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A BASIC STUDY ON THE DEVOLOPMENT OF A SATELLITE DATA ASSIMILATION OF A LAND-ATMOSPHERE COUPLED SYSTEM

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The objective of this study is to develop a new downscaling approach, which can take into account atmospheric and land surface heterogeneities for a better precipitation prediction. We address the effect of land surface heterogeneity on the land-atmosphere interactions through coupling a land data assimilation system with a land-atmosphere coupled model. This system relies on a mesoscale model as atmospheric part, a Land Surface Scheme as a model operator, a Radiative Transfer Model as an observation operator, satellite data and the Simulated Annealing method for minimization. To assess the effectiveness of the new system, a 2-dimensional numerical experiment was carried out in a mesoscale area of the Tibetan Plateau. The results showed significant differences compared with standard regional atmospheric model outputs and were more consistent with satellite microwave brightness temperature observations that improved the spatial distribution of soil moisture, which strongly affected the convection systems.

Key Words: *Regional model, land surface scheme, data assimilation, remote sensing*

1. INTRODUCTION

Since GCMs are still unable to produce mesoscale and local atmospheric phenomena, Downscaling methods are necessary to bridge the gap between a GCM's scale, and other smaller modeling scales. One standard method is nesting using regional atmospheric model, but this approach is till now unable to reproduce local phenomena and extreme events [1)], because nesting does not include effects of both land surface and atmospheric heterogeneities.

In fact, soil moisture, as a surface boundary condition, plays important roles in the partition and estimation of surface fluxes, which in return drive the surface-atmosphere interaction. Thus it is essential that regional models include accurate and robust initial surface condition in order to capture regional atmospheric structure.

On the other hand, heterogeneity of atmospheric parameters especially precipitation, is also very important in atmospheric modeling considering its role in atmospheric thermal control through heat release and absorption.

In the way to overcome these problems related to both land surface (soil moisture) and atmosphere (precipitation), microwave remote sensing due to its global and frequents availability, is an appropriate tool for retrieving the spatial and temporal coverage of those parameters.

But due to the small penetration depth of these satellite measurements, in the case of soil moisture, they can't be directly used by regional models. Integrating satellite observation within a land surface scheme through a data assimilation process would provide soil moisture profiles physically consistent with regional models use.

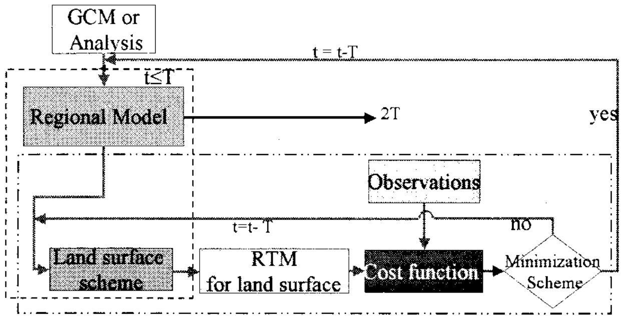

Fig1.Coupled assimilation scheme

So, to overcome the limitations related to the standard nesting method, a new downscaling approach by the assimilation of satellite brightness temperature within a coupled land-atmosphere variational scheme would be considered to take into account both atmospheric and land surface heterogeneities.

As a first step, in this paper; we investigate the effect of introducing land surface heterogeneities on land-atmosphere interactions and their mechanisms by coupling a land data assimilation system -to retrieve the whole soil moisture profile as initial surface condition- with a coupled land-atmosphere model.

2. A COUPLED LAND-ATMOSPHERE DATA ASSIMILATION SYSTEM

(1) General scheme

In this study, a land data assimilation system is coupled with a coupled land-atmosphere model. This is done by first coupling a land surface scheme with a regional model to guaranty fluxes interaction between the two systems, then introducing the surface hetrogeneity by assimilating the microwave remote sensing data into the land surface scheme and feeding back to the land-atmosphere coupled model (**Fig.1**), the scheme component are explained in the following section:

(2) The Land-atmosphere coupled model

a) The atmospheric module

As a mesoscale prediction model which include: a land surface scheme that can reproduce surface fluxes exchanges, and a cloud microphysics module that describe precipitation development, the Advanced Regional Prediction System ARPS elaborated by the Center for Analysis and Prediction of Storms at the University of Oklahoma was chosen for this study. It includes four packages: an atmospheric module, a land surface scheme, a radiation package and parameterization of cloud microphysics.

The atmospheric model is three-dimensional and nonhydrostatic, which describes the dynamics of air motion especially detect the generation of convection system's. The model is governed by momentum equations, thermodynamic equation, continuity equation, three/six transport equations of water-categories, and sub-grid-scale turbulent kinetic energy (TKE) sub model. These equations are transformed from physical domain to computational domain by the terrain-following coordinate and grid-stretching in vertical.

The cloud microphysics includes The NEM[2) (Schultz .P) scheme, the Kessler two-category liquid water scheme and the three-category ice scheme; also modified Kuo cumulus convection scheme is included as well as the Kain-Fritsch convective parameterization. The radiation package includes two options for solar radiation and long-wave atmospheric radiation estimation, a simple calculation option and, a radiative transfer parameterization one. More details about ARPS are found in Xue.et al[3)].

b) The land surface scheme

The land surface scheme originally included in ARPS is the ISBA (interaction between soil, biosphere, and atmosphere) developed by Noilhan and Planton [4)].

Considering the improvement of soil moisture and fluxes estimation, the revised Simple Biosphere Model 2 (SiB2)[5)] was chosen as an alternative to the ISBA.

In fact the SiB2 is a dual-source model in which fluxes are originating from soil surface and from vegetation canopy. It incorporates simple representations of vertical soil moisture transport, plant-controlled transpiration, interception, evaporation, infiltration, and sensible and ground heat fluxes through physically-based mechanisms.

SiB2 includes three soil layers: a surface soil layer of a few centimeters, which acts as a significant source of direct evaporation when moist; a root zone, which is the supplier of soil moisture to the roots and accounts for transpiration; and a deep soil layer, which acts as a source for hydrological base flow and upward recharge of the root zone.

Moreover SiB2 can handle satellite data to specify time varying phenological properties (LAI, FPAR).

(3) The Land data assimilation

The Land data assimilation system assimilates passive microwave radiometer observations of brightness temperature into the land surface scheme. The SiB2 is used as a model operator driven by the outputs of the coupled land-atmosphere model.

The Radiative Transfer Model (RTM), as an observation operator, calculates the brightness temerature which is then compared with the satellite observation through the following cost function:

$$J(x_0)=\frac{1}{2}\sum_{i=0}^{n}(H_i[M(x_0)]-y_i^o)^T R_i^{-1}(H_i[M(x_0)]-y_i^o)+ \frac{1}{2}(x_0-x_0^b)^T B^{-1}(x_0-x_0^b) \quad (1a)$$

here x and M are the model's state vector (Soil moistures at three different layers, surface temperature and canopy temperature) and its corresponding dynamics operator, respectively. y_i^0 is the radiometer observation at time t_i and H is an observation operator. Both H and M are nonlinear operators. R is the observational error covariance matrix and consists of instrumental and representativeness errors. B is an a priori weighting matrix, meant to approximate the error covariance matrix of background. Minimizing J obtains the optimal solution of above cost function[6].

The estimation of the error covariance matrices B and R is achieved by assuming unbiased Gaussian errors distributions. And the practical way to estimate the related error statistics is to assume that they are stationary over a period of time and uniform over a domain so they can be empirically estimated through a number of error realizations since errors cannot be observed directly. In this study, the specification of the matrix B was done using statistics on the departure between many 24h and 48h forecast, while for matrix R the measurement errors added to the brightness temperature values was assumed to have a standard deviation of 1K.

b) Radiative transfer model

Based on the emission behavior of dry soil and liquid water in the microwave region, a zero order physically-based radiative transfer model was developed by Koike et al[7], allowing the estimation of soil moisture from land surface expressed as follow:

$$\begin{aligned} T_{BT} &= T_{bs}e^{-\tau_c}e^{-\tau_r} \\ &+ (1-\varpi_c)(1-\exp(-\tau_c))T_c e^{-\tau_r} \\ &+ \sum_{i=1}^{N}(1-\varpi_{r_i})(e^{-\tau_{ri}})T_{r_i} \end{aligned} \quad (2a)$$

This equation represents the total emission and attenuation from the land surface (s), vegetation canopy (c), and rainfall drop (r). Continuously, T_{BT} is the brightness temperature at the measurement level, T_{bs} is the brightness temperature at the ground level, T is the actual temperature, τ is the optical depth, ω is the single scattering albedo, and N is the total number of rain drops. Given that the atmosphere and rain are transparent at lower frequencies, the above equation is rewriten as[8],

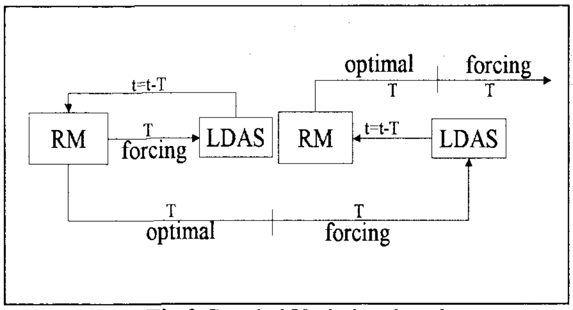

Fig.2 Coupled Variational cycle

$$\begin{aligned} T_{BT} &= T_e\{(1-r_{SP})\exp(-\tau_C) \\ &+ (1-\omega_c)(1-\exp(-\tau_C))(1+r_{SP}\exp(-\tau_C))\} \end{aligned} \quad (2b)$$

where, T_{BT}: is the brightness temperature; T_e: is the effective radiating temperature of the composite soil/vegetation medium; τ_C: vegetation optical depth; r_{Sp}: soil reflectivity; and, ω_c: vegetation single scattering albedo. The τ_C is a function of the vegetation water content w_e[9].

$$\tau_C = bw_e / \cos\theta \quad (2c)$$

where b is a coefficient that depends on the canopy structure and frequency. The soil reflectivity r_{Sp} can be expressed as a function of the dielectric constant of the soil ε_r, which is mainly dependent on our assimilation variable, the soil moisture, m_v [10].

$$\varepsilon_r^\alpha = 1+\frac{\rho_b}{\rho_s}(\varepsilon_s^\alpha - 1) + m_v^\beta \varepsilon_{fw}^\alpha - m_v \quad (2d)$$

where ρ_b is the soil bulk density; ρ_s is the soil specific density; ε_s is the complex dielectric constant of a soild soil having an extremely low moisture content with no energy loss or phase shift, and $\varepsilon_s \approx (4.7\text{-}0i)=4.7$; ε_{fw} is the dielectric constant of free water [11]; α and β are two empirical coefficients that depend on the soil texture[10]; and, m_v is the volumetric soil moisture.

b) Simulated Annealing

A heuristic optimization approach called Simulated Annealing (SA), which is capable of minimizing the variational cost function without using adjoint models is used in this system. SA allows avoiding problems due to strong non-linearity and discontinuity, in finding the global minimum in the hilly structure of the cost function.It is based on a analogous approach to the metal annealing in thermodynamics[12].

(4) Coupled assimilation cycle

In order to have a variational scheme[13], the coupled assimilation cycle is performed as following **Fig.2**:

First: The coupled model (RM) is run for an assimilation window time T to give initial guess and forcing parameters for the Land data assimilation system. We will consider this latter procedure as a land data assimilation system (LDAS) dependent to the coupled model.

Second: The LDAS run for one assimilation window which then feed back the new surface initial condition for the coupled model (RM) at time t = t -T

Third: The coupled model is run for 2 assimilation windows 2T, the 1st window output is then considered as the optimal one and the 2nd will serve as forcing for the next LDAS run.

3. NUMERICAL EXPERIMENT

The Tibetan plateau was chosen for this study firstly because it has a heterogenious soil moisture distribution resulted from its mountain-valley topographical structure, and an active convection system[14], and secondly because of its available comprehensive data sets collected during the GAME IOP 1998 project.

To investigate the effect of the coupled system on the different land surface and atmospheric outputs and mechanism, a 2-dimensionnel numerical experiment was preferred to a 3-dimensional one for its computational efficiency and its ability to effectively address the physical mechanisms rather than focusing on any observational validation.

On the other hand, knowing that the westerly is dominating the flow in the Tibetan Plateau which implies that the West-East direction have more homogenious atmospheric and surface conditions than the North-South direction[14], a 250 km section running south to north and centred at (31.750N, 91.635E) was selected as our experimental domain.

And to be able to trace the land surface heterogeneities and to detect the generation of convective systems, a 5 km spatial resolution was considered.

Moreover,due to its frequent precipitation events the wet monsoon period of July 5 to 10 1998 was chosen as experimental period.

The lateral Boundary conditions were set to periodic in order to avoid external and bigger scale atmospheric effect on our domain. And as for a fast and complete parametrization of the cloud the NEM scheme was applied with the Kain-Fritsch convective parametrization.

For the LSS (SiB2), the 3 soil layers were set to (0-4cm),(4-20cm) and up to 150cm for deep layer, the vegetation type in the Tibetan plateau correspond to grassland which is C4 class in SiB2 according to Sellers et al[5], other static parameters

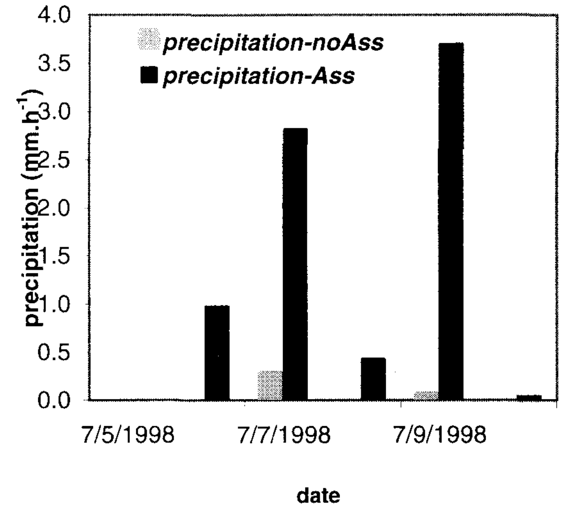

Fig.3 Spatially averaged Precipitation

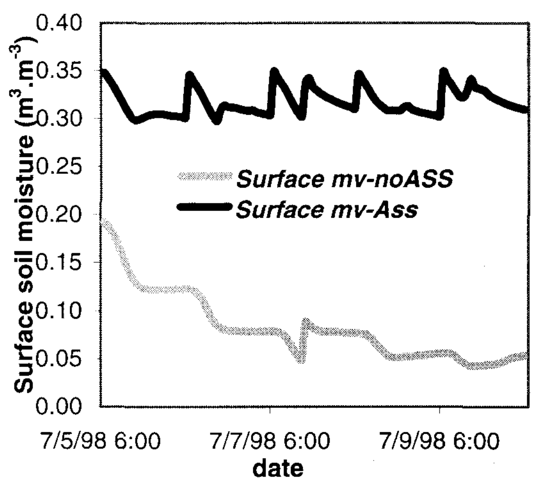

Fig.4 Spatially averaged Surface skin soil moisture

associeted with land cover and soil are also obtained from Sellers et al[5] and the Game-Tibet experiment.

The radiative transfer model parameters were also estimated according to the Game-Tibet experiment[15], and the TMI (TRMM Microwave Imager) brightness temperature of 10.65 & 19.35 GHz were used in the assimilation scheme.

4.RESULT AND DISCUSSION

The variational coupled land-atmosphere assimilation system was tested during the wet monsoon period for 5 days starting from July 5th to 10th, 1998, by two numerical simulations:

Standard nesting case: ARPS-SiB2 run without assimilation (noAss).

- ARPS-SiB2 run in a variational scheme with Land data assimilation (Ass).

Being a very complex variable in atmospheric

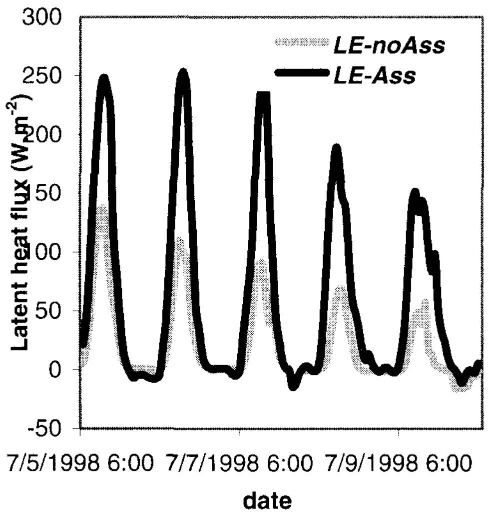

Fig.5 Spatially averaged Latent Heat flux

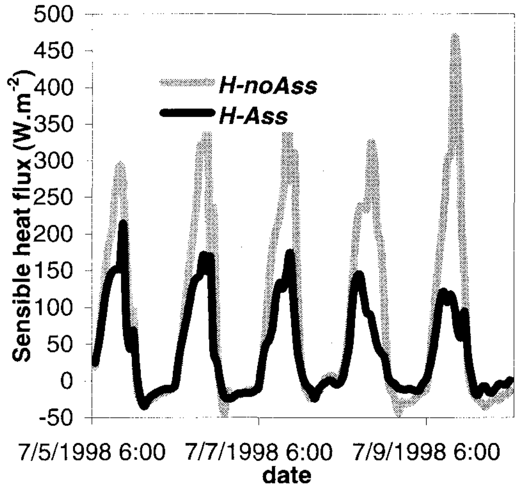

Fig.6 Spatially averaged Sensible Heat Flux

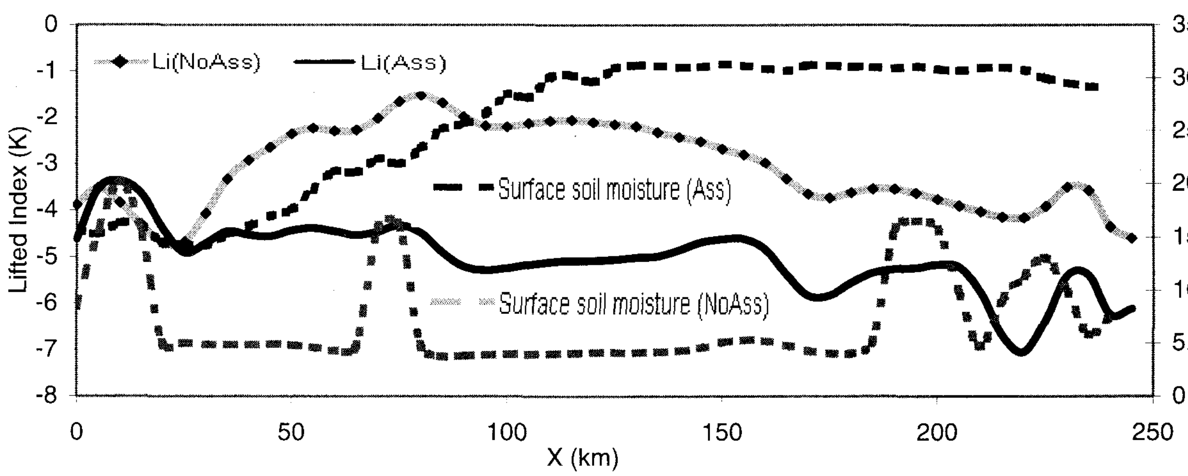

Fig.7 The effect assimilated soil moisture on stability

modeling due to its integration of the surface local state as well as both local and synoptic atmospheric state, precipitation is the most difficult variable to predict; in this experiment, the precipitation results (**Fig.3**) showed that although both cases started from the same wet atmospheric conditions, the (noAss) case generated much less precipitation than the assimilation (Ass) case because the soil condition was wetter due to its correction by the observed estimates through the land data assimilation scheme. In fact **Fig.4** shows that for Soil moisture, while in the noAss case it gradually dry up from 20% to less than 5%, in the assimilation cases it showed an increase of the soil moisture to higher values. This is mainly due to the reason that observed satellite data processed through the radiative transfer model gave higher and more realistic values to the coupled model. The higher amount of precipitation in the Ass case is also explained by the higher values of latent heat flux (**Fig.5**), and lower values of sensible heat flux (**Fig.6**): An increase of soil moisture tend to increase the latent heat flux and therefore atmospheric moisture while at the same time it decreases the sensible heat flux and therefore the air temperature, these changes work in the same direction to increase relative humidity making precipitation more intense and frequent.

This suggests that the precipitation generation in the Tibetan Plateau is strongly influenced by the soil moisture conditions.

To confirm this hypothesis, the local convection systems as driver of precipitation were also investigated. In fact, to check the influence of the surface condition on the local circulation and convection, its general condition of occurrence, which is stability, was analyzed in the following paragraph:

During the day, the sun heats the ground and evaporates water into the air, subsequently the air near the surface become unstable allowing air parcel

from the surface layer to rise and thus initiating the convection process, a useful measure of this process is the lifted Index which express the difference of the rising parcel temperature with its surrounding environment. In **Fig.7**, we plotted the spatial distribution of the lifted index and soil moisture during the noon of the second day of simulation for the Ass and noAss cases. In the Ass case, more atmospheric instability was observed (Li<-4) due to wet convection, which resulted in more frequent precipitations events. In fact in this case, vertical motion "triggers" initiated the deep convection and thus enhanced the vertical moisture transport.
While in the NoAss case, the convection systems were generally unable to produce cloud or precipitation even in some case the dynamical driving force for cloud formation was much stronger because of dry atmospheric and surface conditions.

By coupling a land data assimilation with a coupled land-atmosphere system in variational way, the soil moisture became more consistent with observed satellite brightness temperature. And through the consideration of the surface heterogeneities given by the satellite observation, the assimilation system provided better spatial distribution of soil moisture which had a strong influence on the mechanism of local convection and consequently precipitation events.

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