Plant- and Soil-Parameter-Caused Uncertainty of Predicted Surface Fluxes

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ABSTRACT

Simulated surface fluxes depend on one or more empirical plant or soil parameters that have a standard deviation (std dev). Thus, simulated fluxes will have a stochastic error (or std dev) resulting from the parameters' std dev. Gaussian error propagation (GEP) principles are used to calculate the std dev for fluxes predicted by the hydro–thermodynamic soil–vegetation scheme to identify prediction limitations due to stochastic errors, parameterization weaknesses, and critical parameters, and to prioritize which parameters to measure with higher accuracy.

Relative errors of net radiation, sensible, latent, and ground heat flux, on average, are 7%, 10%, 6%, and 26%, respectively. The analysis identified the parameterization of thermal conductivity as the dominant influence on the std dev of ground heat flux. For net radiation, critical parameters are vegetation fraction and ground emissivity; for sensible and latent heat fluxes, vegetation fraction. Minimum stomatal resistance and leaf area index dominate the std dev of stomatal resistance for most vegetation and soil types. The empirical parameters with the highest relative error are not necessarily the greatest contributors to the std dev of the predicted flux. Based on the analysis high priority should be given to measurements of vegetation fraction, ground emissivity, minimum stomatal resistance, leaf area index in general, and the permanent wilting point and field capacity for clay and clay loam. Moreover, further specification of clay-type soils and tundra-type vegetation may improve the accuracy of the lower boundary condition in Arctic numerical weather prediction. Since GEP showed itself able to identify critical parameters and (parts of) parameterizations, GEP analysis could form a basis for parameterization intercomparisons and for parameter determination aimed at improving models.

1. Introduction

Recent studies showed that major failures in numerical weather prediction (NWP) occur close to the surface (e.g., Hamill and Colucci 1997), the only natural boundary condition in NWP models. These failures may result from inaccurately predicting the fluxes of heat, water vapor, and matter at the surface–atmosphere interface. Systematic errors due to initial conditions, for instance, have been addressed by ensemble modeling techniques or sensitivity studies (e.g., Tracton and Kalnay 1993; Toth et al. 2001). Besides incorrect initial soil conditions, the parameterizations used in land surface models (LSMs) to describe the surface fluxes may cause systematic errors. Such systematic errors have been examined by comparing results from different LSMs. In this context, the great achievements of the Project for Intercomparison of Land Surface Parameterization Schemes (PILPS) must be mentioned (e.g., Henderson-Sellers et al. 1995; Shao and Henderson-Sellers 1996; Chen et al. 1997; Schlosser et al. 2000; Slater et al. 2001; Luo et al. 2003).

PILPS also showed that LSMs strongly differ in accuracy due to empirical parameters (e.g., physiological, phenological, thermal, hydraulic, radiative, etc.) used to represent different vegetation and soil types (e.g., Wilson et al. 1987; Dorman and Sellers 1989). The wide possible parameter range causes a high variability in predicted state variables, energy, and water fluxes (e.g., Avissar 1991; Pollard and Thompson 1995; Mölders 2001) with implications for the structure of the atmospheric boundary layer (e.g., Avissar and Pielke 1989). For example, density of upward shortwave radiation will differ if the albedo value is taken as 0.15 or 0.2. Consequently slightly different temperature conditions and sensible, latent, and ground heat flux densities will

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be established. This phenomenon is known as "parameter interaction."

Various parameter-variation studies have been carried out to examine interaction effects and understand systematic uncertainty arising from parameter choices. Henderson-Sellers (1993), for instance, applied factorial experiments to assess the relative importance of the parameters in an LSM. She found that the most ecologically important parameters are roughness length, porosity, and an empirical factor describing the sensitivity to photosynthetically active radiation, followed by soil and vegetation albedo. Collins and Avissar (1994), for instance, performed a Fourier amplitude sensitivity test to determine the relative contributions of individual parameters to the variance of energy fluxes resulting from a heterogeneous surface. In doing so, they simultaneously varied all parameters according to their individual probability density functions. They found that statistical–dynamical approaches may be simplified by using only the probability density functions of relative stomatal resistance and surface roughness.

Parameter-variation methods address systematic errors. They consider the question of whether slightly different parameters will result in significant perturbations of the model result. However, parameter effects or parameterization deficits that accidentally cancel each other out can remain overlooked (Henderson-Sellers 1993). To minimize parameter interaction, the methods have to be driven by either observation or reanalysis.

Systematic errors from parameter choice, initialization, discretization, model assumptions, and physical parameterizations are not only the source of uncertainty. Another source is stochastic error. Usually a mean value for a vegetation or soil characteristic derived from laboratory or field studies is assigned to a grid element of a NWP model, ignoring natural variance given by the standard deviation. The standard deviations of some parameters, however, can be as great as the mean values themselves (e.g., Clapp and Hornberger 1978; Körner et al. 1979; Cosby et al. 1984; Avissar 1991). Stochastic uncertainty results solely from the fact that the aforementioned mean values of empirical soil and plant parameters are in "error" by the amount of the standard deviation. This error propagates in any quantity calculated by use of these mean parameters; that is, each predicted quantity also has a standard deviation due to the standard deviations of its dependent uncertain parameters. Therefore, uncertainty from stochastic errors also should be kept as low as possible.

Since parameter-variation methods are deterministic, they cannot determine this stochastic uncertainty. Knowledge of a predicted flux's parameter-induced standard deviation, however, is desirable for model development and improvement. Parameterizations, for instance, can be examined prior to implementation in an LSM with respect to the parameter-induced statistical uncertainty of the predicted fluxes. Parameterizations that lead to fluxes with high standard deviations can be identified and replaced or avoided. An equation to calculate the flux may be very insensitive or sensitive to the parameter's standard deviation. Therefore, a priori it is unknown whether a huge (small) standard deviation of a parameter will lead to huge or small standard deviation of the predicted flux. It is of interest to identify the parameters that cause huge standard deviation in the fluxes to measure them with high accuracy even if they themselves have low standard deviation. The parameters causing the highest uncertainty are the ones that will guarantee the greatest potential for reduction of uncertainty in predicted fluxes if these parameters are known with higher a degree of certainty.

Gaussian error propagation (GEP) principles permit calculating the error (variance, standard deviation, or error bar) of a predicted quantity that results as a consequence of the standard deviation(s) of the parameter(s) it depends on (e.g., Kreyszig 1970; Meyer 1975). Thus, GEP permits the tasks mentioned above to be addressed. This method originally stems from engineering and physics. In these disciplines, it has been applied to determine the statistical uncertainty inherent in a calculated quantity (e.g., current) due to standard deviations of parameters it depends on (e.g., resistances within a Wheatstone bridge).

Since, in a mathematical sense, a function to predict a flux is unambiguous; it will always provide the same flux for the same set of state variables, fluxes, and empirical parameters. Thus, for each set of state variables, fluxes, mean parameters, and their standard deviations, GEP can determine the standard deviation of a predicted flux independent of other parameterizations used in an LSM; that is, without parameter interaction or full simulation. Therefore, the standard deviation of predicted surface fluxes can be theoretically analyzed using artificial data for the typical range of environmental conditions.

In this study, GEP is applied to the parameterization of surface fluxes in the hydro–thermodynamic soil–vegetation scheme (HTSVS; Kramm et al. 1996; Mölders et al. 2003) used in various NWP (e.g., Mölders and Rühaak 2002; Mölders and Walsh 2004) and chemistry (e.g., Kramm et al. 1994, 1996) models. The standard deviation of predicted surface fluxes that is caused by standard deviation of empirical parameters is examined theoretically for a typical range of environmental conditions to identify uncertainty-causing parameters and (parts of) parameter-sensitive parameterizations. To demonstrate the importance of the results for NWP and to understand the parameter-induced limitations of NWP, a simulation is carried out for 0000 UTC 20 July–1200 UTC 23 July 2001 for a subarctic/Arctic environment with the mesoscale modeling system of the fifth-generation Pennsylvania State University–National Center for Atmospheric Research (PSU–NCAR) Mesoscale Model (MM5; Dudhia 1993; Grell et al. 1994). Since various other LSMs use parameterizations and parameters similar to those in HTSVS, the results presented here are of interest to a broad NWP community. As a courtesy to the reader, examples of LSMs using similar parameterizations as HTSVS are given.

2. Brief description of the NWP model

a. The atmospheric model

MM5 is run using the five water classes (cloud water, rainwater, ice, snow, graupel) in the cloud microphysical scheme of Reisner et al. (1998). As the typical horizontal extension of cumulus clouds is considerably smaller than the horizontal grid resolution (45 km), a cumulus scheme (Grell 1993) considers these subgrid-scale clouds. The parameterization of turbulent transfer processes follows Hong and Pan (1996). Furthermore, Grell et al.'s (1994) simple radiation scheme is applied.

The model domain uses a horizontal Arakawa–Lamb-B (Arakawa and Lamb 1977) staggering consisting of 39 × 39 dot and 38 × 38 cross grid points with a horizontal grid spacing of 45 km, and 23 vertical layers reaching to 100 hPa. Five snow layers of equal thickness depend on snow depth. Five soil layers are logarithmically spaced between 0.1- and 2.95-m depth. To fulfill the Courant criterion a time step of 120 s is chosen.

b. The surface model

HTSVS consists of a multilayer soil model, a single-layer canopy model (e.g., Kramm et al. 1996; Mölders et al. 2003), and a multilayer snow model (e.g., Mölders and Walsh 2004).

HTSVS calculates the fluxes of momentum, heat, and moisture at the vegetation–soil–atmosphere interface. It considers partly vegetation-covered grid cells by a mixture approach (e.g., Deardorff 1978; Kramm et al. 1996). Other LSMs using this approach are, for instance, the Simple Biosphere model (SiB; e.g., Sellers et al. 1986) and the Community Land Model (CLM; Bonan et al. 2002). Jarvis's (1976) approach for bulk-stomatal resistance (see the appendix) serves to calculate transpiration by plants. The Interaction between Soil–Biosphere–Atmosphere model (ISBA; e.g., Noilhan and Planton 1989), the Biosphere–Atmosphere Transfer Scheme (BATS; e.g., Dickinson et al. 1993), the Oregon State University LSM (OSULSM; e.g., Chen and Dudhia 2001), and SiB, for instance, also apply the Jarvis approach. Some of them even use the same correction functions (e.g., OSULSM for soil water deficit). Water uptake by plants includes a vertically variable root distribution (e.g., Mölders et al. 2003).

The soil model includes heat conduction and water diffusion (including the Richards equation) within the soil, soil freezing and thawing, and the related release of latent heat and consumption of energy, and the effects of frozen ground on the vertical fluxes of heat, moisture, and water vapor (e.g., Kramm et al. 1996; Mölders et al. 2003). Other models using the Richards equation are, for instance, the Canadian Land Surface Scheme (CLASS; e.g., Verseghy 1991) and BATS. Examples of LSMs using a simplified (as compared to HTSVS) formulation of soil heat diffusion are OSULSM, BATS, and CLM.

Tables 1–3 summarize the equations of surface fluxes and their dependent empirical parameters, and the soil and plant empirical parameters, respectively. Most modern LSMs use similar parameters.

c. Initialization

Initial and boundary conditions stem from the (National Centers for Environmental Prediction) NCEP–NCAR Reanalysis Project (NNRP). A weighted combination of the July and August monthly 5-yr mean green vegetation cover (0.15° resolution) derived from the Advanced Very High Resolution Radiometer (AVHRR) data (Gutman and Ignatov 1998) is used to determine the vegetation fraction of each grid cell. The 1-km resolution U.S. Department of Agriculture (USDA) State Soil Geographic Database (Miller and White 1998) and 10-min resolution U.S. Geological Survey (USGS) terrain and vegetation data are applied to define soil texture, terrain elevation, and vegetation type (Fig. 1).

Initial total soil moisture and temperature are interpolated from NNRP data. Partitioning of the total soil moisture between the liquid and solid phase follows Mölders and Walsh (2004). At the bottom of the soil model, soil temperature and total moisture remain constant throughout the simulation.

3. Experimental design

a. GEP

Every surface flux is a function $\phi = f(\chi_1, \ldots, \chi_n)$ of one or more empirical parameters χ_i that are the mean