COMPARISON AND UNCERTAINTY ANALYSIS IN REMOTE SENSING BASED PRODUCTION EFFICIENCY MODELS

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ABSTRACT:

The remote sensing based Production Efficiency Models (PEMs), springs from the concept of “Light Use Efficiency” and has been applied more and more in estimating terrestrial Net Primary Productivity (NPP) regionally and globally. However, global NPP estimats vary greatly among different models in different data sources and handling methods. Because direct observation or measurement of NPP is unavailable at global scale, the precision and reliability of the models cannot be guaranteed. Though, there are ways to improve the accuracy of the models from input parameters. In this study, five remote sensing based PEMs have been compared: CASA, GLO-PEM, TURC, SDBM and VPM. We divided input parameters into three categories, and analyzed the uncertainty of (1) vegetation distribution, (2) fraction of photosynthetically active radiation absorbed by the canopy (*fPAR*), (3) light use efficiency (ε), and (4) spatial interpolation of meteorology measurements. Ground measurements of Hulunbeier typical grassland and meteorology measurements were introduced for accuracy evaluation. Results show that a real-time, more accurate vegetation distribution could significantly affect the accuracy of the models, since it’s applied directly or indirectly in all models and affects other parameters simultaneously. Higher spatial and spectral resolution remote sensing data may reduce uncertainty of *fPAR* up to 51.3%, which is essential to improve model accuracy. We also figured out a vegetation distribution based on Maximum value of light use efficiency (ε^*) and ANUSPLIN method for spatial interpolation of meteorology measurement is also an effective way to improve the accuracy of remote sensing based PEMs.

1. INTRODUCTION

Terrestrial net primary productivity (NPP), defined as the rate of atmosphere carbon uptake by vegetation through the process of net photosynthesis minus dark respiration(Ruimy *et al.* 1994), is the central-related variable summarizing the interface between plant and other processes(Field *et al.* 1995). NPP is sensitive to the environmental factors and is highly various in space and time. Thus, estimating NPP more precisely is a key to understanding the terrestrial carbon cycle.

There are two methods available to estimate terrestrial NPP: (1) extrapolating field measurement for local NPP to the biosphere through a vegetation map; (2) modeling plant productivity at the biosphere level(Ruimy *et al.* 1994). Since direct observation or measurement of NPP is unavailable on a global scale, the modeling method has been widely accepted. There are three main types of productivity model: (1) statistical model: estimating NPP by meteorology measurement and experimental parameters, regardless of physiological and ecological characteristics of vegetation, such as: Miami(Lieth 1972), Thornthwaite(Lieth *et al.* 1972), Chikugo(Zenbei UCHIJIMA *et al.* 1985) and Zhou Guang-sheng (Zhou *et al.* 1995); (2) process model: based on plant physiological ecology principles, estimating NPP by simulating process of photosynthesis. This model has been widely used in local areas, such as: CENTURY(Parton *et al.* 1993), CARAIB (Warnant *et al.* 1994, Nemry *et al.* 1996), KGBM (Kergoat 1998), SILVAN (Kaduk *et al.* 1996), CEVSA(Cao *et al.* 1998), TEM(McGuire *et al.* 1995) and BIOME-BGC (Running *et al.* 1993). (3) production efficiency models (PEMs). The “Light Use Efficiency (ε)” concept (Monteith 1972) has been adopted to decompose into independent parameters such as incoming solar radiation, radiation absorption, and conversion efficiency. The main PEMs include CASA(Potter *et al.* 1993, Field *et al.* 1995), GLO-PEM(Prince 1991, Prince *et al.* 1995), SDBM(Knorr *et al.* 1995), VPM(Xiao *et al.* 2004a, Xiao *et al.* 2004b) and TURC(Ruimy *et al.* 1996).

Along with the increasing availability of remote sensing measurement, (1) most parameters can be obtained by remote sensing data, and (2)with easy access to regional data, reducing errors caused by interpolation is possible, thus the remote sensing based PEMs has been applied more and more to estimatting terrestrial NPP.

However, it is very difficult to evaluate the accuracy of the models for two reasons: (1) acquisition of direct observation is

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unavailable on a regional or global scale, and (2) different models come from different data sources and handling methods, impossible to determine which one is more accurate.

Under the scientific sponsorship of the IGBP, such a model intercomparison has been carried out at the Potsdam Institute for Climate Impact Research(Cramer *et al.* 1999, Ruimy *et al.* 1999). Result shows that global NPP estimates (Fig.1) vary greatly between different models. However, since no field data are available to validate the models, we have no way to determine which result is closer to "true value".

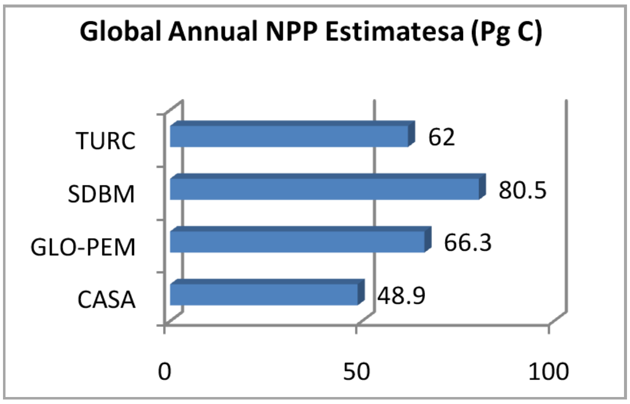


Figure 1. Comparison of global NPP estimations of PEMs

In this study, we focus on the methods of improving the accuracy of remote sensing based on PEMs rather than determining the better one. The input parameters of PEMs are divided into three categories according to acquisition source and the analysis of of each category's influence is performed. We compare the 5 models by taking different data sources as input for each parameter and combining with ground measurement in Hulunbeier and Tibet in order to determine the uncertainty of parameter. The purpose of this study is, first, to identify the most influential input parameters in NPP estimation among the 5 models, and second, to seek access to improvement in model accuracy.

2. PARAMETERS ANALYSIS IN PEMs

PEMs develops from the concept of light use efficiency: NPP has a strong linear relationship in ideal environment with light use efficiency (ε) and absorbed photosynthetically active radiation (*APAR*): NPP=$\varepsilon \cdot APAR$.

APAR is calculated from global solar radiation and fraction of photosynthetically active radiation absorbed by the canopy (*fPAR*) which can be obtained from remote sensing data, and ε is regarded as a conversion scale of *APAR* to NPP, as a result of the interaction of environmental constraints and based on "Maximum value of light use efficiency (ε^*)". These models include various parameters (Tab.1) and focus on different levels of mechanism with inhibition process taken into account. The parameters can be divided into three categories (Tab.2) according to acquisition source.

2.1 Remote Sensing Data

PEMs uses remote sensing data to acquire the land surface condition, especially vegetation type and *fPAR*. In the simulation process, remote sensing data mainly provide the following three types of information:

Model	Influenced by:
CASA	NPP=$f\,(\varepsilon^*, R_S, fPAR, T, EET, PET)$
GLO-PEM	NPP=$f\,(\varepsilon^*, R_S, fPAR, T, VPD, SW, R_A)$
TURC	NPP=$f\,(\varepsilon^*, R_S, fPAR, R_A, T)$
SDBM	NPP=$f\,(\varepsilon^*, R_S, fPAR, CO_2)$
VPM	NPP=$f\,(\varepsilon^*, R_S, fPAR, T, W, P_L)$

R_S: Solar radiation R_A: Plant autotrophic respiration
PET: Potential evapotranspiration   *EET*: Estimated evapotranspiration
P_L: Leaf phenology   *T*: Temperature   *W*: Water capacity

Table 1. Parameters of PEMs

Model	Vegeta-tion Distri-bution	Satellite *fPAR*	Meteorological measurements	Plant Physioe-cology	Other satellite data
CASA	×	×	R_S,T,EET,PET	ε^*	
GLO-PEM		×		ε^*,R_A	R_S,T,VPD,SW
TURC	×	×	R_S,T	ε^*,R_A	
SDBM		×	R_S,CO_2	ε^*	
VPM	×	×	R_S,T	ε^*,P_L	*W*

Table 2. Parameters classification of PEMs

1. Vegetation Distribution Information: According to different spectral characteristics and temporal variation, the accurate and real-time vegetation distribution on the earth can be obtained through appropriate classification algorithm.
2. Vegetation Index: Spectral reflectance of vegetation is influenced by vegetation type, species composition, vegetation cover, chlorophyll content, plant water and so on. Vegetation index is a comprehensive performance of the spectral reflectance, which bears a strong relationship with NPP estimates.
3. Vegetation growth environment information: The environmental factors can be obtained by means of remote sensing in recent years, such as temperature, precipitation, soil moisture and other relevant information, though further study is to be made on the applicability and accuracy .

GLO-PEM is unique among the 5 models because all variables about climate and vegetation distribution are derived from remote sensing data.

2.2 Meteorology Measurement

The process of plant growth appears responsive to environmental conditions. Therefore, the formation of vegetation NPP depends on the regional light, heat, water conditions and so on, as well as the biome production capacity(Zhou *et al.* 1995). Climate factors' control over vegetation productivity is not only present in the vegetation diversity, but also in photosynthesis inhibition. The meteorology measurements in the models such as radiation, temperature, precipitation are all obtained from meteorology stations except GLO-PEM.

2.3 Plant Physiological Data

The plant physioecology mainly concerns how and to what extent the plant growth responds to the environmental factors such as: increasing CO_2 concentration, ultraviolet radiation enhancement, temperature change, sunlight irradiation and the enlargement of salty habitats. All of these factors are closely associated with the process of global climate change.

ε is a fundamental element in PEMs. It was used for the conversion of *APAR* to biomass, and affected by many environmental factors. Each model illustrates its own approach of simulating the process in which environmental factors influence mode.

3. UNCERTAINTY OF INPUT PARAMETERS

Obviously enough, parameters are highly similar in these models. The main differences lie in (1) the way of obtaining and applying vegetation distribution, (2) the way of obtaining *fPAR* and ε and (3) the use of meteorology factors. Thus, it is important for improving model accuracy to analyze uncertainty of each parameter.

3.1 Vegetation Distribution

Vegetation distribution is considered to be the most important determinant of carbon storage, uptake and release from the terrestrial biosphere, and it affects model accuracy mainly in two ways:

3.1.1 Applying Vegetation Distribution: All remote sensing based PEMs assumes the world is covered by vegetation. CASA and VPM uses an actual vegetation distribution from remote sensing including human land use. SDBM and GLO-PEM does not use a vegetation map directly, but the parameters via remote sensing such as temperature , vapour pressure deficit and *APAR* also explain the vegetation cover change. Only TURC uses potential vegetation regardless the human land use. A comparison between actual vegetation data set and potential vegetation data set shows that the human land use and agriculture affect up to 40% of NPP estimate in temperate mixed forests and deciduous forest on a global scale(Ruimy *et al.* 1999). Regionally the simulated NPP with land use constraint in the south portion of NSTEC was about 65% of that without land use constraint(Gao *et al.* 2003). On the other hand, a better classification accuracy has testified its improvement for NPP estimate(Zhu *et al.* 2006).

3.1.2 Determination of other parameters: Vegetation distribution is applied directly or as an intermediate variable to determine the precision of other parameters such as ε^*, R_A, P_L and *EET*. In most models, these parameters are assumed constant or determined by the vegetation maps. However, these plant physiological-related parameters apparently depend on the vegetation type with the classification accuracy taken into account.

It is impossible for us to know exactly how much vegetation distribution is affected, but we definitely know that a real-time, more accurate vegetation distribution can significantly affect the accuracy of the models.

3.2 Remote Sensing Based *fPAR*

fPAR, a significant parameter for calculating *APAR*, truly reflects the status of vegetation canopy's absorption of photosynthetically active radiation, and has a direct impact on the uncertainty of PEMs. Remote sensing provides a means to estimating *fPAR* globally. Most models (CASA, GLO-PEM, SDBM and TURC) utilizes Normalized Difference Vegetation Index (*NDVI*) to obtain *fPAR* (apply different algorithms), while VPM uses Enhanced Vegetation Index (*EVI*) (Tab.3).

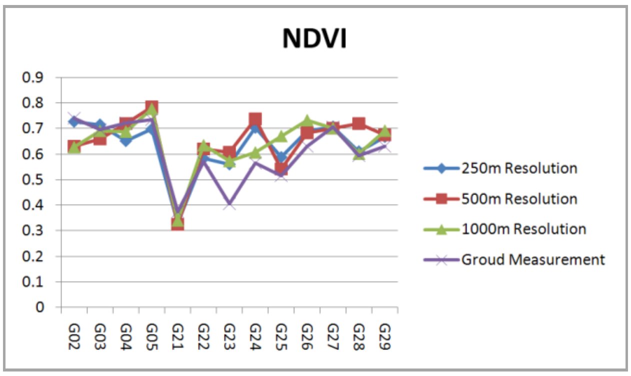
CASA	$fPAR=\min\{(SR-SR_{min})/(SR_{max}-SR_{min}), 0.95\}$
GLO-PEM	$fPAR=(SR-SR_{min})(fPAR_{max}-fPAR_{min})/(SR_{max}-SR_{min})$
TURC	$fPAR=-0.1914+2.186\cdot NDVI$
SDBM	$fPAR=-0.025+1.25\cdot NDVI$
VPM	$fPAR=1\cdot EVI$

$SR=(1+NDVI)/(1-NDVI)$

Table 3. *fPAR* estimation in PEMs

However, some researches indicate that there are limitations in application of *NDVI*, such as (1) tending to be saturated in well-vegetation cover area(Wang *et al.* 2003), and (2)which is sensitive to the soil structure in the low vegetation cover area(Huete *et al.* 1994). One possible solution is using *EVI* which introduced the blue-ray band aiming to reduce atmosphere effect(Huete *et al.* 1994, Huete *et al.* 1997). Although *EVI* was used in VPM for estimating forest NPP, and considered superior in grassland NPP estimation over *NDVI*(Kawamura *et al.* 2005), the further application in different environment on a global scale is still necessary.

It remains unsolved which *fPAR* is more accurate in these models since we cannot have *fPAR* from ground measurement. However, we can improve the precision by using higher spatial resolution *NDVI* and *EVI*. All the models calculate the *fPAR* with a 8*km* resolution *NDVI* derived from NOAA/AVHRR. For the ease of comparison, we use MODIS *NDVI* and *EVI* data (obtained at 2009-07-28 from USGS) with 1*km*, 500*m* and 250*m* spatial resolution, and ground measured spatial data (obtained at 2009-08-02 by FieldSpec® HandHeld Spectroradiometer) from Hulunbeier grassland (Fig.2). The calculation is strictly in accordance with the MODIS algorithm. It should be known that we are not saying the ground measured data is "true", but it is of great reference value. The relative error (Fig.3) shows that the better spatial resolution brings the higher precision. In some extra point, relative error from the 1*km* resolution can reach up to 51.3%.



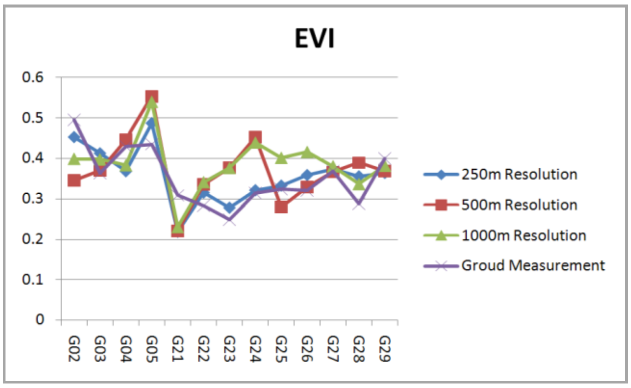


Figure 2. Comparison of *NDVI* and *EVI*

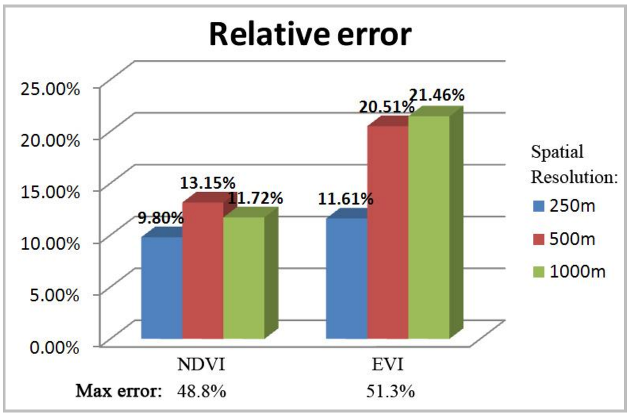


Figure 3. Relative error of *NDVI* and *EVI*

3.3 Estimating Maximum Value of Light Use Efficiency

The light use efficiency (ε) determines the capability that the plants capture and transform environmental resources to dry matter production, and fluctuate with the environmental index such as temperature, moisture, soil, nutrition, plant ontogeny, etc. (Prince 1991). In remote sensing based PEMs, these affections present as constraints of Maximum Value of Light Use Efficiency (ε^*) ranging between 0 and 1. Therefore, $\varepsilon^*$is influential for NPP estimates.

In early researches, ε^* is empirically derived as a conservative quantity(Monteith 1972). CASA takes it as 0.389$gC{\cdot}MJ^{-1}$. However, several researches indicate that ε^* varies due to different vegetation types. And in view of its importance, there is controversy about the value range. Ruimy believes it ranges between 0.108 and 1.580 $gC{\cdot}MJ^{-1}$ and GLO-PEM adopts it between 0.2 and 1.2 $gC{\cdot}MJ^{-1}$. In Guangdong Province of China, the result shows that ε^* range between 0.69 and 1.05 $gC{\cdot}MJ^{-1}$ (Peng *et al.* 2000). Since ε cannot be measured directly, studies about determination of ε generally fall into two types: (1) simulating the plant growth process with the principle of plant ecology, and (2) remote sensing retrieval through PEMs and ground measured NPP. The latter one seems more feasible as plant ecology simulation can hardly be extended to a global scale. By means of remote sensing retrieval, there are methods for improving the precision of PEMs:

1. ε^* should not be considered as a conservative quantity, for it shows difference between different biome.
2. A more accurate and real-time vegetation map could be used which shows the biome distribution.
3. More accurate remote sensing data are uesd for retrieval and plant ecology data have been counted for a more accurate ε^*.

3.4 Spatial Interpolation of Meteorology Measurements

Based on different models, climate factors affect the NPP estimation working as the inhibition of ε^* (Tab.4). However, they are hardly obtained directly through remote sensing data with high accuracy.

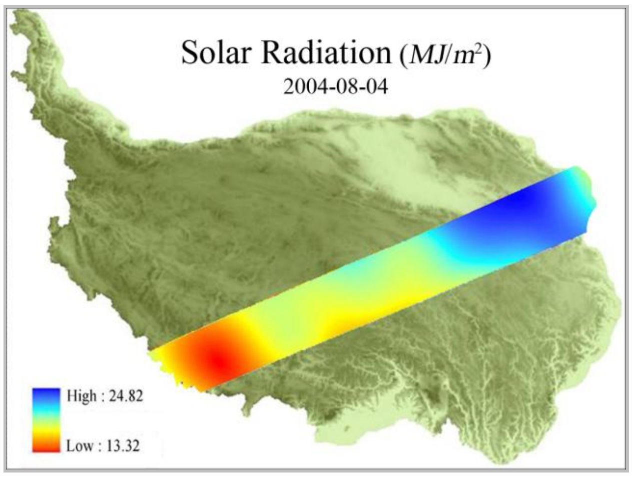
In most cases, the regional and global meteorology distribution are based on station measurement and spatialized by means of interpolation. Therefore, interpolation precision is important in improving accuracy of NPP estimates(Price *et al.* 2000, Wong *et al.* 2003). The precision of meteorology interpolation is mainly influenced by: (1) site's latitude and longitude, (2) site's elevation and (3) regional terrain.

Model	Influenced by
CASA	R_S, T, EET, PET
GLO-PEM [a]	R_S, T, VPD, SW
TURC	R_S, T, R_A
SDBM	R_S, CO_2
VPM	R_S, T, W

[a] All factors in GLO-PEM are obtained from remote sensing data

Table 4. Climate factors in PEMs

A comparisive study of several interpolation method shows that the multiple regression equation had a better performance by introducing elevation and location(Collins 1995). Lin's research demonstrated that Gradient Plus Inverse-distance-squared (GIDS) method is better than others in reflecting temperature change with elevation(Lin *et al.* 2002), but researchers also proved that ANUSPLIN method is better than GIDS(Price *et al.* 2000, Feng 2004). The 88 meteorology station data in Tibet was spatialized using ANUSPLIN method (Liu 2008) combining with $1km{\times}1km$ DEM. The result (Fig.4) proved to be more accurate than other methods.



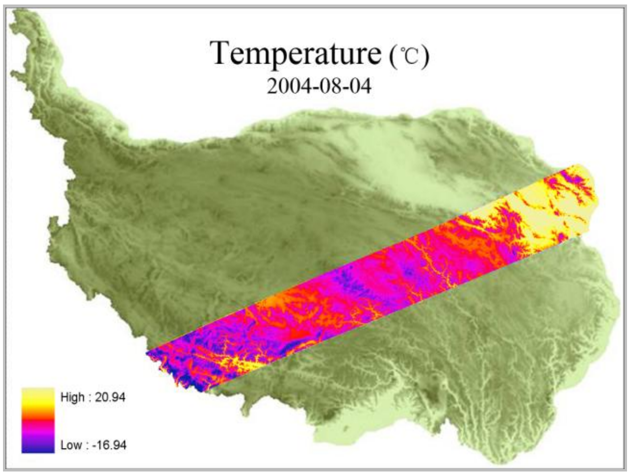


Figure 4. Meteorology interpolation in Tibetan transact

4. CONCLUSION AND DISCUSSION

Remote sensing based PEMs takes good use of the "light use efficiency" theory and adopts several approaches to estimate NPP. Each approach has a theoretical basis for its own. It is not possible to tell which model is "better" since none of them is perfect and cannot be verified on a global scale. NPP estimate varies greatly among models in a comparative research and we have no way to know which result is closer to the "true value". However, there are ways to improve the model accuracy.

Vegetation distribution is the fundamental element among all parameters and has been used directly or indirectly in all models. Apparently, actual vegetation distribution performs much better than potential vegetation distribution while human land use has a great impact on the NPP estimation. Meanwhile, vegetation distribution determines the accuracy of the application of other parameters to a large extent. The uncertainty of vegetation distribution is caused by: (1) inconsistent and ambiguous vegetation types, (2) time inconformity from classification time to current time, (3) mixed pixel of different vegetation types and (4) inconsistent scaling. The developing remote sensing data and techniques provide the possibility to these uncertainties. Overall, a real-time and accurate vegetation map is helpful in greatly improving the accuracy of the PEMs.

The vegetation index is close to photosynthesis by means of determining the *fPAR*. The NOAA/AVHRR *NDVI* is the most common data for NPP estimate. But the 8*km* or lower spatial resolution caused large errors because of mixed pixel. Advanced sensors with better spectral and spatial resolution can provide more accurate *fPAR*. Our experiment in Hulunbeier shows that the better resolution brings higher precision, especially in mixed pixels which have 51.3% relative error.

New vegetation index was introduced for NPP estimate. Although *EVI* proves better to perform vegetation status than *NDVI*, there are still questions about the interrelationship between *fPAR* and *EVI*. It is regarded as a potential solution and needs more research work.

ε^* varies greatly among literatures for there is no convincing method for ground measuring or evaluation. Since ε^* depends on vegetation types, we can enhance the model accuracy by (1) using more accurate vegetation map and (2) combining remote sensing retrieval with plant ecology. Nowadays, ε^* can be obtained precisely by measuring fluxes of CO_2 over whole canopies, and analyzing the relationship between CO_2 exchange and photon flux density. It is generally possible to extract ε^* more representatively though the uncertainty remains to be developed.

Being as constraints of ε^*, meteorology measurement and ε^* determine the plant conversion efficiency together. Spatial interpolation method determines the accuracy of spatialized meteorology data. The chosen method should involve all relating factors, including location, elevation and terrain. Our research shows that the ANUSPLIN method can improve accuracy.

Here, we developed methods to improve parameter accuracy, though the overall accuracy improvement for the model still remains unquantified. Meanwhile, although we are not sure about the interrelation response mechanism between each parameter, it is possible to estimate NPP at a higher precision through applying more accurate parameters.

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