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A GENERAL BAYESIAN APPROACH TO CLIMATE CHANGE DETECTION AND ATTRIBUTION USING ECHAM3-LSG SCENARIO RUNS AND NCEP/NCAR REANALYSIS OBSERVATIONS

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1. INTRODUCTION

During the past ten years several papers on climate change detection and attribution using optimal detection techniques (Hasselmann 1993, 1997; Hegerl et al. 1997; Stott et al. 2001; Paeth and Hense 2001) have been presented. A model generated climate change pattern is compared with respective data from observations where the comparison - based either on a distance or a similarity measure - is done using the Mahalanobis metric with the help of the inverse covariance matrix of natural climate variability. The method requires the specification of the natural variability in observations but the internal variability of the model results especially of the climate change pattern is rarely taken into account (Barnett et al., 1999).

One way to include this information is the Bayesian approach. Additionally this way offers the possibility to consider past experience on models as so called priors. Leroy (1998) was among the first to explore the Bayesian approach in climate change detection. He also pointed out the need for the estimation of model uncertainties. Berliner et al. (2000) used a robust Bayesian approach in one dimension (the amplitude of the fingerprint) to investigate the uncertainties in assessing anthropogenic impacts on climate change resulting from uncertainties described by the priors.

In this study we will present another Bayesian approach for climate change detection and attribution along the lines given by Leroy (1998). The method is applied to a two dimensional case using area averaged temperatures of near surface and 70 hPa level from ECHAM3-LSG simulations and NCEP/ NCAR reanalysis data.

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2. THEORY

Applying the Bayes decision theory, we will treat the detection and attribution problem as a decision process to classify the observation *d* into a certain model m_i. The Bayesian approach defines the decision rule using the posterior probability as a discriminant function (Duda and Hart, 1973). The conditional probability of a certain model m_i given the observation *d* $p(m_i|d)$ (posterior) is evaluated from the marginal probability of the model itself $p(m_i)$ (prior) and the conditional probability of the observation given the model $p(d|m_i)$ (likelihood).

$$p(m_i \mid d) \sim p(d \mid m_i)\, p(m_i) \quad (1)$$

The prior includes the description of the model's internal variability in terms of its individual realizations and a subjective measure of the overall probability of the model. The likelihood contains the description of the observational uncertainty.

Assuming Gaussian distributions of model realizations and observation, the posterior probability of model m_i can be evaluated as:

$$p(m_i \mid d) \sim \frac{1}{\sqrt{2\pi^s}} \sqrt{\frac{\det A_i^{-1}}{\det \Sigma_i \det \Sigma_0}} \exp\left(-\frac{1}{2}\Lambda_i\right) p(m_i) \quad (2)$$

where, *s* is the dimension of data vector, Σ_i is the covariance matrix of model m_i, Σ_0 is the covariance matrix of observation *d*, A_i is the combination of the model and observation covariance matrices, and Λ_i is a generalized distance measure between the model and observation. The *det* means determinant value of a matrix.

The decision rule to attribute the observation into one of the two possible models (control m_1 and a climate change scenario m_2) is based on the log ratio of the two posterior values.

$$\log\left(\frac{p(m_2 \mid d)}{p(m_1 \mid d)}\right) \begin{matrix} > 0 \Rightarrow m_2 \\ < 0 \Rightarrow m_1 \end{matrix} \quad (3)$$

If log value of the ratio is above [below] zero, observation *d* is attributed to the model m_2 [m_1].

Inserting Eq. (2), the decision rule has four terms as follows.

$$\log\left(\frac{p(m_2\,|\,d)}{p(m_1\,|\,d)}\right)=\frac{1}{2}\log\left(\frac{\det A_2^{-1}}{\det A_1^{-1}}\right)$$
$$-\frac{1}{2}\log\left(\frac{\det \Sigma_2}{\det \Sigma_1}\right)-\frac{1}{2}(\Lambda_2-\Lambda_1)+\log\left(\frac{p(m_2)}{p(m_1)}\right) \quad (4)$$

In case of Gaussian probability density functions, identical covariance matrices for two models and observation, and identical priori probabilities for two models, the Bayesian decision rule reduces to a standard linear discriminant function analysis which is the third term of the RHS of Eq. (4).

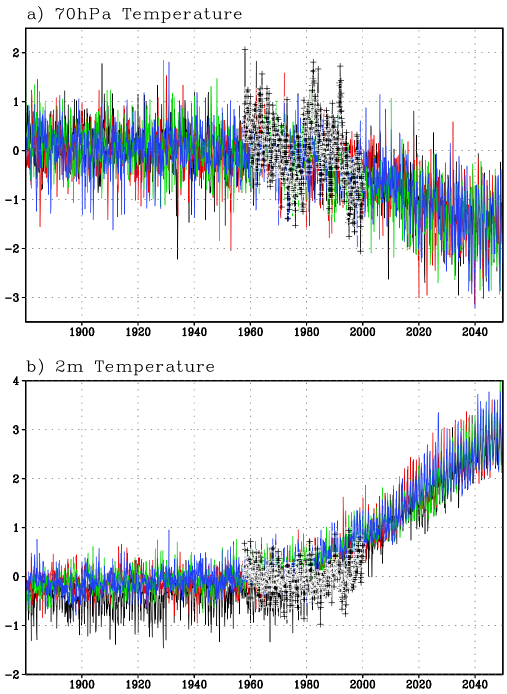

Fig. 1. Time series of Northern hemisphere extratropics (20N-90N) area averaged temperature anomalies in a) 70 hPa and b) 2 m level. NCEP/NCAR Reanalysis data (+ mark) from 1958 to 1999 and ECHAM3/LSG four scenario runs (solid line) from 1880 to 2049.

3. APPLICATION RESULTS

NCEP/NCAR reanalysis data from 1958 to 1999 are used as observation and ECHAM3/T21-LSG scenario runs utilizing the SA90 emission scenario data for the period 1880 to 2049 provide the model data. Spatially averaged near surface temperature and 70 hPa temperature for the Northern hemisphere extratropics (Fig. 1) are selected as detection variables (dimension of the data vector *s*=2). The two model cases are defined from an ensemble of 4 realizations of ECHAM3/LSG, namely, control model m_1 as all simulations for the 100 year period (1880-1979) and the CO_2 scenario model m_2 as the mean of all model realizations in the model year 2000, but with the covariance matrix derived from the trend reduced anomalies from 1980 to 2049.

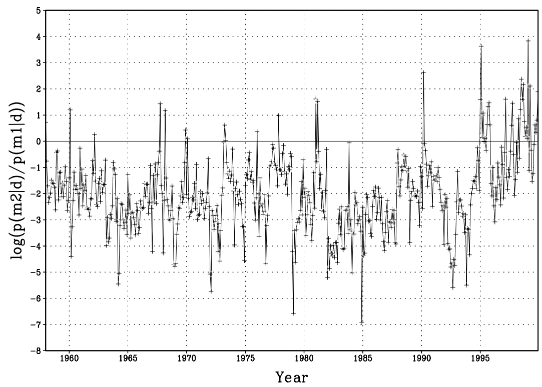

Fig. 2. Attribution of NCEP reanalysis data to the control model (m_1) and the CO_2 scenario model (m_2) in the model year 2000 using a general Bayesian approach in case of identical priors for two models. When the log ratio value is above [below] zero, the observation is attributed to m_2 [m_1].

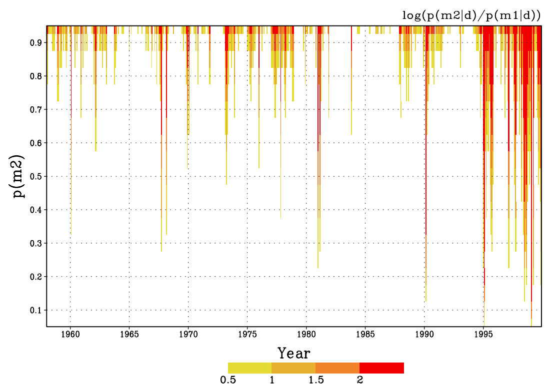

Fig. 3. The change of attribution results in Fig. 2 as the prior probability of the CO_2 scenario model varies from 0.05 to 0.95. The gray shading reflects log ratio (larger than 0.5) of the posterior values for the CO_2 scenario model (m_2) and the control model (m_1),

Applying the decision rule (4) with identical prior for the control and the CO_2 scenario model, the observations (monthly and area mean of 2m temperature and 70 hPa for the Northern hemisphere extratropics) are classified into the CO_2 scenario model with an increasing frequency since the mid 1990s (Fig. 2). By computing the individual posterior values, it is verified that this classification is not due to some exotic positions of data points relative to the models' full priors following the suggestions by Berliner et al. (2000).

Even if the priori for the CO_2 scenario model is as low as 25%, the observations in the late 1990's are still classified into the CO_2 scenario model (Fig. 3).

4. CONCLUSIONS

A general Bayesian approach along the lines by Leroy (1998) is developed and applied to detection and attribution of a climate change signal using NCEP/NCAR reanalysis data (1958-1999) and ECHAM3-LSG scenario runs (1880-2049). It is shown that the Bayes decision technique which maps the prior information on the models to the posteriors with the help of the likelihoods can be a useful tool for the detection and attribution problems. The attribution of observed data to a control model and various climate change scenario models can be made with the Bayes decision rule of a least misclassification error. The specification of a prior of each scenario model represents the quantified degree of subjective belief in the model.

The application results show that climate change signals by CO_2 increase are detected in the late 1990s due to the combined effect of the lower tropospheric warming and the stratospheric cooling. Even if the prior on the CO_2 scenario model gets small, the signal in the late 1990s is still present.

For future work, it is necessary to add other observation data and model scenario runs to ascertain our results. Scenario runs including sulfate aerosols will be added to the attribution study. Also the use of spatially averaged data has to be relaxed in favor of a more detailed spatial description.

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