Chapter 17
Applications of Terrestrial Remote Sensing to Climate Modeling

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Abstract Terrestrial processes are an important component of climate. Climate can be viewed as a nonlinear dynamical system which generates statistics to be compared with observational statistics. The surface is forced by net radiation balanced by sensible and latent fluxes, and by precipitation balanced by evapotranspiration, soil moisture storage, and runoff. These balances depend on detailed geographic descriptions of parameters required by the modeling. These details are constrained by satellite remote sensing (as demonstrated by various recent studies) with consequent substantial improvement in climate models. Some of these parameters, especially those involving vegetation, may be evolved with the climate system.

When climate models characterize their radiative processes consistent with the remote sensing algorithms useful for their detection, they become physically more realistic and provide a suitable modeling framework for forward modeling data assimilation. In particular, the 3D nature of canopy radiation needs to be represented in climate models and how this connects trees and bushes to various underlying surfaces.

17.1 Introduction to the Formulation of Climate Models

Climate dynamical models solve various conservation equations that describe how the climate system evolves in time, and consequently generate numerical data for its statistical characterization. These climate statistics may include, e.g., monthly mean temperature and humidity of near surface air, temperature of leaves and profiles of soil temperature and water content. Additional important statistics involve diurnal variations, annual cycles and year to year variability of such quantities. The terrestrial component of climate consists of various state variables related to the terms

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just mentioned, linked together by process descriptions, and constrained by appropriate observational information. Statistics of the process descriptions are also often examined as part of the study of the climatology of a model.

Exactly what state variables, process descriptions, and constraining observations should be used is determined by the multiple purposes for which the terrestrial system is included in a climate model (e.g., for their contributions to weather prediction, inter-annual climate prediction, projection of long term change from greenhouse gases, study of hydrology and water resources, crop production, ecology of various natural systems, biogeochemical cycling, especially that of carbon, as an ancillary source of information for remote sensing studies, or for forward modeling of remote sensing radiances).

The primary role of the terrestrial system as an interactive component of a climate model is to determine the near surface and surface variables that are used to characterize climate observationally and to control the dynamic and thermodynamic structure of the atmosphere as mentioned above. Major ingredients of this control are the surface exchanges of energy, moisture, and momentum.

Land surface models have evolved from quite simple treatments of these exchanges to increasingly complex descriptions. For earlier reviews, cf. Dickinson (1983, 1984, 1989, 1992, 1995a, b), Dickinson et al. (1991), Sellers et al. (1997), Pitman (2003), Yang (2003). Land is most simply treated as a single reservoir for whatever quantities it is supposed to exchange with the atmosphere. Earliest climate models also averaged over the diurnal and annual cycles so that climate was a "steady state" system. The land component of such early models required a statement as to what fraction of the incident solar radiation it would absorb; that is, its albedo. It also required a specification of heat capacity and water holding capacity and a rule relating its evaporation to that which would come from a wet surface, depending on how much water was stored.

Later models have become much more complex. Dai et al. (2003) describes one example of current models. Such models include descriptions of the global distribution of vegetation and various mechanisms changing with model time-step by which vegetation returns water to the atmosphere. They may also describe overall energy and water balances and fluxes from lakes, wetlands, glaciers; river-flows are determined as an input to ocean dynamics. Rather than describe the details of any particular such approach, we frame the problem somewhat abstractly. All appropriate approaches to modeling the land surface in a climate model, although they may look quite different, are implementations of essentially the same ideas.

17.2 What Does the Land Surface of a Climate Model Consist of?

The terrestrial surface in a climate model consists of either soils covered by vegetation or bare soil. It includes wetlands and lakes and a description of land elevations at the resolution of the atmospheric model. An initial question might be: what soils and what vegetation should the model have. This question could be responded to by the various descriptive names that observed such vegetation is given: e.g., a given grid-square in a climate model may be covered by an open forest with an understory of grass, overlying a soil classified as an "Alfisol". Such names, alone, are useless for quantitative physical modeling. However, they may be used through their correlation with needed properties to infer what is needed. One application of terrestrial remote sensing has been to extrapolate over wider areas names that have been given to particular kinds of vegetation at the surface. This assignment of a geographic distribution of land cover is useful for other purposes but may be losing some of the information needed by climate modelers. If so, this is regrettable since much of the quantitative information measured by a satellite sensor, especially such as provided by reflectance imagery, is closely connected to the information directly needed by climate modelers.

Initial geographic characterization of land cover was provided by Wilson (1984), Matthews (1984). More recent land cover data sets have come from AVHRR (e.g., Strugnell et al., 2001) and now MODIS (Friedl et al., 2002).

17.3 Water and Energy Balance Requirements

Energy exchange at the terrestrial surface is dictated by its net absorption of solar energy. The solar flux incident at the top of the atmosphere is determined by location, time of day, and time of year. In passing through the atmosphere, some radiation is absorbed by atmospheric molecular constituents and some scattered, i.e., Raleigh scattering by molecules, and Mie scattering by aerosols and cloud droplets. Overall, on average, about 20% is absorbed and about the same lost by upward scattering. More than half the incoming solar radiation remains to reach the terrestrial surface. This radiation incident at the surface is approximately half downward scattered from the atmosphere (much less on clear days and nearly 100% on cloudy days). It can in the short term be stored, but on longer time scales must be balanced by net upward long-wave thermal radiation and turbulent fluxes carrying internal energy from atmospheric temperature (sensible fluxes), and the energy stored in evaporated water (latent fluxes).

Different surfaces act in different ways to achieve a balance between their absorption of solar radiation and the thermal radiation and turbulent flux exchanges that collectively provide this balance. Because the net thermal emission and storage variation (e.g., thermal conduction into soil) are relatively regular, during the daytime these are commonly lumped for diagnostic purposes with the absorbed solar radiation to get a net forcing of the sensible and latent fluxes. As by construction, this net radiation plus storage must balance the turbulent fluxes, the primary issue is then what determines the relative amount of each. This partitioning between the turbulent flux terms is commonly characterized by the ratio of sensible to latent fluxes, referred to as "the Bowen ratio".

According to the above generalities, state variables should be connected to components of the system that store water and energy and change in time as this storage is modified. Additional "diagnostic" variables are used to relate the state variables to fluxes. The amount of energy stored in a given material is proportional to its temperature with this proportionality factor, a heat capacity. Furthermore, sensible energy exchanges are driven by the differences in temperature between two reservoirs and moisture exchange by some difference in moisture potentials. In sum, the temperatures and moisture of various system elements must be distinguished. Models address how these elements are heated by the sun and how they lose energy to each other or to the atmosphere.

The most significant contributors to these elements to be modeled are the vegetation, surface water in the form of snow or free water (e.g., lakes), and "soil", where "soil" refers to mineral or dead organic matter stratified vertically. Vegetation generally consists of individual surfaces such as leaves or branches with spatial scales from a few mm to meters. These surfaces have an area in contact with air that is large compared to the flat area of underlying soil (thus, acting in some ways as a porous medium, but on a relatively large spatial scale). They respond to solar heating by increasing their temperatures until their heating is balanced by turbulent and convective air motions carrying thermal energy and water. Soils and snow are also porous but their spatial scales are only on a nanometer to micrometer scale so that water moves through them as a very viscous fluid and thermal energy by conduction. Soil by volume is about half mineral or organic materials, and the rest some combination of air and water. Snow consists of crystalline ice with quite a bit of air.

In simple terms, the modeled atmosphere delivers solar radiation and precipitation to the modeled terrestrial surface. How this energy and water is returned to the atmosphere depends on quite a few modeling details. From the climate viewpoint, the details of the return fluxes in amount and timing can be important for temperatures and precipitation. Precipitation may either be lost at nearly the same time it falls through evaporation from canopy (referred to as interception loss) or can infiltrate the soil and be extracted weeks later as part of the transpiration fluxes (e.g., Dickinson et al., 2003). Solar heating of springtime boreal vegetation may either return directly to the atmosphere or be used to melt the snow pack. The latter is often invoked as a vegetation feedback on snow melting. More concrete descriptions of particular processes will be addressed in the following discussion of current issues that emerge in the context of remote sensing data requirements.

17.4 Role of Solar Radiation in the Climate Model Terrestrial System

Climate models determine the solar radiation absorbed by the various components of the terrestrial system to determine separate energy and water balances. For example, the solar radiation incident at the surface may heat a canopy, its understory, and the underlying soil. If all these terms are lumped together into a single complex surface, the solar radiation absorbed is simply the complement of (one minus the) albedo, which is quantified by remote sensing data products such as from MODIS (e.g., Gao et al., 2005). However, surfaces treated in more detail will determine total solar absorbed as the sum over the absorption by individual terms, and hence observed albedo becomes a "constraint" rather than a simple boundary condition.

Climate models use leaves, green or brown, and the underlying woody stems to determine the canopy contribution to absorption of solar radiation. This absorbed solar radiation raises the vapor pressure of water inside green leaves to higher values than that of the air outside the leaves and consequently forces the leaves to transpire. Since the storage of water inside leaves is commonly small, this water loss must be compensated by extraction of water stored in the soil by plant roots. The contribution of leaves is quantified in the model in terms of the leaf-area-index (LAI). This quantity is the one-sided area of leaves (flattened if necessary, to be a spatial projection) per area of soil surface. MODIS (Myneni et al., 2002) provides remote sensing estimates of the global distribution of leaves. This term has been determined over periods of 8 days from the beginning of the year 2000 to the present. It is accompanied by a product FPAR which provides that fraction of the absorbed visible solar radiation that is taken up by the canopy. The characterization of dead leaves and stems is more problematic as not yet supported by remote sensing data.

The most common approach to address sub-grid variability in vegetation is to portion the climate model grid square into various sub-grid tiles. Some fraction of the grid square must be taken as vegetated, and can be subdivided in terms of plant functional types (pft'*s*) (Bonan and Levis, 2002). For example, a savanna might be covered 80% by grass and 20% by trees, and these are put on separate areas and their radiative exchange determined by one-dimensional models. The estimated area of bare surfaces (i.e., whatever is not directly under a tree or grass canopy) is similarly treated as a separate tile. The area directly under canopies has been treated as bare soil. Such models assume that trees and grass are in separate clumps; consequently, if there are trees overlying grass or soil, the light environment is treated very unrealistically in terms of the effects of the 3D shading of the grass or soil by the trees.

For open canopies, this treatment can underestimate the visible radiation absorbed by the canopy by at least a factor of 2. However, many canopies are closed enough, and reflections from the underlying surface sufficiently compensate, that much smaller errors are seen in comparing the modeled with observed fraction of absorbed visible radiation.

Models of transpiration and photosynthesis have a nonlinear dependence on the intensity of incident light. That is, their dependence on light is linear at low light levels but asymptotes to some constant value (saturation) at high light levels. Direct sunlight either strikes a leaf and is greatly attenuated or does not hit any leaves and continues at the same intensity it started with. Thus, the appropriate statistic for the effect of direct solar radiation on photosynthesis is not average light intensity but rather what is the relative area of leaves that receive the direct sun. Diffuse light, on the other hand is idealized as coming from all sky directions with the same intensity (cf. Pinty et al., 2005, for a relaxation of this assumption.) and consequently strikes all leaf surfaces with the average intensity of the diffuse light at a given level in the canopy. Climate models commonly use an average value of the diffuse radiation, an assumption which may lead to a factor of 2 overestimation of the average shade leaf intensity compared to that from a better scaling (e.g., Dai et al., 2004) and further serious error if light intensities are too strong to be in the light limited regime of transpiration/photosynthesis. Such may happen, e.g., for a midday summer sun, passing through a thin cloud or thick aerosol layer.

Light of average intensity locally attenuates by "Beers Law" either in fractional area of sunlit leaves (direct sun) or its intensity (diffuse radiation) and thus according to

$$\frac{dI}{dL} + G \cdot I = S \tag{17.1}$$

where I is the incident light intensity, L is path length measured in leaf area increment, S is an internal source term, accounting for scattering if needed, and G is a factor for the projection of leaves into the direction of the light (commonly assumed to be a factor of 0.5 approximating the effect of a uniform distribution of leaf orientations). For a canopy idealized as a uniform spatial distribution of leaves, Eq. (17.1) generalizes to a global expression and the path length is the vertical path length divided by a cosine projection factor. However, leaves, especially those in forest canopies, are far from uniformly distributed. The most obvious spatial heterogeneities that must be addressed are the organization of plant canopies as discrete objects, organization of leaves into "clusters" and the variety of path lengths (i.e., number of leaves) that a light ray must pass by.

Although this issue of canopy heterogeneity has been recognized by climate modelers for a long time (e.g., Dickinson, 1983), practical approaches to address it are only now being developed (e.g., Pinty et al., 2006). Ideally, this part of a climate model should not be computationally much more intensive than the evaluation of few exponentials (as in analytic two-stream solutions), thus probably precluding the use of fine layering approaches with multi-scatter iteration or even the direct inversion of a large matrix as might arise out of various idealizations of the situation. The physically most realistic and complete description using Monte Carlo is slow by factors of at least thousands compared to what is needed but can be very useful for validating approaches of low computational cost (e.g., Pinty et al., 2006).

Where climate model treatments of canopy radiation are weakest, they have also been most limited by lack of data. These are the situations where sparse canopies have large openings through which light can directly reach the underlying surface. Thus, however bad the treatments of radiation by climate models may appear from a conceptual viewpoint, they have done the required job within the context of the very little available information. With the archiving of several years of MODIS data, the time has arrived to evaluate and improve the treatments of radiation used in climate models.

Jin et al. (2002) reported a very large range of albedos over snow covered areas depending on the masking by vegetation of the underlying snow surface. Figure 17.1, from Gao et al. (2005) compares observed albedos (visible light) for evergreen forest and grassland covers and for varying degrees of snow cover. It illustrates the increase of albedo with increasing snow but with a much greater darkening of the forested region and less sensitivity to snow. It also shows that an extremely large spatial variability of albedo especially with the largest snow covers (factor of 2

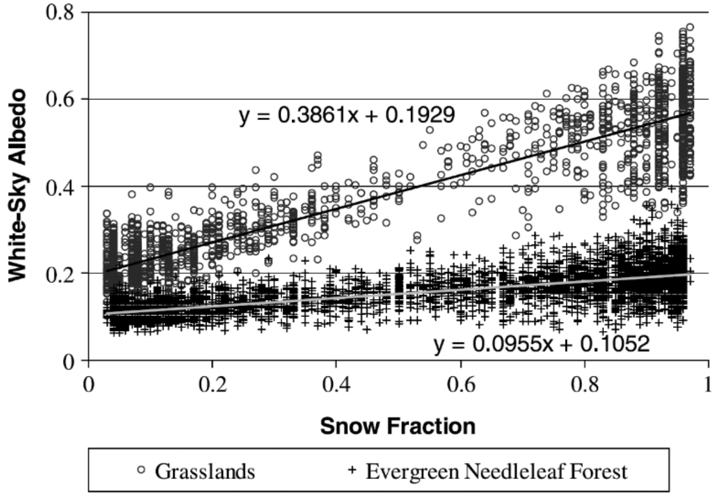

Fig. 17.1 Shows how albedos vary with snow cover fractions (Gao et al., 2005). Points in the figure were extracted from global high-quality retrievals during the whole year of 2001 (23 production periods). Each point in the figure represents a CMG resolution (0.05°) pixel. Grassland albedos are seen to be four times as sensitive to snow fractions as that of an evergreen forest

or more). The masking of snow by forests has been included in at least some climate models since the early 1980s but not with the correct geometric considerations as discussed above. Furthermore, climate modelers have had little basis for incorporating in their global models from first principles or surface observation descriptions of how "open" canopies might be. Prior remote sensing data such as from AVHRR has been of limited value in developing climate model radiation schemes that adequately address such details.

Gao et al. (2005) show that the albedos measured by MODIS have the spatial and temporal patterns appropriate to their underlying land cover classes. The seasonal variations of these albedos are consistent with the phenology of leaf cover (e.g., outside the growing season, deciduous broadleaf forests become much darker in the near-infrared and a bit brighter in the visible). The albedos over areas of sparser vegetation also show influences of underlying soil, e.g., grasslands in the band of 10–20 N and presumably mostly in North Africa, show a much higher albedo than elsewhere.

Tsvetsinskaya et al. (2002) has shown in the context of North Africa how measured MODIS albedos can be applied to characterize the albedos of an arid region. They find over this region, considerable spatial variability in its surface albedos, apparently related to soil mineral composition and geographical characteristics. For example, MODIS shortwave albedos vary by a factor of about 2.5 from the darkest volcanic terrains to the brightest sand over the Sahara. Overall, the Sahara desert has much higher albedos than deserts elsewhere. Climate models have previously assumed a single albedo for desert.

17.5 Climate Model Evaluation Studies

Recent studies have begun to evaluate in the context of the new satellite data the performance of the treatments of radiation in climate models and their various ancillary assumptions such as the leaf area used to produce their radiation. Two studies have evaluated the climate model described by Zeng et al. (2002). This model utilized land surface data developed from AVHRR (e.g., Zeng et al., 2000; Strugnell et al., 2001) and implemented in the CLM model as described by Dai et al. (2003). Zhou et al. (2003) found that largest discrepancies between observed and modeled albedos occur over snow covered regions and in arid regions. They emphasized a lowering of winter albedos compared to that observed by MODIS, resulting from an apparent excess of tree and bush stem areas included in the model. Tian et al. (2004a) compared the LAI assumed in the model with that observed by MODIS and the contributions of differences between model verus observed LAI to model error. They also emphasized that whereas the Zeng et al. (2002) climate model may have overstated the absorption of light by the canopy stems, that this absorption should still be included but with more appropriate optical properties and that the MODIS algorithms for LAI and FPAR have left out their effect entirely.

Zhang et al. (2005a) have further demonstrated that a significant fraction of solar radiation is absorbed by non-photosynthesizing canopy surfaces.

Other studies have evaluated the climate model version described by Bonan et al. (2002). It differs in its modeling of the land surface from that used by Zeng et al. (2002) in replacing some aspects of the previous version of CLM (common land model) with the canopy radiation description developed by Bonan (1996), and with land data sets developed by Bonan and Levis (2002), also from AVHRR. Although the AVHRR satellite data used by Zeng et al. (2002) may have been developed more thoroughly than that of Bonan and Levis (2002), it was expressed in terms of the IGBP classification and Bonan et al. (2002) required the land data to be formulated in terms of plant functional type tiles (pft's) as described in Bonan and Levis (2002). In after-sight, the treatment of canopy radiation by Zeng et al. (2002) suffered some numerical flaws (e.g., as mentioned by Pinty et al., 2006), and other inadequacies so its replacement by the full two-stream computation of Bonan (1996), essentially the same as used in the Sib model (Dickinson, 1983; Sellers, 1985), was likely an improvement. To make a long story short, the CLM "took two steps forward and one step back" as a result of different individual ideas as to what was currently the best way to do canopy radiation and derive land boundary conditions from AVHRR.

This CLM2 model (community land model version 2) described by Bonan et al. (2002) was assessed by Oleson et al. (2003), Wang et al. (2004), in the context of its simulation of albedos. They reported a large negative bias in the albedos over the Sahara in contrast to the large positive bias reported by Zhou et al. (2003). This negative bias was a consequence of the Sahara albedo constrained to fit data from the ERBE instrument, whereas the positive bias was a consequence of data constrained to reproduce albedos inferred from AVHRR. In sum, prior to MODIS, previous less reliable satellite estimates of the albedo of the Sahara may have provided no real information beyond that already available to climate modelers from surface and aircraft observations. For the latter, soils, sands, and rock had only been distinguished by models in terms of their soil hydrological properties and albedo inferred from an original; “light”, “medium” and “dark” color classification. The ratio of near-infrared to visible albedo ratio has been fixed at 2 and any dependence on solar zenith angle neglected. Much more detailed spatial and spectral information, especially over semi-arid regions is now available from MODIS. For example, the ratio of near-infrared to visible albedos observed in MODIS over the deserts of Sahara, Taklimakan, and Australia varies from 1.6 to 2.7 (Zhou et al., 2003) and albedo in the Sahara has been shown to increase significantly with solar zenith angle (Wang et al., 2005). Zhou et al. (2005) has proposed a method using principal component analysis to economically represent a high quality soil albedo dataset over non-vegetated North Africa. An extension of their approach can be used to separate the MODIS albedos into soil and canopy contributions.

Oleson et al. (2003) (as Zhou et al., 2003) reported that the land surface model, CLM2, overall reasonably simulated vegetation albedos but that the two-stream treatment of radiation appeared to have too strong a dependence on solar zenith angle so that the CLM “black-sky” albedo with sun at local noon was in better agreement with MODIS than the “white sky” diffuse radiation. Wang et al. (2004) further documented the substantial differences between model and observed dependences on solar zenith angle. Oleson et al. (2003) also emphasized an overestimate of albedos by the model over snow covered regions in contrast to the emphasis in Zhou et al. (2003) of an apparent underestimate. Evidently, it is easy for climate models to make large errors in regions of snow cover and the shading/masking effects of the vegetation can be either under or over emphasized in different approaches to the canopy radiation that are too oversimplified and unconstrained by observations to be expected to give the right answer.

Tian et al. (2004b) illustrate the usefulness of new land surface datasets developed from MODIS as model boundary conditions. They related LAI, vegetation continuous field, and the land cover maps to the pft formulation of Bonan and Levis (2002), using data “collection 4” for the period of September, 2000–August, 2002. This new dataset showed large differences from the old dataset of Bonan and Levis (2002). The new LAI was larger than the older version by at least 1.5 over the Amazon, central Africa, southeastern Asia, and north Europe, and by about 0.5–1.0 over most areas beyond 60°N in both seasons (Fig. 17.2). These increases in LAI are likely a result of the AVHRR inversion saturating at a lower LAI than that of MODIS. The new LAI was also found to be smaller over many regions (Fig. 17.2). Their use of MODIS data decreased the amount of crops and grass by 20–40% globally, and increased the “bare” category by a large amount (Fig. 17.3). The previous version of the data assumed: “that non-tree covered land in forest, savannas, and grasslands was covered by grasses, in shrub lands by shrubs, in croplands by crops” (Bonan and Levis, 2002). In semi-arid regions, there was no information (Bonan and Levis, 2002) as to the fraction of area covered by bushes so leaves were spread uniformly. This assumption has been found to be incompatible with the existing parameterization of under canopy energy fluxes and a revised approach for the latter was implemented (Zeng et al., 2005).

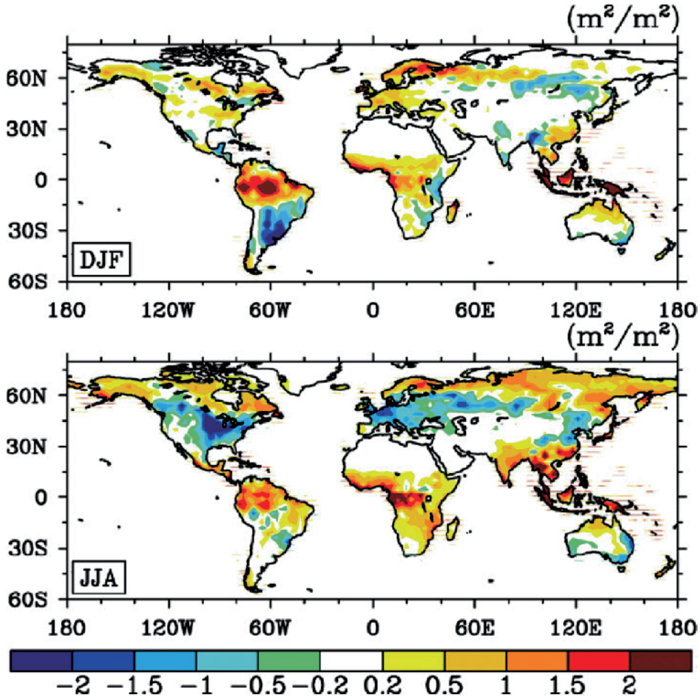

Fig. 17.2 Spatial pattern of LAI difference between the old and new land surface datasets (new-old as derived respectively from MODIS and AVHRR LAI products) in winter (DJF) and summer (JJA) (Tian et al., 2004c)

In the newer MODIS data for fractional tree cover (Hansen et al., 2003) fractional regions are characterized either as trees or shrubs or "bare". Apparently, the bare category in the continuous field data refers to all understory components, but for lack of further information, Tian et al. (2004b) used literally the "bare" classification. Presumably, in semi-arid systems, understories are mostly bare soil, but by contrast, in moist forests they should mostly be dead leaves, mosses, or herbaceous small plants.

Tian et al. (2004b, 2004c) used CLM2 coupled with the Community Atmospheric Model (CAM2) to investigate how the modeled surface variables such as temperature and albedo were modified by the new dataset. For snow-free regions, the increased LAI and changes in the percent cover from grass/crop to tree or shrub decreased albedo, but also decreased surface air temperatures. Increases of canopy evapotranspiration and decreases of ground evaporation over tropical regions improved the modeled surface temperature. MODIS albedo data can be used to adjust model parameters controlling absorption of solar radiation to provide a better fit to the albedo observations (e.g., Liang et al., 2005).

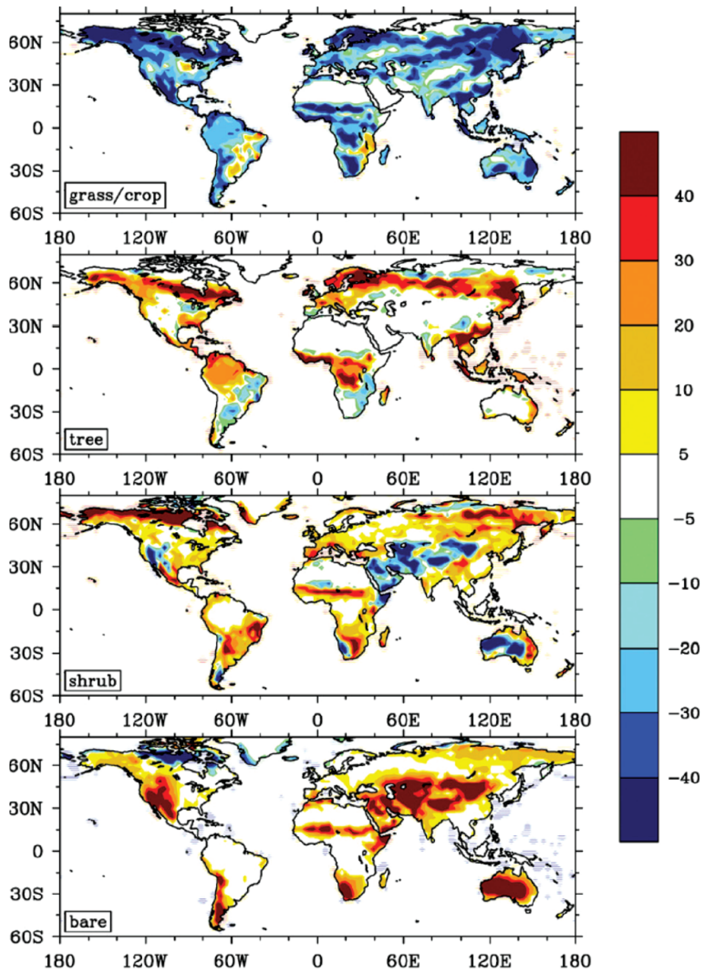

Fig. 17.3 Spatial pattern of percent cover difference (new-old) in grass/crop, tree, shrub, and bare soil at the model spatial resolution as inferred from MODIS land cover classification versus use of AVHRR (Tian et al., 2004c)

17.6 How can Terrestrial Remote Sensing Best Support Climate Models?

Observational characterizations of the terrestrial surface may advance climate models more by providing information that climate models should be using rather than that required by the current formulation of the climate models. For example, we have discussed in Section 17.4, that climate models have oversimplified treatments of the interaction of solar radiation with the terrestrial surface. What observational information could support a more correct treatment of solar radiation? Observations should characterize, to the extent possible, the 3D structure of the surface. A description of fractional tree cover (e.g., Hansen et al., 2003) is a first step in that direction. Besides the fraction of tree cover, other tree statistics needed for climate model details are their size, i.e., height and aspect ratio, and a characterization of their average distance to nearest neighbors (e.g., Widlowski et al., 2001, 2004). In addition, a climate model needs all the smaller scale parameters that contribute to the characterization of surface shading, in particular the relative areas of leaf and stems.

The surfaces beneath a canopy that are affected by the canopy radiatively must be connected to the description of the canopy. Thus, the fractional areas of other surfaces besides trees should be established at an appropriate level of detail, in particular, the fraction that is radiatively connected versus unconnected and the composition of the underlying surface. The concept of radiative connectivity is somewhat vague, but it can be quantified by some simple rules: e.g., it might include all underlying surfaces within a horizontal distance $3 \times H$ from the canopy, where H is the crown height. A description of the underlying surfaces so connected can be relatively simple. What are the characteristics of the dominant material shading the mineral soil, what fraction is photosynthesizing, and what fraction is open to the underlying soil?

As discussed in the preceding sections, understory has been variously characterized as “grass” or “bare”. Either choice of surface may lead to erroneous results in absorption of radiation when, as now done, its shading by the overlying canopy is neglected except for surfaces directly under the canopy (which are currently always taken to be bare soil). Other potentially important under-canopy-cover can be, e.g., dead leaves, moss, lichen, or wetland. In general, if f_c denotes the fractional cover of trees, then the sum of all understory components should be 1, not f_c as currently assumed by climate modelers. The difference between surfaces shaded for overhead sun and those shaded at other times of day is not discontinuous in nature and should not be so modeled.

17.7 Terrestrial Remote Sensing as a Component of Climate Prediction

In the climate context, the use of information from terrestrial remote sensing is still relatively immature. The initial MODIS products involve individual estimates of parameters at a given pixel and composited over enough scene views to obtain a variation of view angles. Views are rejected for cloud contamination and quality flags are set. What is still lacking is utilization of the expected strong space and time correlation of the data. A pixel with, e.g., a pine forest, will have neighboring pixels also classified as pine forest and for the next several years at least, they will mostly remain pine forests. An observation of neighboring pixels can be viewed as all having the same expected value plus a random noise element. There will be real differences in their albedo, LAI, etc. The random noise characterizations simply mean that these differences are too small and irrelevant to be of interest in detail.

Likewise, pixels should look the same from year to year except for random changes. Such changes could be as large as those caused by forest fires, which will certainly be of great interest for some issues, but may not be significant for, e.g., a climate model's albedo over a continent.

The state variables computed by a climate model are necessarily continuous in time and space whereas the pixel by pixel remote sensing products have many data holes caused by clouds, or more rarely by instrument failures. These holes must be filled before statistics can be obtained appropriate for use by climate modelers. Ideally, this filling should be done with no loss of real information. Moody et al. (2005) reports an approach to such filling for albedos measured by MODIS.

What might be the optimum characterization of, e.g., pine forest albedos in July? First, what additional parameters besides the month and land cover description do we expect these albedos to depend on? Probably latitude, and fraction of tree cover need to be considered. After these correlations are quantified, there may still be significant variability that can be ascribed to characteristics of different understories. In principle, any significant variability can be inverted from its cause, provided the radiative model used is realistic enough to include this source of variability. Whatever remains is uninterpreted noise. Characterizing the amplitude of this residual noise is an important aspect of the data analysis.

The state variables of vegetation change in time as a consequence of their interactions with climate. Various approaches have been developed to model this dynamical system. Ecosystems change their structure as a response to competition between different plant functional types (e.g., Lu et al., 2001; Sitch et al., 2003; Bonan et al., 2003; Woodward and Lomas, 2004; Krinner et al., 2005). These models have generated their leaves according to prescribed phenologies based on accumulated "degree days", apparently by itself not on adequate constraint (e.g., Arora and Boer, 2005). The onset of leaves in Northern forests appears to have as much correlation with mid-summer temperature as degree days (Jenkins et al., 2002). In semi-arid or tropical systems, the phenology is largely controlled by the onset of rainy and dry seasons. Their dependences are shown in Fig. 17.4 (Zhang et al., 2005b). Detailed day by day dynamics of leaf growth can be attempted (e.g., Dickinson et al., 1992; 2002), but the underlying principles for this may be inadequately understood. Including dynamic growth of roots is another difficult modeling issue (e.g., Arora and Boer, 2003).

The terrestrial state variable $\boldsymbol{X}$ moves forward in time, formally as a multivariate differential equation:

$$\frac{d\boldsymbol{X}}{dt} + F(\boldsymbol{X}, \lambda) = \boldsymbol{Q}(\beta) \tag{17.2}$$

where λ are various fixed parameters, and $\boldsymbol{Q}$ is a forcing term depending on other parameters β. A satellite measures various reflectance quantities, denoted Y_o, which consists of the "real" $\boldsymbol{Y}$ plus a measurement error term. The model can use its model value of $\boldsymbol{X} = \boldsymbol{X_m}$ to provide an estimate of $\boldsymbol{Y} = \boldsymbol{Y_m}$. For example, $\boldsymbol{X}$ can be some combination of the model soil moisture, or LAI or f_c; the latter two would be changed by dynamic vegetation versions of the model.

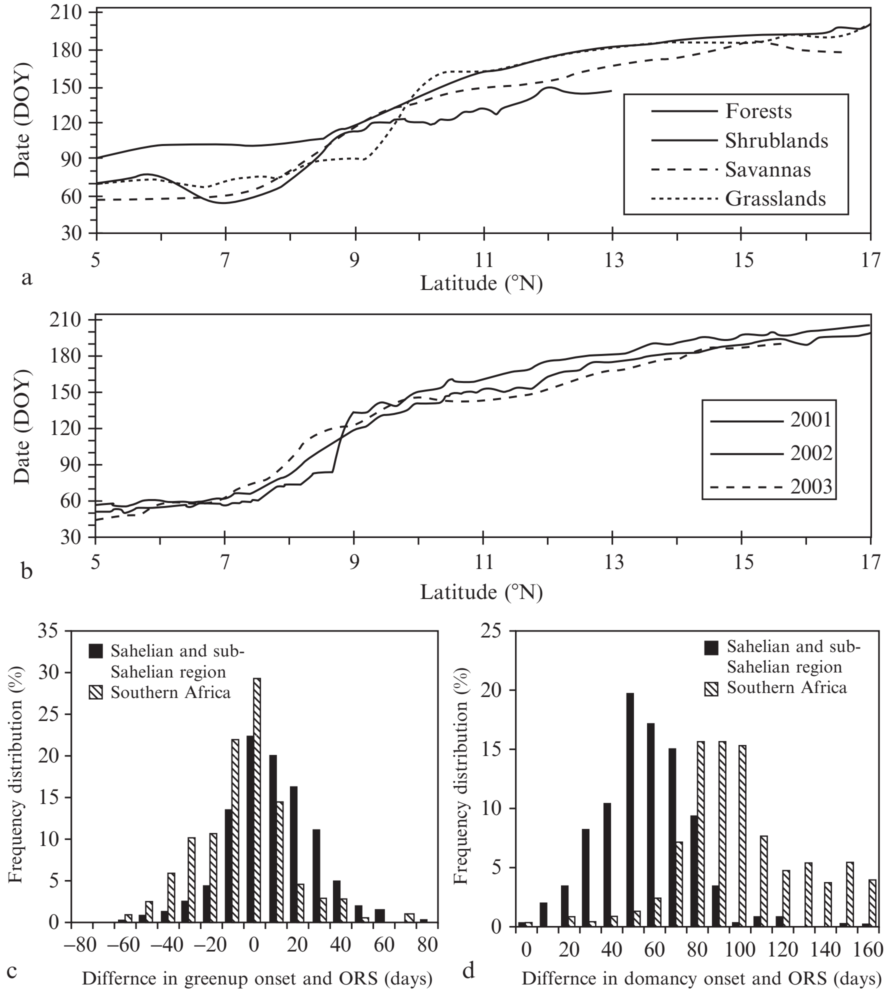

Fig. 17.4 The phenology of vegetation over Africa as time of greenup from beginning of year (a, b) and (c, d) its timing relative to the onset (o) and end (e) of the rainy season (Zhang et al., 2005)

Assume

$$\boldsymbol{Y}_{\mathbf{m}} = \boldsymbol{g}(\boldsymbol{X}_{\mathbf{m}}) \tag{17.3}$$

The term $\boldsymbol{Y}_{\mathbf{m}}$ will differ from $\boldsymbol{Y}$ either because $\boldsymbol{X}_{\mathbf{m}}$ differs from the real $\boldsymbol{X}$ or from structural error in use of $\boldsymbol{g}$. We can require that $\boldsymbol{X}$ and $\boldsymbol{Y}$ be adjusted to be as close as possible to their real values in an *rms* sense, i.e., find an optimum estimate $\hat{\boldsymbol{X}}$ as the minimum value of

$$J = \left|\boldsymbol{X} - \hat{\boldsymbol{X}}\right|^2 + \left|\boldsymbol{Y} - \boldsymbol{g}\hat{\boldsymbol{X}}\right|^2. \tag{17.4}$$

where all parameters have been normalized by error estimates. If $\hat{X}$ is close enough to X_m, Eq. (17.4) can be linearized and solved by matrix computations. In this case, it reverts to linear least squares fitting, as appropriate for a statistical model with Gaussian error terms. The standard technologies of data assimilation in atmospheric models are summarized in Kalnay (2003).

Detailed implementation should make use of known spatial correlations and error characterizations. Some aspects of this issue have already been addressed by hydrologists in the context of the fusion of microwave data and soil moisture modeling (e.g., Entekhabi et al., 2004; Reichle and Koster, 2005). For statistics that change a lot in time, i.e., depend on X, it has been found useful to do ensemble integrations of the system Eq. (17.2). A future target for such a data assimilation approach will be terrestrial carbon (e.g., Hese et al., 2005). Various satellites are under development to measure the variability of atmospheric CO_2 with enough accuracy to infer terrestrial and oceanic sources and sinks. Such estimation can be substantially improved with the inclusion of these measurements in atmospheric data assimilation schemes along with terrestrial and oceanic process modeling.

Assimilation of terrestrial reflectance imaging into models for the time evolution of canopy structure and LAI will become another major component of this activity. The implementation of such assimilation will require more advanced algorithmic approaches to canopy radiation so that the climate model simulations are realistic enough to reproduce the reflectances seen by remote sensing data.

17.8 Conclusions

Climate models have become increasingly realistic in their descriptions of land surface processes. They absorb solar radiation and emit long wave radiation depending on structural details such as arrangement of leaves and soil moisture. Remote sensing instruments measure the same radiation as reproduced by climate models. Various aspects of vegetation change in time in response to variations in climate. Climate models have begun to include such changes in terms of "dynamic vegetation". However, the climate models still use much less realistic treatments of terrestrial radiation than have been achieved by the remote sensing community.

By simplification and improved efficiencies, the treatments of radiation used in remote sensing can be adopted into climate models. With such, many terrestrial remote sensing products should be derivable through forward calculations in data assimilating climate models. The logic, as used today, for atmospheric observations is that the climate model provides a first estimate, which in principle has incorporated in it all past observational information. Current observations then provide a correction to this a priori estimate. The resulting optimal estimate is essentially a weighted average of two estimates, where the weighting is determined by an understanding of correlated error statistics. Although assimilating terrestrial data should involve these general principles, the details of approaches needed will be vastly different because of very different time and space scales of the dynamics and observations. In particular, vegetation is only spatially coupled on climate scales, has very fine spatial sampling structure, and its temporal sampling by satellite is sparse.

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