Net Primary Productivity Evaluation for Mao’er Mountain Forest Vegetation based on Cloud Computing and GIS

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Abstract

For the problems in net primary productivity estimation of forest vegetation such as complex model, great difficulty in parameter acquisition, only appropriate for specific area and slow remote-sensing data processing platform computation speed, etc., the improved net vegetation primary productivity estimation model (Cloud-ICASA) is proposed by using the domestic GF-1 high resolution image based on the specific ecological environment of research region Mao’er Mountain forest farm. The Spark-based remote-sensing data processing platform is constructed to process the remote-sensing image in parallel environment. The research results show that the improved Cloud-ICASA model simplifies the parameters, improves the estimation accuracy and is appropriate for estimation of net primary productivity for the vegetation in research region. The Spark based remote-sensing data processing improves the node utilization rate, increase the computation speed and can satisfy the real-time dynamic evaluation requirements.

Keywords: cloud computing; net primary productivity; GIS; Cloud-ICASA model

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I. Introduction

Under the background of global climate change, the forest ecological service function evaluation focuses on the terrestrial ecosystem carbon cycle. As the difference value between Carbon absorbed in green vegetation photosynthesis and released in autotrophic respiration, the net primary productivity (NPP) directly reflects the vegetation production capacity in the natural environmental condition. NPP is the main factor to evaluate the ecosystem carbon source carbon sink process and plays an important role in the global change and carbon balance as well as ecosystem NPP research [3,9].

In recent years, the domestic and foreign researches on NPP estimation model mainly included the physiological ecology process model, climate relevance model and remote-sensing estimation model [11]. He et al. simulated the NPP for Larix Olgensis forest in Wangqing Forestry Bureau, Jilin based on BIOME-BGC model [7]. Zhang et al. improved BIOME-BGC model and simulates the water-carbon flux for such area based on relevant data from Harvard Forest Environment Monitoring Station [16]. Field et al. estimated NPP for New Zealand based on GLOPEM model [5]. He et al. analyzed the spatial-temporal characteristics and influence factors of NPP in North China in 1952-2008 by using BIOME-BGC model [6]. Cenk et al. simulated the spatial-temporal pattern of vegetation NPP of selected districts of the semi-arid region of India by using GLOPEM model [2]. However, these models have many problems; for example, they are complex, require a large number of parameters, have difficulty in acquiring the parameters and are not beneficial to regional promotion [17]. Yu et al. proposed the light energy utilization rate model and simulated the land vegetation NPP for the East Asia region [15]. Yang et al. used CASA model to drive an ecosystem productivity model [12]. Deng et al. applied MODIS time series data to estimate NPP for Ruoergai wetland and analyze its vegetation change characteristics based on GIS, RS and CASA model [1]. Yang et al. researched the vegetation change characteristics in 2000-2006 for the Yangtze and Yellow Rivers by using CASA model and MODIS data [14]. CASA was improved in experiment operability and scientific in theories and could obtain the nation-wide data by the remote-sensing technology. However, these researches are based on the specific climate conditions and vegetation conditions and cannot be directly used in other areas. The parameters should be optimized based on the climate and vegetation environment in the experiment area.

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With increasing remote-sensing data quantity, the traditional remote-sensing processing algorithm requires a large number of iterative operations such as the logistic regression method used for classification and the SVD method used for feature extraction. In order to solve such problems at present, the common method includes the high performance computing based on GPU acceleration and distributed cluster based on Hadoop[8]. CUDA is the parallel computing programming model based on the graphics processing unit (GPU), suitable to be used in massive calculation and increases the computation speed; however, it has low efficiency in data intensive computing and is complex in data debugging [13]. By combination of distributed technology and GIS, the algorithm implemented based on Map Reduce by Hadoop-GIS is greatly improved in algorithm performance in data batch processing [10]. However, in many tasks implemented by iteration, the intermediate data set should be loaded from hard disk, the frequent I/O operation will consume plenty of time, cause lower node utilization rate and limit the speed advantage of Map Reduce. Spark is an open-source distributed computing framework based on memory computing and its core data structure is the resilient distributed dataset (RDD); it has advanced directed acyclic graph execution engine and can effectively process the cyclic data flow [4]. Therefore, based on Spark distributed memory computing framework and by taking full advantage of Spark iteration data processing, the Spark-based remote-sensing data processing platform is constructed, the compute and get-Partitions method in RDD is rewritten and the image registration and mosaic efficiency is improved.

2. CASA Model

The CASA (Carnegie-Ames-Stanford Approach) model is the light energy utilization rate model used for estimation of regional vegetation NPP. The model is driven by the remote-sensing data, temperature, rainfall, solar radiation, vegetation type and soil type etc. The vegetation NPP is determined by absorbed photosynthetic active radiation (APAR) and light energy utilization rate (ε).

\[
NPP_{x,t} = APAR_{x,t} \times \varepsilon_{x,t}
\]  \hspace{1cm} (1)

where \( APAR_{x,t} \) represents the absorbed photosynthetic active radiation of picture element \( x \) in the \( t \) month (MJ•m\(^{-2}\)), \( \varepsilon_{x,t} \) represents the actual light energy utilization rate of picture element \( x \) in the \( t \) month, \( x \) represents the spatial position and \( t \) represents the time. Equation (1) states that the estimation of NPP is relates to \( APAR \) and \( \varepsilon \) value.

2.1. Absorbed photosynthetic active radiation (APAR)

In CASA model, \( APAR \) is determined mainly by the photosynthetic active radiation and absorbing ration of vegetation stratum to the photosynthetic active radiation as Equation (2):

\[
APAR_{x,t} = PAR_{x,t} \times FPAR_{x,t}
\]  \hspace{1cm} (2)

where, \( PAR_{x,t} \) represents the photosynthetic active radiation (MJ•m\(^{-2}\)) and \( FPAR_{x,t} \) represents the absorbing ratio of vegetation stratum to the photosynthetic active radiation.

2.1.1. Photosynthetic active radiation (PAR)

In model, \( PAR \) is the energy source for ground surface vegetation photosynthesis and is generally replaced by 0.5 times of total solar radiation value in vegetation modelling as Equation (3):

\[
PAR_{x,t} = 0.5 \times SOL_{x,t}
\]  \hspace{1cm} (3)

where, the constant 0.5 represents the ratio of effective solar radiation used by the vegetation (wavelength coverage: 0.4μm-0.7μm) in the total solar radiation, \( SOL_{x,t} \) represents the total solar radiation (MJ•m\(^{-2}\)) of picture element \( x \) in \( t \) month.

2.1.2. Fraction of photosynthetic active radiation (FPAR)

At present, the widely-used FPAR calculation method is shown as Equation (4). \( FPAR_{x,t} \) represents the fraction of photosynthetic active radiation absorbed by the vegetation stratum and \( NDVI \) represents the normalized differential vegetation index.
FRAR_{x,t} = \begin{cases} 0 & \text{NDVI} < 0.075 \\ \min\{1.163 \times NDVI_{x,t} - 0.0439\} & \text{NDVI} \geq 0.075 \end{cases} \quad (4)

In APAR estimation process, the PAR value is generally lower than half of total solar radiation and is greatly changed over time and climate condition. The general use of 0.5 times of total solar radiation value directly influences the estimation accuracy. The FPAR value is jointly influenced by the vegetation cover condition and vegetation type. The vegetation in research region should be classified.

2.2. Light energy utilization rate(ε)

The light energy utilization rate is the efficiency that the vegetation transforms the absorbed photosynthetic active radiation (APAR) into organic carbon. Under the ideal condition that the external environment is the most suitable, the vegetation has the maximum light energy utilization rate value. However, in the actual natural environment, the light energy utilization rate is influenced by many factors. The main influence factors include the temperature and moisture. The widely used ε calculation method is shown as Equation (5), Equation (6), Equation (7), and Equation (8).

$$\varepsilon_{x,t} = T_{1(x,t)} \times T_{2(x,t)} \times W_{x,t} \times \varepsilon_{\text{max}}$$ \quad (5)

$$T_{1(x,t)} = 0.8 + 0.02T_{\text{opt}} - 0.0005(T_{\text{opt}}) \frac{\varepsilon}{\varepsilon_{\text{max}}}$$ \quad (6)

$$T_{2(x,t)} = \frac{1.1814 \times e^{[0.3(\varepsilon_{\text{max}} - 0.5) + T_{\text{opt}}]}}{1 + e^{[0.2T_{\text{opt}}(\varepsilon_{\text{max}} - 0.5)]}}$$ \quad (7)

$$W_{x,t} = 0.5 + 0.5 \times \frac{E_{1(x,t)}}{E_{2(x,t)}}$$ \quad (8)

where $T_{1(x,t)}$ and $T_{2(x,t)}$ respectively represent the impacts of low and high temperature on the light utilization rate, $W_{x,t}$ represents the water stress influence coefficient and reflects the influence of water conditions, $\varepsilon_{\text{max}}$ is the maximum light energy utilization rate in ideal condition, $E_{1}$ is the actual evaporation capacity, $E_{2}$ is potential evaporation capacity and $T_{\text{opt}}$ represent the average temperature in the month with maximum NDVI, $\varepsilon_{\text{max}}$ is the maximum light energy transformation rate in ideal condition.

In the literature11, Potter et al. thinks that the maximum light energy transformation rate of global vegetation is 0.389gC·MJ. Subsequently, the scholars continue to use such value in the research process. However, the maximum light energy utilization rate is mainly influenced by the vegetation type. Therefore, the $\varepsilon_{\text{max}}$ value should be determined for different vegetation types on the basis of vegetation classification.

3. Cloud-ICASA Model

Based on the special vegetation and climate conditions of Mao’er Mountain experiment forest farm, the CASA model is improved and Cloud-ICASA model is proposed. In Cloud-ICASA model, the vegetation NPP is represented by absorbing the rate of photosynthetic active radiation, photosynthetic active radiation and light energy utilization rate. This can be seen in Equation (9):

$$\text{NPP}_{x,t} = \text{PAR}_{x,t} \times \text{FPAR}_{x,t} \times T_{1(x,t)} \times T_{2(x,t)} \times W \times \varepsilon_{\text{max}} \quad (9)$$

3.1. Improvement of absorbed photosynthetic active radiation(\text{APAR})

3.1.1. Photosynthetic active radiation(\text{PAR}) parameter optimization

In the actual photosynthesis process, the solar radiation, which can be used by the vegetation, is generally lower than half of total solar radiation and is relevant to the scattered radiation and direct radiation etc. Therefore, in the research area of
Huiling Liu, Guangsheng Chen, Yanjuan Li, and Weipeng Jing

Mao’er Mountain forest farm, by using the measured PAR data in 2014, its relationship with the total radiation and direct radiation of horizontal plane, net radiation of ground surface and scattered radiation is constructed. The long-term PAR estimation model for Mao’er Mountain is obtained by estimation and the relation formula is shown as Equation (10):

\[
RAR_{i,t} = \begin{cases} 
0.52Q_D + 0.37Q_S + 0.14Q_N + 1.8 & SOL < 400 \\
0.26Q_D + 0.25Q_H + 0.27Q_S + 3.2 & SOL \geq 400 
\end{cases}
\]  

(10)

where SOL is the monthly total solar radiation, \(Q_D\) is the scattered radiation, \(Q_H\) is the direct radiation of horizontal plane and \(Q_N\) is the net radiation of ground surface. By comparing the error between the estimated value (PAR) and observed value, it can be known that the relevance of two sets of values in the model reaches at 0.973, which satisfies the accuracy requirements. This is illustrated in Figure 1.

3.1.2. Parameter optimization for fraction of photosynthetic active radiation (FPAR)

In model, FPAR is jointly influenced by the vegetation cover conditions and vegetation type and the vegetation type is reflected by \(NDVI_{\text{min}}\) and \(NDVI_{\text{max}}\). Therefore, based on the forest stand type graph of experiment forest farm, \(NDVI_{\text{min}}\) and \(NDVI_{\text{max}}\) are respectively extracted for each type of vegetation to estimate FPAR and the relation formula is shown as Equation (11):

\[
FRAR_{i,t} = \frac{(NDVI_{\text{min},i} - NDVI_{\text{min},\text{max}}) - (FRAR_{\text{min},i} - FRAR_{\text{max},\text{min}})}{NDVI_{\text{max},i} - NDVI_{\text{min},i}}
\]  

(11)

where \(NDVI_{\text{min},i}\) and \(NDVI_{\text{max},i}\) respectively represent the maximum and minimum NDVI of \(i\) type of vegetation, \(FRAR_{\text{min},i}\) and \(FRAR_{\text{max},i}\) is not relevant to the vegetation type, \(FRAR_{\text{min},i}\) represents that the ground coverage is not the vegetation and the empirical value is taken as 0.001; \(FRAR_{\text{max},i}\) represents that the ground is completely covered by the vegetation, its value is close to 1 and the empirical value is taken as 0.95.

3.2. Parameter optimization of light energy utilization rate (\(\varepsilon\))

The maximum light energy utilization rate depends on the vegetation type. The larger the vegetation leaf area, the more light energy captured by the vegetation and the more chemical energy accumulated through photosynthesis. On the other hand, the thicker the leaf, the lower the light transmission and the light energy utilization rate is improved. To determine the \(\varepsilon_{\text{max}}\) value for different type of vegetation, NDVI is used to estimate FPAR for three types of vegetation as basic classification unit and make classification adjustment for the maximum light energy utilization rate; the value range is (0.38, 1) and improved \(\varepsilon_{\text{max}}\) algorithm is shown as Equation (12):

\[
\varepsilon_{\text{max}} = 0.38k_1 + k_2NDVI
\]  

(12)
Based on the maximum error principles, the maximum light energy utilization rate is simulated for each vegetation type. In the formula, 0.38 is adjustment coefficient and its function is to ensure that the value range of maximum light energy utilization rate is (0.38, 1). When the vegetation index is lower than 1 (the ground is nearly the bare land), \( k_1 \) and \( k_2 \) value is taken as 0, the maximum light energy utilization rate is 0; when the grassland vegetation index is approximate to the maximum value and its value is approximate to 1 (the ground is completely covered by the vegetation), the upper limit of maximum light energy utilization rate is 1. The value adjustment results are shown in Table 1.

<table>
<thead>
<tr>
<th>Number</th>
<th>Vegetation types</th>
<th>( \varepsilon_{\text{max}} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Broad-leaved forest</td>
<td>0.692</td>
</tr>
<tr>
<td>2</td>
<td>Coniferous forest</td>
<td>0.389</td>
</tr>
<tr>
<td>3</td>
<td>Mixed broadleaf-conifer forest</td>
<td>0.741</td>
</tr>
</tbody>
</table>

4. Research region and method

4.1. Overview of research region

Located in the Experimental Forest Farm of Northeast Forestry University, Mao’er Mountain, Heilongjiang Province, the Ecological Station in Mao’er Mountain Forest belongs to the offset of Changbaishan Range and extends to the northwest offset of the Zhangguangcai Range. It has an average elevation of 400m, average gradient of 15°, annual average temperature of 3.1℃, annual rainfall of 629mm, and annual average evapotranspiration of 864mm. It is warm and humid in summer, and cold and dry in winter. It has four distinct seasons, belonging to typical continental monsoon climate. Figure 2 is the location diagram.

4.2. Remote sensing data acquisition and processing

The GF-1 satellite data used in this research is derived from the geospatial spatial data cloud platform with a spatial resolution of 16m, a monthly temporal resolution and a time series from January 2014 to December 2014, and a total of 16 remote sensing data is available. Spatial resolution is 16m. Geometric correction, atmospheric correction, cloud removing and other performance corrections are conducted for all the data so that the data is consistent and comparable.

4.2.1. Parallel mosaic of remote sensing image based on custom RDD

In order to improve the efficiency of multi-node parallel processing in overlap region estimation of remote sensing image, this paper uses overlap region estimation as an operator of custom RDD in Spark cluster and extends it to construct RDD for remote sensing image processing, and then calls the custom RDD function method in the application through implicit conversion to complete the mosaic.

RDD in Spark is an abstract class that provides the data sets for many operating interfaces and there are many operation methods which can be called to convert the RDD into a new RDD so as to implement a customized algorithm in it. This paper rewrites the compute method and the get-Partitions method. During the mosaic of remote sensing image, the Spark cluster selects the time to start the calculating operation for the entire application based on the different types of operators. RDD operators include Transformation and Action: Transformation operator is a chain logic Action, records the evolution of RDD, and will not really trigger the calculation operation; Action will actually trigger Transformation to start the calculation.
Operation will be triggered only when Action operation is performed due to the lazy-loading nature of the Transformation-type operator (that is, RDD will not actually perform the operation no matter how many times Transformation operations are performed). In image mosaic, each operation step requires a lot of calculation operations. Based on the above two points, the 3 operators in the parallel mosaic algorithm are designed as the Transformation type and will not perform calculation in the process, but the actual operation is triggered when the final mosaic image generated needs to be written to the disk or the file system, this idea can effectively reduce the time consumption in parallel image mosaic.

Rewritten parallel processing algorithm idea for remote sensing image is that Master node distributes the mosaic task to multiple Worker nodes which perform overlap region estimation on the image, image registration, integration operation to improve the processing efficiency of the field observation region estimation when the client submits the remote sensing image data to the Master node in the Spark cluster. During the process, all the worker nodes enable the Executor process for loop execution of overlap region estimation, image registration and integration operations in turn until the final image is generated. With this method, nodes can be fully utilized to improve the utilization of nodes and the data in the process is stored in the memory of the Executor process without necessity, thereby solving the problems of frequently reading and writing data.

4.2.2. Extraction of forest cover classification map

Stand ages are classified at the time of forest classification, which requires high-resolution remote sensing image. This paper uses 16m-resolution WFV data. Vegetation classification is carried out with the supervised classification method to extract the vegetation type coverage maps and conduct a statistic for the vegetation areas in different stand ages in the research region according to the field observation data and the forestry census data of fixed sample plots in the Experimental Forest Farm and based on the stand composition and dominant tree species in small classes. The vegetation types are divided into coniferous forest, broad-leaved forest and mixed broadleaf-conifer forest, and each type is divided into young forest, half-mature forest, near-mature forest, mature forest, and over-matures forest according to different stand ages. After classification, the interpretation accuracy is evaluated by means of Kappa coefficient and GPS field survey positioning data, and both the charting accuracy and user accuracy reach more than 95%, which meets the experimental requirement. Figure 3 is the forest cover type map.

4.3. Meteorological data acquisition and processing

The meteorological data in this paper is derived from China Meteorological Data Sharing Network. The daily data and monthly data in 2014 are collected from 36 weather stations in Heilongjiang Province, and the data contents include monthly total precipitation, monthly average temperature, monthly total solar radiation, daily total solar radiation, scattered radiation and the meteorological stations longitudes, latitudes and altitudes. Meteorological data is processed with the statistical-based interpolation method ---- Kriging interpolation method.

4.4. Field measurements and statistics

Field investigation is carried out in Mao’er Mountain Forest Farm, and the region to be surveyed is predicted by using the remote sensing image data provided by Google Map Software and the sample lot representing the local stand characteristic
is selected before the survey. A total of 80 plots are set up under the stand type of balanced coniferous and broad-leaved trees. The sample plot occupies an area of 0.06 hm$^2$, and the data (tree height, diameter at breast height, tree species composition, stand composition, accumulation, biomass, radiation) of the fixed sample lot and the yield table are collected. The statistics are derived from China Forestry Statistics Database, and the meteorological data and flux data in 2014 are also collected from the Ecological Station in Mao’er Mountain.

5. Experimental environment and technical route

5.1. Experimental environment

In this research, five nodes are used to construct a Spark cluster, which include a Master with a host configuration of Inter Xeon E5-2620 six-core 2.1GHZ processor and four Workers with a host configuration of Dawning I450-G10 tower server. Each node is equipped with RedHat6.2, Linux kernel version is 2.6.32, Hadoop version is hadoop 2.5.2, and Spark version is spark 1.2.0.

5.2. Technical route

Figure 4 is the technical roadmap of this paper.

6. Experimental result and analysis

6.1. Model accuracy verification

As the vegetation in Mao’er Mountain is luxuriant and the net productivity NEP is approximately equal to NPP, the simulated NPP of the model is verified with the flux data NEP of Mao’er Mountain in the research region. Substitute the model parameter measured in the field into the model to calculate the daily NPP and compare it with the daily NEP. NEP is slightly higher than the NPP estimated by the model because of the difference in soil respiration; however, there is a close relationship between the two data, which indicates that Cloud-ICASA model is suitable for estimating vegetation NPP in Mao’er Mountain. This is illustrated in Figure 5.

To further verify the applicability of the Cloud-ICASA model, the NPP data simulated by the model for Mao’er Mountain is compared with MODIS NPP product data, which is widely used at present, and the results are shown in Figure 6.

The correlation between the two is obvious, reaching significant correlation level. The results show that the simulation results of the improved model are ideal, the estimation results accurately reflect the actual growth process of forest vegetation, and the model is suitable for NPP research of forest vegetation in the research region of Mao’er Mountain.

The NPP of each vegetation type simulated by Cloud-ICASA model is compared with the measured data of different types of vegetation collected and different models, and the results show that Cloud-ICASA simulation results are between the measured ranges, indicating that the model is reliable. The differences in the results of different models are related to the model itself and the data quality.
Table 2. Comparing NPP values

<table>
<thead>
<tr>
<th>Vegetation types</th>
<th>Cloud-ICASA</th>
<th>Literature [1]</th>
<th>measured values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coniferous forest</td>
<td>432</td>
<td>447</td>
<td>179-824</td>
</tr>
<tr>
<td>Broad-leaved forest</td>
<td>483</td>
<td>643</td>
<td>114-717</td>
</tr>
<tr>
<td>Mixed broadleaf-conifer forest</td>
<td>455</td>
<td>469</td>
<td>257-717</td>
</tr>
</tbody>
</table>

6.2. Experimental efficiency verification of cloud platform

Based on the Cloud-ICASA model, the remote sensing images with different data volumes are selected to compare the variation trends of the run time of the serial platform and the cloud computing parallel experiment platform with the increase of the data volume and analyze the improvement of cloud computing platform for the data processing efficiency. The experimental results are shown in Figure 7.

The comparison results show that the cloud computing parallel experiment platform has more obvious computational advantages with the increase of the data volume and can improve the efficiency exponentially in the batch processing of remote sensing images and remote sensing image pre-processing.

6.3. Mao'er Mountain NPP results analysis

6.3.1. Extraction of forest cover classification map

The relationship between the NPP and the stand age of the three stands in Mao'er Mountain forest area is shown in Figure 8. The NPP of the three stands rapidly increases to the maximum and then gradually decreases to a stable value with the increase of the tree age. NPP rapidly accumulates in the stage of the young forest and half-mature forest, reaches to the maximum in the near-mature forest, starts to decrease in the stage of mature forest, and basically remains stable or slowly decreases in the stage of over-mature forest.

The year in which the maximum NPP occurs also varies with stand type. Broad-leaved forest has the maximum NPP within about 10 years, which is followed by the mixed broadleaf-conifer forest within about 20 years. Meanwhile, NPP peak occurs in the coniferous forest, which grows at the slowest speed within about 20-30 years.
6.3.2. Relationship between NPP and stand and season in Mao’er Mountain

According to the vegetation types, Mao’er Mountain Forest Farm is divided into coniferous forest, broad-leaved forest and mixed forest. The average annual NPP of three vegetation types is the largest in the broad-leaved forest followed by the mixed forest and the smallest in the coniferous forest. The monthly average NPP of the three shows an obvious unimodal status, indicating a clear seasonal difference. The experimental results are shown in Figure 9.

![Figure 9. NPP Time Distribution Pattern in Mao’er Mountain Experimental Forest Farm](image)

The variation trend analysis of NPP in the figure shows that the monthly accumulated NPP is almost 0 from January to March and December and is few in April and November. During the six-month period, temperature is the main influencing factor, with a monthly average temperature of 2 °C, which could not meet the requirements of vegetation growth. From May, the NPP of three types of vegetation rapidly accumulated as the temperature rose. In June, the monthly average NPP continued to increase while the hydrothermal conditions were suitable for growth as precipitation also started to increase when the air temperature met the need, and the accumulation reached the maximum in July. The accumulation started to decrease in August as precipitation was sufficient but temperature was too high. However, the precipitation reduced and the temperature also gradually decreased from September, so NPP accumulation continued to decline until the winter when the temperature is not suitable for crop growth come.

6.3.3. Analysis on annual average NPP in Mao’er Mountain

Figure 10 shows annual NPP distribution of Mao’er Mountain in 2014, with air variation ranging from 25-840 gC·m⁻²·a⁻¹ and an average of 458.85 gC·m⁻²·a⁻¹. From the perspective of distribution range, NPP value is low in the northern and the southernmost region and high in the southcentral region of Mao’er Mountain because the local environment of low mountains and hills is conducive to the vegetation growth and the forest area is also large. The Beilin Forest farm mixed Forest Farm dominated by the Pinus Sylvestris and the Pinus Koraiensis, which are evergreen trees, is the forest farm with the largest net primary productivity of vegetation in Mao’er Mountain Experimental Forest Farm.

7. Conclusions

Based on the study of a variety of models, this paper proposes Cloud-ICASA model for Mao’er Mountain Forest Farm, which simplifies the parameters and has strong operability. The model can use the full remote sensing method to obtain the data in real time and effectively and dynamically monitor the service functions of Mao’er Mountain Forest Farm, so as to provide guidance for management planning of the forest farm. This paper introduces the concept of cloud computing and sets up a parallel processing platform based on cloud computing to improve the storage and processing speed of remote sensing data. In the quantitative evaluation for the service functions of forest ecosystem, different standards are used in different regions, which is detrimental to the comparison between regions. In this paper, the age group is also divided and the change law of NPP with stand age is analyzed on the basis of stand classification and according to the Specifications for Assessment of Forest Ecosystem Services in China (LY/T1721-2008) issued by the State Forestry Administration. The next step is to evaluate value quantity and service volume for carbon fixation and oxygen release service function of Mao’er Mountain with reference to the national industry standards, so as to provide the basis for the operation and management decision-making of Mao’er Mountain.
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References


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