A Bayesian approach for solar resource potential assessment using satellite images

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Abstract. The need for a more sustainable and more protective development opens new possibilities for renewable energy. Among the different renewable energy sources, the direct conversion of sunlight into electricity by solar photovoltaic (PV) technology seems to be the most promising and represents a technically viable solution to energy demands. But implantation and deployment of PV energy need solar resource data for utility planning, accommodating grid capacity, and formulating future adaptive policies. Currently, the best approach to determine the solar resource at a given site is based on the use of satellite images. However, the computation of solar resource (non-linear process) from satellite images is unfortunately not straightforward. From a signal processing point of view, it falls within non-stationary, non-linear/non-Gaussian dynamical inverse problems. In this paper, we propose a Bayesian approach combining satellite images and in situ data. We propose original observation and transition functions taking advantages of the characteristics of both the involved type of data. A simulation study of solar irradiance is carried along with this method and a French Guiana solar resource potential map for year 2010 is given.

1. Introduction
The knowledge of the global solar radiation incident on the earth’s surface and its geographical distribution is of prime importance for numerous solar-based applications (Climate change assessment, solar renewable energy systems). Satellite sensors can provide an alternative to the sparse coverage of radiometric networks since they can produce database over large regions. However the computation of solar radiation by means of satellite images is unfortunately not straightforward. The satellite image is a top-of-the-atmosphere (TOA) observation. The pixel value represents the flux density of the upward solar radiation emerging from the atmosphere, and the solar radiation absorbed by the ground is the fraction of the flux density of the downward solar radiation incident on the atmosphere. Determination of models capable of deriving global solar radiation at ground level from satellite images at high spatio-temporal resolution is an open issue in environmental research and solar applications.

Several mathematical models were studied, in order to estimate solar radiation from satellite images. Statistical models [1] from the one hand physical models from the other hand [2] However, despite their increasing complexity and an improved usage of numerous available data, recurring obstacles (e.g., the difference in spatiotemporal scale between the model and measurements; measurement errors; or the simplification of physical processes) still introduce a significant amount of uncertainty into the model predictions. In this paper we consider a Bayesian filtering approach to the
dynamical estimation of the global solar radiation at ground level from satellite images. We defend the idea that an inverse approach based on sequential Monte Carlo filtering [3] helps to relax several assumptions and constraints while keeping estimations results in accordance with those of existing methods. Among these constraints, one can note the physical model and its parameter estimation. In fact, using a stochastic model allows, if the amount of data samples is sufficient, to associate (in a statistical sense) the satellite data to their corresponding in situ samples. This conducts to infer the radiation measure in a continuous way of a geographic map with a precision comparable to the well established methods.

The paper is organized as follows: after presenting the stochastic model along with the observation and transition laws in Section 2, we explain the sequential Monte Carlo sampling in Section 3. Section 4 presents our experiments and results. Section 5 concludes and presents future directions.

2. Methods

Stochastic models are commonly used to describe the behavior of many processes. Model variables can be divided into hidden variables (that are not measured) as solar radiation estimates at surface, and observed variables as satellite image pixels. A combination of hidden and measured variables can be used to represent the dynamic behavior of the nonlinear process as described before.

2.1. Data and notation

A common assumption underlying solar irradiance signal is that it can’t be regarded as a stationary process due to the diurnal and annual variation related to the sun’s changing angle. To remove these effects and obtain a weekly stationary stochastic process solar irradiance is often normalized by dividing solar radiation at the earth surface by the extraterrestrial solar irradiance. The result is defined as the clearness index. Let $x_k$ denote the clearness index at time $k$:

$$x_k = \frac{G_k(i,j)}{G_0k(i,j)}$$  \hspace{1cm} (1)

where $G_k(i,j)$, is the horizontal global irradiance at ground level for the time $k$ and the pixel $(i, j)$ and $G_0k(i,j)$ is the horizontal irradiance outside the atmosphere for the time $k$ and the pixel $(i, j)$. They are expressed in W.m$^{-2}$. Observations of our model refer to the apparent albedo $\rho(i,j)$ observed by the satellite sensor for the pixel $(i, j)$ (containing the ground location). $\rho(i,j)$ has no unit and is equal to the bidimensional reflectance:

$$\rho(i,j) = \frac{\pi L(i,j)}{(I_{sc}E_0\cos\theta_s(i,j))}$$  \hspace{1cm} (2)

where $L(i,j)$ is the observed radiance, $I_{sc}$= 1367 W/m² is the solar constant, the extraterrestrial irradiance normal to the solar beam, $E_0$ is the excentricity correction factor and $\theta_s(i,j)$ is the sun zenithal angle at pixel $(i,j)$. The filtering problem can be formulated as:

$$x_k = f_k(x_{k-1}) + v_{k-1}$$  \hspace{1cm} (3)

$$z_k = h_k(x_k) + w_k$$  \hspace{1cm} (4)

$x_k \in \mathbb{R}^n$ is a state vector evolving according to the following equation (3), $x_k$ is i.i.d. random noise with unknown probability distribution function (pdf). At discrete times, observations $z_k \in \mathbb{R}^p$ become available and are related to the state vector via the observation equation (4), $v$ and $w$ are the process noise and the observation noise. The state transition density is fully specified by $f_k$ and the process noise distribution and the observation likelihood are fully specified by $h_k$ and the observation noise distribution.

2.2. The transition law (process law)

The first part of the stochastic model (eq. 4) is the transition law. In this work we use a transition law based on the ARMA (Auto-Regressive Moving Average Model) process called TAG (Time-dependant Autoregressive, Gaussian model) developed by Aguiar and Collares-Pereira [4] and designed to be
independent of location and time of the year. This model generates synthetic daily sequences of the
normalized hourly clearness index as a Markov chain.

2.3. The observation law
Apparent albedo $\rho_{k}(i,j)$ extracted from the digital satellite image over the time-interval are observations $z_k$. Observations are used to estimate what should be the hidden state $x_k$, clearness index at time $k$, by the knowledge of the observation law $h_k$.

The nonlinear function $h_k$ may be obtained using physical laws such as radiative transfer functions. However, due to the complexity of physical processes, it is difficult to develop accurate and reliable nonlinear function, in particular in a tropical area (our area of study). One approach for estimating $x_k$ is modeling of the joint distribution $p(x, z)$ with a learning dataset of clearness index data and apparent albedo data. The inference task has three folds:

1. obtain the joint density $p(x,z)$;
2. estimate the conditional distribution $p(x|z_k)$, for apparent albedo $z_k$ and
3. obtain an estimate $\hat{x}_k$ from such distribution.

We rely on a Monte Carlo approach to construct the joint density of $p(x, z)$. The regular steps of a particle filter can generate an approximation of the joint pdf $p(x, z)$ as the superposition of (equally weighted) local Gaussian kernel densities centred about each sample $(x_i, z_i)$, drawn from the learning set. Each kernel can be propagated by using a local linearization yielding a continuous output distribution $p(x|z)$. Identifying the distribution of the clearness index state variable conditioned on the apparent albedo variable, $p(x|z_k)$, reduces to identifying a marginal of this joint distribution. The conditional distribution $p(x|z_k)$, is the section of $p(x)$ at $Z = z_k$. Given the distribution of the clearness index $x$ conditioned on the apparent albedo $z_k$, the user has the freedom to choose any estimates of $X$. We choose the maximum a posteriori (MAP):

$$\hat{x}_{MAP} = \text{argmax}_x p(x|z_k)$$

Figure 3. Bayesian Network of the Hidden Markov Model. Clearness index, $x_k$, is the hidden state and apparent albedo extracted from the digital satellite image, $z_k$, is the observation.

3. Bayesian filtering
Solar radiation estimate through satellite images is a problem of causally estimating a hidden state sequence from a sequence of observations that satisfy the Hidden Markov Model (HMM) assumption. The problem is to recursively compute the “posterior” at time $k$ using the posterior at time (k-1) and the current observation (probability density function of the current state conditioned on all observations until the current time). In others words, the problem is to find an update formula from $p(x_{k-1}|z_{1:k-1})$ to $p(x_k|z_{1:k})$ where $z_{1:k}$ denotes all observation $\{z_1, \ldots, z_k\}$. 
For most nonlinear or non-Gaussian state space models, the posterior cannot be computed analytically. However, it can be efficiently approximated using a particle filter (PF) based sampling technique. A PF is a Sequential Monte Carlo technique. A PF is a recursive algorithm which produces at each time k, a cloud of N “particles” (Monte Carlo samples), along with their corresponding weights, whose empirical measure closely approximates the true posterior for large N.

Time evolution is achieved with an importance sampling distribution via sequences of sampling and importance weighting. For simplicity reasons, we choose the importance density as the prior \( p(x_k|x_{k-1}) \). In order to overcome the major problem of PF techniques, the particles degeneracy, we introduce a resampling strategy. SIR particle filter simulations were conducted according to the observation dataset. Initial distribution is chosen to be a white noise distribution with a zero mean and initial set of particles is formed with uniform weights.

4. Results

4.1. Solar irradiance estimates

In order to develop and validate the particle filter model a set of 4454 high resolution satellite images (GOES EAST) from the visible channel \((0.4\mu m-1.1\mu m)\) covering a 207 days period from the year 2010 has been selected. This selection allows for various sky coverages. The apparent albedo observed by the satellite sensor is determined for cell of \(0.2^\circ x 0.2^\circ\) in size by averaging several pixels. The joint probability distribution function (pdf) between clearness index and apparent albedo is obtained using a learning dataset including randomly chosen satellite images and measurement data from 4 ground meteorological stations from French National Meteorological Service spread over the 84000 km² of the French Guiana territory.

![Figure 4. Comparison between hourly measured and hourly estimated irradiance](image)

Hourly and daily solar irradiance for each station were estimated using a test dataset (with data not used in the learning dataset) processed by the SIR particle filter with 400 samples. In Figure 4, the particle filter based estimates are compared with solar radiation measurements from the ground stations on an hourly basis. The results indicate that the models overestimated the radiation for lower irradiances. Figure 5. shows comparisons between daily measured and daily estimated irradiance.

The performance of the particle filter based model was estimated using statistical errors: root mean squared error (RMSE) and mean bias error (BIAS) defined below. Statistical errors on a daily basis are presented in Table 1. Relative BIAS and RMSE are also given as a percentage of the daily averaged measured irradiance. Relative RMSE obtained for Particle Filter based model is similar to average RMSE obtained with others methods [6].
Figure 5. Comparison between daily measured and daily estimated irradiance

\[
\text{RMSE} = \left( \frac{\sum (R_{\text{me}} - R_{\text{est}})^2}{n} \right)^{1/2}
\]

\[
\text{BIAS} = \frac{\sum (R_{\text{me}} - R_{\text{est}})}{n}
\]

where \( R_{\text{me}} \) is the measured ground solar radiation value and \( R_{\text{est}} \) is the estimated solar radiation value.

### Table 1. RMSE and BIAS between daily solar irradiance measurements and daily solar irradiance estimates (values in W/m² and percentage)

|            | RMSE (W/m²) | Bias (MBE) |
|------------|-------------|------------|
| Unity      | 566         | 220        |
| Relative   | 10%         | 4%         |
| Other      | ~10%        | ~5%        |

4.2. Solar resource potential assessment

Solar resource potential estimates are obtained by using the following formula:

\[
E_i = G_i h
\]

where \( E_i \) is the potential of solar energy (Wh/m².day), \( G_i \) is the global irradiance at the surface (W/m²) and \( h \) is the number of hours in a day [7].

We estimated annual mean daily solar energy potential on four locations (the same locations for which GOES satellite images pixel values were extracted). It would have been possible to extract values of all pixels for the French Guiana territory and proceed them in order to estimate energy potential received at the surface for each pixel (this work is in progress). Here, a simple interpolation of the four stations values was achieved throughout French Guiana with the ANUSPLIN software, and a solar resource potential map was established using ArcGIS software (Figure 6). Results show that the optimal sites for the production of solar energy lies west of French Guiana, in this region the mean daily potential reach its maximum value: 5100 Wh/m².day.

5. Conclusion

A procedure has been developed for estimating solar resource potential which involves solar irradiance estimate from satellite images using a Bayesian method. The methodology consists of a broad set of principles and techniques which may be used to forward knowledge concerning solar energy potential. This knowledge is critical to determining land-use planning, sustainable initiatives and potential photovoltaic deployment in a region.

The developed method connects global and local dynamics of solar irradiance in a Bayesian framework by using the existing relation between clearness index data and satellite apparent albedo. A Bayesian approach has been developed to estimate solar radiation at surface using satellite images. The proposed method incorporates statistical model for observation process. The joint distribution of state variable and observation variable is not restricted by any prior assumption and gives a
probabilistic perspective based on conditional distribution estimates. The observation model takes advantage of the statistical relationship between the clearness index data and apparent albedo of satellite image to avoid introduction of complex radiative transfer equations while keeping estimation results in accordance with those of existing methods.

We demonstrate the use of a SIR particle filter for deriving solar radiation estimates using remote sensing. However, the method needs to be improved for low daily solar irradiances. It may be supposed that a substantial reduction of the daily RMSE can be gained by optimizing the joint pdf and state estimates choice and further investigations will be made in this direction. Future works need to be pursued on a global scale and on various ground covers.

Figure 6. Map of solar photovoltaic potential in French Guiana for year 2010 (annual average on a daily basis)

6. References
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