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A Bayesian Model to Study Spatio-Temporal Variability of Latent Heat Flux and Its Trend

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Abstract

This paper talks about two models. First model is presented to study space-time variability of latent heat flux, where latent heat flux has been decomposed into three periodic terms, spatio-temporal process term, long term trend and a term due to covariates. And the second model is presented to characterize the long term trend and its possible causes. For both the models Bayesian approach was adopted. The method presented is particularly useful for characterizing environmental spatio- temporal processes variability. The model parameters were sampled using a Markov chain Monte Carlo simulation technique. The models were used for studying latent heat flux components in the Indian Ocean for the period of January 1985 to April 2010. The results showed that in LHF variability, dominant factors were annual variability, spatio-temporal variability and variability due to covariates. Further it has been found that the long term positive trend of LHF is dominated by the increase in wind speed. In some regions of Indian Ocean, increase in sea surface temperature has also been the cause for increase in LHF.

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Keywords: Bayesian modeling, latent heat flux, wind speed

1. Introduction

Transfer of heat between sea surface and lower atmosphere through latent heat is a key driving force of the atmospheric circulation. The latent heat flux (LHF) is a source of energy for intra tropical convergence zone. There exists a strong relationship between precipitation and latent heat flux ([1]). Study on global warming

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infers that slightly more increase in atmospheric temperature can trigger unmanageable climate variability ([9]). Much of the heat is stored in the ocean which will be released to the atmosphere in coming time ([10]). Much of the heat released by ocean will be in the form of latent heat flux. Increased wind speed together with the increased heat content of ocean has made study of latent heat flux more important.

Earlier studies on LHF variability mainly concentrated on variability on different time scales ([4,7,12]). Some study has been done on relationship between climate parameters and latent heat flux ([2-3]). More recently there are studies on latent heat flux trend. Study on latent heat flux trend is done by [16] and the positive trend in LHF is associated with sea surface temperature (SST) increase. Study done by [8] on decadal-scale trend based on four types of data sets, associated the positive trend of LHF to increase in wind speed trend. Study of LHF on different time scales was done by [12] in the Indian Ocean. Their study shows that net heat flux has positive trend and since latent heat flux is the main contributor, the trend must be associated with latent heat flux positive anomaly. They showed that wind speed has a positive trend since 1960 and specific humidity difference also has a positive trend from 1970. Therefore, they concluded that LHF positive trend is due to wind speed and specific humidity difference. Study of latent heat flux trend over the southern Ocean is done by [15].

The focus of this paper is to model the relationship of LHF with wind speed and sea surface temperature (SST).The relationship will be used to estimate the proportion of contributions by wind speed and SST for the increase in LHF. To extract the trend component and to model LHF, Bayesian hierarchical spatio-temporal modeling approach was used. Bayesian hierarchical method (BHM) is a space time model technique, in which we first define model parameter and hyper parameters and their prior statistical distributions. Bayes theorem can be used to calculate posterior distribution for model parameters. Using the posterior distribution, model parameter samples can be simulated. These samples are then used for analysis of the spatio-temporal process. For the purpose of this study objectively analyzed (OA) heat flux data was used. More information about OA air-sea heat flux data set can be found in [16]. The OA LHF data used in the study is downloaded from Indian national centre for ocean information services (INCOIS) Hyderabad, India website with spatial resolution 1° × 1°.

2. Model

This section describes two models, one describes the latent heat flux and the other describes the trend in latent heat flux. For the purpose of study, the Indian Ocean is divided into 8 regions as in [12]. Table 1 describes regions in the Indian Ocean.

Table 1. Regions of Indian Ocean as in [12]

Region id	Region
1	Arabian sea
2	Bay of Bengal
3	South China sea
4	South of region 1 and north of 5ºS latitude
5	South of region 2 and north of 5ºS latitude
6	South of region 3 and north of 5ºS latitude
7	South of region 4, 5, 6 and north of 20ºS latitude
8	South of region 7 and north of 40ºS latitude

The ocean surface latent heat flux varies with space as well as with time. Since LHF is a process due to air-sea interaction, it shows temporal variations in different frequencies. In this study three major frequencies of LHF are used. Due to seasonal variations in climate variables, LHF shows a frequency with 12 months period. Due to inter annual variations of climate variables, LHF also shows a frequency with 20-30 months period. Exploratory data analysis shows that some regions have semi-annual variation. Global warming has also contributed some positive trend in LHF. Independent of above mentioned frequencies and long term trend, there exists a spatio-temporal characteristic of LHF. The spatio-temporal characteristics define the dynamic nature of LHF. LHF being a part of air-sea interaction process is not independent of other environment variables such as wind speed, humidity and sea surface temperature. The LHF variability therefore also depends on the anomaly of these environmental variables.

Based on the factors discussed above, the stochastic model for LHF is conditional spatio-temporal term, a term due to covariables and a long term trend along with the three frequencies terms. For t = 1 to T and n=1 to N

$$L(t, n) = X(t, n) + Y(t, n) + U_1(t, n) + U_2(t, n) + U_3(t, n) + V(t, n) + \varepsilon_l \quad (1)$$

Where L is the LHF X is the spatio-temporal component, Y is the term due to covariates, U_1 is semiannual term, U_2 is annual term, U_3 is the intra annual term and V is the long term trend of the LHF. The error term of the model in equation 1 is represented by ε_l. T and N represent number of time instance and number of regions respectively. X is modeled as vector autoregressive model, Y is the linear regression model with covariates as repressors, U are represented as sinusoidal waves and V as a linear model with t as independent parameter. The model in equation 1 is similar in line with [11, 13, and 14].

To simulate the model parameters Gibbs sampler has been used, which is a Markov chain Monte Carlo technique. 50000 samples were simulated for each parameter of the model. Since number of regions is only 8, there are no issues with computations as pointed out by [11]. The model is implemented using c++ on Linux machine with 8 GB main memory.

Is wind speed trend or the sea surface trend is the main forcing component? For answering this, the long term component extracted from the model of equation 1, was represented as a regression model with wind speed trend and SST trend as independent variables.

$$V(t, n) = a_v(n)\times W(t, n) + b_v(n)\times S(t, n) + \varepsilon_v \quad (2)$$

Where V is the long term trend in LHF, W is the trend in wind speed and A is the trend in SST. Error term in the equation 2, is represented by ε_v. The time and region id index are represented by t and n respectively. To get trend component from wind speed and SST, regression model with time as independent parameter was used

The method proposed by [6] has been adopted to find the variability of different components of the model. Given a simulated sample of a parameter, spatial or temporal variance of the parameter can be computed. The mean of variances of N number of simulated samples gives measure of the variability of the parameter. Let U(t,n) be a component. One sample at a fixed region n, has T values of U corresponding to T time points. Let v be the variance of the T values of U. If we have N samples for the parameter U and v_i, i=1, 2, 4,…, N be the variances of each sample or U. The expected value of the measure of variance of the parameter U is the mean of v_is.

3. Results and discussion

Table 2 shows the expected variance of $a_v\times W$ and $b_v\times S$ together with their covariances. Variance $a_v\times W$ of equation 2 gives the measure of variability of wind speed trend which contributes to the variability of LHF trend. Similarly $b_v\times S$ gives the variability of SST trend which gives contribution towards LHF trend variability. From table 2 it is seen that in LHF trend variability is dominated by wind speed variability in region 1, region 3, region 4, region 5 and region 7. Sea surface temperature trend variability is dominant in region 2, region 6 and region 8.

Table 2. Mean of the variances and covariances of the terms in the regression model of long term trend

Regions	1	2	3	4	5	6	7	8
$V[a_v \times W]$	5.38	12.34	92.59	10.03	13.22	11.30	25.84	0.07
$V[b_v \times S]$	2.18	53.68	31.02	0.06	0.44	53.76	4.63	6.62
Cov(row 1 and 2)	-3.57	-25.74	-53.59	-0.748	-2.41	-24.65	-10.93	-0.66

Based on the results discussed above it can be conclude that the long term trend of the LHF is mainly due to variability in the wind speed. Similar analysis on the components of the equation 1 shows that LHF variability, dominant factors were annual variability, spatio-temporal variability and variability due to covariates. The model presented can also be used for forecasting of LHF in a region. The method presented here can be used for other spatio-temporal environmental processes. The frequency terms in the model can be extended to take more frequency terms as needed. Few frequency terms can be dropped from the model in some cases. In long term trend analysis of other environmental variables more covariates can be taken.

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