Land Surface Model

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Land Surface Models (LSMs) are important components of the climate models, which help to capture the water, energy, and momentum exchange between the land surface and the atmosphere, providing lower boundary conditions to the atmospheric models.

machine learning | land surface | land-atmosphere interactions | parameterizations | model uncertainty

1. LSMs: Importance, Then and Now

As mentioned in the introduction, LSMs are numerical models that simulate land surface processes, such as absorption and partitioning of radiation, water, and carbon between the land surface and atmosphere. Provided with meteorological forcing as inputs (from an atmospheric model either in 'coupled' mode or an 'uncoupled' mode), they estimate latent heat fluxes (LH), sensible heat fluxes (SH), carbon fluxes, surface runoff, deep drainage, reflected solar and emitted longwave radiation as output [1][2]. While LH and SH control the boundary layer properties and precipitation; net carbon flux influences the atmospheric CO_2 content. These estimates play a critical role in determining the effects of human-modified land surface and human emissions on changes in the climate. LSMs are perhaps the most efficient tools to predict how the continuously evolving earth surface will modify the hydroclimate in coming years and centuries. The extents of modeling activities with LSMs include multiple interlinked disciplines (such as atmospheric modeling, crop modeling, and hydrologic modeling) relevant to this overarching problem.

LSMs were originally developed by the atmospheric modeling community who needed physical boundary conditions consisting of energy and moisture partitioning, albedo, and surface roughness to indicate the impact of the surface on the atmospheric processes. Richardson [3], in 1922, first mentioned the importance of stomatal conductance on weather processes. Early studies, such as Charney et al. [4] used albedo as a proxy for vegetation and started investigating the effects of deforestation in terms of it. Starting from the 1980s, scientists started understanding the land surface-atmosphere interactions [5][6]. Garatt et al. [7] summarized the importance of land surface in climate modeling in a review paper. He discussed different boundary layer schemes and the results from global climate model (GCM) sensitivity studies using these schemes. He concluded that the regional and global climate is significantly influenced by albedo, surface moisture and roughness, and the inclusion of vegetation. However, till then, it was not clear how much spatial detail of the surface is sufficient to accurately represent the lower boundary conditions. For that decade, improvements of LSMs were driven by the need to understand the effects of deforestation in various parts of the world. In the 2000s, scientists started to visualize the importance of land in the context of sub-seasonal to seasonal forecasting. The land surface was identified as a slowly varying component of the earth system, which has a major role in modulating the atmospheric response at a longer timescale than weather prediction. Koster et al. papers [8][9], in connection with the Global Land-Atmosphere Coupling Experiment (GLACE), identified soil moisture as an important factor altering evaporation and precipitation. They also highlighted the regions where strong coupling between soil moisture and precipitation exists. For the first time, they introduced the concept of 'coupling strength' to quantify such coupling, which is still being widely used in land-atmosphere interaction studies. However, while modeling these interactions, there exists a huge variation among the global models, attributable to the uncertainties in terrestrial and atmospheric branches, and the models fail to represent the land-surface coupling accurately [10]. Specifically, they found systematic biases in near-surface temperature, humidity, and precipitation, which contribute to the uncertainty. Seneviratne et al. [11] summarized the findings related to soil moisture-precipitation relations in a review paper and concluded that the relationship between soil moisture and precipitation is evident in observations and models. However, significant uncertainty remains in quantifying those in terms of the strength of coupling, and persistence characteristics. These studies indicate the need for further improvement in land surface models. The need for LSMs to quantify such biogeophysical and biogeochemical feedbacks to the climate system has formed the basis of their recent development efforts.

At present, LSMs have expanded from their initial simple biophysical configurations [12] to include representations of stomatal functioning [13], scaling information from leaf to canopy [14], soil moisture dynamic and surface hydrology [15][16], crop processes [17][18], land surface heterogeneity [19], dynamic vegetation [20][21], urban environment [22], land cover management [23][24], plant demographic processes and plant hydraulics [25], groundwater dynamics [26], soil microbial dynamics [27], leaf mesophyll process, nitrogen, phosphorus, carbon cycling and their mutual interactions [28]. The incorporation of processes in LSMs is driven by the need for extensive user communities, including ecologists, crop modelers, atmospheric scientists, biogeochemists, hydrologists, who explore interactions between different components of the system. Some widely used LSMs across the globe include Interaction Soil-Biosphere-Atmosphere (ISBA, [28]), The Community Land Model (CLM, [23]), JSBACH [29], Joint UK Land Environment Simulator (JULES, [30]), LPJ-GUESS [31], Noah-MP [32]. Along with the increasing capability of representing processes, LSMs are enhancing their spatial resolution as well, with the improvement in resolution of the atmospheric models. As the scope of LSMs broadens with the support of computational advancements, the questions of cognitive uncertainty and unresolved heterogeneity emerges as a challenge.

2. Complexity and Limitations of LSMs: Prospect of ML

The diversity of the interconnected processes in the terrestrial system, and the levels of entanglement present in these processes, pose a hurdle to build tractable land models. The propensity of scientists to focus on their own specific area of interest and the reality that the earth system is indeed complex are both responsible for this complex nature. Often, this reaches a point where no individuals are able to completely understand all aspects of any particular model, and the development teams strive to meet all the requirements placed on modern LSMs [2]. Even though, large uncertainty remains in our understanding and modeling of the interactions between atmospheric and terrestrial branches of the hydrologic cycle due to the non-trivial mechanisms at the land surface. Figure 1 illustrates the convoluted and connected processes in a typical LSM. The major parts, such as, atmosphere, hydrology, urban processes, agriculture; and plant physiology, soil biogeochemistry, soil physics related to each of those, are interlinked in an LSM. These major components are further segregated into smaller yet complicated processes. For example, agriculture includes fertilizer and pesticides usage, biomass burning, harvesting, irrigation, tillage, residual treatment etc. (Figure 1). The interactions are defined by the exchange of information between different parts of the model. However, some of the processes are still oversimplified in modeling. As such, most of the LSMs classify plant species into plant functional types (PFTs), within which the parameters are undifferentiated. Simulations consisting of a limited number of PFTs ignore biodiversity within a simulation grid. This may lead to uncertainty in the strength of climate responses when coupled to a climate model. Furthermore, understanding the combined effects of major greenhouse gases, such as Carbon dioxide, Methane, and Nitrogen dioxide on global warming are still at early stages due to constraints in the measurements of multiple gases. Limited models have the capacity to simulate such effects, which requires realistic carbon and nitrogen cycling processes.

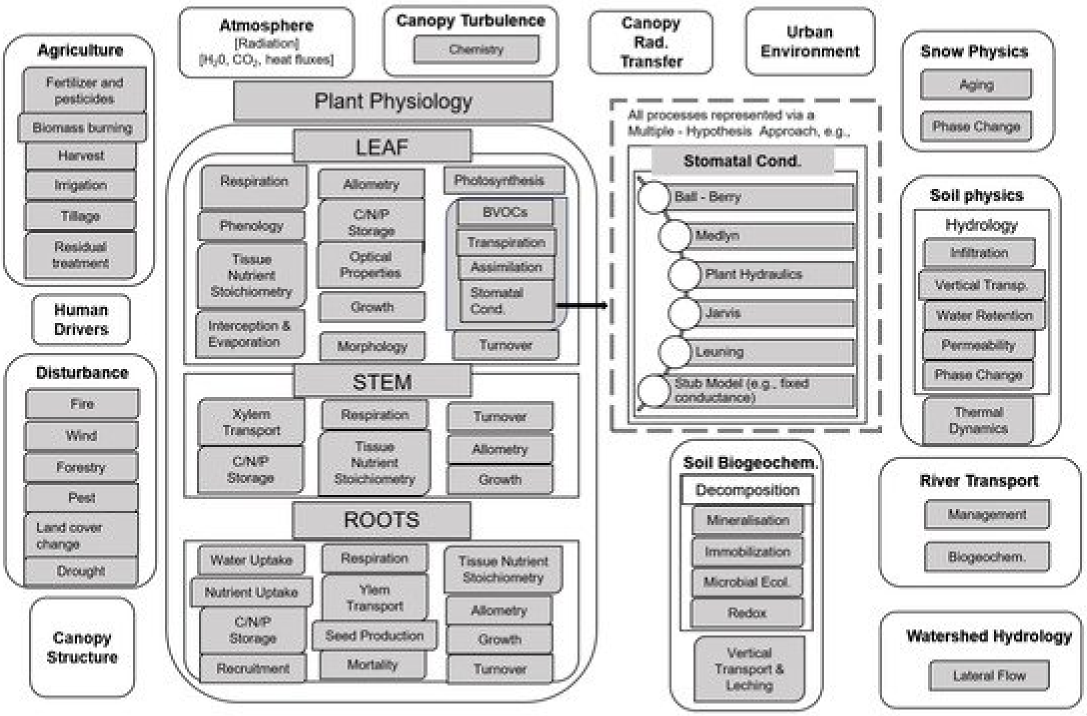

Figure 1. Interconnected complex processes included in a typical LSM. Adapted and modified from Fisher et al. [2].

LSMs are often applied at large spatial scales aimed to simulate the interactions between climate and land surface. Nonetheless, validation data for these models are obtained from flux tower sites. This geographical gap usually limits the accuracy of the models. Microbes may play fundamental roles in altering biogeochemical cycling as 'ecosystem engineers' [33]. However, very few LSMs include the effects of such organisms in an explicit manner. This limits our ability to estimate the climatic impacts of changes in soil biological community composition and diversity. In addition, the unavailability of high-resolution land-surface data affects the LSMs in capturing the effects of spatial heterogeneity. The development of high-accuracy fine resolution data is important for the interpretation of observations and model simulations.

Some of the limitations of LSMs can be highly benefited from the enormous information currently available from satellite data. However, extracting useful knowledge from terabytes of data provided by observation and LSM simulations is challenging. In contrast, ML models are simple in nature in terms of structure and easy to simulate the output once trained properly. Figure 2 illustrates the general structure of a multilayer perceptron model, which is a commonly used feedforward ANN type ML model and uses supervised learning techniques for training. Compared to LSMs (Figure 1), the structure is much simpler and furthermore, the model parameters are data driven. ML techniques can help and complement LSMs in several ways, including surrogate modeling, physics-guided machine learning, parameter estimation, and data assimilation to reduce the uncertainties and generate useful knowledge from large amounts of observational data. Some of the ML applications in land modeling are described in the next section.

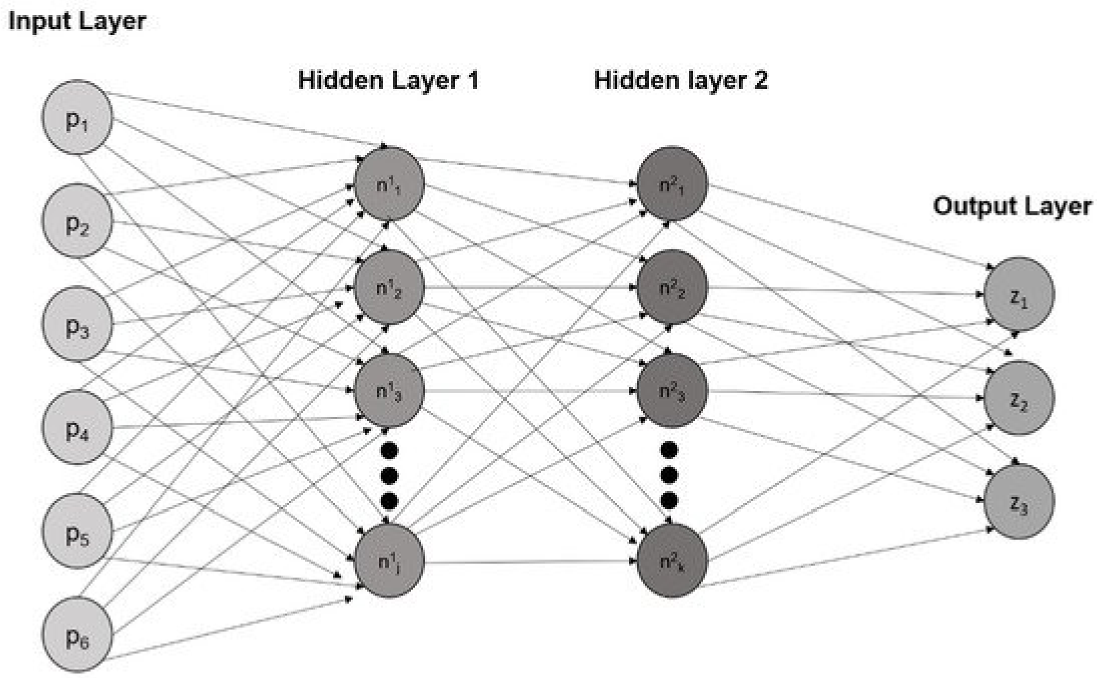

Figure 2. General structure of a multilayer perceptron model.

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