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Towards Global Radiative Energy Mapping: Integrating Scalable Computation and Earth Observation

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Abstract: Reliable and moderate to fine resolution estimates of radiative energy are required for mapping solar energy potentials and understanding land-atmosphere interaction as well as ecosystem water use. However, time-series data records of moderate resolution estimates of radiative energy are not available and consequently, it is challenging to develop multi-year estimates of radiation at scales that are relevant for policy and decision-making. This limitation is primarily associated with the intensive computational requirement to effectively use time-series Earth observation data. To support the retrieval of global shortwave radiation and consequent analysis of large amounts of spatio-temporal data, we integrate interactive tensor factorization and decomposition techniques with MODIS (Moderate Resolution Imaging Spectroradiometer) satellite radiances. This approach offers unique advantages for activity characterization in spatio-temporal and multi-relational data analysis. A simplified shortwave radiation model was implemented using TensorFlow, an open source software library developed by Google for numerical computation conducting machine learning and deep neural networks research using data flow graphs. TensorFlow uses a tensor data structure to represent all data, but general enough to be applicable in a wide variety of other domains as well. Comparison with a recently released global shortwave radiation product showed that the retrieved shortwave radiation agreed well with global measurements across a wide range of sky conditions.

Keywords: Shortwave radiation; MODIS; heliosat; scalable computation; TensorFlow; radiative energy potential.

1 INTRODUCTION

Spatially explicit radiative energy flux data, particularly shortwave radiation ($R_g$), is important for mapping global renewable energy potential, evapotranspiration and crop yield modeling, and understanding the land-atmosphere interactions. $R_g$ contributes to 70 – 75% of the total global net radiation and is the primary driver of photosynthesis and transpiration.

Atmospheric radiative transfer models (ARTM) are generally used to retrieve $R_g$, but estimating $R_g$ from high spatial resolution satellite data (e.g., LANDSAT, ASTER and Airborne sensors) or from moderate resolution MODIS level-3 1 km data is challenging due to the complexity of the ARTMs, computational demand, and unavailability of atmospheric optical property information at high spatial scale. Therefore, simple methods with low computational time need to be developed to retrieve high and moderate spatial resolution shortwave radiation.
Current work demonstrated the use of time-series MODIS optical reflectance data into a simplified algorithm for estimating $R_G$, and integration of the entire algorithm into an interactive tensor factorization and decomposition techniques for generative spatially-explicit shortwave radiation at 1 km spatial resolution.

2 METHODOLOGY

$R_G$ is determined by the solar constant ($S_c$, 1367 W/m^2), solar zenith angle ($\theta$, radian), atmospheric transmissivity ($\tau$), and Earth-Sun distance in astronomical unit ($d$, AU).

$$R_G = \tau \frac{S_c}{d^2} \cos \theta$$  \hspace{1cm} (1)

Estimation of $d$ and $\cos \theta$ can be done using standard astronomical equations. But the estimation of $\tau$ is most critical and requires information on atmospheric optics. To avoid the complexities of estimating $\tau$ using ARTMs, $R_G$ is estimated using the cloudiness index relationship as developed in the Heliosat method (Cano et al., 1986) with some simple modifications.

The cloud index $n_t(i,j)$ at instant $t$ and for pixel $(i,j)$ is defined as follows.

$$n_t(i,j) = \left[ \frac{\rho_t(i,j) - \rho_g(i,j)}{\rho_{cld}(i,j) - \rho_g(i,j)} \right]$$  \hspace{1cm} (2)

Here $\rho_t(i,j)$ is the reflectance or apparent albedo observed by the Spaceborne sensor for the time $t$ and at the pixel $(i,j)$. $\rho_{cld}(i,j)$ is the apparent albedo of the brightest clouds, and $\rho_g(i,j)$ is the apparent albedo of the ground under clear skies.

$$\rho_t(i,j) = \frac{\pi L_t(i,j)}{I_0 \cos \theta(t,i,j)}$$  \hspace{1cm} (3)

Where $L_t(i,j)$ is the observed radiance, $I_0$ is the total radiance in the visible channel for the satellite sensor. $\rho_g(i,j)$ is taken as the most frequent value for each pixel, and different values are used for each month. $\rho_{cld}$ is the reflectivity of a very dense cloud cover; taken as the 96 percentile point for all pixels from a time series.

The Heliosat method is based on an empirical relationship between the cloud index and the clear sky index $k$ defined by:

$$k = \frac{R_G}{R_{Gclr}}$$  \hspace{1cm} (4)

$R_{Gclr}$ is the global solar irradiance estimated by clear sky model. The relation between $k$ and $n_t'$ is used for estimating $k$.

$$k = 1.2 \text{ for } n_t' \leq -0.2$$

$$k = 1 - n_t' \text{ for } -0.2 \leq n_t' \leq 0.8$$

$$k = 31 - 55n_t' + 25(n_t')^2/15 \text{ for } 0.8 \leq n_t' \leq 1.1$$

$$k = 0.05 \text{ for } n_t' > 1.1$$  \hspace{1cm} (5)

This formulation ensures that $R_G = R_{Gclr}$ when $n_t' = 0$ and not less than 5% of $R_{Gclr}$ even under the thickest clouds. The role of the clear sky model is actually to estimate the absorption of the shortwave radiation in the atmosphere.
3 APPLICATION OF HELIOSAT ALGORITHM USING MODIS DATA

We used the MODIS surface reflectance channels to adapt the Heliosat algorithm. The aim was to generate shortwave radiation ($R_0$) under both clear and cloudy sky at the time of satellite equatorial crossing time. The methodology comprised of series of steps:

1. Using the daily surface reflectance values (MOD09GA) (0.01° spatial resolution, global), we derived daily albedo. This daily albedo consists of both the clear sky and cloudy sky albedo. Albedo was estimated from the narrowband reflectance using narrow band to broadband conversion formula (Liang, 2000).

2. For every month block we estimated the maximum and minimum albedo from the time series. This gave us the estimate of $\rho_{\text{t,cld}}(i,j)$ (i.e., maximum) and $\rho_{\text{t,g}}(i,j)$ (i.e., minimum) for every month.

3. Use equation 2 to estimate $n'(i,j)$.

4. Estimate $k$ according to the different classes of $n'(i,j)$ according to equation 5.

5. Estimate clear sky shortwave radiation ($R_{\text{G,clr}}$) using standard equations.

6. Use equation 4 to estimate $R_0$.

The most fundamental and obvious task for the designer of a parallel programming system (Cole, 1991) is the problem decomposition, i.e the identification of parallelism by deciding which part of the problem to be handled implicitly and which to leave to the programmer. We attempt to improve the understanding of the underlying equations and data structures from an analytical, a geometric and a dynamical systems perspective using Tensorflow. Tensorflow offers implicit parallelism and distributed execution. The entire algorithm was processed through scalable computation exploiting TensorFlow. Tensors are multidimensional and dynamically sized data arrays. Tensorflow uses a tensor data structure to represent all data. This structure can have different levels of complexity, from scalar to even an n-dimensional matrix. Rank- the structure of the Tensor is parameterized by its Rank, Shape defines the dimensionality and the Type describes the structure of the kind of data we are going to deal with in order to operate with it.

The TensorFlow programming model splits the algorithmic part from the execution part; this enables to target either regular CPUs (central processing unit) or GPUs (graphical processing unit) without modifying the algorithmic parts. Under the hood of the TensorFlow runtime, this separation allows for aggressive optimizations directly at the dataflow graph level such as constant propagation, operators fusion, tensor vectorization, and so on. These pre-compiler optimizations coupled with the regular optimizations from the compiler that TensorFlow uses behind the scene (LLVM) makes it very performant and suitable for computing complex simulations such as a global radiative energy mapping.

4 RESULTS

Results are presented in the context of a case study that occurred during the summer monsoon season (June to September) in India for the year 2007 and by comparing the Heliosat derived solar radiation with respect to a recently released MODIS solar radiation product (mcd18a1). Some statistical error metrics of the Heliosat derived $R_0$ versus mcd18a1 $R_0$ comparison are presented in the following tables for each month. The statistical error metrics are mean absolute error (MAE), mean bias error (MBE), and root mean square error (RMSE).

As it can be seen in Table 1, during the months of June the errors (in W/m2) are larger than during the months of July to September. However, the magnitude of $R_0$ is generally high during June, the percentage errors are small during the early summer. The MBE and RMSE in $R_0$ for all the month are comparable to the recommended error limits by The United Nations Environmental Programme (UNEP) in (Hoyer-Klick et al., 2010). The recommended values for instantaneous $R_0$ data are expected to have a MBE smaller than 5% and a RMSE smaller than 160 W/m2.
Table 1. Statistical error metric of instantaneous $R_G$ with respect to MCD18a1 product

<table>
<thead>
<tr>
<th></th>
<th>June</th>
<th>July</th>
<th>August</th>
<th>September</th>
</tr>
</thead>
<tbody>
<tr>
<td>MAE (W/m$^2$)</td>
<td>100</td>
<td>89</td>
<td>82</td>
<td>81</td>
</tr>
<tr>
<td>MBE (W/m$^2$)</td>
<td>37</td>
<td>29</td>
<td>23</td>
<td>15</td>
</tr>
<tr>
<td>RMSD (W/m$^2$)</td>
<td>145</td>
<td>117</td>
<td>108</td>
<td>108</td>
</tr>
</tbody>
</table>

Examples of the spatial distribution of $R_G$ for the four consecutive months revealed substantial pixel-to-pixel variability of the derived $R_G$ (Figure 1). Maximum $R_G$ variability was found during July and August (200 to 1000 W/m$^2$) due to high cloud variability, whereas minimum pixel-to-pixel variability was apparent in June (700 to 1000 W/m$^2$) because of low cloud variability.

Figure 1. Illustrated examples of spatial distribution of shortwave radiation at the time of MODIS Terra overpass for different days during summer monsoon season in the Western India.

5 CONCLUSIONS

The modified Heliosat methodology is applicable for mapping shortwave radiation from polar orbiting satellites without the need of any site specific calibration and also in data poor regions where no ground measurements of $R_G$ are available. An extended analysis and validation of this modified Heliosat approach is needed under variable atmospheric conditions with respect to cloudiness, aerosol optical thickness, water vapour, and seasonality before extending the application of this
method for renewable energy potential mapping, crop yield and biomass modeling, and net radiation and evaporation mapping etc.

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