Estimation of Applicability of Thermodynamic Phases on the Planet

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Abstract:

A new method that allows the estimation of the thermodynamic parameters of the biosphere has been developed. It results in the subdivision of the four phase states of the biosphere: three equilibrium states as "white planet" with high albedo and low entropy;. temperate forest in winter with high entropy; and desert with high entropy; and one nonequilibrium state: the so-called "active forests" with low entropy, high information gain and the highest exergy values. The phase shift to a nonequilibrium state happens when albedo is less than 0.2. We show that in winter, the global system is in a nonequilibrium state and in summer, the Northern Hemisphere is in a relative equilibrium, all of which determine the different types of energy and matter cycling. Exponential dependence of exergy on solar radiation leads to a high climate sensitivity to fluctuations in the solar constant. It is important to further develop the methods of direct measurement of informational entropy, reducing the need for the calculation of their values based on physical models and postulated principles, thus minimizing uncertainties.

Keywords: biosphere, entropy, information, principle of maximum entropy, exergy

1. Introduction.

The multispectral scanning by space satellites of solar radiation reflected from a terrestrial surface provides the earth sciences with an essentially new measuring system for the fundamental processes of transformation of solar energy by the biosphere. Jorgensen and Svirezhev (2004) were the first to develop estimation methods of the thermodynamic variables of the biosphere, based on AVHRR satellite observations with 5^{o} resolution. Their methodology was later adapted for Landsat satellite measurements with a resolution of 30m for a region in southern taiga (Sandlersky and Puzachenko, 2009). Gornyy et al. (2010) applied a modification of this updated method to estimate the state of ecosystems.

According to one of V. Vernadsky's axioms (1926), constituting the base of his empirical generalization method, introduced to study such a complex system as the

Biosphere, there is a constant exchange of matter and energy between living and inorganic components and namely these fluxes support the existence of the biosphere itself. Since it is an open thermodynamic system, it also requires the permanent inflow of solar energy which, since the very beginning of the Earth's history, has controlled the global biogeochemical cycles. Vernadsky (1926) described the function of living matter in the Biosphere as transferring solar radiation into other types of energy (chemical, heat, mechanical etc.).

In accordance with our research tasks, this paper examines basic physical aspects of the remote measurements of thermodynamic variables from satellite Terra MODIS, as well as the main characteristics of their spatio-temporal dynamics. Our estimations (entropy, at the first place) are compared with the results of traditional measurement methods. Additionally, we study the possible connection between variation and fundamental processes of latent heat transfer in the atmosphere and their sensitivity to incoming solar radiation. It shows high informativeness of the estimations of thermodynamic variables by remote sensing from satellite MODIS and suggests that long-term measurements would significantly contribute to our understanding of the bio-geosphere functioning.

2. Measurable thermodynamic variables.

According to general theory, the balance of energy in a thermodynamic system is described by:

$$R_{abs}=G+U+ST \qquad (1)$$

where R_{abs} is the absorbed solar radiation, G is the free Gibbs energy, U is the internal energy, S is entropy, T is the thermal stream and ST is unavailable, or dissipated through heat energy. Free energy represents work that is spent on evaporation and photosynthesis in ecosystems. Internal energy in the biosphere can be viewed as the kinetic energy of interaction between its parts or elements. Albedo (a_i) or absorbed radiation (R_{abs}^{i}) in each spectral channel (i) are calculated directly from the remote sensing data. Their sum and a thermal stream (T) in the corresponding frequency are measured in degrees (temperature of an active surface) and in watts per square meter, respectively. Other thermodynamic variables are calculated on this basis. Entropy is calculated as:

$$S = -\sum_{1}^{7} \frac{E_v^{out}}{E^{out}} \log \frac{E_v^{out}}{E^{out}} \qquad (2)$$

where E_v^{out} is the reflected energy in W/m^2 for a frequency v and $E^{out} = \sum_{1}^{7} E_v^{out}$.

Taking into account all the above, let us consider four (of many) definitions of entropy (Thoma, 1977):

(1) Phenomenological entropy is a component of heat exchange (model of the thermal machine).

(2) Statistical entropy is a measure of disorder during heat exchange.

3) Entropy is a quantity of information that is transferred during communication processes (the theory of communications).

(4) Fedoskin (1999) introduced the fourth definition of entropy: “Entropy characterizes the structure of a system from the energy distribution point of view, i.e., a measure of particles’ linkendness and interaction inside or around a system”. He also shows that different definitions of entropy can be seen as different methods of measuring the same phenomenon.

Phenomenological entropy, being the necessary condition that follows from the first law of thermodynamics, is the component of the internal energy of a system or quantity of energy in the heat-exchanger, that cannot be transformed into work. According to this model, entropy production in climatology is expressed as:

$$\sigma = R_{abs}\left(\frac{1}{T_{\min}} - \frac{1}{T_{\max}}\right) \qquad (3)$$

where R_{abs} is the absorbed radiation, T_{Max} the temperature of a heat source and T_{min} the receiver’s temperature. Entropy production is measured in Wm^{-2} K^{-1} (watt per square meter per Kelvin degree) (Kleidon and Lorenz, 2005, Peixoto and Oort, 1992).

Statistical or Bolzmann entropy is measured as the logarithm of a number of possible shifts of the microparticles that do not influence the macrocondition of a system multiplied by the Bolzmann constant (relating energy with temperature). Depending on the type of system, microparticles can be represented by photons, atoms, molecules, or individuals in populations. In a general case, there should be respectively a different constant for at each level of matter organization (Fedoskin, 1999, Khazen, 2000). Tribus

(1961) using Jaynes' formalism (Jaynes, 1957), has shown that it was possible to derive from Shannon entropy:

$$S = -k\sum_{i}^{n} p_i \log p_i \qquad (4)$$

where p_i is the probability that a particle belongs to a class (i), n is the number of classes and k is the Bolzmann constant; all canonical thermodymanical variables for extreme equilibrium Gibbs distribution by using Lagrange's method of undetermined multipliers. Tribus (1961) basically shows that this entropy is in fact the same as Shannon information, but from an information point of view is a measure of uncertainty in a choice or variability, which at the binary base of the logarithm provides the exact number of steps necessary to choose a particle belonging to a specific class. At the same time, it is also a measure of disorder, since during the transformation of matter and energy, competitive interactions increase in proportion to informational entropy and energy dissipation. There is extensive literature describing the relationship between entropy and information, see for example (Khazen, 2000, Haitun,1996, Thuillier et al., 2003). Ferster (1964) has shown the dual nature of informational entropy by using the measure of order: Or = 1 – S/logn. Puzachenko (1992) determined parabolic relationships between indicators of communities functioning from Or. Vyatkin (2009) discovered similar relations for various systems and has shown that systems in the course of self-evolution tend to a certain measure of order. At the same time, the question of total similarity of entropy in statistical mechanics and information entropy remains open. The interpretation of results must therefore take into account the system's properties.

In our particular case, we have the data about reflected energy on a clear day in seven spectral channels. This energy stream is associated with the number of photons of corresponding frequencies that have a certain degree of freedom. Since vegetation cover is basically an absorbing surface, any change in morphological and biochemical structure can occur over time and space only as a result of information gain by the system from its environment and from energy of solar spectrum. It is possible to measure this through Kullback information:

$$K = \sum_{v=1}^{7} p_v^{out} \ln\left(\frac{p_v^{out}}{p_v^{in}}\right) \qquad (5)$$

where $p_v^{out} = \dfrac{E_v^{out}}{E^{out}}$, $p_v^{in} = \dfrac{E_v^{in}}{E^{in}}$, $E^{in} = \sum_{v=1}^{7} E_v^{in}$, and E_v^{in} is the solar constant for a frequency *v*. Kullback information is equal to zero if the distributions of incoming and reflected radiation for the spectrum channels are identical and, consequently, the information receiver is in equilibrium with the transmitter. If Kullback information is more than zero, it is possible to speak about an information increment, or gain, in the receiver (Haken, 1991, Jorgensen and Svirezhev, 2004) and the reflecting surface is not in equilibrium with the spectrum of solar radiation.

Based on this, Joergensen and Svirezhev (2004) have estimated the free energy, or exergy (Ex), for nonequilibrium system as:

$$Ex = (E^{in} - R_{abs})\left[K + \ln\left(\frac{E^{in} - R_{abs}}{E^{in}}\right)\right] + R_{abs} \qquad (6)$$

If K = 0, exergy is equal to the free energy. The logarithm in this formula is always less than zero and free energy is always less than the absorbed one. Exergy exceeds free energy in value and is equal to information gain multiplied by the reflected energy. Thus, based on remote sensing information, we estimate values of all variables except internal energy, which is defined as the remaining member in the balance equation for the absorbed energy.

We must also introduce a unit of measurement for information, corresponding to the base of logarithm. However, for the time being, let us consider the variables to be dimensionless. While it is possible to express entropy and information in energy units through the Bolzmann constant and vise versa, it is not certain that this will correspond to the Boltzmann model. Assuming these quantities as being dimensionless does not change their spatio-temporal variability, but excludes the precise calculation of the energy balance. At the same time, let us re-examine the calculation of entropy S using equation (1):

$$R_{abs} - Ex = U + ST \quad \text{and} \quad (U/T + S) = (R_{abs} - Ex)/T \qquad (7)$$

where the right-end side of this equation includes measurements that are independent of S. Hence, if S is functionally connected with other variables of the balance equation, there should exist a statistically significant correlation between S and (U/T + S), and the remaining part of the regression equation must correlate with U/T. If such dependency exists, then the entropy estimation is correct.

3. Reproduction of the spectrum of solar radiation by MODIS.

This section describes how the Terra MODIS system displays the solar spectrum. Fig. 1 shows the solar spectrum as represented by Thuilier et. al. (2003) and the MODIS spectral bands.

The net solar radiation (E^{in}) estimated for this spectrum is 1315468.73 μW/m^2, which is slightly less than the standard mean of 1366220 μW/m^2. The average energy over a distribution interval (step) d=0.267715816 μm is 160.188593 μW/m^2 .

The informational entropy of solar energy for this spectrum with the above step is:

$S_d = -\sum_1^k p_i^{\text{in}} \log_2 p_i^{\text{in}}$ = 11.4473671 bit (7.93471024 nit), with a number of discrete states k = 8213. The evenness of the entropy $S_n = S_d$/log8213=0.880316584. The entropy, expressed in terms of the quantity of energy per bit of information, is: $SE_d = -\sum_i^k E_i^{\text{in}} p_i^{\text{in}} \log p_i^{\text{in}}$ = 10278.9701 bit*nW/m^2. The mean energy of an information bit is Boltzmann's constant analog $k_S = SE/S_d$ = 897.933 nW/m^2. The Boltzmann's constant analog for discrete distribution depends on the width of a discrete step. When changing the distribution step, we determine the empirical dependence of k_S on entropy as distribution function: $k_S = 1315.469*2^{-0.930503S}$ W/(bit*m^{2}K^{-1}), where R^2 = 99.023% and the mean-square error equals to 0.009597. Evidently, k_S with entropy growth as defined by quantisation, tends to value as close as possible to zero: the greater the gradation in k, the less analogous it is to Boltzmann's constant.

$*10^{-15} – 5.097*10^{-16}$Wm^{-2}K^{-1}, which is seven times more than the original Boltzmann's constant, k = $1.38*10^{-23}$Wm^{-2}K^{-1}. The empirical equation shows that the constant is highly dependent on quantization, but since there are large-scale distortions in the empirical data of the solar spectrum, it is difficult to calculate the constant for microconditions. Nevertheless, the type of quantic itself determines the semantic link between informational entropy and Boltzmann's constant. Based on a theoretical model of photon's energy and entropy, Kirwan (2004) showed the relationship between these two forms of entropy.

The entropy of a photon, estimated from it's energy at a temperature of 5800K is $4.74*10^{-23}$ W/K, and, correspondingly, the entropy flow s = 0.16116 $Wm^{-2}K^{-1}$, with entropy equal to 934.73 W/m^2 (ZeShao et al., 2008). Employing a black-body model estimate, Wu and Liu (2010) determined solar radiation entropy flow as
0.079 $Wm^{-2} K^{-1}$, while a solar temperature of 5760K gives an entropy of 455.04 W/m^2. Kleidon and Lorenz (2005), using a phenomenological model, estimate entropy flow as
0.041$Wm^{-2}K^{-1}$ with total entropy 455.04 W/m^2. Entropy estimation by Kabelac's (2008) equation gives entropy flow from net solar radiation as 0.157 $Wm^{-2}K^{-1}$, and entropy as 913.7 W/m^2. In addition, Jorgensen and Svirezhev (2004) state that the entropy of solar energy $S \approx 240$ W/m^2.

Therefore, different estimates of net solar radiation entropy flow lie in the range 0.041 - 0.161 $Wm^{-2}K^{-1}$, and we could expect that normalized evenness of entropy flow,
$s_n \approx 0.1136$ $Wm^{-2}K^{-1}$ per unit of evenness. Using this empirical constant, we can express entropy flow in energetic terms, based on evenness of informational entropy estimations for every light spectrum, using multispectral measurements. In essence, we can estimate entropy by multiplying the spectrum by active (radiating) surface temperature. Thus, it is correct to use the solar spectrum energy distribution (wave bands) for entropy estimation.

MODIS measurements resize 16.58% of the spectrum of the solar energy flow. Entropy of the incoming solar radiation is estimated by seven MODIS bands as S_m=2.314391 bit, with an evenness of 0.824. Reflection of solar radiation in these spectral bands (Fig. 2) is related to specific physical processes (Asner, 1998, Brogea and Leblanc, 2000, Glenn et al., 2008, Goetz et al., 1997, Gutierrez and Reynolds, 2010, Kokaly et al. 2009, Majeke et al., 2008, Numata et al. 2007, Ustin et al. 2004, Zarco-Tejada and Sepulcre-Cantó, 2007), where different frequencies contain vast amounts of useful information for assessment of vegetation cover at every organizational level, i.e. from an ecosystem as a whole to the cellular level. In other words, morphological, biochemical and biophysical adaptation processes are determined by the differences in frequency bands, and create species-specific structures in response to fluctuating environmental variables.

In remote sensing, this powerful information is indirectly used for the construction of indexes, that are algebraic combinations of absorbed solar radiation in different spectral bands, displaying certain properties of an active surface and, in particular, vegetation cover. In general, MODIS satellite's spectral bands contain high-quality information about important properties of active surface. Band 3, the blue band (459 – 479 μm) and band 4, the green band (545 – 565 μm), do not play a great role in photosynthesis, but are good indicators for snow conditions. Chlorophyll actively absorbs radiation in the visible red zone of the spectrum, band 1 (RED, 620 – 670 μm). Band 2, the near-infrared band (NIR, 841 – 876 μm), reflects the structure of cells, i.e. the greater the cell density, the greater the reflection in band 2. Hence, the difference between these bands, (band 2 – band 3) = (NIR – RED) indicates biological productivity. The higher the NIR, the better the cells are formed and the reflection is therefore higher. On the other hand, the lower the reflection in RED, the higher the radiation absorption by chlorophyll. With the maximal NIR, energy is not used for cell formation, but rather on biological productivity. Generally speaking, these four bands associate with the main energy flow from the solar spectrum, contributing the most in terms of entropy and information increment. Infrared bands 5 (1230-1250 μm) and 6 (1628 – 1652 μm) indicate moisture contents in vegetation, while the far-infrared band 7 (2105 – 2155 μm) reflects the total moisture of the ecosystem, i.e. the higher moisture, the lower the reflection.

4. Seasonal dynamics of thermodynamic variables

Unlike the strictly symmetric seasonal flux of direct solar radiation, the fluxes of exergy and, to a greater degree, temperatures in the northern hemisphere are asymmetric. Increments in the absolute values of exergy and heat flux are less in spring than in autumn and the maximum in thermal flux is attained approximately half a month later than the exergy maximum. In the southern hemisphere, exergy flux is almost symmetric, with temperature reaching its maximum at the beginning of summer. Fluctuations of exergy and thermal flux between the hemispheres show considerable spatial nonequilibrium in the climatic system during winter time.

In the southern hemisphere, the seasonal variations of variables are half of those existing in the northern hemisphere. The dynamics of entropy and Kullback information is also considerably different between the hemispheres. In the northern hemisphere, entropy is at its maximum during winter and Kullback information is at a minimum, i.e., the system is very close to equilibrium. By contrast, in the northern hemisphere summer, entropy is minimal and Kullback information is maximal, hence the system reaches maximum nonequilibrium condition. Meanwhile, in spring and in the first half of summer, the entropy change is negative; in other words, the system is self-organizing and its stability increases. In the southern hemisphere, throughout the year, entropy is lower than in the northern hemisphere, while its maximum is reached during spring when albedo in the infrared spectrum is minimal, as is precipitation. Entropy reaches its minimum during the autumn of the southern hemisphere, when the information is maximal. Kullback information is high during the course of the whole year, reflecting the almost constant non-equilibrium state of the biosphere. In addition, only in the southern hemisphere winter, the Kullback information is slightly lower than in the northern. Thus, due to seasonal changes in the thermodynamic variables of the hemispheres, the biosphere is asymmetric and in a state of spatial nonequilibrium. Therefore, seasonal dynamics show that, on average, the biosphere of the southern hemisphere is substantially more stable than in the northern.

5. Spatial variability of thermodynamic variables

Generally, in the northern hemisphere summer, the useful work of the biosphere is substantially higher than in winter. This is reflected in the seasonal variations in precipitation over the continents. During the three northern winter months, from December to February, the average precipitation is 576 mm, while during the three summer months (June – August) it is 910 mm.

Entropy and information fluctuations reveal the spatial shifts between equilibrium and nonequilibrium phase states. In addition, it is important to note that entropy is high in polar deserts during the northern hemisphere summer months. Actually, the above conclusions are valid, since the higher the vegetation activity, the higher the information gain and useful work spent by the system on the intensification of water and biogenic cycling are, and entropy is lower. This is apparent from the Figures. 4b and 5b, which show that the maximums of information gain and exergy are primarily attributed to rainforest and to the taiga belt with abundant coniferous forests. For a belt of broad-leaved forests, the values of these thermodynamic variables are noticeably lower.

The high information gain can be a result of vegetation obtaining it from solar energy, when it is multiplied by information that is contained in mineral elements and moisture. In essence, this information gain creates highly organized structures that maximize exergy (productivity and transpiration) and minimize energy dissipation via entropy production and heat flux. According to remote sensing data, during the day from 10 a.m. to 11 a.m., the temperatures ranged from 21.4 to 28.8^{o}C with a mean of 24.8^{o}C, which is identical to the temperatures in coniferous forests of the northern hemisphere.

6. Results.

The finding that deserves particular attention is the asymmetry of exergy fluxes between the southern and northern hemispheres during December to February. These large differences in exergy between hemispheres may be responsible for the high gradient in the partial pressure of water vapour in the atmosphere. As a result, a large quantity of latent heat in the form of water vapour passes the subtropics, enters the stratosphere and is inevitably transported to the northern hemisphere. It appears that this gradient generates the Brever-Dobson circulation. The value of exergy in regions with high incoming solar radiation is rather sensitive to the fluctuation of the latter. (Fig. 6). This dependence on the inclination level with R^2 = 73.038%, recalculated for the total solar spectrum is described by the function Ex = 8.8497exp (0.0036E^{in}), where the derivative of this function is dEx/dE^{in} = 0.0318589exp (0.0036E^{in}). According to observations from the Active Cavity Radiometer Irradiance Monitor (2010), between 1978 and 2010 the solar constant varied from 1362.076 to 1368.925W/m^2, with an average of 1366.1302W/m^2. Over this range, the exergy increment in the tropics per watt of solar constant is 4.3579W/m^2 with exergy varying over the range 1192.56 to 1222.33W/m^2. Since practically all of this exergy is spent on evaporation, then, with an increase in the solar constant, it also exponentially increases, as does latent heat transport to the northern hemisphere. At the same time, an increase in heat expenditure on evaporation in rainforest can slightly reduce temperature (and thermal flux), while in the winter of the northern hemisphere it will rapidly increase.

Evidently, this reflects the effect of the latent heat transfer. In an equatorial zone and generally in the southern hemisphere, the values of this component are positive, while in continental areas of the northern hemisphere, they are negative (Fig. 7). In other words, if the temperature in the southern hemisphere decreases, it increases in the northern hemisphere, and, in fact, does so by a factor of 1.2. Over the studied 100-year period, however, the temperature in areas of tropical rainforest remained unchanged, or even decreased. The same effect caused by fluctuations in the solar constant from 1980 to 2006 is described.

The transfer of moisture into the northern hemisphere is indirectly reflected in the deviation from regressions between precipitation sum and temperature from the actual sum of precipitation. This deviation is considerably bigger than the same in the state of equilibrium, thus proving the global precipitation distribution (fig. 8). Therefore, an increase in solar radiation appears to influence climate by increasing the intensity of the functioning of the biosphere in the southern hemisphere, primarily in the tropical rainforest zone. Hence, energy transfer in the form of latent heat can lead to a nonlinear growth of temperature in proportion to the change in the solar constant in the northern hemisphere - and over the planet as a whole.

Before we further discuss the variability of the entropy, let us estimate the actual validity of its estimation on the basis of the multispectral remote sensing information. For this purpose, we estimate the parameters from the equation of regression between independently measured variables $(U/T + S) = (R_{abs} - Ex)/T$ and S. We obtain $[(U/T + S) = (R_{abs} - Ex)/T] = 0.392S$ with $R^2 = 0.431$. The remaining part of the regression equation, theoretically connected with internal energy, is described by U/T with $R^2=0.60$ and by U with $R^2 = 0.879$. Thus, this independent test of the entropy, measured as the distribution of reflected solar radiation by MODIS, shows that it does not contradict the basic energy balance equation, and constitutes about 40% from remainder variation, independently measured absorbed radiation and exergy. Therefore, information entropy can be considered as a thermodynamic variable.

Most likely, the direct relationship between entropy and evaporation is true only for a closed adiabatic system. In the case of the earth system, evaporation occurs at the expense of external energy supply and is not directly connected to entropy production.

Correspondingly, our maps and profiles of entropy for land cover are generally similar to that based on multispectral measurements. It shows the relationship between entropy and information, with albedo for the analysed data in comparison with a calculation of entropy flux for the model of a black body. Informational entropy increases with the decrease in albedo, and Kullback information is close to zero, both in the model and according to the measurements. It is obvious that this area is in a state of equilibrium with very small entropy values over snow and very large values over the desert. When albedo decreases, the biosphere moves to a nonequilibrium state with a minimum of entropy, large information gain and high exergy. However, if Kullback information increases step-wise with the decrease in albedo, exergy on average grows exponentially. Although Kullback information positively contributes to exergy, absorbed radiation contributes more.

It is possible that information has its own physical meaning. From Fig. 12, it follows that Kullback information is connected almost linearly (at least, in the area of its greatest values) with the *Normalized Difference Vegetation Index* (NDVI), which reflects vegetation productivity. This means that with the low albedo, information grows and entropy decreases, since reflection decreases in the red spectral channel and increases in the near-infrared. Thus, it is possible to assume that exergy mostly shows the expenditure of solar energy for evaporation, when Kullback information reflects, to a larger degree, the structural changes that are determined by the nonequilibrium state of the system. These changes are determined by the processes of photosynthesis (when information has high values) and by changes in snow cover (with low values of information and negative NDVI).

Finally, it was proven that forest vegetation is a special phase state of the biosphere, is far from thermodynamic equilibrium, and has a leading role in supporting it in its nonequilibrium state by the maximum useful work spent on an intensification of global cycling of matter (for synthesis of biological production).

In conclusion, it is necessary to stress again the quite different seasonal dynamics of the thermodynamic variables in the northern and southern hemispheres. During a year, the ecosystems of the southern hemisphere remain in one phase state, while in the northern hemisphere, they rapidly shift ("jump") from "rest" to a state of high activity.

Such different modes should inevitably lead to the development of adaptation mechanisms at all scales, i.e., from cellular to ecosystem levels and substantially altering morphogeny and species formation.

7. Conclusions.

The analysis presented in this work demonstrates how multispectral space-based measurements can be used to determine the thermodynamic variables of the biosphere. Specifically, this method provides the capacity for the direct calculation of entropy and information values that reflect actual, structural, and functional processes in ecosystems - and in the biosphere as a whole, However, direct measurements of information entropy and Kullback information do not confirm its generality and applicability to the local temporal state of the biosphere. At the same time, it is shown that this independent measurement of information entropy does not contradict the equation of thermodynamic balance.

As a result, within the framework of the measurements discussed in this work, systems that are farthest from the state of equilibrium (with the set energy level) are characterised by the least entropy and the lowest entropy production, while information gain is at its maximum. The above is therefore in full agreement with Prigogine´s principle of minimum entropy production in a system close to steady state, or local equilibrium. In other words, a system that is far from equilibrium has the most order and supports it by means of information gain from its environment and solar energy. In this state, the dissipation of energy is at its possible minimum our results do not deny the principle of maximum entropy production, but only demonstrate the necessity of its cautious application and the development of methods for the direct measurement of informational entropy. The actual possibility of information gain requires the environment to have a large capacity for entropy production. The resulting maximum of entropy is generated when the system passes from equilibrium to the nonequilibrium state. Regarding the current state of the biosphere, it in general minimizes entropy and exergy production, but mainly with the help of forests. In principle, comparing entropy and information flux from the Sun with its thermodynamic variables, calculated on the basis of multispectral remote-sensing measurements, presents the possibility of calculating the values for the full solar spectrum and the analysis of their functional dependence on partial pressure and precipitation. In addition, the same scheme can be used to calculate the thermodynamic variables of our planet's cloud systems and the world's ocean.

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