure 1 Schematics of a radiation index (RI) based on the radiation balance and its relationship with gross primary productivity (GPP). *Rn* is the net radiation which indicates the net energy balance of an ecosystem; DSR, DLR, USR and ULR are the downwelling short- and long-wave radiations and upwelling short- and long-wave radiations, respectively; and *I* is the effective radiation which reflects the net heat transmissions within a system through long-wave radiations.

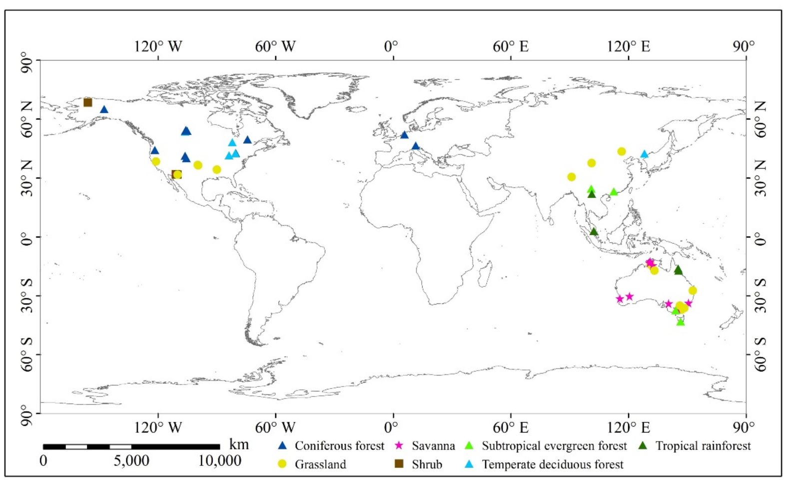

Figure 2 Distribution of the 54 FLUXNET, OZflux and ChinaFlux sites (for details, refer Table S1). The dataset consists of a total of 267 site-years and covers a wide range of vegetation types, including tropical rainforests, subtropical evergreen forests, temperate deciduous forests, coniferous forests, shrub lands, savannas and grasslands across North America, Europe, Asia and Australia.

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image3.emf available at https://authorea.com/users/733871/articles/711275-a-new-radiation-index-predicts-the-gross-primary-production-of-diverse-terrestrial-ecosystems

Figure 3 Variations of Rn /DSR and I /DSR in the selected tropical rainforest, subtropical evergreen forest, temperate deciduous forest, coniferous forest, shrub land, savanna and grassland ecosystems.

Figure 4 Correlations of the monthly radiation index and the gross primary productivity in the selected tropical rainforest, subtropical evergreen forest, temperate deciduous forest, coniferous forest, shrub, savanna and grassland ecosystems.

Figure 5 Correlations of the daily radiation index and the gross primary productivity in the selected tropical rainforest, subtropical evergreen forest, temperate deciduous forest, coniferous forest, shrub, savanna and grassland ecosystems.

Figure 6 Correlation between annual gross primary productivity and radiation index from 54 flux sites of diverse ecosystems.