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Toward a new generation of satellite surface products?

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[1] Despite the abundance and variety of remote sensing measurements, land surface characterization from satellite observations is still very challenging. The links between the three sources of surface information, namely the satellite observations, the in situ measurements, and the land surface model outputs, are complex. Innovative techniques have to be developed to merge these information sources and optimize the use of satellite measurements for better surface products and more predictability. Concepts such as multi-instrument/multiparameter retrieval algorithms are discussed, as well as the synergetic use of satellite observations, model outputs, and in situ data. The need for careful satellite calibration is stressed, and the scaling problem is emphasized. Recent results are reviewed to indicate what the land surface remote sensing problems are and how they might be attacked. Two concrete applications are presented: an ‘‘all weather’’ retrieval of surface skin temperature from combined microwave and infrared observations and a soil moisture analysis from the merging of multisatellite observations and land surface model outputs. This paper is intended to stimulate debates and collaborations between the land surface modelers and the satellite remote sensing community for the design of the next generation of land surface products.

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1. Introduction

[2] In addition to their key role in many applications (e.g., hydrology or agriculture), land surface satellite-derived products are very important in the framework of Land Surface Models (LSM): first as inputs, to initialize the models, to serve as boundary conditions, or for assimilation; second, to validate the model outputs in order to complement the in situ measurements that are spatially and temporally limited. Depending on their use in the LSM and depending on the model application (e.g., energy-water exchanges, biochemistry, ecosystem function), the set of necessary land parameters differs as well as their spatial and temporal requirements.

[3] The International Satellite Land Surface Climatology Project (ISLSCP), started in 1983, provides a large number of global gridded land surface data sets, related to land cover, hydrometeorology, radiation, and soils, over 10 years (more for some variables) with spatial resolution from 0.25° to 1° (see *Sellers et al.* [1995], *Hall et al.* [1995], and the other papers in this special ISLSCP issue). The available surface products are not all estimated from satellite observations, some being derived from meteorological reanalysis (e.g., ECMWF or NCEP reanalysis) or from upscaling of in situ measurements (e.g., the Climate Research Unit near surface information or the GlobalView CO_2 and CH_4 products). Most satellite products directly derived from the ISLSCP activity focus on the vegetation and land cover characterization, using essentially visible and near infrared observations.

[4] A wealth of Earth satellite observations is now available, over long time series, covering the entire globe and providing a large diversity of information, from the visible to the microwave. However, land surface characterization from satellite observations is still very challenging:

[5] 1. The signal received by the satellite is generally the combination of contributions from different surface characteristics (vegetation, soil, soil moisture, snow, roughness, among others) and disentangling these various effects to quantify one variable is often very difficult. In addition, depending on the wavelength, the atmospheric contamination might need to be subtracted.

[6] 2. Limitations also come from the fact that no Radiative Transfer Model (RTM) for soil/vegetation/snow is satisfactory for global applications and for each wavelength range. Empirical relationships are often fitted locally for a given frequency range and their extension is questionable. In addition, even if such RTM existed, it would need a large variety of ancillary information that are not available at a global scale.

[7] 3. The spatial resolution of the satellite observations is not always compatible with the model scales, especially when local processes are involved. Within a given satellite field-of-view, the land surface parameters can exhibit large spatial variability (e.g., soil moisture or vegetation), making

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it difficult to compare the satellite estimates with in situ point measurements or with model outputs. Aggregation and disaggregation techniques need to be developed in order to change scales.

[8] 4. Up to recently, there was no satellite optimized for the observations of key surface parameters like the soil moisture. This means that the designs of the satellite payloads are not optimal for the retrieval of these parameters in terms of frequency selection or spatial/temporal resolution and as a consequence, estimating these parameters is more difficult. The GRACE mission launched in 2002 [*Tapley et al.*, 2004] is the first mission specifically designed to quantify the terrestrial hydrological cycle, including the aquifer, the soil moisture, and the snow pack, through the gravimetric measurements of the vertically integrated water mass changes. The Advanced Microwave Scanning Radiometer–EOS (AMSR-E) is a passive microwave radiometer on board the Aqua satellite, launched in 2002. It observes atmospheric, land, oceanic, and cryospheric parameters, including soil moisture [*Njoku et al.*, 2003]. The European SMOS [*Kerr et al.*, 2001] is a soil moisture dedicated mission with measurements at low microwave frequencies (L-band) that will be launched in 2007.

[9] Figure 1 evidences the complex relationships between the three sources of land surface information: the satellite observations, the LSM, and the in situ measurements. The objective of this paper is to analyze these links and suggest methodologies to derive optimum land surface information from the combination of these three sources.

[10] Since the start of the ISLSCP, the needs of the land surface modelers in terms of satellite-derived products have grown dramatically. *Entekhabi et al.* [1999] proposed an agenda to answer the priority science questions in hydrology, and it included optimizing the use of remote sensing products. As an example, calibration of a model parameterization was traditionally performed over a given region and for a given period of time, using comparisons between one model output and the corresponding in situ measurements. There is today a demand to account for the full variability of the model dynamics, temporally and spatially, and simultaneously for different outputs of the model [*McCabe et al.*, 2005]. In addition, several models are now often intercompared (e.g., the Global Soil Wetness Project (GSWP) [*Entin et al.*, 1999]) and multimodel approaches tend to evaluate the model uncertainties by using outputs from different models [*Murphy et al.*, 2004]. In these cases, the role of the satellite observations could be to diagnose problems in one model (or to invalidate one model), not to validate a model: this difference in perspective can induce significant changes in the way the satellite/model relationship is considered.

[11] The three sources of land surface information have their own limitations. One model using different sources of inputs for the same variable can produce differences in outputs that are difficult to explain [e.g., *Schaake et al.*, 2004]. Even separating the effects of erroneous forcing from a lack of realism in the model is not obvious [*Robock et al.*, 1998]. Model intercomparisons have shown that even when fed with the same inputs, the model outputs can be significantly different (e.g., the Project for Intercomparison of Land Surface Parameterization Schemes (PILPS) [*Henderson-Sellers et al.*, 1995]). Although often considered as the "truth," in situ measurements are by nature very local, are often labor intensive, and for the measurements of some variables the experimental protocol can vary from a campaign to the other with resulting biases. Satellite remote sensing is clearly the solution for large-scale and long-term calibration of the model as it encompasses all the variability of the land surface system. However, as already stressed, developments of the satellite retrieval is often difficult and if several surface parameters have to be examined simultaneously, consistency is necessary between the retrieved parameters.

[12] How to reconcile and merge the three sources of information for a better final product and for more predictability? How to optimize the use of satellite observations for that goal?

[13] 1. Satellite retrieval is very often an ill-posed problem. Retrieval schemes have to optimize the use of complementary observations and ancillary data. Merging of different satellite observations is an attractive option.

[14] 2. For an efficient use of the satellite information in the models, consistency has to be reached between the three sources of land surface information, as well as between the different satellite-derived parameters if several of them have to be used. The simultaneous use of the three spatially different information requires special attention to the scaling problem.

[15] 3. Each information source having its own errors, it is important to design techniques that can handle these uncertainties.

[16] 4. The satellite derived parameters have to have consistent characteristics globally and over long time series, especially for climate monitoring objectives, thus imposing strong constraint on the satellite intercalibration.

[17] These new challenges make it necessary to develop new strategies. In this paper, we will focus on the methodologies to put in place to optimize the combined use of satellite, model, and in situ data, and in particular, to optimize the use of satellite data in the framework of land surface modeling. We do not intend to examine each issue and to suggest solution for each one, but rather to suggest a few elements of reflection, describe few general strategies, and list original efforts to make progress.

[18] We will first discuss the different possibilities and describe some promising methodologies. The discussion will be limited to schemes that can be realistically implemented at a global scale. Second, examples of derived parameters using these types of techniques will be briefly presented in order to illustrate the concepts. Although these examples concern the hydrometeorology, similar methodologies can be applied to other parameters as well. The conclusion tends to describe, pragmatically, how to proceed, insisting on the necessity of a dialog between modelers and satellite product experts to optimize the use of satellite observations in the land surface modeling framework.

2. Retrieval Methodologies

[19] The radiation that impinges on the satellite is often the result of several contributions from the land surface. Even for a homogeneous field-of-view, the satellite will receive radiation from the soil, the vegetation, and potentially the snow. The problem is even worse for a heteroge-

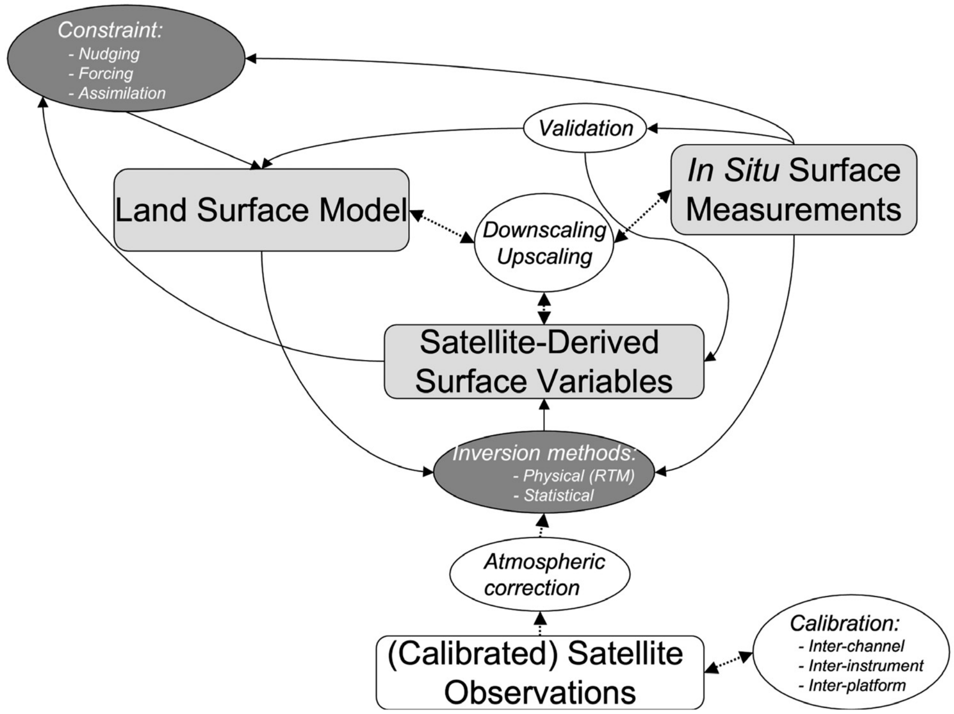

Figure 1. Schematic representation of the complex links between the three sources of land surface information.

neous pixel. Depending on the wavelength, contamination from the atmosphere (gases, clouds, or rain) might also interfere with the signal and needs to be accounted for by using ancillary atmospheric data sets from satellites, models, or mixed outputs (e.g., reanalysis). Retrieval of land surface parameters from the satellite measurement is thus often an ill-posed problem that can require multiple and independent measurements as well as quality a priori information in order to disentangle the mixing effects in the observations.

[20] There are different solutions to retrieve one or multiple land surface parameters, using one or several instruments from one or different satellites at the same time. The various solutions are now discussed, from the simplest to the most complex ones.

2.1. Satellite-Only Methods

2.1.1. One Instrument/Multi-Instrument

[21] Methodologies are developed that use one type of wavelengths, measured on board one satellite to derive a single land surface parameter. In order to suppress ambiguities related to the contribution from other surface parameters, these algorithms exploit the complementarity of close frequency bands, of various incidence angles or the temporal information available from consecutive measurements. The Normalized Difference Vegetation Index (NDVI) for instance combines visible and near infrared observations to isolate the effect of the vegetation photosynthetic activity on the absorption in the visible and limit the contribution from the soil [e.g., *Tucker*, 1979; *Tucker et al.*, 1985]. The soil moisture index developed by *Wagner et al.* [2003] from the ERS scatterometer observations at 5.25 GHz capitalizes on the multiangle observations and the temporal evolution of the signal to subtract the vegetation effect.

[22] These methods have the advantage to provide parameters that are independent from other sources of information, for potential comparison with other estimates. However, the apparent simplicity of the algorithm should not mask specific difficulties, like the treatment of the atmospheric contamination in the case of the NDVI [*Gutman*, 1999]. In addition, these methodologies can suffer from their limited spectral range. This can translate into saturation effect: for instance, although the NDVI offers a good sensitivity over crops and grasslands, it tends to saturate over denser vegetation types. The retrieval can also experience interference with other surface parameters. As an example, the estimation of snow depth from the differences of two passive microwave channels is hampered by contamination from vegetation as well as by the snow metamorphism during the winter season [*Kelly et al.*, 2003]. Since the variations of the contaminating variables are treated implicitly as random noise, they affect the quality of the retrieved quantity.

[23] A strategy to avoid such deficiencies consists in gathering satellite observations in different wavelength ranges that have different sensitivities to the various surface parameters. The synergetic use of satellite observations helps separate the contribution of the various parameters. For example, in clear sky condition, passive microwave signal in window channels depends on both the surface temperature and the surface emissivity: another source of information like thermal infrared measurements can help untangle the contribution of these two parameters [*Aires et al.*, 2001].

[24] The sensitivity of the different satellite observations for a given parameter has to be investigated, to analyze their complementarity, and to assess the ability of combinations of these satellite measurements for the estimation of the parameter. A detailed information content analysis has to be performed, on a global basis, to select the optimum satellite information to be merged.

[25] The estimation of one parameter using several wavelength ranges can involve one satellite only if the various instruments are on the same platform. This could be the case for precipitation retrievals that would use the synergy between the radar and the radiometer on board the Tropical Rain Measuring Mission (TRMM). In the case of multiplatforms, the appropriate time window has to be selected to allow meaningful merging of the information. In both cases, the satellite measurements from different instruments have to be collocated in space, with potential problems related to the various spatial resolutions.

[26] An additional benefit of satellite data fusion is that the retrievals are more robust to noise since they use more information. They can also be less sensitive to missing data in one sensor. Furthermore, it can help fill up temporal and spatial gaps. This is the case when infrared observations from geostationary satellites are used to complement the rain estimates from microwave instrument on board polar satellites like in GPCP [*Adler et al.*, 2003]. It can also help "calibrate" one retrieval with the other: this is the case when the passive microwave rain retrieval is used to "calibrate" the rain estimates from infrared measurements.

[27] A multi-instrument retrieval scheme in this paper refers to an algorithm that uses simultaneously or hierarchically the observations of two or more instruments in order to benefit from the instrument synergy. The a posteriori combination of retrievals derived independently from each instrument does not constitute a multi-instrument retrieval since there is no benefit from the synergy of instruments in this case.

2.1.2. One Parameter/Multiparameter

[28] For the retrieval of a surface parameter (e.g., the soil moisture), it is often necessary to use an auxiliary information (such as surface temperature). This auxiliary information can be derived from another satellite information, and no control is possible on the coherency between these two quantities. Independent and inconsistent calibration or assumptions can be made for the two retrievals. These various parameters put together can lack coherency, or contrarily be too much dependent, because they are derived from a very limited number of observations. Even if the independence of the retrieved parameters was satisfactory and would allow for the intercomparison of the retrieved products, it is clear that the next step would consist in using together multiple satellite observations and benefit from their synergy in the retrieval of multiple surface parameters. One major advantage of merging satellite observations for multiple parameter retrieval is that the various retrieved parameters are coherent. This means that the same set of assumptions is adopted for the two retrieved parameters, that these assumptions are controlled and known. This also constrains part of the incoherencies among parameters (incompatible surface temperature and soil moisture for instance).

[29] Once the satellite observations are merged, in spatiotemporal collocation, two basic strategies can be used: the retrieval of the different parameters can be hierarchical or simultaneous. In a hierarchical scheme, a major surface parameter (e.g., the surface temperature) is first retrieved by using all available satellite observations. Then, this retrieved parameter is used together with the satellite measurements for the subsequent retrieval of another variable (e.g., soil moisture). This approach uses the fact that some surface parameters are dependent on others and that some specific retrieval algorithms need to follow this dependency structure. As an example, within the International Satellite Cloud Climatology Project (ISCCP) [*Rossow and Schiffer*, 1999], using IR observations from both geostationary and polar satellites, the cloud presence is first analyzed and then, for clear scenes, the surface skin temperature is estimated. An inconvenience of this scheme is the cascade of errors in the suite of retrieval algorithms. The other approach consists in performing the multiparameter retrieval at the same time in the algorithm. One advantage of this strategy is that the uncertainty characterization is easier. The solution is determined simultaneously for each parameter (called "global solution"). This is preferable from an optimization point of view than a solution built piece by piece. The optimization process might be more difficult, but it is easier to obtain a compromise choosing a solution that satisfies all the satellite observations.

[30] A multiparameter retrieval scheme refers to the simultaneous or hierarchical retrieval of two or more parameters using a single algorithm in order to benefit from the coherency among the retrieved variables. Again, the a posteriori association of various parameters retrieved by independent algorithms does not constitute a multiparameter retrieval because the dependence among retrieved parameters is not exploited.

2.1.3. Illustration With a Synthetic Example

[31] To illustrate the two concepts of multi-instrument and multiparameter retrievals, a highly idealized example is presented here that uses information content ideas [*Tarantola*, 1987]. The general principles are developed in the classical references [*Twomey*, 1977; *Rodgers*, 1976, 2000]. We use a bivariate/two-measurement linear case (or a linearized nonlinear model):

$$F = A \cdot f + e \tag{1}$$

where $f = (f_1, f_2)$ is the state vector composed by two geophysical variables (with covariance matrix S_f) that we intend to retrieve from the measurements $F = (F_1, F_2)$, $e = (e_1, e_2)$ is the measurement noise (with covariance matrix S_e) and A is the forward model (linear in this case) that needs to be inverted.

[32] A Bayesian solution to the inverse problem is, under Gaussian hypothesis:

$$f = f_g + \left[A' \cdot S_e{}^{-1} \cdot A + S_f^{-1}\right]^{-1} \cdot A' \cdot S_e^{-1} \cdot \left(F - F_g\right) \tag{2}$$

where f_g is the first guess for f to which is associated the measurement F_g, A' is the transpose of matrix A, S_e is the covariance matrix of the measurement errors e, and S_f is

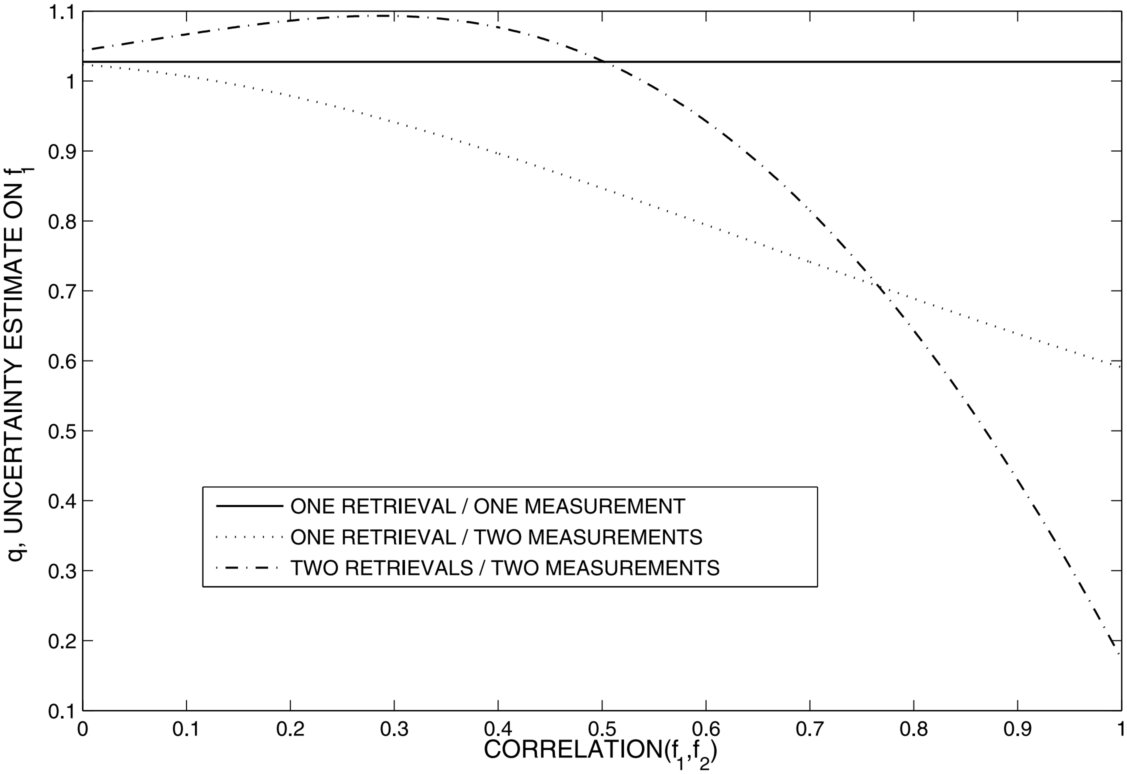

Figure 2. Sensitivity of the error estimate to $cor(f_1, f_2)$, the correlation between the two geophysical variables to retrieve: for one retrieval and one measurement (solid line), for one retrieval and two measurements (dotted line), and for two retrievals and two measurements (dot-dashed line).

the covariance matrix of the first guess errors [*Chédin et al.*, 1985]. The uncertainty matrix on this retrieval is:

$$Q = \left[A' \cdot S_e^{-1} \cdot A + S_f^{-1}\right]^{-1} \quad (3)$$

For illustrative purpose, we use the following numerical values:

$$S_f = \begin{pmatrix} 3 & cor(f_1,f_2) \cdot \sqrt{3}\sqrt{4} \\ cor(f_1,f_2) \cdot \sqrt{3}\sqrt{4} & 4 \end{pmatrix}$$

$$S_e = \begin{pmatrix} 1 & 0 \\ 0 & 2 \end{pmatrix}$$

and

$$A = \begin{pmatrix} 0.8 & coef(f_1, F_2) \\ 0.1 & 0.9 \end{pmatrix}$$

The values of S_f and S_e impose that $coef(f_1, F_2) = [cor(f_1, f_2) - 0.08]/0.9$. Only $cor(f_1, f_2)$, the correlation between the two geophysical variables f_1 and f_2, is now varying.

[33] This formulation allows to study the sensitivity of $q = Q(1,1)$ (i.e., the uncertainty estimate on f_1) to the parameter $cor(f_1,f_2)$. In Figure 2, three curves for three different retrieval configurations are represented:

[34] 1. In case 1, only one observation F_1 and one retrieval f_1 are considered in the top curve (continuous line). Since the measurement F_2 is not used here for the retrieval of f_1, $coef(f_1,F_2)$ has no impact on q and the curve is flat with an uncertainty level at:

$$q = \left(0.8 \cdot 1^{-1} \cdot 0.8 + 1/3\right)^{-1} = 1.0309$$

[35] 2. In case 2, a unique variable f_1 is retrieved but the two observations $F = (F_1, F_2)$ are used in the dotted curve. As expected, the higher $cor(f_1,f_2)$ is, the higher $coef(f_1, F_2)$ is, and the lower the uncertainty q becomes.

[36] 3. In case 3, the dotted/dashed curve is for the full problem that considers the two measurements $F = (F_1, F_2)$ and the two variables to be retrieved $f = (f_1, f_2)$. In this configuration, again, the higher $coef(f_1, F_2)$ is, the lower the uncertainty becomes. Furthermore, it can be noticed that when $cor(f_1,f_2)$ is lower than about 0.6, retrieving only f_1 gives better results than retrieving both geophysical variables f_1 and f_2, meaning that the retrieval of f_1 is hampered, part of the information $F = (F_1, F_2)$ being "diverted" to retrieve f_2 which reduces the quality of the f_1 retrieval. When $cor(f_1, f_2)$ is higher than 0.6, the uncertainty on f_1, using the same measurements $F = (F_1, F_2)$, can decrease dramatically and make a significant difference with case 2. This improvement is only due to the simultaneous retrieval of the second geophysical variable f_2. The explanation is that f_1 being correlated to f_2 and the second measurement F_2 being a f_2 information-carrier, the retrieval of f_1 benefits from this indirect relationship.

[37] This example illustrates well how information about the dependencies among the geophysical variables can be extremely beneficial for the retrieval.

[38] It has been shown that multi-instruments cannot bring improvements in some situations (no synergy) but that it will not degrade results. On the contrary, the use of multiparameter techniques can be detrimental (when there is independence of the retrieved parameters) but is extremely beneficial in some cases (strong correlations among geophysical variables). No dogma in the use of such or such methodology should be imposed: each application has its specificities and the needs have to be carefully analyzed to design the optimum retrieval scheme. The good news is that with the kind of simple tools used in this section, we can quantify the possible synergies and therefore the type of approach to be used.

[39] The example provided here is a linear model, or the linearization of a nonlinear model. It should be pointed out that the linear methods could be insufficient because the relationships can be highly nonlinear among the surface variables. This is particularly true with surface problems that undergo high discontinuities, with threshold effects and very different interactions depending upon the situations. This means that the synergy can be different in some situations and the use of nonlinear techniques is a plus.

2.1.4. Technical Implications for the Multivariate Case

[40] In this section, we comment on some technical implications arising when multivariate strategies are used. The major requirement for this kind of approaches is the exploitation of the dependencies between the measurements, that need to be coherent, and between the geophysical variables to be retrieved.

[41] We first consider multichannel, multi-instrument or multiplatform algorithms. Such retrieval strategies need to use coherent measurements. Is it possible to rely on RTMs to elaborate physically based retrieval algorithms? The radiation emerging from the surface is sensitive to a large number of surface parameters, through intricate mechanisms for each surface type. For instance, even for a bare soil in the microwave, the response will depend upon the surface roughness (at small and large topographic scales), upon the dielectric properties of the medium (related to the soil composition, texture, and humidity), and potentially upon volume scattering below the surface. In addition, it is also related to the observation characteristics, its wavelength, its incidence angle, and its polarization among other parameters. The interactions between the surface and the radiation are complex to model, being dependent on a large number of highly variable and difficultly accessible parameters. Efforts have been made to better understand the mechanisms responsible for the interaction between the surface and the radiation, from both theoretical analysis and field experiments, at all the wavelength ranges of interest. Ground or airborne based measurements have also been performed to help develop the RTM. The resulting RTMs, even the most elaborated ones, still have difficulties to perform well for all environments at the global scale, although they can be efficient for the specific conditions for which they have been tuned. Even assuming that a perfect land surface RTM exists for a given wavelength range, would the inputs it will require (e.g., soil composition, texture, surface roughness, vegetation density, geometry, water content) be available on a global basis with a resolution compatible with the satellite one and with the required accuracy? The problem is even more complex when using multiple instruments that cover different wavelength ranges: the RTM should be coherent and perform identically well over the full frequency domain. Even for the same wavelength range, it can be difficult to simulate the radiative transfer with the same accuracy when combining active and passive modes. For instance, there are very few RTMs developed to simulate both the active and passive responses of the surface in the microwave for a joint analysis of microwave radiometer and radar observations.

[42] Most classical inversion techniques are able, and were actually designed to deal with multiparameter retrievals. In equation (2), an inversion formula was given, describing the Bayesian estimator with Gaussian hypotheses. Classical variational assimilation or iterative methods are also based on the same estimator. Neural Network (NN) schemes are technically different but are based on the minimization of similar quality criteria, so the essence of the estimation is very similar, and the same type of a priori information is required (e.g., measurement characteristics, statistics on the variable dependences). Each technique needs to use an information describing the dependencies among the physical variables to be retrieved. (First guess error dependencies are also very important, for example in variational assimilation [*Rabier et al.*, 1998].) When a physical relationship linking two or more of the variables exists, it is extremely interesting to use it in the retrieval process. For example, during the retrieval of atmospheric water vapor, if one instrument provides information on the total vertical content and another instrument gives a profile description, then the total content can constrain the profile retrieval. This type of physical constraints can be used in each step of the iterative inversion methods or it can be added as an additional strong constraint in the quality criterion used by statistical techniques. Most of the time, however, the dependencies are described statistically. In the estimator of equation (2) (Bayesian, iterative, or variational assimilation), it is given by the covariance matrix S_f. For neural networks, the learning data set describes implicitly the various complex relationships and the NN disentangles them during the learning stage to reproduce them adequately. This approach could appear easier to use because no hypothesis is formerly required a priori. In reality, extreme care needs to be exercised during the development of the learning data set, with sometimes the use of complex a priori information. For example, in the work by *Aires et al.* [2001] the distributions of liquid water cloud top temperature are carefully analyzed and then used in the development of the learning data set.

[43] Finally, as already mentioned in the previous section, the relationships between the geophysical variables can be dependent on the situation. This is referred to as the nonlinearity of the a priori relationship and the retrieval scheme has to be flexible enough to account for it. A NN inversion is by nature designed to deal with this difficulty. For classical approaches, a sensitivity analysis of the a priori information must be conducted. For example, the first guess errors on specific humidity are dependent on the atmospheric situation and for atmo-

spheric temperature, a different covariance matrix is used for each 10° latitude bands [*Rabier et al.*, 1998].

2.2. In Situ Measurements of Land Surface Model Outputs to Help Satellite Retrievals

2.2.1. In Situ Measurements

[44] The complexity of surface parameter retrieval together with the inadequacy of current surface RTMs make the use of in situ measurements an attractive source of additional information.

[45] First, in situ measurements are essential to understand at a local and detailed scale how the parameters interact with the radiation. This is generally done during well-documented measurement campaigns that combine in situ measurements of the land parameters with coincident observations from ground-based or airborne instruments (e.g., radiometers, radars, lidars). However, this analysis can also be performed with coincident in situ and satellite measurements: it enables comparisons over longer time series and more diverse environments, provided that a large data bank of consistent in situ measurements exists for the variable of interest. This exercise has been recently conducted for the surface soil moisture using the Global Soil Moisture Data Bank [*Robock et al.*, 2000] and a suite of satellite observations [*Prigent et al.*, 2005a], as well as for the snow depth using a large collection of in situ measurements in the Northern Hemisphere in coincidence with satellite measurements [*Cordisco et al.*, 2006].

[46] Second, in situ measurements can also be exploited for the parameterization of the retrieval algorithms. Many surface retrieval algorithms are actually based on the parameterization (also called calibration) of regression models between the satellite observation and the surface variable of interest. When performed on a reduced number of locations during a restricted period of time, the validity of the parameterization for other conditions is questionable. For instance, when developing a soil moisture algorithm, the large-scale variability of the vegetation can be misrepresented by a parameterization performed on a local basis. For a retrieval algorithm to be valid globally, its parameterization needs to use as diverse as possible in situ measurements to sample local and large-scale variabilities. The parameterization data set should account for the spatial and temporal variability of the parameters in the satellite observations. Note that depending on the variable, the relevant temporal scale can span from the hour to several years.

[47] Finally, in situ measurements are necessary for the evaluation of the retrieval algorithms. This imposes that independent measurements are available for the parameterization of the algorithm and for its evaluation. A portion of the in situ measurement data set is used to parameterize the retrieval algorithm (i.e., the learning data set) and the remaining part can be exploited to validate it (i.e., the testing data set).

[48] One essential difficulty in using in situ measurements is related to the scaling problems. Models and satellite measurements have different spatial resolutions, which makes difficult the direct comparison with point in situ measurements. The link has to be found between the two scales (i.e., local measurements and large pixels from models or satellite observations) (see section 3.3).

[49] In addition, except for well-organized measurement campaigns [e.g., *Leese et al.*, 2003], the large majority of in situ measurements performed regularly by multiple institutions is very difficult to access, and can show very different accuracy. An effort has to be done to create homogeneous and quality-controlled collections of the key surface variables that are not part of the weather station routine measurements. *Entekhabi et al.* [1999] already insist on this necessity for hydrological purposes. The Global Soil Moisture Data Bank [*Robock et al.*, 2000] is such a database for the soil moisture and similar efforts should be encouraged for other variables.

2.2.2. Land Surface Models

[50] More and more studies couple LSM outputs and satellite observations to help solve the retrieval of land surface parameters by using the relationships between surface variables and satellite observations. The inversion problem being ill-posed, the LSM can provide auxiliary information that helps constrain the retrieval.

[51] Outputs from a LSM can be directly adopted as auxiliary input information to the retrieval algorithm. For instance, a snow depth retrieval scheme could require a LSM derived surface temperature information as input [*Boone et al.*, 2006].

[52] Differently, LSM outputs can be used to generate databases from which a retrieval algorithm is derived. For example, *Lakshmi et al.* [1997] adapt a LSM and couple it to a RTM to simulate soil moisture and the corresponding microwave responses that could be the basis for a retrieval algorithm. In the work by *Aires et al.* [2005], the link between the modeled surface variables and the satellite observations is statistical: a database of coincident multi-satellite observations and soil moisture model outputs is created and an updated estimation of the soil moisture is deduced. In these cases, the retrieval is clearly linked to a specific LSM.

[53] The LSM can also be part of an iterative least square inversion schemes. For instance, *Ramillien et al.* [2005] develop such a method based on the LaD model [*Milly and Shmakin*, 2002] to separate the contribution of the various water reservoirs (surface water, soil moisture, ground-water, and snow pack) that are vertically integrated within GRACE gravimetric measurements.

[54] The important message is that the choices should be clearly stated so that the user of the retrieved products knows about the different assumptions and about the potential links between the variables, other instruments, and other variables. Otherwise, satellite retrieved parameters could be illegitimately used to validate LSM from which they are not independent.

2.3. Constraining Land Surface Models With Satellite Data

[55] Methodologies have to be developed to combine optimally satellite observations and land surface schemes in order to produce better final products and more predictability. As already mentioned, it is very difficult to simulate the satellite observations directly from the surface parameters (e.g., soil moisture, vegetation, snow) using a RTM. As a consequence, traditional direct assimilation of raw satellite observations is difficult. Satellite remote sensing is a solution to constrain the model for

one or several variables over large-scale and long time periods. The retrieval parameter can be assimilated as a state variable in the model, or as a geophysical variable linked physically to the state variables of the model (i.e., wind, temperature, humidity, surface fluxes for soil moisture retrievals [*Mitchell et al.*, 2004]).

[56] The recent interest for techniques that evaluate simultaneously different outputs predicted by the model [*Gupta et al.*, 1999; *Franks et al.*, 1999; *Beven and Freer*, 2001; *McCabe et al.*, 2005] is driven by the fact that the calibration of one variable only can bias the model toward that variable while the others are not well reproduced. Multiobjective calibration tends to evaluate the set of model parameterizations that best reproduces multiple outputs. However, several parameter combinations can reproduce similarly different sets of one output (the "equifinality" as defined by *Beven and Freer* [2001]). Likelihood methods such as the Generalized Likelihood Uncertainty Estimation (GLUE) are developed within the LSMs to select the parameterization that fits the observed parameters better [*McCabe et al.*, 2005].

[57] Variational assimilation is a particular technique to perform the assimilation of observations (satellite observations, weather station measurements, radiosondes) into a numerical model [*Ide et al.*, 1997]. Kalman filtering is another technique that emphasizes the sequential assimilation in forecasting problems. In the work by *Reichle et al.* [2002a], soil moisture is assimilated using the ensemble Kalman filter, an extension that uses ensembles of runs to estimate the error covariances instead of propagating them theoretically which is computationally intensive. An experiment in similar conditions is conducted by *Reichle et al.* [2002b] to test the extended Kalman filter designed for nonlinear problems. Nudging is also a possible way to constrain models with observations [*Mitchell et al.*, 2004].

[58] A simpler approach consists also in using the satellite remote sensing soil moisture to initialize climate model simulations [*Walker and Houser*, 2001]. Other more specialized methods have been developed. For example, in the work by *Cordisco et al.* [2006] a surface model is calibrated by using in situ snow depth measurements from a network of stations.

[59] For use in LSM, the absolute requirements on the satellite retrievals in terms of accuracy or spatial and temporal resolutions are often unclear (see the analysis for soil moisture in the work by *Walker and Houser* [2004]). However, there is a clear demand for consistency between the satellite retrievals and the model variables, prior to the use of the satellite retrievals within the model. *Berg et al.* [2003] insist on the impact of potential biases in data sets to force models and recommend the implementation of bias reduction scheme to reduce the associated errors. *Reichle et al.* [2004] compare soil moisture estimates from Scanning Multichannel Microwave Radiometer, modeled soil moistures, and in situ measurements, for nine years all over the globe. The time averaged fields from the model and the satellite agree well but the magnitude and variability of the soil moisture estimates are very different. Local bias correction or rescaling have to be performed before assimilation of the satellite data into LSMs: tuning the local statistics of the satellite retrievals to the model ones can be a solution.

[60] Classical variational assimilation in surface models suffers from limitations. First, surface parameters can have a very strong spatial inhomogeneities with strong discontinuities. Second, relation between surface parameters and observations can be highly nonlinear. Lastly, no RTM dedicated to surface is fully satisfactory. For all these reasons, we believe that special techniques need to be developed when using observations into a surface model. Instead of the traditional approach that assimilates directly the satellite observations, we suggest to use the inverse model derived from a remote sensing algorithm. This has various benefits: (1) It avoids the estimation of the Jacobians of the RTM, (2) it does not add up uncertainties from the forward model to the uncertainties from the Jacobians, and (3) it makes it possible to work directly with the surface state variables that are more directly related to the numerical model.

3. Ancillary Data Processing

[61] Several processing steps are often necessary, especially when homogeneous long time periods of accurate global products are expected, derived from multisatellite approaches. Although sometimes neglected and often strenuous to perform, these processings are crucial if quality land surface parameters are required. It is particularly important to quantify the errors associated to these treatments (or their absence) and to document them well.

3.1. Satellite Calibration

[62] A reliable instrument calibration is a prerequisite for any remote sensing algorithm. The calibration has to be stable over long time period and free from any biases. For instance, *Colton and Poe* [1999] performed significant intercalibration work on the series of SSM/I microwave instruments. Even if only one type of instrument is involved, satellite drift within the life span of one given satellite and satellite intercalibration between successive satellites of the same family can be very difficult to achieve. The analysis of the AVHRR NDVI over long time series suffers from these difficulties [*Gutman*, 1999]. In addition, when trying to cover the whole globe and the full diurnal cycle, the simultaneous use of several satellite types is necessary and stringent constraints are then imposed on the satellite intercalibration. For instance, the ISCCP [*Rossow and Schiffer*, 1999] that supplies global cloud information every three hours, combines all the visible and infrared observations from the NOAA polar orbiters and the geostationary satellites to provide both the spatial and temporal coverages. A huge effort has been dedicated to the accurate radiance calibration and intercalibration of all the instruments over the long time series to archive the ISCCP results [*Brest et al.*, 1997].

[63] In addition to a detailed and systematic analysis of each sensor calibration from an engineering point of view, various methodologies have to be developed to intercalibrate the observations. In order to perform multiparameter retrievals from multiple satellite observations, the calibration of the instruments needs to be consistent at several levels. First, the calibration has to be consistent among the various channels of a given instrument. From an information theory point of view, it is not optimal to calibrate

independently the various channels (essentially by monitoring the mean and standard deviation over the time, or by indirect comparison with in situ measurements). The covariance among channels can be exploited to perform the calibration and this potential should be examined. At least, monitoring the interdependence among the channels can help check the calibration quality. However, caution has to be exercised in this procedure as too stringent constraints could mask some real extreme behavior in one channel. Second, the intersatellite calibration has to be performed and consistency has to be ensured across platforms. Observations from coincident overpasses can be compared, provided that the measurements are performed exactly in the same conditions (frequency, incidence angle, polarization); otherwise, products retrieved from the two coincident satellite measurements can be compared. Rigorous statistical comparison of RTM calculations and satellite observations can also be performed, with the same assumptions for the two satellites, in order to diagnose the radiance biases between instruments. The retrieved products across satellites can also be compared.

[64] A generic calibration method that includes many of these above aspects is under development at NOAA/NESDIS to intercalibrate radiometer in the visible, infrared, and microwave [*Weng et al.*, 2005]. It has already been applied to MSU. In the Global Precipitation Mission framework, efforts are also conducted to intercalibrate the passive microwave imagers on a common standard to ensure consistency among precipitation products [*Kummerow et al.*, 2001; see also http://mrain.atmos.colostate.edu/LEVEL1C/index.html].

[65] Having together all the satellite observations, and using the same methods and data to calibrate them would inevitably benefit the retrieval. For instance, it is worrying to realize that there is not one uniformly calibrated set of SSMR and SSM/I observations over the full period of satellite operation that is easily available to the community. A strong effort, with dedicated funding, should be supported by the agencies to systematically apply these new calibration approaches. The resulting multiplatform calibrated data sets should be easily accessible to the community and would stimulate the developments of the next generation of retrieval algorithms.

3.2. Subtracting the Atmospheric Contribution

[66] Depending on the wavelength, the satellite observations can be contaminated by the atmospheric contribution. At low microwave frequencies, the atmospheric effect is negligible, making this wavelength range particularly suitable for land surface analysis (e.g., the ERS scatterometer data at 5.25 GHz [*Prigent et al.*, 2001, 2005b]). For other wavelength ranges, even if this effect is limited, it can modulate the received signals both in time and space and be mistakenly interpreted in terms of land surface variations. Suppressing the atmospheric signal is particularly important when analyzing the interactions between the land surface and the atmosphere. Different techniques are adopted to eliminate this effect. For instance, the traditional NDVI processing relies on the selection of the maximum value of the NDVI for a location for a given period of time to minimize the atmospheric contamination [*Holben*, 1986]. Physical methods based on radiative transfer calculations have also been developed. In the ISCCP analysis the surface skin temperature is retrieved from clear IR radiances using the TOVS products to specify the atmospheric temperature and humidity profiles and a RTM to calculate the atmosphere radiative contribution. The passive microwave observations up to 37 GHz are adopted in a large number of studies to provide information on soil moisture [*Vinnikov et al.*, 1999], snow [*Kelly et al.*, 2003], or floods [*Sippel et al.*, 1998]: usually, the brightness temperatures are directly used in the algorithms, assuming that the atmospheric effect is negligible. However, as noted by several authors [e.g., *Kerr and Njoku*, 1993], atmospheric effects, especially cloud cover, may be responsible for a large part of the 37 GHz signal, casting doubt on the interpretation of simple brightness temperature combinations solely in terms of surface properties. In addition, although very sensitive to some surface parameters like the snow [*Cordisco et al.*, 2006], the 85 GHz channel that is present on the SSM/I or TMI is often not used because it is deemed too contaminated by the water vapor absorption. In order to avoid such limitations, some work has been conducted to extract from the passive microwave observations the information that is directly related to the land surface, its emissivity, by removing the contributions from the atmosphere, clouds, and rain using ancillary satellite data, atmospheric profiles from meteorological reanalysis, and a RTM [*Prigent et al.*, 1997, 2006].

[67] This preprocessing step is often strenuous, as it can involve significant amount of coincident ancillary information as well as complex RTM to estimate the atmospheric contribution. However, it is necessary if unambiguous surface information is required, with good accuracy.

3.3. Scaling

[68] Spatial and temporal scales of observed or measured surface variables cover a wide range. General principles of upscaling (i.e., aggregation (when the scale change is performed in the same variable, which is not always the case) or downscaling (i.e., disaggregation) have been developed to link one scale to another but the definition of such general terms is sometimes confusing. In this paper, we simply refer to the ‘‘downscaling’’ (respectively ‘‘upscaling’’) as a technique that increases (respectively decreases) the spatial resolution of the original data.

[69] ‘‘Regionalization’’ [*Von Storch et al.*, 1993] is one application of the downscaling: it makes it possible to describe the specific behavior of a region by combining large-scale outputs from a climate model with small-scale information from the surface. It is not directly of interest in the study. Another application of the down-/up-scaling is the simple scale change of a particular field with the same variable in both scales: the terms ‘‘aggregation’’ for ‘‘upscaling’’ and ‘‘disaggregation’’ for ‘‘downscaling’’ could be used for clarity purpose. This (dis)aggregation is performed for various reasons. For example, the downscaling from a satellite estimate or a climate output to a local measurement allows for the comparisons of the sources of information and can be used for validation or the calibration of models and retrieval algorithms. Techniques for (dis)aggregation require some knowledge of the scale spectrum of variation magnitude.

[70] In dynamical/physical approach, a physical model describes the dynamics of the system at the regional

resolution of interest. The physical model is then run under some constraints coming from the other information scale. This can be done through simple forcing, nudging, or (variational) assimilation. The inconveniences of this approach are twofold: such physical model is not always available and it can be computationally prohibitive.

[71] Statistical methods try to infer cross-scale relationships using a random or a deterministic function. The relationship is deduced from a data set of pairs of cross-scale samples, derived from observations (empirical scale change) or from model outputs (model-based scale change). A statistical technique (e.g., singular value decomposition, canonical correlation analysis, regular regression, classification, or neural networks) is "trained" to reproduce the link between each pair. Different approaches can be used: (1) The weather generator is a stochastic model defined to describe the evolution of the (dis)aggregated field. For example, a Markov chain can be used, allowing for temporal coherency in the field. This approach is essentially a complex random generator that depends upon cross-scale information. The sample data set is used to calibrate the stochastic model. (2) In the weather typing approach, weather regimes are defined (by using the data set of samples) and a classification algorithm links one scale-field of the weather regimes to the other scale in a deterministic or stochastic way. (3) In the transfer function method, a deterministic or stochastic model is defined to perform the cross-scale transfer, using a linear regression technique (e. g., singular value decomposition, canonical correlation analysis, regular regression) or a nonlinear one (e.g., artificial neural networks [*Cavazos*, 1999], kriging [*Biau et al.*, 1999]). Weather typing could also be included in this general approach when considering the categorization of the transfer function response. Other techniques are interpolation schemes (e.g., cubic spline, geostatistics).

[72] Statistical methods are computationally inexpensive and very flexible so that they can be adapted to specific situations. However, their extension to unobserved conditions is questionable (for global warming experiments or for regions not yet observed).

[73] The data set used to parameterize the statistical models has to describe correctly all the relationships among the variables. Spurious results such as artificial correlations can be misleading. Furthermore, small-scale heterogeneities relevant to the (dis)aggregation must be represented. For example, a few ground stations inside a large-scale cell can help estimate this heterogeneity. When this data set is available, the (dis)aggregation process uses explicitly or not this heterogeneity information. Some methods require a statistic-only information (geostatistics use a variogram (covariance of a same variable but at two varying distant locations) [*Wackernagel*, 2003]) but this information might not represent well enough the spatial nature of the information, in relation with surface properties (vegetation, elevation, geology of the soil, etc.). In this case, very fine geographic information must be extracted from the spatial patterns in the observed or modeled output data sets. The limitation of this approach is that the fine spatial information is region-dependent and cannot be extrapolated to other regions. Depending on the particular problem to solve and the quality of the available data set, a compromise will be find between using very fine-scale information specific to a region and more widely applicable statistic analysis.

4. Examples of Retrieved Surface Parameters Using Some of These Methods

4.1. Surface Skin Temperature: An Example of Multisatellite/Multiparameter Retrieval

[74] The surface skin temperature and the soil moisture largely control energy and water exchanges at the land-atmosphere interface. The skin temperature represents the soil skin temperature for bare soil, the canopy surface temperature in densely vegetated region, and an average of the above for sparse vegetation. Measurements of the skin temperatures are required to study the energy and water exchange processes at the land-atmosphere interface, with time resolution high enough to resolve the diurnal cycle under all synoptic conditions, and covering a long enough period to examine how different seasonal and interannual conditions affect them.

[75] In situ surface skin temperature can be calculated from observations with an infrared radiometer, if the land surface emissivity is known: this measurement is not performed at weather stations and is not part of the conventionally measured data. Skin temperatures have been estimated from satellite infrared observations, with the limitation that cloud free observations are required (i.e., infrareds are blocked by clouds). Microwave land surface skin temperature retrieval is a very promising complement to infrared estimates, with the significant advantage that it can be effective even under cloudy conditions. However, because of the larger surface emissivity variations in the microwave than in the infrared, a combined analysis is required to isolate the temperature variation accurately.

[76] The analysis of microwave observations over land to determine atmospheric and surface parameters is still limited because of the complexity of the inverse problem. A Neural Network (NN) having the particularity of using first-guess information has been developed in [*Aires et al.*, 2001] to retrieve simultaneously the surface skin temperature, the integrated water vapor content, the cloud liquid water path, and the microwave surface emissivities between 19 and 85 GHz over land from SSM/I observations. The simultaneous retrieval of all these quantities improves the results for consistency reasons. A database to train the NN has been calculated with a RTM and a global collection of coincident surface and atmospheric parameters extracted from NCEP reanalysis, from ISCCP data, and from microwave emissivity atlases previously calculated. The results of the NN inversion are satisfactory. The theoretical r.m.s. error (based on radiative transfer simulations) of the surface temperature (T_s) retrieval over the globe is 1.3 K in clear sky conditions and 1.6 K in cloudy scenes. Similar methodology has also been applied with success over snow and ice regions [*Prigent et al.*, 2003b].

[77] The thorough evaluation of the retrieved product is difficult. In the absence of routine in situ surface skin measurements, retrieved T_s values have been evaluated by comparison with the surface air temperature T_{air} measured by the meteorological station network [*Prigent et al.*, 2003a]. The $T_s - T_{air}$ difference shows all the expected variations with solar flux, soil characteristics, and cloudi-

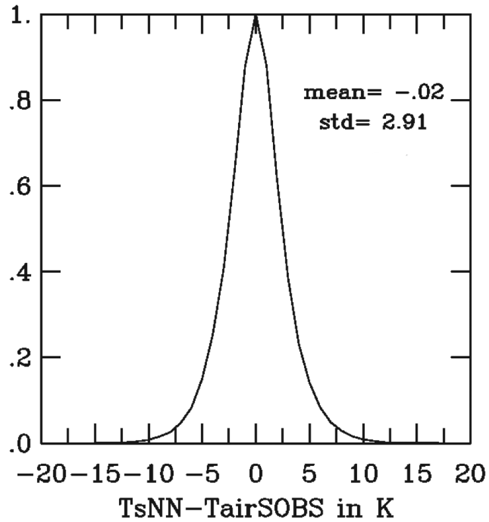

Figure 3. Normalized histogram of the difference between retrieved surface skin temperature from combined microwave and infrared observations and the surface air temperature at meteorological stations, for all coincident sites, accumulated over July and December 1992. The diurnal cycle has been removed from the two data sets separately.

ness. During daytime the $T_s - T_{air}$ difference is driven by the solar insulation, with positive differences that increase with increasing solar flux. With decreasing soil and vegetation moisture, the evaporation rate decreases, increasing the sensible heat flux, thus requiring larger $T_s - T_{air}$ differences. Nighttime $T_s - T_{air}$ differences are governed by the longwave radiation balance, with T_s usually closer or lower than T_{air}. The presence of clouds dampens all the difference. After suppression of the variability associated to the diurnal solar flux variations, the T_s and T_{air} data sets show very good agreement in their synoptic variations, even for cloudy cases, with no bias and a global r.m.s. difference of ~2.9 K (Figure 3). This value is an upper limit of the retrieval r.m.s. because it includes errors in the in situ data as well as errors related to imperfect time and space collocations between the satellite and in situ measurements.

[78] The diurnal cycle of surface skin temperature has also been analyzed almost globally (60°N–60°S over snow-free areas), using a Principal Component Analysis (PCA) [*Aires et al.*, 2004]. The first three components are identified as the amplitude, the phase, and the width (i.e., daytime duration) of the diurnal cycle and represent 97% of the variability. The PCA is used to regularize estimates of the diurnal cycle at a higher time resolution. A new temporal interpolation algorithm, designed to work when only a few measurements of surface temperature, has been developed on the basis of the PCA representation and an iterative optimization algorithm using good quality monthly climatological first guess information. The method is very flexible: only temperature measurements are used (no ancillary data), no surface model constraints are used (which is interesting for the comparison to model outputs, or for the assimilation of satellite estimates on surface models), and the time and number of measurements are not fixed. The performance of this interpolation algorithm has been tested for various diurnal sampling configurations. In particular, the potential to use the satellite microwave observations to provide a full diurnal surface temperature cycle in cloudy conditions has been investigated [*Aires et al.*, 2004]. Figure 4 represents the resulting averaged diurnal cycle amplitude of the surface temperature in June 1993. No geostationary satellites were available at that time over large parts of Eurasia explaining the impossibility to estimate accurate surface temperature diurnal cycles. The next step is to use AMSU (from NOAA platforms) or AMSR (from Aqua or Adeos II missions) radiometers in addition to the SSM/I instruments. The time sampling of these various instruments should provide a better characterization of the full diurnal cycle of T_s, even under cloudy skies.

[79] An all-weather time record of land surface skin temperatures has been produced from the merging of 10 years of microwave SSM/I satellite measurements and ISCCP products. The resulting global satellite observations of land surface skin temperature is now merged with surface weather observations of near-surface air temperature, humidity, and winds to study the diurnal, synoptic, and

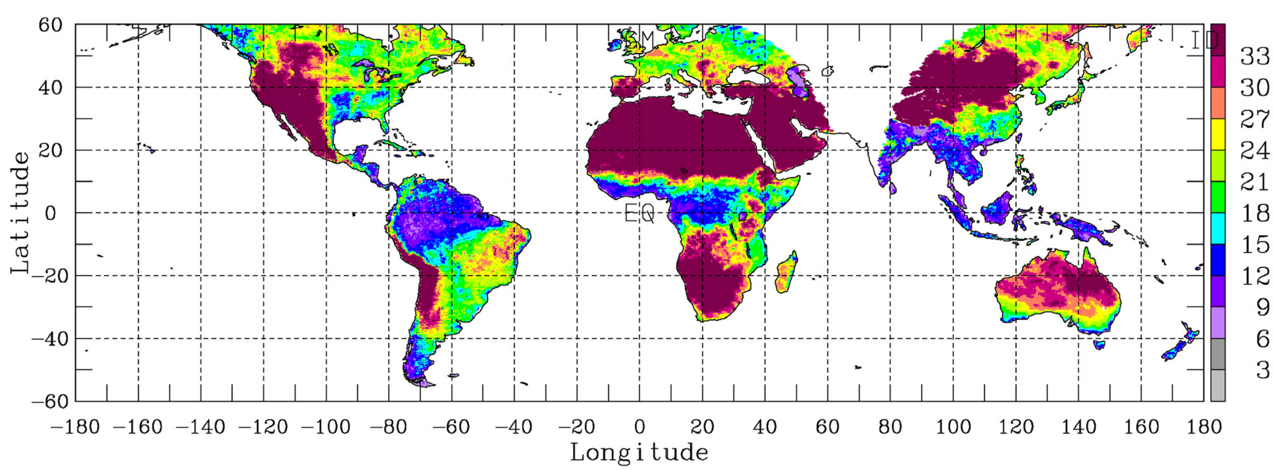

Figure 4. Amplitude of the reconstructed surface skin temperature diurnal cycle for June 1993 (in K).

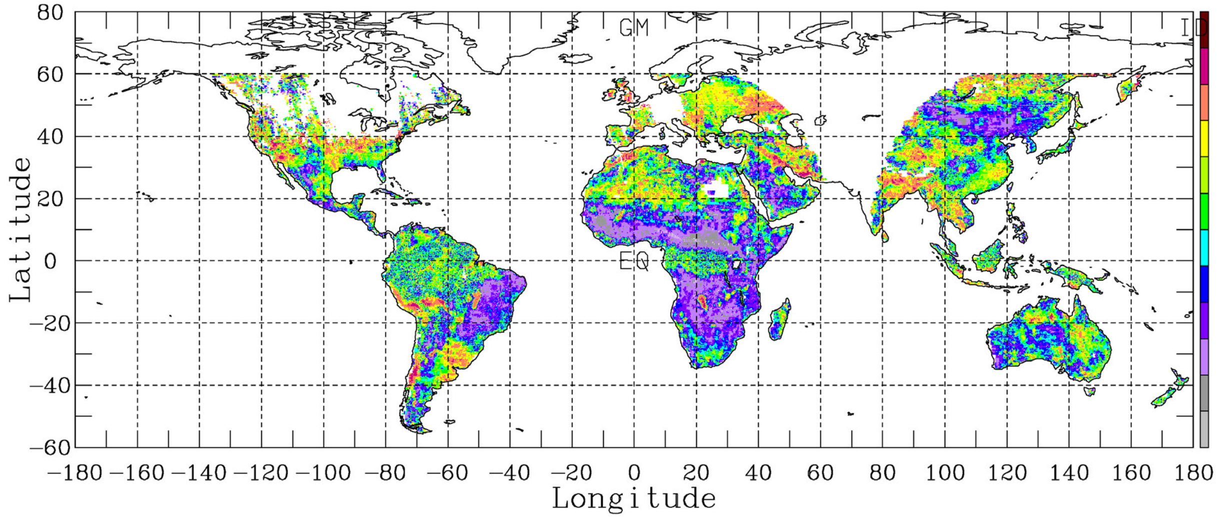

Figure 5. Linear correlation between the SSM/I emissivity polarization difference at 19 GHz (V-H) and the ECMWF surface soil moisture estimates, for the 1993–1994 period.

seasonal variations of land-atmosphere energy and water exchanges.

4.2. Soil Moisture: An Example of Synergetic Use of Multisatellite Observations and LSM Outputs

[80] Soil moisture is a key land surface variable that partly controls the surface energy and water exchanges at the atmosphere interface. It is also very important for agriculture, water management, or flood monitoring. The SMOS dedicated mission that will provide soil moisture estimates from measurement in L-band (1.4 GHz) will not be launched before several years. Land surface modelers are now producing soil moisture estimates (e.g., GSWP-2) and there is an urgent need for consistent global data sets to evaluate model outputs [*Entin et al.*, 1999]. What can be done now with the available observations?

[81] A number of existing satellite observations have shown sensitivity to the soil moisture: it includes passive and active microwave measurements, as well as thermal infrared observations. Most studies are geographically limited but there are at least two global attempts. *Owe et al.* [2001] derive a global soil moisture index over 9 years from SMMR observations. The 6.63 GHz polarization difference makes it possible to take vegetation into account whereas the 37 GHz band gives access to the surface temperature. *Wagner et al.* [2003] analyze the temporal variation of the ERS scatterometer observations at 5.25 GHz to retrieve a global soil water index over 10 years from ERS.

[82] We examined systematically and objectively the sensitivity of the available satellite observations on a global basis, in order to analyze their complementarity, and to assess the ability of combinations of these satellite measurements for soil moisture estimation [*Prigent et al.*, 2005a; *Aires et al.*, 2005]. For each type of observations, the optimum products are selected. The thermal infrared observations come from both the NOAA polar orbiters and the geostationary meteorological satellites, as processed by the ISCCP to obtain direct determination of the diurnal cycle of land surface skin temperature [*Aires et al.*, 2004]. Passive microwave information is provided by the SSM/I from which the microwave land surface emissivities have been calculated; this analysis separates the atmosphere, T_s, and emissivity contributions to the observed signal, unlike previous studies [*Prigent et al.*, 1997, 2006]. The active microwave observations are extracted from the ERS scatterometer. In addition, the AVHRR NDVI is used to quantify and eventually separate the vegetation contribution from the other factors.

[83] First, for a two year period (1993–1994), the selected satellite observations are compared to the Global Soil Moisture Data Bank [*Robock et al.*, 2000] that provides in situ soil moisture measurements in five separate regions. This analysis makes it possible to objectively compare the sensitivity of each measurement type to the soil moisture, and to estimate the relative contribution of the vegetation for each one. Most studies are limited to one instrument, usually assuming it is the best for the given purpose, and it is very difficult to assess the relative sensitivity of the observations to the studied surface characteristic. The linear correlation coefficients between the in situ soil moisture measurements and the satellite variables are low when considered over all regions (−0.15 for the microwave emissivity polarization difference at 19 GHz from SSM/I and 0.41 for the active microwave ERS scatterometer measurements at small angles). Each satellite observation is differently sensitive to a large number of surface characteristics such as soil moisture, vegetation, soil texture, or roughness. Some of these parameters vary strongly from region to region but not strongly at each location and locally, the time variability of some of these parameters being limited, the correlation between the satellite information and the soil moisture is much stronger [*Prigent et al.*, 2005a].

[84] Second, the in situ soil moisture data set being unable to represent the full range of variability, outputs from Numerical Weather Prediction (NWP) reanalysis from ECMWF and NCEP along with the satellite variables have been analyzed over the globe, for two years. Figure 5 shows the linear correlation between the SSM/I emissivity polarization difference at 19 GHz (V-H) [*Prigent et al.*, 1997,

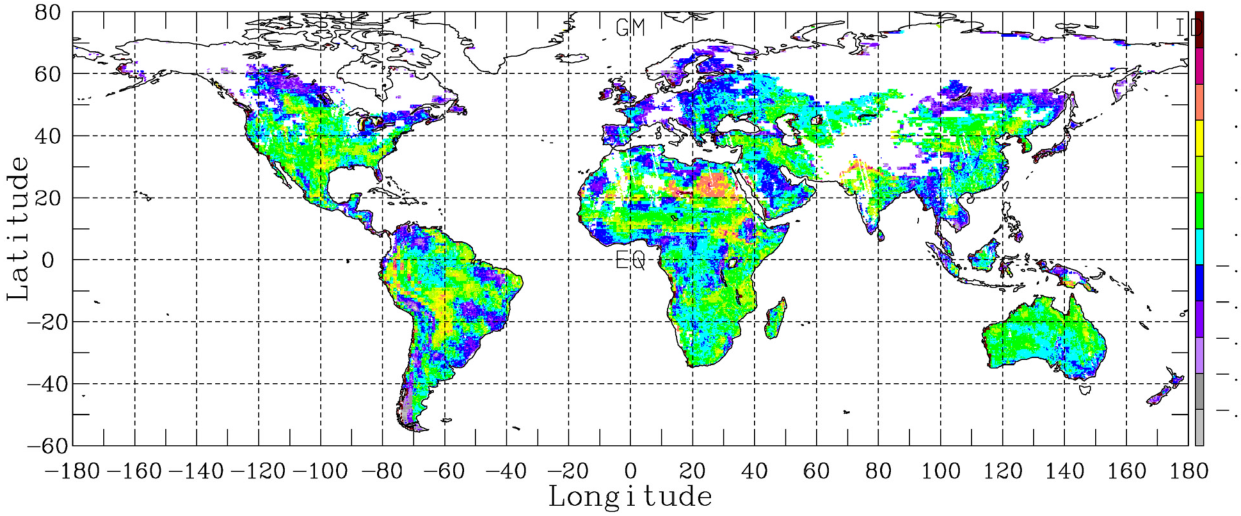

Figure 6. Volumetric soil moisture difference between the ECMWF estimate and the NN retrieved values for October 1993.

2006] and the ECMWF surface soil moisture estimates, for the 1993–1994 period. A positive correlation is expected between these two variables: with increasing soil moisture, the emissivity polarization difference should increase. In midlatitude regions, this is confirmed. However, strong negative correlations dominate in semiarid regions, the passive microwaves reacting primarily to the vegetation density. When the vegetation density and the soil moisture are negatively correlated, the passive microwaves vary as expected with soil moisture only because of the opposing effects of soil moisture and vegetation on the signal. This confirms what was observed with in situ measurements. On the basis of the statistical analysis of the comparison between the NWP soil moisture estimates and the satellite variables in addition to the understanding gained from the study with coincident in situ measurements, a method is derived to establish a statistical relationship between the soil moisture and satellite observations. A NN model is developed to describe the link between the satellite observations and the NWP soil moisture. No RTM today can accurately replicate this link on a global basis, for the wavelength range covered by the observations used. The NN model can reproduce the NWP soil moisture outputs (Figure 6) with a r.m.s. error of 5% volumetric soil moisture, close to what is expected from the future SMOS mission retrieval (4% volumetric soil moisture). More details are given by *Aires et al.* [2005].

[85] Although the NN model cannot be strictly considered as a retrieval algorithm because of its tight relationship with the NWP soil moisture, the fact that the independent satellite observations can be related to model outputs with this level of accuracy is a positive sign for relating these observations to the real-world soil moisture. The fact that the NN model is able to work on a global scale comes from the synergetic use of observations from various wavelengths.

[86] Comparisons between the NN model outputs and the NWP soil moisture reanalysis revealed some particular problems with the NCEP land surface models that have been confirmed by modelers. This statistical link can be used to check the consistency between modeled soil moisture and satellite measurements and diagnose specific model problems (i.e., to invalidate them). We suggest applying the same analysis to the GSWP-2 results.

[87] The soil moisture estimates from our NN model can be assimilated in the LSM model. The necessary consistency between the satellite estimate and the LSM [*Reichle et al.*, 2004; *McCabe et al.*, 2005] is intrinsically verified.

5. Conclusion and Perspectives

[88] A great diversity of satellite measurements exists today and they are sensitive to various land surface parameters. Although these satellite observations might not be optimal for surface estimates, they have already shown some potential and optimized methodologies can be developed to fully exploit these satellite data for continental surface characterization. In this paper, innovative retrieval schemes are suggested that benefit from the synergy between the satellite observations, in addition to in situ measurements or land surface model outputs. Two concrete examples are presented for illustration: an "all weather" retrieval of surface skin temperature from combined microwave and infrared observations and a soil moisture analysis from the merging of multisatellite observations and LSM outputs.

[89] This study focuses on the application of the land surface remote sensing for land surface modeling. However, similar methodologies can also benefit other applications such as hydrology or agriculture as the primary objective of these methods is to derive better land surface products.

[90] How to proceed in a practical way to extend the use of the new methodologies and provide the community with improved satellite land surface products?

[91] First, the multi-instrument approaches have to be adopted, although it is more complex to put in place. Different methods can be applied and the selection of a specific one depends upon the application and upon the variable of interest. The retrieval methodology has to be clearly documented for the users and a detailed analysis of

the uncertainties associated with the satellite estimates has to be performed. The underlying assumptions and the use of any ancillary information have to be described. Modelers are often reluctant to use remote sensing data: the retrieval algorithms are unclear and there are doubts on their accuracy. As a consequence, they often prefer the in situ measurements that they know well and that represent the "truth." With better estimates of the errors, the remote sensing data could be used more quantitatively in the models [*McCabe et al.*, 2005].

[92] Second, there is a strong need for consistent and accurate calibration of satellite data, across instruments and across platforms, over the life spans of the missions. Within the ISCCP framework, IR and visible radiances are carefully intercalibrated, over more than 20 years and for a large number of platforms. Similar work has to be performed for other sensors. Some actions have recently been undertaken but this tedious long-term effort has to be strongly supported.

[93] Third, the in situ observations required to evaluate the satellite retrieval and the models have to be easily accessible, over long periods of time and covering a large range of environments. Variables that are not part of the routinely measured meteorological observations are generally difficult to access, although frequent measurements might be performed all over the world. Initiatives such as the Global Soil Wetness Database must be encouraged, to foster the development of databases of unified, well formatted, and quality controlled long-term in situ measurements. In addition, there is a need for the development of measurement sites for some key variables such as turbulent fluxes for which only a limited number of observations exists.

[94] These efforts could be conducted within the framework of a future ISLSCP initiative, that would aim at providing a synthetic data record in which inconsistencies among LSMs, satellite data, and in situ measurements are reconciled to the degree possible. In order to reach these ambitious goals, an improved communication between the different actors of the land science community is necessary. The link between modelers and the field experimenters has been naturally and historically tight. There is now a necessity for the satellite community to work in close collaboration with the land surface modelers to understand their needs and define common strategies. This collaboration will benefit both communities.

[95] The next challenge of the satellite community is the estimation of the turbulent fluxes over land, at a global scale, which are key variables of the land surface models. It will inevitably require a synergetic use of multiple sources of information, including a large range of satellite observations and model outputs. This can be a very good opportunity for the modelers and the satellite experts to join forces toward a common goal.

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