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Estimating the Value of Global Ecosystem Structure and Productivity: A Geographic Information System and Emergy Based Approach

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ABSTRACT

We have used the coverages of renewable emergy input developed from satellite derived data to determine the emergy supporting ecosystem productivity and biotic natural capital. In addition, the impact on global productivity and biotic natural capital that has resulted from human induced land cover change was evaluated. The actual evapotranpiration (AET), which is the portion of rain that is used by vegetation was the most significant driver of ecosystems. However, the accumulation of biomass over time is not only affected by the available water used, but also by solar input and negatively affected by wind. Additionally, we have estimated the value of ecosystem function and storages. In pre-anthroponcene era, total annual emdollar value of global gross primary production was em$ 12.3 trillion and the total emdollar value of biotic natural capital which includes below and above ground biomass as well as the soil carbon was em$ 578.5 trillion. However, total losses of biotic natural capital from land cover change since the anthropocene began equal to em$88.5 trillion or about 16% of total pre-anthropocene value.

1. Introduction

Recently, there has been much attention given to valuing ecosystems based on their service contributions to humans under the rubric of “ecosystem services”. In this study we discard the term ecosystem services in favor of ecosystem functions (biological, geochemical and physical processes that take place within an ecosystem) that global ecosystems perform. We draw a distinction between services, a truly anthropogenic term, (i.e. services to whom?) and functions, the naturally occurring processes of ecosystems that support not only humans but also the biosphere as a whole. By separating these two concepts, issues of anthropocentrism are minimized.

Services are things that human value and benefit from, which can be evaluated based on human preferences, or technological expenditures to replace them. Ecosystem functions, on the other hand, are not easily valued within a human value system for they have no markets and people do not know what they are worth, violating the two basic tenets of economic valuation, a functioning market and perfect information. Therefore, to better estimate the value of ecosystem function, a donor-determined value, such as Emergy, can be used. Emergy is the available energy of one kind previously used up directly and indirectly to make a service or product (Odum, 1996, 1988).

1.1. Emergy Basis for Global Ecosystem

Global ecosystems are driven by a tripartite combination of renewable emergy that has been termed the Geobiosphere Emergy Baseline or GEB (Brown et al., 2016; Brown and Ulgiati, 2016a; Brown and Ulgiati, 2010) composed of solar radiation, tidal momentum absorbed by the Earth and relic geothermal energy from within the planet. Partitioning of the GEB between the countless physical and ecological systems of Earth has become increasingly important, as more and more emphasis has been placed on understanding and quantifying global flows of renewable resources supporting humanity. At the global scale (Figure 1) the primary emergy of the GEB is partitioned into secondary (precipitation and wind) and tertiary (chemical and geo potentials of runoff, ocean currents) renewable flows (Brown and Ulgiati, 2016b)

It is the GEB that supported all life on Earth through millions of years of planetary evolution, developing ecosystems, hydrologic systems, and atmospheric systems and the interconnections between them. It is the amalgamation of the primary flows of the GEB with the secondary and tertiary renewable flows that provides the emergy basis for ecosystem structure and functions. Measuring the emergy basis of global ecosystems will provide necessary quantification for determining global values of ecosystem structure and functions.

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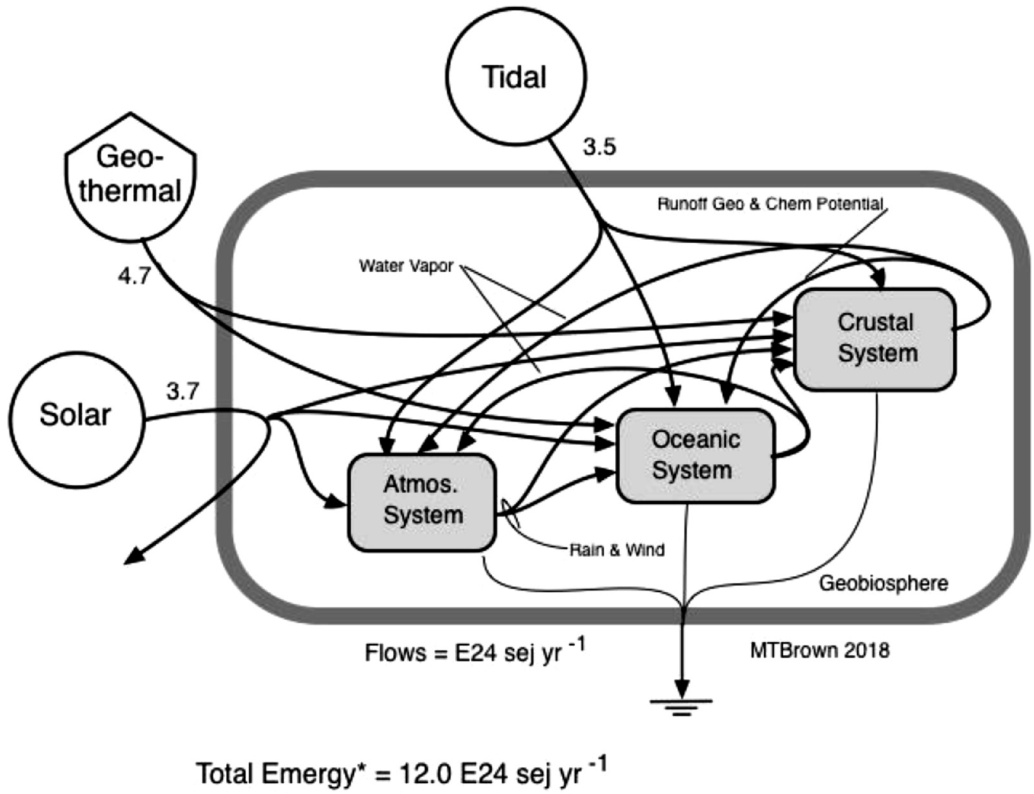

Figure 1. System diagram of the geobiosphere showing the tripartite sources of the Geobiosphere Emergy Baseline (GEB) and the secondary and tertiary renewable sources driving global ecosystems.

1.2. Emergy and Ecosystem Development

A main theoretical paradigm of energy systems theory (Odum, 2007, 1996, 1994, 1983) is that the quantity and quality of a system's output is directly related to the quantity of available energy of its inputs with one caveat...if the inputs are too "energetic" output may diminish as a result of induced stresses. From an emergy perspective, theory suggests that with increased inputs of emergy, ecosystems should have higher productivities and produce greater quantities of biomass, also subject to the above-mentioned caveat. On the other hand, productivity may be enhanced less by the total emergy input and instead, output maybe maximized with an appropriate mix of different emergy inputs (emergy signature[1]) in an amalgamation of primary, secondary and tertiary renewable sources.

We next review the literature regarding evaluations of global ecosystems and biomes, beginning with economic evaluations and ending with emergy evaluations of biomes.

1.3. Economic Evaluations of Global Ecosystem

The value of global ecosystems was estimated by Costanza et al. (1997), updated in 2011 (Costanza et al., 2014), and recently future values were modeled (Kubiszewski et al., 2017) based on economic valuation techniques. The original paper (Costanza et al., 1997) valued the Earth's ecosystem services at $33 trillion per year. In 2014, Costanza et al (2014) re-evaluated their earlier estimate, placing it at $145 trillion. They then valued global ecosystem services in 2011 as $125 trillion per year, suggesting a $20 trillion decrease between 1997 and 2011. The 2011 value was used as the baseline for the future projections by Kubiszewski et al. (2017), which resulted in projections between a decline of $51 trillion per year and an increase of $30 trillion per year depending on the future scenario.

Using the global land-cover dataset and the ecosystem service values from Costanza et al. (1997), patterns of conventional GDP and the value of non-marketed ecosystem services were spatially analyzed (1 km^2 resolution) by Sutton and Costanza (2002) to estimate the total value of the ecosystem services of the lands and waters of each nation. Several indices (gross domestic product, ecosystems services product, subtotal ecological–economic product, % ecosystem product) were calculated for each square kilometer of land surface and then aggregated for each nation of the world. Indices were compared to the Environmental Sustainability Index and the Ecological footprint index.

de Groot et al. (2012), using a database of value estimates from literature sources, provided an overview of the value of 10 main Earth biomes in monetary units. They did not attempt to sum values of biomes to provide a global value, but did provide mean, minimum, and maximum values for each on a hectare basis. Mean values ranged from INT$ 490 ha^{-1} yr^{-1} for the open ocean to INT$ 350,000 ha^{-1} yr^{-1} for coral reefs.

The dynamics of seven ecosystem services were modeled globally using a STELLA model named GUMBO (global unified metamodel of the biosphere) across eleven biomes by Boumans et al. (2002). A range of five future scenarios representing base case and four future scenarios. The relative value of ecosystem services was estimated to be about 4.5 times the value of Gross World Product (GWP) in the year 2000.

On the other hand, Alexander et al. (1998) investigated several approaches for valuing global ecosystem services. Instead of using willingness-to-pay (WTP) or other value transfer methods, the global ecosystem was assumed to be owned by a monopolist who was charging the population for the services. Their estimates indicated that global ecosystem services are worth between 44% and 88% of the global GDP.

Patterson (2002) used "Ecological pricing theory" applied to the valuation of biosphere processes and services in 1994 and obtained a total value of primary ecological services to be nearly $US 25 trillion.

[1] Emergy signature is the characteristic distribution of quantities of emergy among inputs to a system

Ecological prices measure value of nature in terms of the biophysical interdependencies in the system, ultimately quantifying how much value is contributed to an ecological commodity (e.g. plant biomass) by another commodity (in this case solar energy) in the system.

1.5. Emergy Evaluations of Global Ecosystems

While there many papers that use the emergy method to assess the value of ecosystem services of small -scale systems, we restrict our review here to those that are large in scale such as global systems or biomes.

Brown and Ulgiati (1999) estimated the emergy value of the Earth's natural capital (environmental resources) including freshwater, soil organic matter, and plant and animal biomass totaling 575 E+25 sej (or $5.3 E+15, based on 1998 dollars). Water and soil organic matter were responsible for 51% and 40% of the total emergy value, respectively.

Using economic values of ecosystem services from Sutton and Costanza (2002), Coscieme et al. (2014) derived emergy money ratios for ecosystem services for countries calculating values that varied between 2.02 E+11 sej $\$^{-1}$ and 6.82 E+11 sej $\$^{-1}$, values equal to 1 to 2 orders of magnitude lower than the emergy money ratio of the country when non-renewable emergy is included. They suggested that this difference means that ecosystems can provide services at much lower costs than the economy can.

Lu et al. (2017) computed the donor value of the subtropical forests in southeast China by using emergy analysis and compared it with the receiver value estimated by monetary value to estimate the efficiency of different types of ecosystem. Their result revealed that forests and plantations had 2 orders of magnitude higher efficiency than the current Chinese economic system in providing service, showing the importance of afforestation.

Rugani et al. (2014) estimated the solar energy demand (SED; annual emergy used) in Luxembourg from 1995 to 2009. The SED of Luxembourg was 23 times larger on average than all of the free energy, raw materials and natural cycles associated with the territorial system of Luxembourg.

Choi (2010) has estimated the emergy values of terrestrial plants using annual emergy input, NPP, and phytomass. Transformity of annual increment of phytomass was computed by dividing the emergy input by the dry mass of annual NPP. To compute the emergy of biomass storage, Choi multiplied standing stock by the transformity of NPP, not recognizing that the transformity of NPP is not an appropriate transformity for biomass, which is an accumulation of annual NPP over the biomass turnover time.

Recently Yang et al. (2020) conducted an emergy-based ecosystem service valuation of China's grasslands by spatially analyzing the emergy values of provisioning, regulating, cultural and supporting services of China's grasslands. Zhang et al. (2019) evaluated the ecosystem services of tidal wetlands, fresh water wetlands and agricultural systems of Chongming Island in Eastern China using emergy. Yang et al. (2019) used emergy to evaluate ecosystem services of aquatic systems of China. Xu et al. (2020) evaluated the changes in ecosystem services in Northwestern China before and after the conversion of a desert shrub system to a plantation system based on emergy analysis. Sun et al. (2018) estimated marine ecosystem services values in 11 coastal provinces and cities of China from 2005 to 2014, and then analyzed the changes in services values across the different regions and across time.

In 2012, Campbell and Brown, using the emergy approach, estimated the value of ecosystem service provided by the National Forests managed by the US Forest Service (USFS) to be ^{em}\$197 billion (emdollars) in 2005 and its natural capital to be ^{em}\$24.3 trillion (Campbell and Brown, 2012). They used the ecosystem service categories suggested in Millennium Ecosystems Assessment (2005), which categorizes ecosystem services into 4 main categories of provisioning services, regulating services, supporting services, and cultural services.

Campbell and Tilley (2014), computed biophysical quantities for the yearly provision of ecosystem services from a typical hectare of forest in Maryland and converted them to emergy by multiplying by the solar equivalent exergy (SEE)[2] required per biophysical unit of exergy.

The quantity of ecosystem services was assessed for the national economy and national ecosystem mosaic of Brazil, in historical series (1981–2011) (Giannetti et al., 2017), showing that the contributions from renewable sources have fallen from about 75% of the total economy in 1981 to about 20% in 2011.

Almeida et al. (2018) assessed the ecosystems service of urban parks by accounting climate regulation (evapotranspiration and CO_2 sequestration), water regulation (water retention in soil), and supporting service (net primary production). They considered evapotranspiration and CO_2 sequestration as a co-product while considering climate regulation and water regulation as a split. Emergy of ecosystem service in regions of China have been done by several authors (Dong et al., 2012, 2014; Ma et al., 2015; Sun et al., 2018; Wang et al., 2019). These studies selected a few services from the ecosystem service categories suggested in Millennium Ecosystems Assessment (2005) and summed the emergy value of each service estimated by multiplying the products (e.g. energy of evapotranspired water, energy of biomass in net primary production) with its unit emergy values (UEVs) from other studies.

1.6. Summary of Global Evaluations

All in all, while emergy has been applied to evaluation of numerous ecosystems and regions, only one attempt has previously been made to evaluate global ecosystems using emergy (Brown and Ulgiati, 1999). In that study the emergy of global natural capital was estimated on the basis of assessments of total mass of soil organic matter, fresh surface and ground water and animal and plant biomass. That study did not evaluate the spatial distribution of natural capital, only relying on global estimates of mass.

Several studies have been completed using a variety of economic methods to estimate the value of global ecosystem services to humans, including at least one spatial analysis. These studies did not evaluate ecosystem functions per se, but rather ecosystem services. This is not a criticism of economic valuation, only to say that they did not evaluate ecosystem functions. In general, few previous studies, whether economic or emergy evaluations, have valued functions, instead they have focused on services.

To our knowledge, there have been no economic evaluations of global natural capital, even though at least one of the global papers (Costanza et al., 1997) included the term in its title.

In this study we answer the following questions using emergy and GIS data sets

1 What is the emergy supporting global ecosystems (biomes)?
2 What is the emergy of global ecosystem biomass and soil carbon?
3 Do ecosystems maximize total emergy, or is maximum productivity and biomass the result of the interplay of the suite of renewable emergy sources?

What is the impact on global productivity (GPP) and biotic natural capital (BNC) that has resulted from human induced land cover change?

Combined these questions are intended to facilitate a better understanding of some very fundamental questions, assertions and suppositions of emergy theory. The first question above relates to a fundamental question ..." how to evaluate ecosystems and their

[2] Solar equivalent exergy is computed as an equivalence between solar energy and the other exergy sources comprising the GEB (tidal and geothermal) recognizing that these independent sources driving the geobiosphere are not transformations of solar energy as was discussed by Brown et al. (2016)

properties?” We suggest that evaluation using emergy leads one to distinctly separate ecosystem services from ecosystem functions. In order to answer what is the emergy of ecosystem functions we must answer the first question above, *what is the emergy supporting global ecosystem productivity?* According to emergy accounting procedures, the emergy of productivity is equal to the emergy driving the system, thus by evaluating the emergy driving the global biomes, we have identified the emergy of all functions of these biomes.

The second question above, relates to the assertion that the value of a stored product is the emergy required to produce it. Thus, evaluating the driving emergy (Question 1) is essential to answering this question, along with the knowledge of the turnover time of the stored product. As a consequence, the most valuable stored resource is not always the result of the largest driving energy but can be the largest because of a longer generation time. With this quantitative understanding of donor value, comparisons can be made, and policies directed to better serve global sustainability objectives.

The third question relates to a supposition that the structure and productivity of systems is directly proportional to the emergy driving the system (i.e. the more emergy the more productive, the more emergy the larger structure can be supported). Numerous researchers have suggested that systems may not respond to total emergy, but instead produce maximum production and structure from the interplay of suite of input energies (Brown et al., 2006; Ulgiati and Brown, 2009; Ulgiati et al, 2011;) with this data set we are better positioned to confirm that supposition, but unfortunately it leads to still another quandary. If systems produce maximum productivity or biomass that is a function of the emergy signature rather than the quantity of driving emergy, then evaluating ecosystem functions based on the driving emergy in a static accounting may not be appropriate. Instead, it may be that dynamic evaluations must be conducted rather than static ones that assume steady-state conditions (but this is a topic for another paper).

The fourth question relates to an overall concern regarding human sustainability on planet Earth. How far down the path of unstainable development have we gone? Tracking anthropogenic alteration in a quantitative manner can provide benchmarks of human destruction of planetary ecosystems (or progress, if we begin to regenerate natural systems). Tracking both biomass and productivity losses provide needed benchmarks that offer information on the flows and storages of ecosystems with which appropriate sustainable policy can be generated.

2. Methods

In this study we used GIS and the emergy analysis method to compute values of global ecosystem functions (EF) and biotic natural capital (BNC)[3]. Emergy values of annual EF of global biomes were computed by using the renewable emergy coverages developed in Lee and Brown (2019) and a global biome boundary coverage (Olson et al., 2001) at 10 arc minute resolution. The emergy values of BNC were computed using biomass estimates of major biomes (Gibbs, 2006) and a soil carbon coverage produced by the Oak Ridge National Laboratory, USA (Ruesch and Gibbs, 2008).

The most recent global emergy baseline (GEB), 12.0 E+24 sej yr^{-1} (Brown et al., 2016), was used as the basis from which all unit emergy values were computed.

2.1. Biome Categorization

Shown in Figure 2 is the biome and habitat classification scheme used in this study. Olson et al. (2001) delineated 14 biomes, as well as lakes, and ice/rocky areas, and ocean. We added estuaries and rivers to their biome coverage yielding a total of 19 distinct habitats. The boundary data of estuaries was derived from The Sea Around Us Project (Alder, 2003). The river habitat, based on stream order higher than six (Vanote et al., 1980), was developed using the flow accumulation routine in ArcGIS, and assigning any 10 arc minute cell with stream order greater than 6 as river habitat.

2.2. Estimating Driving Emergy of Biomes and Habitats

Emergy of biomes was evaluated by “clipping” global renewable emergy coverages (Lee and Brown, 2019) with a global biome coverage. In all, there were 9 renewable emergy coverages, solar, geothermal, tidal, wind, rain chemical potential, actual evapotranspiration (AET), runoff chemical potential, runoff geopotential, and water chemical potential. The water chemical potential coverage was computed as the sum of AET and runoff chemical potential.

A final coverage of renewable emergy inputs was produced by applying the max renewable algorithm from Brown and Ulgiati (2016a) on a biome basis as follows:

$$R_{MAx} = Max\ ((\sum S,\ T,\ G),\ \mathrm{W},\ \mathrm{P},\ R_{gp}, H_2\mathrm{O}_{cp}\ )$$

The max renewable algorithm was used to minimize double counting of renewable sources. The computation was done in the following order. First each of the 9 renewable emergy inputs was summed on a cell-by-cell basis within each biome, yielding a total renewable emergy for each input within each biome. Then the max renewable algorithm was computed at the biome level based on the totals of each input, yielding the maximum renewable input (MaxR) for each biome.

Once annual MaxR inputs for each biome were derived from the coverages of renewable emergy inputs biome aerial empower intensity (AEI) was computed by dividing by the area of each biome. Additionally, the annual MaxR was used to compute the input to biome GPP and biomass.

2.3. Estimating GPP of Biomes and Habitats

NASA's Land Processes Distributed Active Archive Center (LP DAAC) developed the Terra/MODIS NPP and GPP product (MOD17A3), which provides yearly average global NPP and GPP in 30 arc second resolution (Zhao et al., 2005). Total annual global GPP was used as the total work performed by global biomes. A coverage of average global GPP for the year 2001-2003 is provided in the Supplemental Material (Figure S-2). Since these data included areas of land that were occupied by human dominated uses it was necessary to evaluate pre-anthropocene GPP by removing all cells that were within agricultural and urban classifications. Using the anthropogenic biome data (Ellis, 2015; Ellis et al., 2010; Ellis and Ramankutty, 2008), all cells that were occupied by their land cover classifications that were primarily urban built up and agricultural (details are provided in Supplemental Material) were removed. The remaining cells were then clipped with the biome coverage and an average GPP per unit area was computed by summing the GPP of all cells and dividing by the area of those cells.

The concept of Anthropocene has evolved since it was first proposed (Crutzen, 2002). However, this study uses the European industrial resolution as a turning point between pre-anthropocene and Anthropocene (Brondizio et al., 2016).

Since the GPP data from NASA only contained the data for terrestrial biomes, it was necessary to add data for land cover classes not included by the NASA data. Terrestrial biome data was augmented with GPP data from Whittaker and Likens (1975) for river (0.25 kg C $m^{-2}yr^{-1}$), lake (0.25 kg C $m^{-2}yr^{-1}$), estuary (1.5 kg C $m^{-2}yr^{-1}$), and ocean (0.13 kg C $m^{-2}yr^{-1}$).

[3] We use the term biotic natural capital to refer to above and below ground biomass and soil organic matter (as carbon) of ecosystems to distinguish them from other natural capital such as minerals, fossil fuels, water, etc.

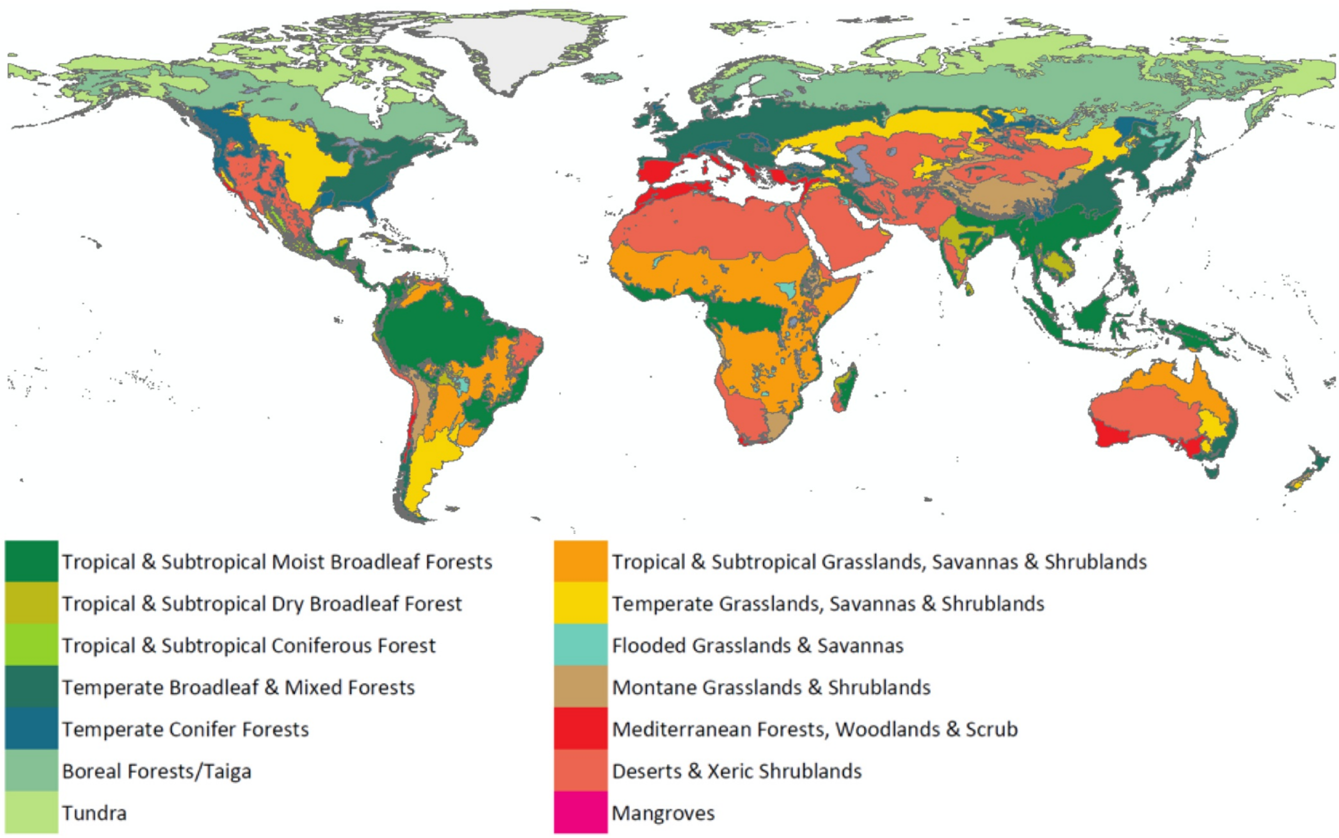

Figure 2. Map of Terrestrial Ecosystem Of the World (TEOW), (Olson et al. 2001)

2.4. Estimating Biotic Natural Capital (BNC) of Biomes and Habitats

We considered two aspects of BNC, biomass (sum of above and below ground) and soil carbon. First, we compute BNC for the Earth during the pre-anthropocene, and second, we subtract areas of urban and agriculture (Ellis, 2015) to compute the change as of 2010. Methods and data sources for biomass and soil carbon are given next.

2.4.1. Biomass

Whittaker and Likens (1975) provided one of the first comprehensive estimates of global biomass followed by Olson et al. (1985) who developed a database of carbon in live vegetation (above and below ground) in major world ecosystems. Gibbs (2006) updated Olson's database using more contemporary land cover conditions of the Global Land Cover Database (GLC2000) based on VEGA 2000 dataset from SPOT 4 satellite. In this study we used Gibbs (2006) data combined with data from both Whittaker and Likens (1975) and Olson et al. (1985) to develop the biomass data listed in the final column of Table 1 to yield a global coverage of above and below ground biomass (kg C m^{-2}) for each 10 arc minute cell of the biomes (Figure S-3, Supplemental Material).

2.4.2. Soil carbon

Soil carbon (Figure S-4, Supplemental Material). was derived from The International Geosphere-Biosphere Program Data and Information System (IGBP-DIS) coverage at a resolution of 5 arc minute. (Global Soil Data Task Group, 2000). The data were clipped using the global biome coverage to yield total soil carbon for each biome.

2.5. Emergy of Biotic Natural Capital

Emergy value of biotic natural capital of each biome was computed from the biome's annual emergy input and turn over time of the soil and biomass compartments.

2.5.1. Biomass

The annual emergy input for each 10 arc minute cell was derived from the emergy coverages as outlined above. Turnover time of biome biomass was estimated using a autocatalytic simulation model (Odum and Odum, 2000) and emergy input (Lee and Brown, 2019). The Supplemental Material provides details of the simulation model. Total emergy of biomass was computed as the product of annual emergy input and turnover time.

2.5.2. Soil carbon

The International Geosphere-Biosphere Program Data and Information System (IGBP-DIS) provided 5 arc minute resolution global surface data for soil-carbon density (kg C m^{-2}). Turnover time of soil carbon was derived from literature estimates (Raich and Schlesinger, 1992).

The emergy of soil carbon of each biome was computed by multiplying the emergy input by soil carbon turnover time.

2.6. Analyzing Relation Between GPP and Biomass to Driving Emergy

To answer the question pertaining to the relation between emergy and productivity and standing stock, the relations were tested using simple linear regression, multiple regression, and classification and regression trees (CART). First, scatter plots of the data were developed which showed that AET and MaxR had the greatest promise to predict GPP and biomass. Then simple linear regressions of AET vs biomass, AET vs GPP, MaxR vs Biomass and MaxR vs GPP were conducted. To test if additional forms of driving emergy might help to explain some of the error in the simple regressions, multiple regressions on GPP and biomass were conducted using all the input emergy forms (AET, solar, rain, wind, geothermal, and MaxR). Finally, Classification & Regression

Table 1
Global biomass estimates from literature and final values used in this study

Biome Type	Biomass (g C m^{-2}) Whittaker and Likens, (1975)	Olson et al. (1985)	Gibbs, (2006)	This study
Tropical & Subtropical Moist Broadleaf Forest	22,500	12,000	12,000	12,000
Tropical & Subtropical Dry Broadleaf Forest	17,500	6,000	6,000	6,000
Tropical & Subtropical Coniferous Forest	17,500	13,000	12,000	12,000
Temperate Broadleaf & Mixed Forest	15,000	9,000	9,000	9,000
Temperate Conifer Forest	17,500	13,000	13,000	13,000
Boreal Forests/Taiga	10,000	6,000	7,000	7,000
Tropical & Subtropical Grassland, Savanna & Shrubland	2,000	900	900	900
Temperate Grassland, Savanna & Shrubland	800	900	900	900
Flooded Grassland & Savanna	7,500	2,000	–	2,000
Montane Grassland & Shrubland	800	900	900	900
Tundra	300	500	–	500
Mediterranean Forest, Woodland & Scrub	3,000	3,000	–	3,000
Desert & Xeric Shrubland	350	300	–	300
Mangroves	–	–	12,000	12,000
River	10	–	–	10
Lake	10	–	–	10
Rock & Ice	10	–	–	10
Estuary	500	–	–	500
Ocean	3	–	–	3

Table 2
Renewable emergy inputs of world biomes

Biome Type	Solar	Geothermal	Tidal	Wind	AET Chem. Pot	Runoff Chem. Pot. (10^{21} sej yr^{-1})	Water Chem. Pot. [a]	Runoff Geo. Pot	MaxR [b]
Terrestrial Biomes									
Tropical & Subtropical Moist Broadleaf Forests	147.8	131.3	17.5	599.6	2670.0	73.5	***2743.5***	171.6	***2743.5***
Tropical & Subtropical Dry Broadleaf Forest	24.6	22.1	1.7	130.8	278.1	0.2	***278.3***	2.5	***278.3***
Tropical & Subtropical Coniferous Forest	6.2	6.1	0.0	37.5	61.7	0.0	***61.7***	0.0	***61.7***
Temperate Broadleaf & Mixed Forest	73.7	78.6	27.7	643.6	853.1	8.7	***861.8***	12.1	***861.8***
Temperate Conifer Forest	25.5	32.9	1.9	177.8	239.9	0.4	***240.4***	0.7	***240.4***
Boreal Forests/Taiga	67.9	85.3	6.8	536.5	594.9	13.7	***608.6***	24.7	***608.6***
Tropical & Subtropical Grasslands, Savannas & Shrubland	178.5	128.0	7.9	906.1	1604.6	39.7	***1644.2***	56.4	***1644.2***
Temperate Grasslands, Savannas & Shrubland	64.8	62.2	4.3	350.7	419.4	3.2	***422.6***	79.6	***422.6***
Flooded Grasslands & Savanna	8.1	6.5	0.3	54.6	70.9	2.7	***73.6***	2.5	***73.6***
Montane Grasslands & Shrubland	42.8	37.7	0.0	***233.9***	211.4	0.2	211.5	4.1	***233.9***
Tundra	45.7	82.2	35.2	***732.2***	205.2	1.8	207.0	5.1	***732.2***
Mediterranean Forests, Woodlands & Scrub	24.7	25.7	0.2	***130.6***	136.1	0.1	***136.2***	2.4	***136.2***
Deserts & Xeric Shrubland	241.5	198.8	4.9	884.8	444.9	11.0	456.0	11.2	***884.8***
Mangroves	2.4	2.3	5.1	11.7	30.0	0.0	***30.0***	26.7	***30.0***
River	23.2	20.4	0.1	100.6	213.7	122.7	336.3	***1123.0***	***1123.0***
Lake	6.6	5.7	0.0	7.6	50.8	1.7	***52.5***	1.5	***52.5***
Rock & Ice	56.9	83.2	1.7	***974.9***	26.0	0.1	26.1	0.1	***974.9***
Marine Biomes									
Estuary	2.2	2.5	5.5	11.1	18.5	3576.4	***3595.0***	2147.4	***3595.0***
Ocean	***2686.8***	***3653.0***	***3474.7***	5475.5	12.6	2.0	14.6	186.6	***9814.5***

[a] . Water chemical potential is the sum of chemical potential emergy of AET and runoff.
[b] . MaxR is the maximum renewable emergy input based on the max emergy algorithm (Brown and Ulgiati, 2016)

Trees (CART) were constructed using the driving emergy sources (solar, geothermal, wind, rain and AET) as drivers of GPP and biomass of biomes to create models that predict GPP and biomass.

During the analysis of the relation between driving emergy and GPP and biomass we observed that there appeared to be differences in the variance between the same biomes on different continents. Ultimately, the idea was that instead of classifying the geobiosphere into 16 biomes, a more fine-grained approach might be warranted. As a result, the global coverages were reclassified into biomes by continent and then a t-test of the differences in mean values of AET and MaxR between the same biomes on different continents was conducted (see Supplemental Material) under the null hypothesis that the means were the same.

2.7. Estimating the Global Impacts of Land Cover Change

To estimate the changes in GPP and biotic natural capital that has resulted from human induced land cover change, we used the coverage of anthropogenic biomes (Ellis, 2015; Ellis et al., 2010; Ellis and Ramankutty, 2008). The change in above and below ground biomass was computed by subtracting all areas occupied by urban, settlements, and villages, croplands and populated rangelands. To estimate the change in GPP we used the most recent data from the Terra/MODIS NPP and GPP product (Zhao et al., 2005), and compared these data to the constructed GPP coverage as outlined above. The difference between the two coverages represents the net effect on global GPP. We report the data on a biome by biome basis.

To estimate the changes in GPP and biotic natural capital that have resulted from human induced land cover change, we used the coverage of anthropogenic biomes (Ellis, 2015). The change in above and below

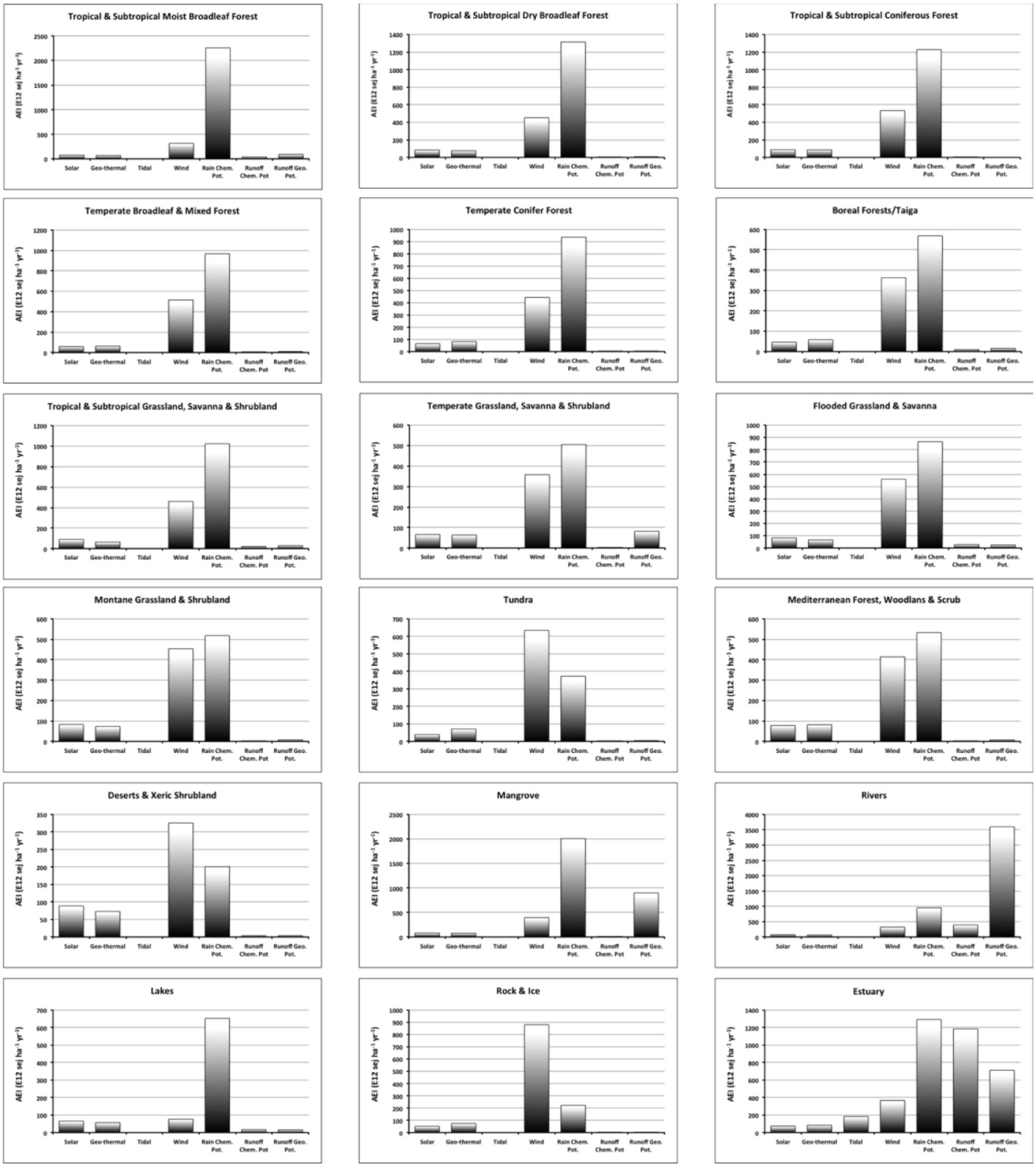

Figure 3. Emergy signatures of global biomes expressed as aerial empower intensity (AEI). Note Y-axis is NOT the same scale for all biomes. (data are from Lee and Brown, 2019)

ground biomass was computed by subtracting all areas occupied by urban, settlements, and villages, croplands and populated rangelands. To estimate the change in GPP we used the most recent data from the Terra/MODIS NPP and GPP product (Zhao et al., 2005), and compared these data to the constructed GPP coverage as outlined above. The difference between the two coverages represents the net effect on global GPP. We report the data on a biome by biome basis.

To compute the change in biomass the following assumptions were made. First, it was assumed that 100% of above and belowground biomass was removed from forested lands that were occupied by anthropogenic land cover. Second, 50% of above and belowground biomass was removed from grassland and scrub biomes that were occupied by anthropogenic land cover. The change in soil carbon was estimated based on the data and analysis of Sanderman et al. (2017) where they found that 133 PgC have been lost due to soil erosion across nearly all biomes. The total loss of carbon (133 PgC) was proportioned between each of the biomes based on the percent change of land cover within each biome.

Finally, the emdollar value of the losses was estimated by converting biomass and soil carbon to emergy (see above for the method of computing emergy of BNC) and then dividing by a global emergy dollar ratio of 2.0 E + 12 sej/$. The purpose of this study is to estimate the emergy value of ecosystem functions, however, to make it easier to sense the magnitude of these values, we also present the results as emdollars using the average global conversion factor (Emergy Money Ratio).

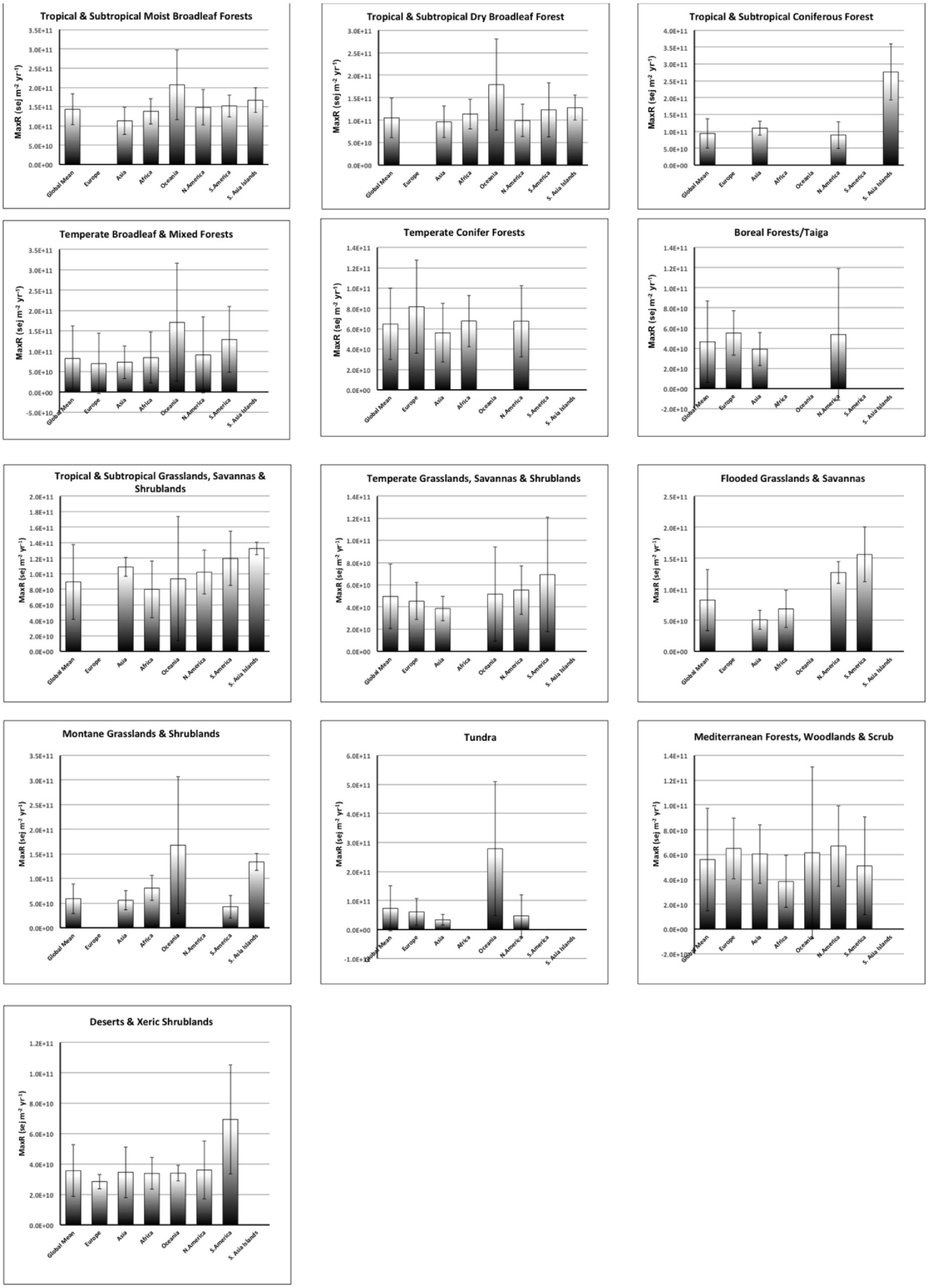

Figure 4. MaxR (maximum renewable empower) of major terrestrial biomes. Note the vertical axis on each graph is not the same scale.

Table 3
Aerial Empower Intensity (AEI) of world biomes

Biome Type	Area (10^9 ha)	MaxR Biome [a] (10^{21} sej yr^{-1})	AEI [b] (10^{12} sej ha^{-1} yr^{-1})
Terrestrial Biomes			
Tropical & Subtropical Moist Broadleaf Forest	1.9	2743.5	1437.5
Tropical & Subtropical Dry Broadleaf Forest	0.3	278.3	962.3
Tropical & Subtropical Coniferous Forest	0.1	61.7	880.1
Temperate Broadleaf & Mixed Forest	1.2	861.8	690.4
Temperate Conifer Forest	0.4	240.4	598.1
Boreal Forests/Taiga	1.5	608.6	411.9
Tropical & Subtropical Grasslands, Savannas & Shrubland	2.0	1644.2	835.5
Temperate Grasslands, Savannas & Shrubland	1.0	422.6	431.8
Flooded Grasslands & Savannas	0.1	73.6	753.9
Montane Grasslands & Shrubland	0.5	233.9	453.7
Tundra	1.2	732.2	634.5
Mediterranean Forests, Woodlands & Scrub	0.3	136.2	431.9
Deserts & Xeric Shrubland	2.7	884.8	325.7
Mangroves	0.03	30.0	1011.3
River	0.3	1123.0	3597.3
Lake	0.1	52.5	527.6
Rock & Ice	1.1	974.9	880.7
Marine Biomes			
Estuary	0.30	3595.0	11906.6
Ocean	36.3	9814.5	270.4

[a] . From Table 2
[b] . Equal to MaxR divided by area

Table 5
Biome soil carbon

Biome	Soil Carbon [a]	
	10^{15} gC	kgC m^{-2}
Tropical & Subtropical Moist Broadleaf Forests	223.8	11.7
Tropical & Subtropical Dry Broadleaf Forest	31.6	10.9
Tropical & Subtropical Coniferous Forest	9.2	13.1
Temperate Broadleaf & Mixed Forests	161.7	13
Temperate Conifer Forests	54.6	13.6
Boreal Forests/Taiga	347.9	23.5
Trop. & Subtropical Grasslands, Savannas & Shrublands	166.2	8.4
Temperate Grasslands, Savannas & Shrublands	110.5	11.3
Flooded Grasslands & Savannas	12.3	12.6
Montane Grasslands & Shrublands	51.5	10
Tundra	150.4	13
Mediterranean Forests, Woodlands & Scrub	30.1	9.6
Deserts & Xeric Shrublands	152.0	5.6
Mangroves	5.9	19.9
Total	1507.8	

[a] . soil carbon data from Global Soil Data Task Group (2000)

3. Results

3.1. Empower of Global Biomes

Given in Table 2 are the renewable inputs to global biomes. Starred (*) values in the table are the MaxR values for each system. The dominant emergy sources for a majority of the biomes is water chemical potential (sum of AET and runoff chemical potential). Wind is the largest input in montane grasslands & shrublands, tundra, deserts & xeric shrublands, and rock & ice biomes. Rivers are dominated by runoff geopotential.

Figure 3 shows graphs of emergy signatures for the global biomes (ocean is not included). Wind and rain dominate the renewable inputs in almost all biomes. Rivers are the exception, where runoff geopotential is the dominant input. Of interest is the three largest inputs to estuaries, rainfall, runoff chemical and geopotential emergy, as might

Table 4
Gross Primary Production and biomass of world biomes

Biome Type	Area [a] (10^9 ha)	Total Biome GPP [a] (10^{15} gC yr^{-1})	Total Biome Biomass [b] (10^{15} gC)	Biome GPP [c] per unit area (10^6 gC ha^{-1} yr^{-1})	Biome Biomass [d] per unit area (10^6 gC ha^{-1})
Terrestrial Biomes					
Tropical & Subtropical Moist Broadleaf Forest	1.9	48.5	229.0	25.4	120.0
Tropical & Subtropical Dry Broadleaf Forest	0.3	5.8	17.4	20.2	60.2
Tropical & Subtropical Coniferous Forest	0.1	0.9	8.4	13.1	119.7
Temperate Broadleaf & Mixed Forest	1.2	15.9	112.3	12.7	90.0
Temperate Conifer Forest	0.4	3.5	52.2	8.6	129.9
Boreal Forests/Taiga	1.5	8.6	103.4	5.8	70.0
Tropical & Subtrop. Grass & Shrubland, & Savanna	2.0	22.3	17.7	11.3	9.0
Temperate Grassland, Savanna & Shrubland	1.0	3.7	8.8	3.8	9.0
Flooded Grassland & Savanna	0.1	1.1	2.0	11.1	20.5
Montane Grassland & Shrubland	0.5	1.1	4.6	2.1	8.9
Tundra	1.2	2.6	5.8	2.2	5.0
Mediterranean Forest, Woodland & Scrub	0.3	2.2	9.5	7.1	30.1
Desert & Xeric Shrubland	2.7	3.3	8.2	1.2	3.0
Mangrove	0.0	0.5	3.6	15.5	120.2
Rivers	0.3	1.96	0.03	6.3	0.1
Lakes	0.1	0.81	0.01	8.1	0.1
Rock & Ice	1.1	0.02	0.1	0.02	0.1
Terrestrial Total	***14.7***	***122.7***	***583.0***	***8.4***	***39.78***
Estuary and Ocean					
Estuary	0.03	0.5	0.2	15.0	5.0
Ocean	36.3	47.1	1.1	1.3	0.03
Global Total	***51.0***	***170.2***	***584.3***	***3.3***	***11.5***

[a] . Data were computed from satellite derived coverages (Zhao et al., 2005)
[b] . Computed by multiplying biome biomass (column 6) by area (column 2)
[c] . Computed by dividing total biome GPP (column 3) by area (column 2).
[d] . Data from Table 1.

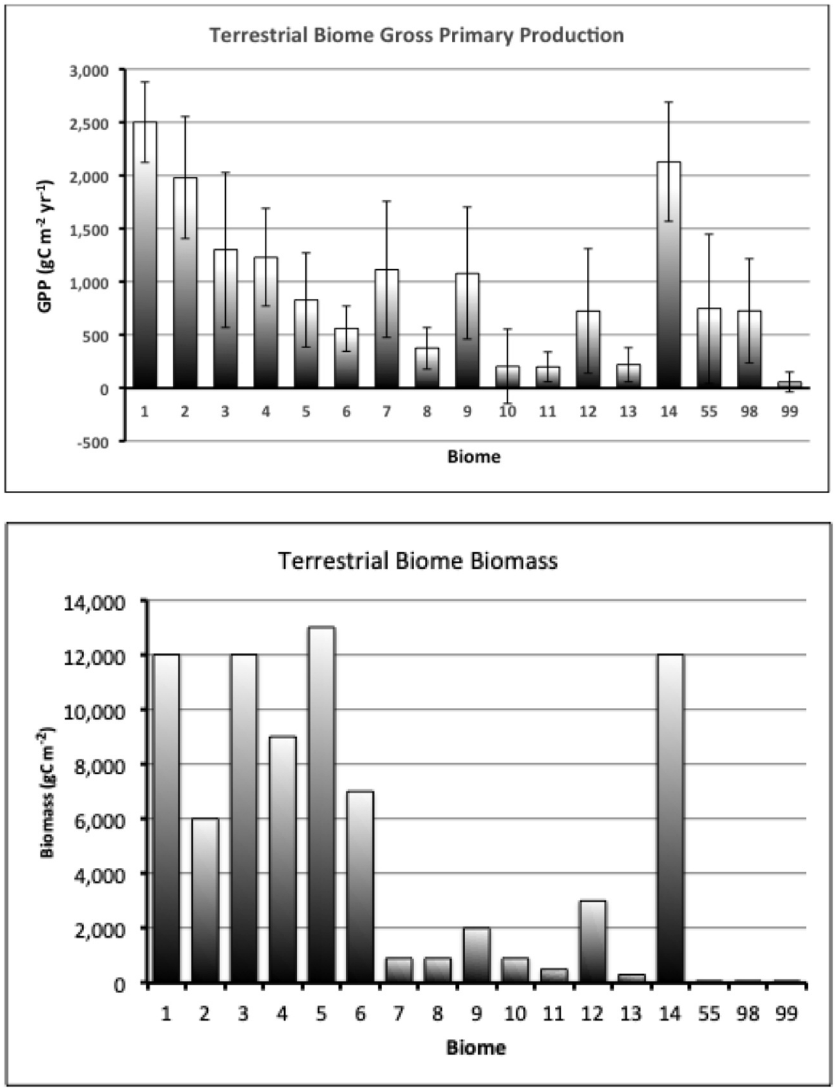

Figure 5. Terrestrial Biome GPP (a) and biomass. Biomes are as follows: 1. Tropical & Subtropical Moist Broadleaf Forests,2. Tropical & Subtropical Dry Broadleaf Forest, 3. Tropical & Subtropical Coniferous Forest, 4. Temperate Broadleaf & Mixed Forests, 5. Temperate Conifer Forests, 6. Boreal Forests/Taiga, 7. Tropical & Subtropical Grasslands. Savannas & Shrublands, 8. Temperate Grasslands. Savannas & Shrublands, 9. Flooded Grasslands & Savannas, 10. Montane Grasslands & Shrublands, 11. Tundra, 12. Mediterranean Forests. Woodlands & Scrub, 13. Deserts & Xeric Shrublands, 14. Mangroves, 55. River, 98. Lake, 99. Rock & Ice

be expected.

After analysis of the global data revealed differences in empower driving biomes on different continents, we analyzed MaxR for biomes by continent (a global coverage of the continental boundaries is given in Figure S-8, Supplemental Material). Figure 4 summarizes the continental MaxR data for each of the biomes. The data indicated some interesting outcomes; specifically note that the oceanic continent (composed primarily of Australia) has the largest difference from the global mean data and the largest standard deviation for most biomes except for the desert and shrubland biome. This may be due to the fact that more than half of the Australian landcover consists of desert and shrubland while other biomes are in small sizes and fragmented which is likely to result in larger standard deviation.

3.2. Aerial Empower Intensity of Global Biomes

Summarized in Table 3 is the aerial empower intensity (AEI) of the global biomes computed by dividing the biome empower by the area of each biome. Estuaries have the highest AEI of all biomes, followed by rivers and then tropical & subtropical moist forests. Estuaries possess an AEI that is over 8x the AEI of tropical & subtropical moist forests, the result of the very large input of chemical potential energy of terrestrial runoff. Not surprising is the fact that rivers have a large AEI, due to the geopotential energy of runoff that is concentrated within the river systems of the globe.

3.3. Biome GPP and Biotic Natural Capital

Table 4 and Figure 5 summarize pre-anthropocene GPP and biomass for global biomes. Of the total terrestrial GPP (122.7 PgC yr^{-1}) the largest single contribution is from tropical and subtropical moist forests (48.5 PgC yr^{-1}) followed by tropical and subtropical grass, schrublands & savannas (22.5 PgC yr^{-1}). The computed global GPP of 122.7 PgC yr^{-1} was within 2% of the total (125 PgC yr^{-1}) suggested by Zhang et al., (2017). When expressed on an areal basis the most productive biomes were the tropical and subtropical moist and dry forests (25.4 MgC ha^{-1} yr^{-1} and 20.3 MgC ha^{-1} yr^{-1} respectively), followed by mangroves (15.5 MgC ha^{-1} yr^{-1}) and tropical and subtropical coniferous forests (13.1 MgC ha^{-1} yr^{-1}).

Total global terrestrial biomass (Table 4) was 583.0 PgC of which tropical and subtropical moist forests contributed the largest percentage (about 33% or 229 PgC) followed by temperate broadleaf and mixed

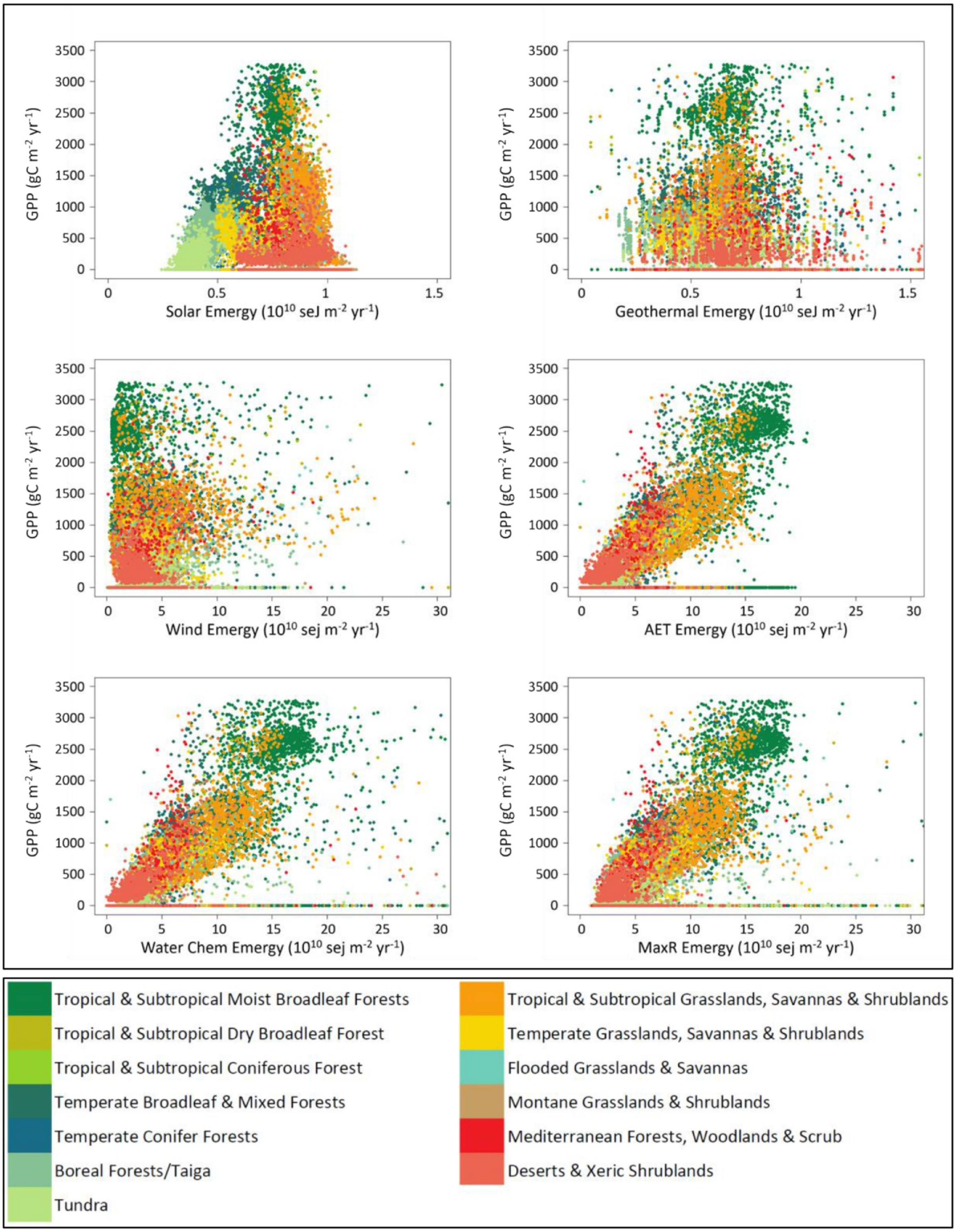

Figure 6. Scatter plots of driving emergy forms vs. GPP (gC m^{-2} yr^{-1})

forests (about 16% or 112.3 PgC). Expressed on an areal basis, the largest standing stock per unit area was coniferous temperate forests (~130 MgC ha^{-1}) followed by Tropical & Subtropical Moist Broadleaf Forest, Tropical & Subtropical Coniferous Forest and mangroves (all have a standing stock of about 120 MgC ha^{-1}.The ocean and estuary make up an insignificant portion (about 0.2%) of total global biomass, while contributing about 28% of global GPP.

Table 5 lists the biomes and computed soil carbon. By far the largest stock of soil carbon is found in the boreal forests ~348 PgC, followed by tropical and subtropical moist forests (~223 PgC) and tropical and subtropical grasslands, savanna, and shrubland (~166 PgC). When expressed on an areal basis the largest stocks are still the boreal forest (23.5 kgC m^{-2}), followed by mangrove forests (19.9 kgC m^{-2}), Temperate Conifer Forests (13.6 kgC m^{-2}) and Tropical & Subtropical Coniferous Forest (13.1 kgC m^{-2}).

3.4. The Relation Between Driving Emergy and Biome Biomass and Productivity

Scatter plots of pre-anthropocene GPP and biomass versus a suite of

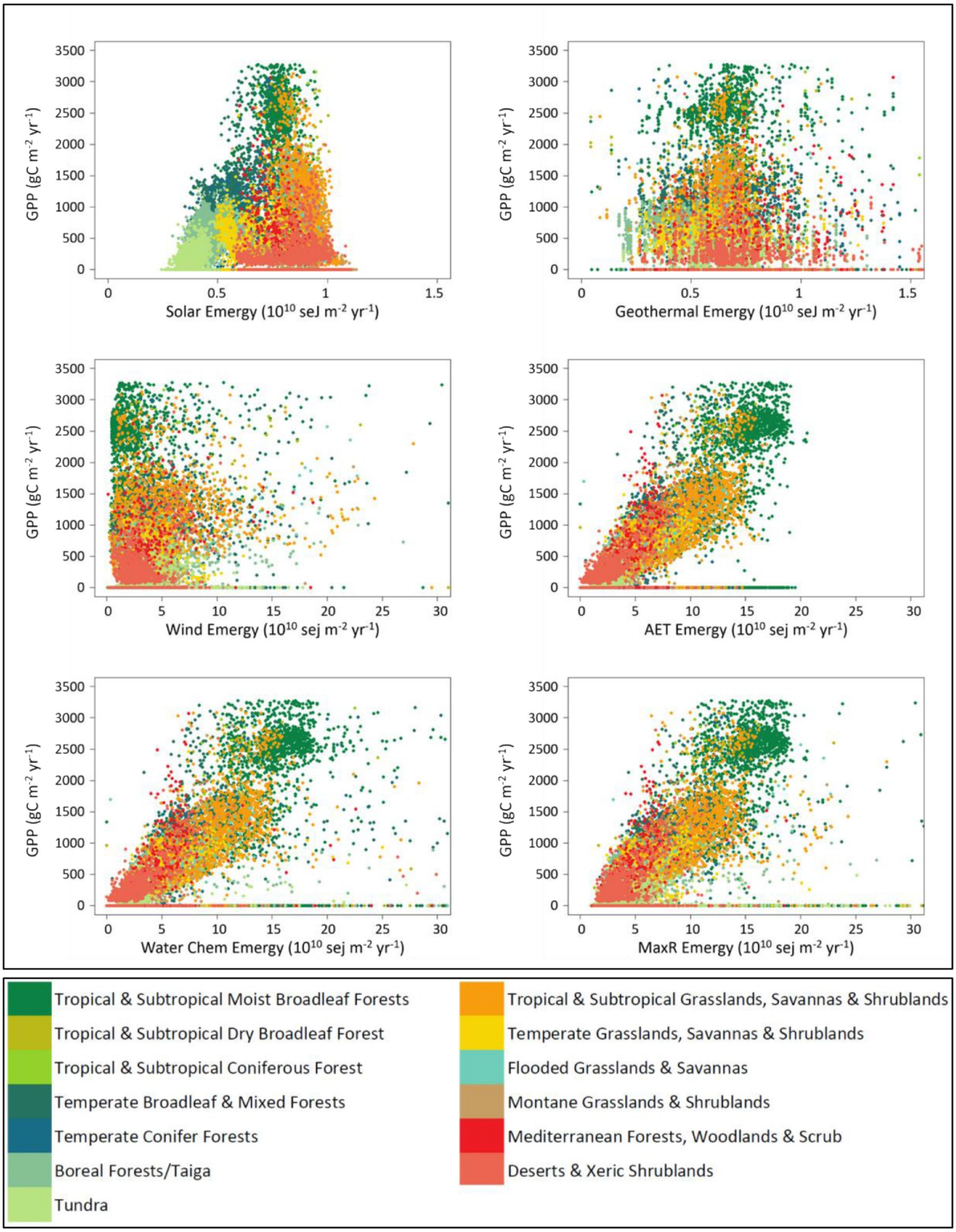

Figure 7. Scatter plots of driving emergy forms vs. biomass (gC m^{-2})

driving emergy is shown in Figures 6 and 7. Each data point in the graphs represents one 1 arc degree cell from the global coverage. The Y-axis is GPP and biomass (gC m^{-2} yr^{-1} or gC m^{-2}) and the X-axis is the log of driving emergy (sej m^{-2} yr^{-1}). Forms of driving emergy that exhibited the best GPP and biomass predictive value were AET, water chem. (chemical potential of AET plus runoff), and MaxR. AET and water chem appears to be the stronger predictor (and very similar) of both GPP and biomass with slightly more scatter exhibited by MaxR.

In addition to the scatter plots, a principal component analysis (PCA) was conducted where all the driving emergy forms were included. The analysis revealed the first principal component was AET and the second was solar input (see Supplemental material).

Screening of the data helped to inform further analysis of the relations between emergy and productivity and standing stock. Figures 8 and 9 show linear regressions of the emergy of AET, rain, waterchem and MaxR vs. GPP and biomass for terrestrial biomes. AET, rain, and waterchem are all generally good predictors of GPP (R^2 ~ 0.89-90 [$F < 0.001$]). The lower R^2 ($R^2 = 0.75$) of MaxR is due to several biomes lower on the productivity scale that had wind as the dominate emergy source (montane grasslands & shrublands, tundra, deserts & xeric

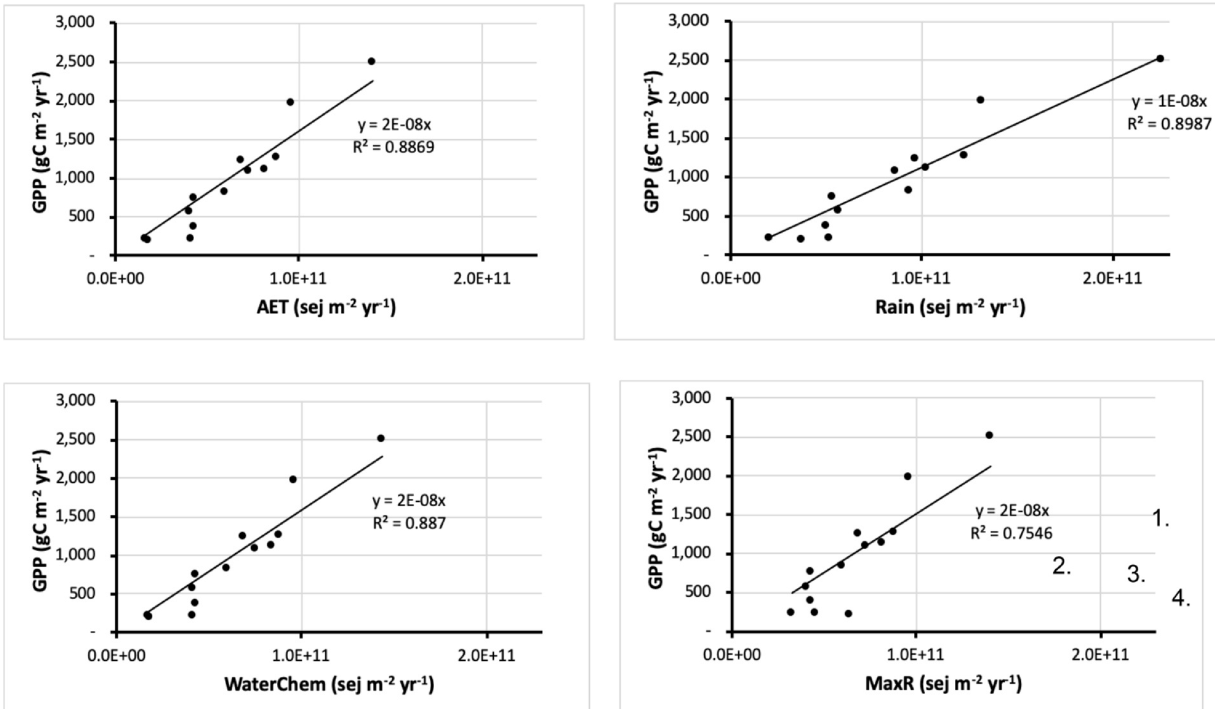

Figure 8. Linear regressions of AET, rain, waterchem and MaxR vs. GPP. Numbers correspond to: 1. Tundra, 2. Deserts & xeric scrub, 3. Montane Grasslands & Shrublands, 4. Rock & Ice

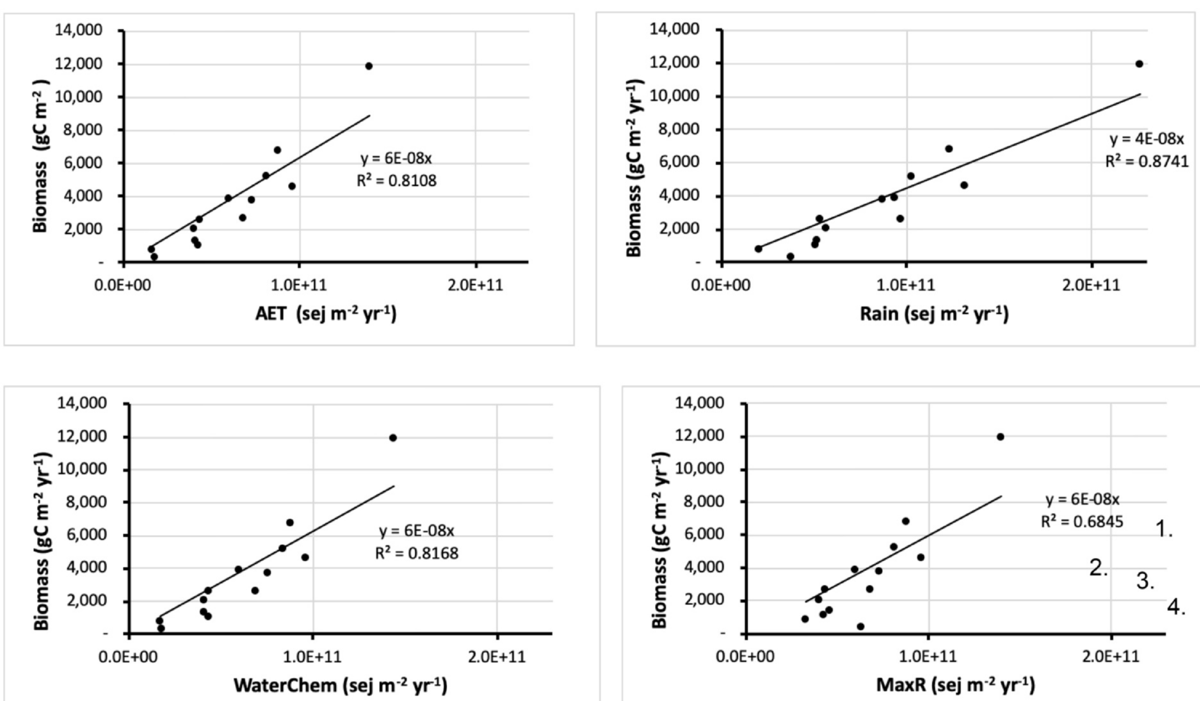

Figure 9. Linear regressions of AET, rain, waterchem, and MaxR. Numbers correspond to: 1. Tundra, 2. Deserts & xeric scrub, 3. Montane Grasslands & Shrublands, 4. Rock & Ice.

shrublands, and rock & ice). The regressions of AET, rain, waterchem and MaxR vs. biomass (Figure 9) were not as good at explaining variation as the GPP regressions, yielding R^2 of .37 and 0.28 respectively (In all cases significance, $F < 0.01$).

Because of the observation that there were differences in the variance in GPP between the same biomes on different continents, we also generated linear regressions of GPP by continent vs. AET and MaxR (Figure S-10, Supplemental material). It is apparent that there is greater variability in the data and thus the regressions are somewhat weaker (AET, $R^2 = 0.79$ and MaxR, $R^2 = 0.65$) but still significant ($F < 0.001$).

Checking to determine if multiple emergy sources may be responsible for global productivity and that the interplay of these sources might generate stronger predictive models, multiple linear regressions of GPP and biomass were conducted. Tables 6 and 7 show the output

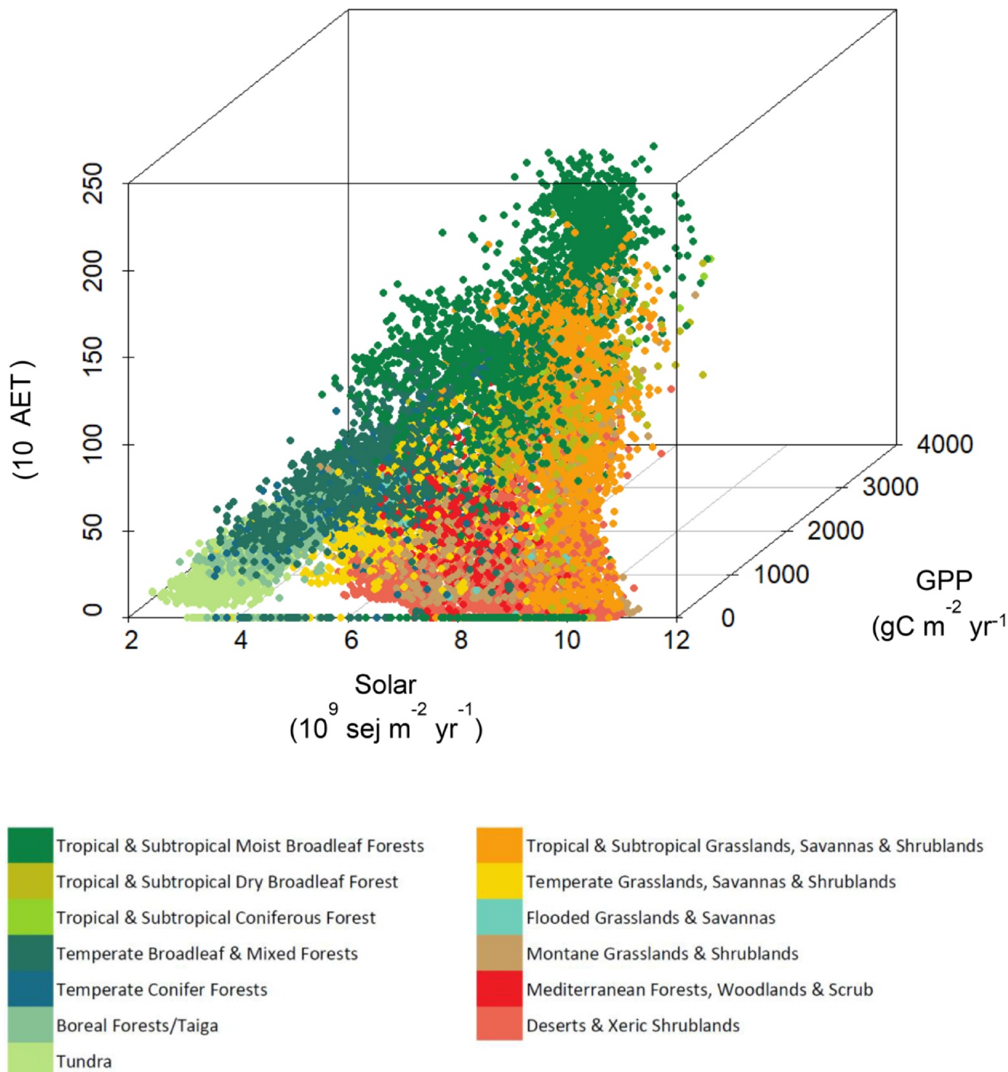

Figure10. 3-D scatter plot of GPP vs. AET and solar radiation.

Table 6
Results of the multiple linear regression of normalized driving emergy vs. GPP of global biomes

	Estimate	Std. Error	t value	Pr(>|t|)	Signif.
(Intercept)	-0.037105	0.003733	-9.94	2.00E-16	***
AET	0.862482	0.016246	53.088	2.00E-16	***
Solar	0.025066	0.004857	5.16	2.52E-07	***
Wind	0.040174	0.01745	2.302	0.0213	*
Rain	0.168996	0.025301	6.679	2.56E-11	***
Geothermal	-0.129744	0.031422	-4.129	3.68E-05	***
MaxR	-0.192413	0.047624	-4.04	5.39E-05	***

Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 290.7 on 8052 degrees of freedom
Multiple R-squared: 0.7923, **Adjusted R-squared: 0.7922**
F-statistic: 5120 on 6 and 8052 DF, p-value: < 2.2e-16

Table 7
Results of the multiple linear regression of normalized driving emergy vs. biomass of global biomes

	Estimate	Std. Error	t value	Pr(>|t|)	Signif.
(Intercept)	-2700.72	70.83	-38.127	2.00E-16	***
AET	18278.3	308.28	59.291	2.00E-16	***
Solar	2540.22	92.17	27.56	2.00E-16	***
Wind	**-4603.2**	331.12	-13.902	2.00E-16	***
Rain	3613.77	480.1	7.527	5.75E-14	***
Geothermal.	1056.57	596.23	1.772	0.0764	.
MaxR	6934.7	903.69	7.674	1.87E-14	***

Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 1690 on 8052 degrees of freedom
Multiple R-squared: 0.844, **Adjusted R-squared: 0.8439**
F-statistic: 7261 on 6 and 8052 DF, p-value: < 2.2e-16

from the R software package showing that each of driving energy sources explains some of the error with the exception of wind for GPP, and solar and geothermal for biomass. As expected AET had the largest explanatory power ($p = 0.001$) followed by rain ($p = 0.001$) for GPP. As with Biomass, the largest explanatory power for biomass was AET ($p = .001$) followed by rain ($p = .001$) and wind ($p = 0.001$). The driving emergy that was not significant ($p = 0.1$) for biomass was geothermal. The adjusted R^2 for both multiple regressions were 0.79 and 0.84 for GPP and biomass prospectively.

Finally, we explored in three dimensional plots of the two most important driving emergy sources and their relation to GPP, biomass and soil carbon (Figures 10, 11, and 12). The plots use AET and solar energy which are from the previous analyses suggested the strongest relations to GPP and biomass. The color plots show very well the locations of the biomes in the space defined by AET and solar radiation.

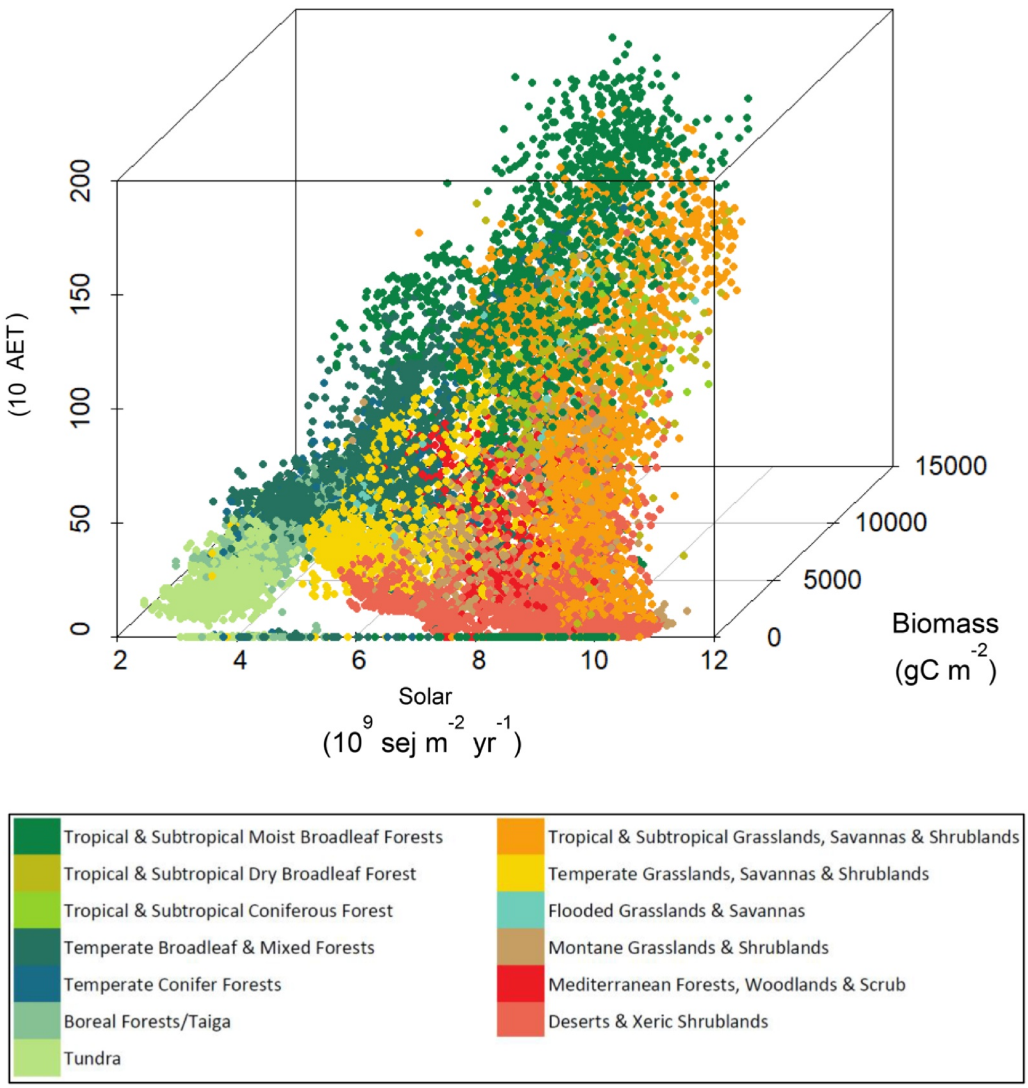

Figure 11. 3-D scatter plot of biomass of global biomes vs. AET and solar radiation.

3.5. Emergy and Emdollar Value of Global GPP

Given in Table 8 are the emergy and emdollar value of the GPP of global biomes in the pre-anthropocene. Total emdollar value of global GPP was ^{em}\$ 12.3 trillion. The largest contributor was the ocean (^{em}\$ 4.9 trillion) followed by estuaries (^{em}\$ 1.8 trillion) and rain forests (^{em}\$ 1.4 trillion). To place emdollar value of the work of ecosystems of the biosphere in perspective, the GDP of USA in 2004 was equal to \$ 12.3 trillion (USBEA, 2019). In recent years, others have evaluated global “ecosystem services” (Costanza et al., 2014, 1997; de Groot et al., 2012) determining that they were worth between \$33 trillion and \$145 trillion per year.

3.6. Emergy and Emdollar Value of Biotic Natural Capital (BNC)

The emergy of pre-anthropocene BNC was evaluated using the turnover time of the stock multiplied by the AEI of each biome. Table 9 lists the emergy and emdollar value of soil carbon and Table 10 lists the emergy and emdollar value of biomass. Total emergy of soil carbon was 708.3 E+24 sej, equivalent to ~ ^{em}\$354.2 trillion. Biomes with the larges emergy in soil carbon were tundra (358.8 E+24 sej = ^{em}\$ 179.4 trillion), followed by tropical & subtropical moist broadleaf forests (104.3 E+24 sej = ^{em}\$ 52.1 trillion).

Total emergy of biomass (including the marine biomes) was 448.6 E+24 sej or about 63% of the emergy of soil carbon (Table 10). The equivalent emdollar value of biomass was ^{em}\$ 224.3 trillion. Biomes with the largest biomass were tropical & subtropical moist broadleaf forests (~140 E+24 sej = ^{em}\$ 70 trillion) followed by boreal forest/taiga (61.5 E+24 sej = ^{em}\$ 30.7trillion)

Combine the total global emergy and emdollar value of biotic natural capital was 1156.9 E+24 sej and ^{em}\$ 578.5 trillion. For reference the estimated nominal gross world product (GWP) in 2017 was \$80.3 trillion (CIA, 2019) or only about 14% of the emdollar value of natural capital.

3.7. Impact of Human Induced Land Cover Change

We compared pre-anthropocene GPP with the GPP derived from Terra/MODIS NPP and GPP product (ca. 2000; Zhao et al., 2005) to estimate the impact of land cover change on the global productivity.

Table 11 lists estimates of land cover change and changes in GPP for the pre-anthropocene and the year 2000, based on Zhao et al., (2005). Land cover change has resulted in rather dramatic decreases in the area of many biomes. Between 43% and 82% of all tropical and subtropical ecosystems have been altered. Nearly 80% of Mediterranean forest, woodland, and scrub ecosystems have been converted and over 60% of tropical and flooded grassland & savanna systems. Our analysis suggests that the tundra biome, for all intents and purposes, remains untouched,

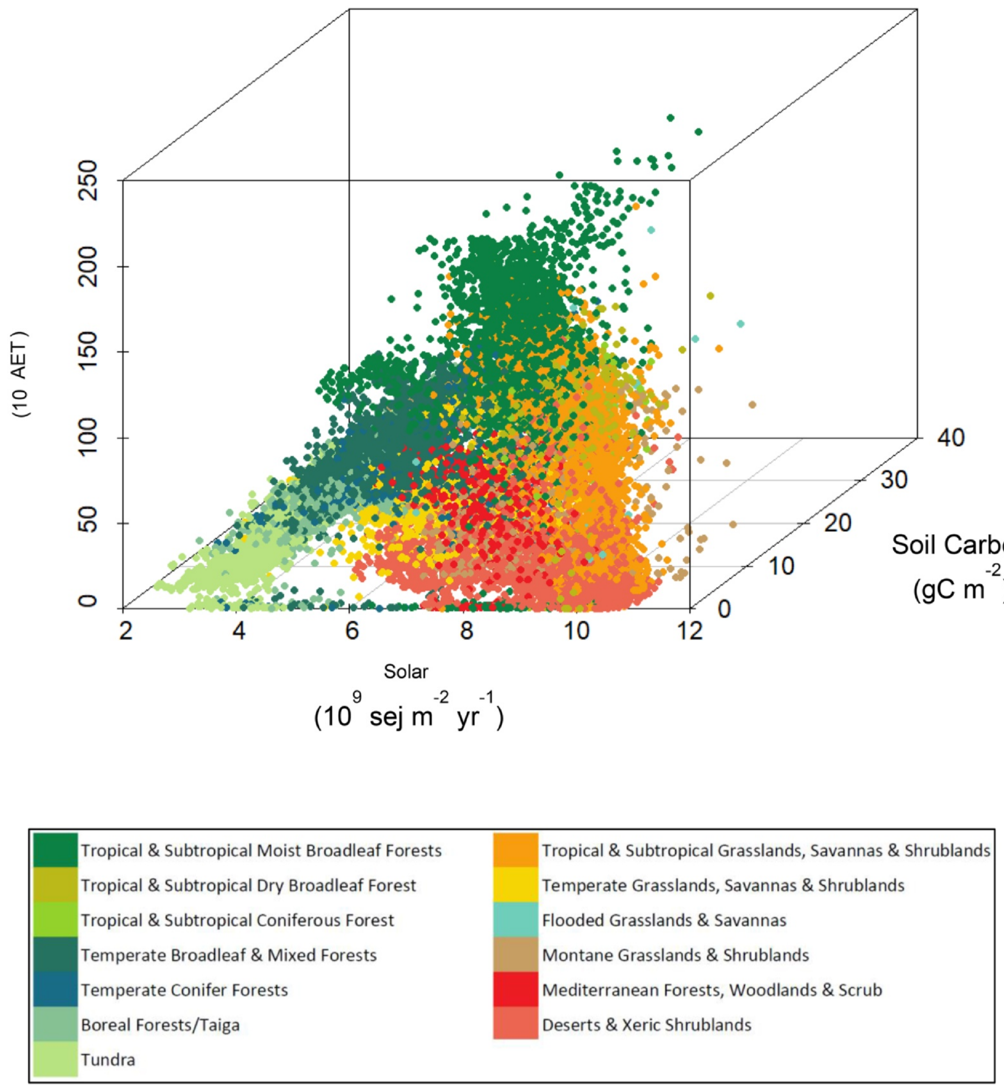

Figure 12. 3-D scatter plot of soil carbon of global biomes vs. AET and solar radiation.

while the boreal forest ecosystems show a decline of about 4% in cover. Land cover area of mangrove ecosystems has declined over 50%. It is interesting to note that estuarine areas of declined by about 42%. In all, total cover of pre-anthropocene terrestrial biomes has declined by 38%.

It is most interesting that the models used to estimate GPP do not agree with the land cover changes (Table 11). Gross primary production as measured by satellite does not show nearly the same magnitudes of decrease. In fact, while all biomes show a decrease in area (with the exception of the tundra) some biomes show increases in GPP; some remarkably much greater than the pre-anthropocene production (montane grassland & shrubland, +100%; temperate grassland, savanna & shrubland, +37%; desert & xeric shrubland, 38%). The largest decreases in GPP were exhibited by tropical & subtropical dry broadleaf forest (-33%) and temperate broadleaf & mixed forest (-15%). Obviously when some ecosystems are replaced by irrigated and fertilized agriculture, the “greenness” and therefore the estimates of GPP may be considerably higher than the initial ecosystem, resulting in the fact that many biomes show increases in GPP while their initial land cover has been much reduced. Overall, our analysis suggests that while 43% of the original land cover has been altered, this has resulted in only an overall decline in GPP of 5%.

Changes in biotic natural capital (BNC) were also evaluated as the sum of the losses of biomass and soil carbon storage. The assumption was that 100% of standing forest biomass and 50% of biomass on nonforested biomes was removed on areas dominated by human uses. Given in Table 12 are estimates of the decreases in terrestrial biomass. Total emdollar value of terrestrial biomass loss was ^{em}\$70 trillion or about 12% of total BNC value. The largest losses occurred in Tropical & Subtropical Moist Broadleaf Forest (^{em}\$30.1 trillion) and Temperate Broadleaf & Mixed Forest (^{em}\$18.4 trillion). No land cover changes were observed in the tundra biome. Table 13 lists the emergy and emdollar losses of soil carbon due to land cover change. Total losses equal to em\$18.5 trillion, the largest of which resulted from land cover change in tropical forests (^{em}\$7.8 trillion) and Flooded Grassland & Savanna (^{em}\$2.5 trillion).

Overall the total losses of BNC from land cover change since the anthropocene began (~310 years) equal ^{em}\$88.5 trillion or about 16% of total pre-anthropocene value, and roughly equal to the world gross domestic product in 2017 (\$80.3 trillion, (CIA, 2019)).

4. Discussion

This study explored four questions related to global ecosystems and their driving emergy designed to elicit a better understanding of some very fundamental questions, assertions and suppositions of emergy theory. The questions were as follows:

1 What is the emergy supporting global ecosystem productivity?

Table 8
Emergy and emdollar value of biome GPP

Biome Type	MaxR Biome [a.] (10^{21} sej yr^{-1})	Emdollars [e.] (Trillion^{em}\$)
Terrestrial Biomes		
Tropical & Subtropical Moist Broadleaf Forest	2743.5	1.37
Tropical & Subtropical Dry Broadleaf Forest	278.3	0.14
Tropical & Subtropical Coniferous Forest	61.7	0.03
Temperate Broadleaf & Mixed Forest	861.8	0.43
Temperate Conifer Forest	240.4	0.12
Boreal Forests/Taiga	608.6	0.30
Trop. & Subtrop. Grassland, Savanna & Shrubland	1644.2	0.82
Temperate Grassland, Savanna & Shrubland	422.6	0.21
Flooded Grasslands& Savanna	73.6	0.04
Montane Grassland & Shrubland	233.9	0.12
Tundra	732.2	0.37
Mediterranean Forests, Woodlands & Scrub	136.2	0.07
Deserts & Xeric Shrubland	884.8	0.44
Mangroves	30.0	0.02
River	1123.0	0.56
Lake	52.5	0.03
Rock & Ice	974.9	0.49
Terrestrial total	***11102.3***	***5.55***
Marine Biomes		
Estuary	3595.0	1.80
Ocean	9814.5	4.91
Global total	***24511.76***	***12.26***

[a] . From Table 2
[b] . MaxR divided by 2.0 E12 sej/^{em}\$

2 What is the emergy of global ecosystem biomass and soil carbon?
3 Do ecosystems maximize total emergy, or is maximum productivity and biomass the result of the interplay of the suite of renewable emergy sources?
4 What is the impact on global productivity (GPP) and biotic natural capital (BNC) that has resulted from human induced land cover change?

To answer these questions, global coverages of earth's renewable driving energy (multiplied by transformities to convert to emergy) were combined with global coverages of productivity (GPP) soil carbon and biomass.

We begin this discussion by first examining two constraints that are the result of the data we used and thoughts regarding “services” vs. functions . We then turn to addressing each of the above questions and their related theoretical questions, assertions and suppositions.

4.1. Biomes

Biomes play a significant role in this study as the concept is used to explore the relationships between driving emergy and structure and productivity of global ecosystems. How the world's ecological systems are classified ultimately dictates relations one might find between driving emergy and ecosystem properties.

The geobiosphere, composed of numerous ecosystems has been classified into generalized biomes, or collections of flora and fauna with common characteristics occupying a shared environment having similar climatic conditions. The term was first used by Clements (1917) to describe biotic community. Tansley (1935) added a soil component and climatic conditions to the concept. The International Biological Program (1964-74), an internationally coordinated effort to conduct large scale ecosystem studies, increased awareness of the concept. Following the IBP program there were (and continue) numerous efforts to classify global biotic communities(Allee et al., 1949; Bailey, 1989; HOLDRIDGE, 1947; Olson et al., 2001; Olson and Dinerstein, 1998; Whittaker, 1962).

Most of the classification schemes that have been devised rely on two abiotic elements, water and temperature. For water, while evapotranspiration is sometimes used, the most common water parameter in the majority of the classification schemes was annual precipitation. The classification scheme of Olson et al. (2001), adopted here, relied on climatic zones or regions (tropic, subtropic, temperate etc.) and moisture regimes (humid, semi humid, arid, etc.). Thus, it is somewhat obvious, if the classification scheme relies in a large part on water availability and temperature (solar input), then the most important driving energy sources would be highly correlated to these two variables.

4.2. Biome Productivity

The productivity of global biomes (Figure 5 and Table 4) was derived from global coverages generated as one of the many products of NASA's Moderate Resolution Imaging Spectroradiometer (MODIS) program. Since the GPP data derived from MODIS is contemporaneous, it was necessary to derive GPP for biomes without the presence of human land uses. This required that we subsample the MODIS data for

Table 9
Emergy and Emdollar values of terrestrial biome soil carbon

Biome	Soil Carbon [a.] (10^{15} gC)	Turnover Time [b.] (yrs)	Tot. MaxR [c.] (sej yr^{-1})	Emergy [d.] (10^{24} sej)	Emdollars [e.] (Trillion^{em}\$)
Tropical & Subtropical Moist Broadleaf Forests	223.8	38.0	2.7E+24	104.3	52.1
Tropical & Subtropical Dry Broadleaf Forest	31.6	38.0	2.8E+23	10.6	5.3
Tropical & Subtropical Coniferous Forest	9.2	38.0	6.2E+22	2.3	1.2
Temperate Broadleaf & Mixed Forests	161.7	29.0	8.6E+23	25.0	12.5
Temperate Conifer Forests	54.6	29.0	2.4E+23	7.0	3.5
Boreal Forests/Taiga	347.9	91.0	6.1E+23	55.4	27.7
Tropical & Subtropical Grasslands, Savannas & Shrublands	166.2	10.0	1.6E+24	16.4	8.2
Temperate Grasslands, Savannas & Shrublands	110.5	61.0	4.2E+23	25.8	12.9
Flooded Grasslands & Savannas	12.3	520.0	7.4E+22	38.3	19.1
Montane Grasslands & Shrublands	51.5	61.0	2.3E+23	14.3	7.1
Tundra	150.4	490.0	7.3E+23	358.8	179.4
Mediterranean Forests, Woodlands & Scrub	30.1	14.0	1.4E+23	1.9	1.0
Deserts & Xeric Shrublands	152.0	37.0	8.8E+23	32.7	16.4
Mangroves	5.9	520.0	3.0E+22	15.6	7.8
Total	***1507.8***		***9.0E+24***	***708.3***	***354.2***

[a] . soil carbon data from GlobalSoil Data Task Group (2000).
[b] . Turnover time from Raich and Schlesinger (1992)
[c] . Total MaxR is from Table 2.
[d] . Emergy is the product of MaxR in column 4 and turnover time in column 5.
[e] . Emdollars are computed by dividing the emergy in column 5 by the world emergy money ratio (2.0 E12 sej \$$^{-1}$)

Table 10
Emergy and emdollar values of terrestrial biome biomass

Biome Type	Biome Biomass [a.] (10^{15} g C)	AEI [b]. (10^{21}sej yr^{-1})	Turn over time [c.] (yr)	Emergy [d.] (10^{24}sej)	Emdollars [e.] (Trillion em$)
Terrestrial Biomes					
Tropical & Subtropical Moist Broadleaf Forest	229.0	2743.5	51	139.9	70.0
Tropical & Subtropical Dry Broadleaf Forest	17.4	278.3	37	10.3	5.1
Tropical & Subtropical Coniferous Forest	8.4	61.7	84	5.2	2.6
Temperate Broadleaf & Mixed Forest	112.3	861.8	60	51.7	25.9
Temperate Conifer Forest	52.2	240.4	121	29.1	14.5
Boreal Forests/Taiga	103.4	608.6	101	61.5	30.7
Trop. & Subtrop. Grass & Shrubland, & Savanna	17.7	1644.2	11	18.1	9.0
Temperate Grassland, Savanna & Shrubland	8.8	422.6	18	7.6	3.8
Flooded Grassland & Savanna	2.0	73.6	26	1.9	1.0
Montane Grassland & Shrubland	4.6	233.9	44	10.3	5.1
Tundra	5.8	732.2	29	21.2	10.6
Mediterranean Forest, Woodland & Scrub	9.5	136.2	45	6.1	3.1
Desert & Xeric Shrubland	8.2	884.8	46	40.7	20.4
Mangrove	3.6	30.0	89	2.7	1.3
Rivers	0.03	1123.0	0.6	0.7	0.3
Lakes	0.01	52.5	0.6	–	–
Rock & Ice	0.1	97.5	14	1.4	0.7
Terrestrial Total	***583.0***	***10224.9***		***408.4***	***204.2***
Estuary and Ocean					
Estuary	0.2	3595.0	3	10.8	5.4
Ocean	1.1	9814.5	3	294.4	14.7
Global Total	***584.3***	***23634.3***		***448.6***	***224.3***

[a] . From Table 4.
[b] . equal to renewable emergy input (MaxR) from Table 2.
[c] . from simulation model (see supplemental material)
[d] . Product of AEI (column 3) and turnover time (column 4)
[e] , World emergy/money ration in 2014 = 2.0 E12 sej/$

Table 11
Change in land area and GPP of biomes from human induced land cover change

	Land Area (10^9 m^2)			GPP (10^9 kg y^{r-1})		
Land Cover Type	Pre-Anthropocene	ca. 2000	% Change	Pre-Anthropocene	ca. 2000	% Change
Terrestrial Biomes						
Tropical & Subtropical Moist Broadleaf Forest	19085.4	10821.9	-43%	47,670	41,798	-12%
Tropical & Subtropical Dry Broadleaf Forest	2891.8	510.5	-82%	5,720	3,819	-33%
Tropical & Subtropical Coniferous Forest	701.6	195.7	-72%	908	966	6%
Temperate Broadleaf & Mixed Forest	12482.6	3570.3	-71%	15,645	13,295	-15%
Temperate Conifer Forest	4018.7	2602.7	-35%	3,421	3,443	1%
Boreal Forest/Taiga	14774.8	14192.1	-4%	8,567	8,689	1%
Trop. & Subtrop. Grassland, Savanna & Shrubland	19680.0	7592.1	-61%	20,780	19,582	-6%
Temperate Grassland, Savanna & Shrubland	9787.3	2890.7	-70%	3,676	5,069	38%
Flooded Grassland & Savanna	976.2	322.0	-67%	945	920	-3%
Montane Grassland & Shrubland	5155.9	2406.2	-53%	1,018	2,038	100%
Tundra	11539.8	11533.2	0%	1,726	1,730	0%
Mediterranean Forest, Woodland & Scrub	3153.3	697.9	-78%	2,178	2,378	9%
Desert & Xeric Shrubland	27170.1	20859.2	-23%	3,228	5,250	63%
Mangrove	296.3	144.0	-51%	591	525	-11%
River	3121.7	1425.7	-54%	2,785	2,889	4%
Lake	994.2	955.2	-4%	232	256	10%
Rock & Ice	11069.6	11047.7	0%	20	23	17%
Subtotal	***146899.2***	***91766.9***	***-38%***	***119110.0***	***112671.2***	***-5%***
Marine Biomes						
Estuary	301.9	174.2	-42%	416	423	2%
Ocean	362266.5	362081.6	0%	6,537	6,796	4%
Grand Total	***509467.6***	***454022.8***	***-11%***	***126063.0***	***119890.2***	***-5%***

areas without human land cover change, by masking all human dominated areas. This left, in some regions of the globe, a relatively small number of pixels from which to compute GPP for the entire biome (Table B-5, Supplemental Material). It also became apparent that the same biome on different continents exhibited different mean GPP (Figure 13). While few of these differences were statically significant, the differences did point out the fact that a global biome map that homogenizes all similar ecosystems across the planet, may be a simplification that helps to hide some relationships between driving emergy and productivity. The relatively small number of pixels in some biomes/continents may have contributed to the observed differences in GPP when computed separately by continent.

4.3. Ecosystem Services vs Ecosystem Functions

Ecosystem services' (ES) are the ecological characteristics, functions, or processes that directly or indirectly contribute to human wellbeing: that is, the benefits that people derive from functioning

Table12
Estimate of the emergy and emdollar losses of terrestrial biomass due to land cover change

Biome Type	Emergy [a] (10^{24}sej)	% Land area change [b]	% BNC change [c]	Total % Change [d]	Emergy [d] (10^{21}sej)	Emdollars [e] (Trillion em$)
Terrestrial Biomes						
Tropical & Subtropical Moist Broadleaf Forest	139.9	-43%	100%	-43%	60165.5	30.1
Tropical & Subtropical Dry Broadleaf Forest	10.3	-82%	100%	-82%	8443.3	4.2
Tropical & Subtropical Coniferous Forest	5.2	-72%	100%	-72%	3734.4	1.9
Temperate Broadleaf & Mixed Forest	51.7	-71%	100%	-71%	36711.3	18.4
Temperate Conifer Forest	29.1	-35%	100%	-35%	10179.1	5.1
Boreal Forests/Taiga	61.5	-4%	100%	-4%	2458.9	1.2
Trop. & Subtrop. Grass & Shrubland, & Savanna	18.1	-61%	50%	-31%	5516.4	2.8
Temperate Grassland, Savanna & Shrubland	7.6	-70%	50%	-35%	2662.6	1.3
Flooded Grassland & Savanna	1.9	-67%	50%	-34%	641.0	0.3
Montane Grassland & Shrubland	10.3	-53%	50%	-27%	2727.6	1.4
Tundra	21.2	0%	50%	0%	0.0	0.0
Mediterranean Forest, Woodland & Scrub	6.1	-78%	50%	-39%	2390.0	1.2
Desert & Xeric Shrubland	40.7	-23%	50%	-12%	4680.6	2.3
Mangrove	2.7	-51%	100%	-51%	1363.4	0.7
Rivers	0.7	-54%	Na		–	–
Lakes	–	–	Na		–	–
Rock & Ice	1.4	0%	Na		–	–
Terrestrial Total	***408370.9***	***-38%***			***141674.1***	***70.8***

[a] . from Table 8.
[b] . from Table 11
[c] . assume 100% loss of forested systems and 50% loss of grassland systems
[d] . product of Emergy in column 2 and total % change in column 5
[e] , computed by dividing emergy in column 6 by the world emergy/money ratio in 2014 = 2.0 E12 sej/$

ecosystems (Costanza et al., 1997; Millennium Ecosystem Assessment (MEA), 2005). Ecosystem functions (EF), on the other hand, are the ecological processes that control the fluxes of energy, nutrients and organic matter through an ecological system. There is a very simple yet important reason for this distinction on our part, that is a direct result of emergy accounting principles. Since the functions of ecosystems are co-products, i.e. they occur simultaneously within systems driving by the same emergy, they cannot be added. Thus, the emergy assigned to GPP is the same emergy assigned to evapotranspiration, or nutrient cycling, or O_2 production or CO_2 sequestration of a particular ecosystem. Simply put, the value of an ecosystem's functions is the emergy driving the system.

Services are another thing...they are, first and foremost, a product of human imagination. Services are aimed at humans and are defined as actions of assisting or doing work for someone. Therefore, ESs are actions by ecosystems that help or do work for humans. There are numerous ways of evaluating ESs, mostly in monetary terms (avoided cost, replacement cost, factor income, travel cost, hedonic pricing, and contingent valuation), It is these methods of evaluation that make the distinction between functions and services important. Each of these methods rely on some form of willingness-to-pay and therefore are "receiver value systems". Emergy is a donor value system, so to evaluate ecosystem functions we compute the emergy required to produce them. To evaluate the services that and ecosystem provides we compute what people are willing to pay for it. Quite simply, to opposing views of value.

In this paper we have compared our computed values of ecosystem functions to economic values by converting emergy to monetary units using a global emergy money ratio. We have refrained from suggesting that one is better than the other, since they measure two very different things. The utility of converting to emdollars is merely the fact that humans recognize dollar values and are proficient at distinguishing relative importance based on them.

4.4. Drivers of Biome Productivity and Structure

Throughout the analysis of biomes and driving emergy, water and temperature played significant roles in determining productivity and structure of global biomes. The analysis of biome driving emergy showed that the chemical potential emergy of water (AET + runoff) was the dominant emergy (Table 2) for a majority of the biomes (11 out of 16 terrestrial biomes plus the coastal estuary biome). These corresponded to the moist climatic provinces[4] (perhumid[5], humid, and subhumid). Interestingly, the biomes of the dry climatic provinces (semiarid; and arid) were dominated by wind as the driving energy. The dominate input emergy of a system has been termed MaxR, which is a contraction of maximum renewable.

According to emergy theory, systems should respond to the emergy driving them. Therefore, one might expect that the higher the emergy input the greater total work that can be done by a system. In ecosystems, total work is measured by GPP, thus correlations between GPP and MaxR should be a test of the general proposition. Generally, this is true, GPP as a measure of total work shows an increasing trend with increasing driving emergy (compare data in Tables 3 and 4).

The suite of emergy inputs to ecosystems, also called "emergy signature" was shown in Figure 3. The two dominate driving emergy forms for nearly all biomes were rain and wind. In the moist climatic regimes rain dominated, while in the dry regimes, wind was the dominate input. If the theory that systems respond to emergy and not necessarily to the form of the emergy input, then a test of correlation between MaxR and productivity should yield strong correlation regardless of the input emergy forms. Simple linear regressions of MaxR vs GPP (Figure 8) yielded strong correlations, especially with those biomes whose dominate input was rain ($R^2 = 0.75$). In the same regression, biomes whose dominate input was wind exhibited lower than expected GPP, suggesting that the proposition that maximum emergy, regardless of form is a strong indicator of productivity is inaccurate. A second regression of AET vs GPP found a much stronger correlation between the two variables ($R^2 = 0.89$) further explaining the lack of correlation of the dryer

[4] Moist climates are those with a positive moisture index and dry provinces are those with a negative index (Thornthwaite,1948)

[5] Defined by Thornthwaite (1948) as the wettest type of climate having a humidity index value greater than 100.

Table 13
Estimates of emergy and emdollar values of terrestrial biome soil carbon losses

Biome	Soil Carbon [a] (10^{15} gC)	Land use change [b]	% Soil Carbon Loss [c]	Soil Carbon Loss [d] (10^{15} gC	UEV [e]	Emergy [f] (10^{24} sej)	Emdollars [g] (Trillion em$)
Tropical & Subtropical Moist Broadleaf Forest	223.8	-43%	-31%	29.7	4.66E+08	13.9	6.9
Tropical & Subtropical Dry Broadleaf Forest	31.6	-82%	-16%	4.2	3.34E+08	1.4	0.7
Tropical & Subtropical Coniferous Forest	9.2	-72%	-18%	1.2	2.56E+08	0.3	0.2
Temperate Broadleaf & Mixed Forest	161.7	-71%	-19%	21.5	1.55E+08	3.3	1.7
Temperate Conifer Forest	54.6	-35%	-38%	7.3	1.28E+08	0.9	0.5
Boreal Forest/Taiga	347.9	-4%	0%	0.0	1.59E+08	0.0	0.0
Trop & Subtrop Grassland, Savanna & Shrubland	166.2	-61%	-22%	22.1	9.89E+07	2.2	1.1
Temperate Grassland, Savannas & Shrubland	110.5	-70%	-19%	14.7	2.33E+08	3.4	1.7
Flooded Grassland & Savanna	12.3	-67%	-20%	1.6	3.10E+09	5.1	2.5
Montane Grassland & Shrubland	51.5	-53%	-25%	6.8	2.77E+08	1.9	0.9
Tundra	150.4	0%	0%	0.0	2.38E+09	–	–
Mediterranean Forests, Woodland & Scrub	30.1	-78%	-17%	4.0	6.33E+07	0.3	0.1
Deserts & Xeric Shrubland	152.0	-23%	-58%	20.2	2.15E+08	4.4	2.2
Mangroves	5.9	-51%	0%	0.0	2.65E+09	–	–
Total	***1507.8***			***133.4***		***37.0***	***18.5***

[a] . soil carbon data from Table 5
[b] . % land use change from Table 11
[c] . Percent soil carbon loss based on total loss of 133 PgC (Sanderman et al. 2018)
[d] . Computed as product of column 2, 3 and 4.
[e] . Computed from Table 5 by dividing total emergy by carbon stock.
[f] . Emergy is computed as the product of UEV and soil carbon loss
[g] . Emdollars are computed by dividing the emergy in column 5 by the world emergy money ratio (2.0 E12 sej $$^{-1}$)

biomes who were dominated by wind. The fact that the R^2 improved when AET was used implies a stronger relation to available water, rather than just maximum emergy.

When GPP was computed for each continental biome and then the results regressed against AET and MaxR (Figure 9), the regressions that resulted were a bit weaker (R^2=.079 and R^2= 0.65, for AET and MaxR respectively). The suggestion is that the "smoothing' that results from computing global means for biome GPP results in a stronger relation between driving emergy and ecosystem productivity. In other words, using global means for GPP rather than using GPP for each continental biome reduces the variability in overall GPP and therefore increases the R^2 of the regressions.

When regressions were conducted to evaluate correlations of AET and MaxR with biome biomass, the results were far less strong (bottom graphs in Figure 8). The variability was much greater, yielding an R^2 = 0.37 for AET vs. biomass and R^2 = 0.28 for MaxR vs. biomass. It appears that accumulation of biomass is only slightly related to the intensity of the driving emergy. Other factors may be involved for instance temperature, which modify environmental conditions.

4.5. Maximum Emergy or Multiplicity of Emergy?

Multiple regression analysis of biome productivity and biomass (Tables 6 and 7) suggested that while all the forms of driving renewable emergy explained some of the variation in GPP and biomass, by far, rain and solar energy were the most important, and positively correlated, while wind and geothermal were negatively correlated. Interestingly, the multivariate adjusted R^2 values were quite different from the R^2 of the univariate regressions. The multivariant adjusted R^2 for GPP (Table 6: R^2 = 0.79) decreased from the univariate AET vs. GPP value (Figure 8: R^2= 0.89), while the multivariate adjusted R^2 for biomass (Table 7: R^2 = 0.84) was relatively similar to the univariate regression for rain and AET (Figure 9: R^2 = 0.87 and R^2= 0.81 respectively). The addition of solar energy had a positive effect in explaining some of the variance in biomass, while it had little or no effect on GPP. Apparently while rain alone is a relatively good predictor of GPP, the best model for biomass was a multiple regression that included solar energy and to a lesser degree wind.

It should be kept in mind that AET is always between 95% and 99% of MaxR (see Table 2), in the moist ecosystems, since MaxR is composed of AET and runoff chemical potential. In the dry biomes, AET makes up only between 3% (rock and ice biome) and 50% (desert biome) of MaxR. The better fit of AET alone compared to MaxR for the univariate regressions does suggest that runoff chemical potential might add a confounding factor to MaxR. It also suggests that while MaxR is a pretty good correlate with productivity, water used is a stronger one. Without the dry biomes, MaxR appears to be as good a predictor as AET.

The univariate and multiple regressions (Tables 6 and 7) suggest that rain (and AET) are the most important variables explaining variation in GPP. Odum (1996) had hypothesized (based on computations of transformities of global rainfall) in many of land-based systems analyzed in his book, that rain and more specifically, the portion of rain that is used by vegetation (AET) was the most significant driver of ecosystems. The analysis of multiple driving emergy sources confirms Odum's original evaluations and strongly suggests that the water used by ecosystems (AET) is the dominate determinant of productivity.

Interestingly, the best model for biomass was a multivariant regression the strongest variable of which were AET, solar, and wind (negative effect). Presumably the accumulation of biomass over time is not only affected by the available water used, but by solar input and negatively affected by wind. Wind can be both a positive and negative influence on ecosystems. At low velocities wind can be a positive driver of productivity by increasing evapotranspiration which in turn increases nutrient transport from roots to leaves, for example. At high velocities it has an increasing negative impact on the development of biomass as a result of defoliation and windthrow. The univariant

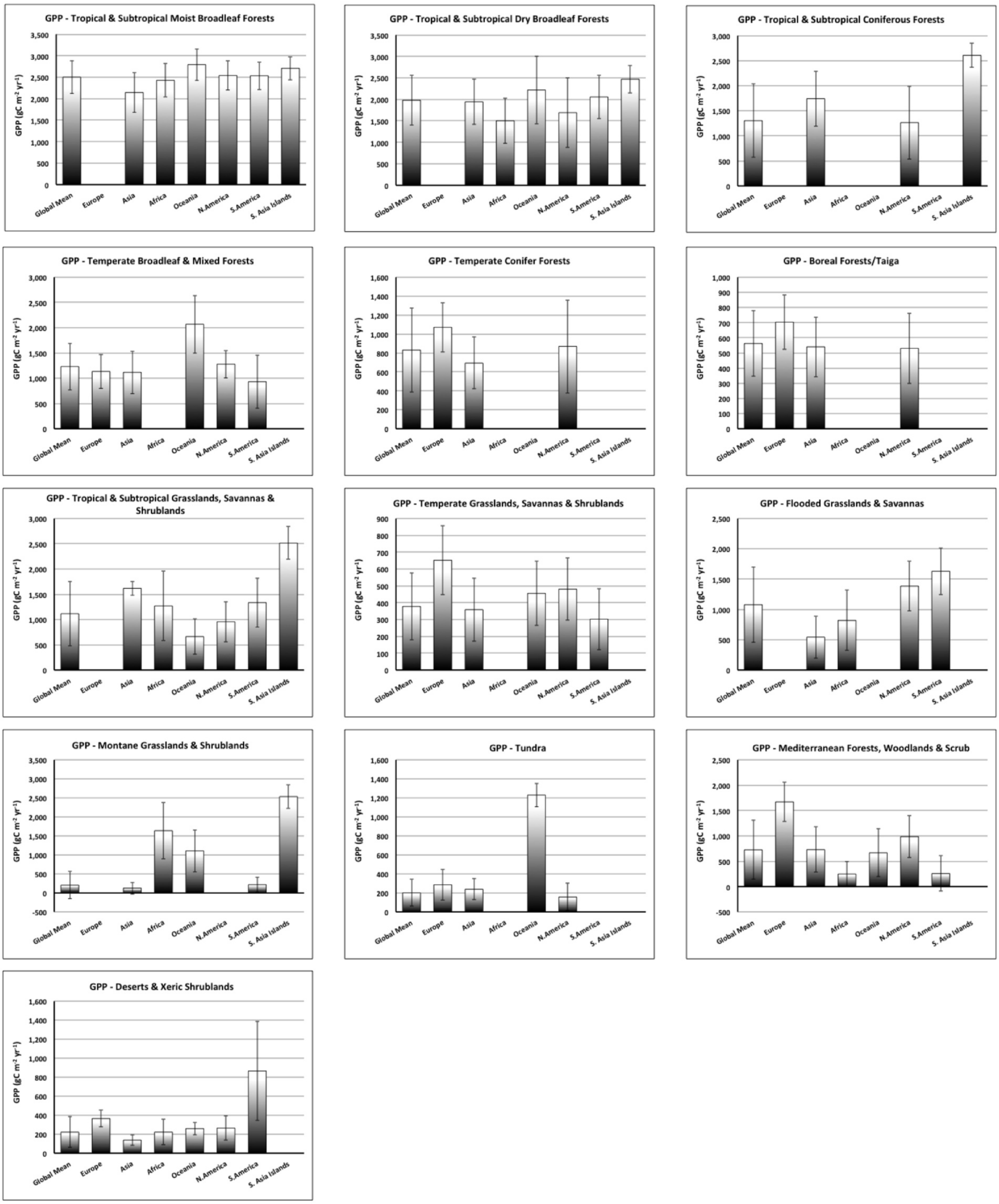

Figure 13. Gross primary production of global biomes showing the global mean and continental means.

regressions supported a singular dominate driver (rain), but the addition of solar and geothermal resulted in a slight increase in explaining the variation in biomass.

4.6. The Impact of Human Induced Land Use Change

Without question, humans have altered the land cover of planet Earth. The year 1700 was taken as the boundary between "pre-anthropocene" and the anthropocene. It was felt that prior to 1700 there was very little influence from fossil fuel use, for it was the arrival of the industrial revolution in mid-1700 that coal began to replace biomass as the main source of energy. In the roughly 300 years since 1700, there has been a significant change in land cover, resulting in 38% of the pre-anthropocene terrestrial biome land area changed to human dominated land cover (Table 11). A majority of the terrestrial biomes (nine out of 16) exhibit per cent change greater than 50%. The large tundra (0% change) and boreal forests (4% change) are the reason that the total pre-anthropocene terrestrial landcover is not greater than 50%.

Using satellite imagery to evaluate current (2010) GPP and comparing to our estimates of pre-anthropocene GPP resulted in a net change of -5% with many biomes exhibiting positive changes (Table 11). While we did not include agricultural lands in our analysis (they were subtracted out before doing analysis of GPP), those biomes with the largest increases in GPP were the biomes where human influences were dominated by agriculture. This is presumably the result of several things, first, it is possible that some agricultural lands were inadvertently included and not masked out and when viewed from satellite sensors show the relatively high productivities characteristic of irrigated and fertilized land cover. A second possibility is that of a "spill-over effect", where runoff from agricultural lands increases productivity of surrounding natural areas.

Of course, the difference in production is not only that measured as GPP, but also, the ultimate fate of the productivity. On the pre-anthropocene earth, productivity was cycled and recycled within ecological systems supporting diverse food chains of organisms. In the current system, the productivity increases that are seen in most biomes is used to support a diverse and complex human system. With such declines in available productivity, there must be an accompanying decline in the quantity and diversity of organisms that the global ecosystems can support.

Studies of the human appropriation of net primary production (HANPP) have shown that between 13% and 40% of NPP is being appropriated by humans (Haberl et al., 2014, 2007; Krausmann et al., 2013; Vitousek et al., 1986). If we assume that the areas of human occupation are equivalent to appropriated productivity, then this study quantifies the HANPP in 2000 to be 38% of total available productivity (Table 11) a quantity within the upper bounds of the current estimates. Interestingly, not only has this quantity of productivity been sequestered by humans, but actually the productivity of these lands has been increased through management, fertilization and irrigation, so that if we again assume that all the lands under human domination are subsidized with water and nutrients, the quantity of NPP has increased while the overall decrease exhibited (about 5%: Table 11) can be attributed to bare and urban lands.

Without detailed measurements of standing biomass we can only estimate the losses of BNC that have resulted from human induced land use changes from available aerial coverage data. The assumption of losses of 100% of above and below ground biomass from forested lands converted to other uses and 50% of above and below ground biomass from grassland and shrubland biomes resulted in losses totaling about 12% of standing biomass (Table 12). When converted to emdollars, the loss represents ^{em}\$ 70 trillion. We used the data of Sanderman et al. (2017) to estimate soil carbon losses at 133PgC since the beginning of the Anthropocene (Table 13), which when converted to emdollars totaled about ^{em}\$18.5 trillion

5. Conclusion

The emergy supporting the geobiosphere based on the solar, tidal and geothermal inputs totals 12.0 E+24 sej yr^{-1}. When the emergy supporting the biomes of the geobiosphere is summed it totals 24.5 E+24 sej yr^{-1} (See Table 7, Global total), slightly over twice the geobiosphere emergy baseline (GEB). Many would ask…*" how is this possible, there is more energy supporting the biomes, than is supporting the geobiosphere as a whole; either there is an accounting error, or there is some sort of double counting."*

It is possible that there is some double counting, but there are two factors that contribute the most to this apparent problem. The first factor is a interesting and well-known phenomena in spatial analysis known as the Modifiable Areal Unit Problem (MAUP) that we identified in a previous paper (Lee and Brown, 2019). The MAUP results from spatial aggregation and scale of analysis and ultimately results in statistical bias when summary statistics are computed from spatial data. The second factor contributing this this apparent problem is related to the fact that the geobiosphere is a complex network of energy conversion processes, where primary renewable emergy sources (solar, tidal and geothermal) are transformed into secondary and then tertiary sources. Lags in the system, storages of materials and potential energy storages result in more emergy transfer between components, than is driving the system. The dynamic interconnected nature of the geobiosphere strongly presupposes that simple static addition of the driving emergy does not account for feedback or cycling of emergy over time scales greater than one year. While static evaluation considers inputs over a 1-year timeframe, it is well known, that the atmosphere, oceans, and land masses have turnover times much greater than one year. It is therefore entirely reasonable that when the driving emergy of each biome is summed it totals more than twice the emergy that annually drives the geobiosphere. As Aristotle (and many individuals since his time) have stated…"the whole is greater than the sum of its parts".

Each biome is driven by a unique signature of emergy sources. Yet emergy theory suggests that it is not the sum of the emergy inputs that drives ecosystems, but the largest, since embodied in each input is some emergy from the other inputs (because of the interconnected nature of the biosphere network of emergy flows and transformations. This study questions that assumption. The simplistic mathematical conversion of taking the largest, is just that…simplistic. It does not recognize the complexity of the geobiosphere network, but assumes a series of rather linear transformations of the GEB that result in rain, wind, river geopotential etc. If this study did nothing else, it calls into question this rather naive assumption of linearity.

The impact of humans on the geobiosphere is pervasive and far reaching. Still there are large areas of Earth that remain somewhat untouched, the tundra and boreal forests, for instance. While exhibiting nearly imperceptible land use change, non-the less they are under significant potential change from global climate effects. How they adapt to these changes, whether they will increase in productivity or whether biomass decreases markedly from fire and human exploitation remains uncertain. While in the past it was suggested that the great expanse of tropical and sub-tropical rain forests were the Earth's systems that provided large scale buffering to global changes, as they show marked signs of increased human induced change, the only biomes left relatively intact may soon begin to go the way of all the others. Currently, about 12% of the Earth's biomass has been lost and about 8% of soil carbon. This begs the question…what is the appropriate quantity of untouched ecosystem function required to maintain a stable Earth ecosystem? Are we approaching that limit?

Dong Joo Lee: Methodology, Formal analysis, Data curation, Writing Original draft **Mark Brown:** Conceptualization, Methodology, Writing-Reviewing and Editing, supervision

Declaration of Competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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