Global Modeling of Precipitation Partitioning by Vegetation and Their Applications

7

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Abstract

The partitioning of precipitation by vegetation canopies into throughfall and evaporation can have a large effect on water availability for both ecosystems and human consumption. Canopies are often the first point of contact between precipitation and the land surface, yet the complexity and inaccessibility of this interface make measurements extremely difficult, and as a result our attempts to understand and model the relevant processes are only weakly constrained. Here, we describe common approaches to modeling canopy interception processes, particularly in global models. These models use a wide variety of parameterization and parameters internally, suggesting that we do not have a good understanding of how to model canopy interception on a global scale. To begin to quantify how big a problem this may be, we present a few ideal model experiments exploring a range of modeling approaches and assumptions to document what effect these choices have on the projection of changes in inputs to the eco-hydrologic system. Perhaps unsurprisingly, these effects vary with vegetation type and density, as well as precipitation type, intensity, and changes in precipitation. In many cases, these effects are likely dwarfed by the uncertainties in predicted changes in regional climate, but not accounting for our lack of certainty in canopy processes can lead to an overconfident, and in some cases likely incorrect, projection of future changes in water availability. This should serve as a call to action for those studying canopy interception processes to better document and consider how theories can be put into a numerical framework.

Keywords

Model • Weather prediction • Vegetation • Interception • Evaporation • Climate hydrology • Streamflow

7.1 Introduction

Models provide a mechanism to test the combined effect and interrelationships between all our hypotheses of how a system works, and models provide a key application by allowing scientific discoveries to translate into better predictions for streamflow forecasting, climate assessments, weather prediction, and a host of other human endeavors. As such, the canopy interception and precipitation partitioning model behavior can be thought of as an emergent hypothesis of how one component of the larger earth system works. This book is filled with discussions ranging from detailed implications of vegetation precipitation partitioning on soils (Chap. 12) and biogeochemistry (Chap. 11), to the processes controlling evaporation (Chap. 3), stemflow and throughfall (Chap. 2), to microbiology (Chap. 14), and economic impacts (Chap. 15). Many of these processes are represented in land surface and hydrology models, though often in fairly simplistic ways (storage and drip), and many of these are absent from them (e.g., stemflow, microbiology, and throughfall heterogeneity). Here, we review the state of canopy interception modeling in widely used hydrology and land surface models.

A review of this sort is critical for this book because it puts the state of operational modeling in perspective of the amazing advances described elsewhere in this book and will perhaps allow the reader to see where new observations could

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be used to improve models, where models can (or cannot) be used to inform our study, and where existing theory and observations can be better integrated into these models.

Our ability to model precipitation partitioning by vegetation is important for a wide variety of applications. One of the primary effects of canopy interception on the water cycle occurs through its impact on evaporation (Porada et al. 2018). Intercepted canopy water is stored on a widely distributed surface (leaves, needles, stems, and epiphytic vegetation) often high off the ground where the wind is stronger, and thus evaporative fluxes can be much greater. Our ability to model this evaporation is important for water resources because evaporated water is lost as supply to local soil water recharge and streamflow. In addition, this evaporation has multiple important effects on the weather; evaporated water is added back to the atmosphere thus influencing downwind humidity and precipitation (van der Ent et al. 2014), and that evaporation has a local cooling effect thus decreasing the local air temperature (Davies-Barnard et al. 2014). Both evaporation and the simple mechanism of storing water in the canopy affect streamflow (Swank and Douglass 1974). The evaporative losses mean that water is not added to the soil where it is slowly released into the stream channel, and the temporary storage in the tree canopy provides an additional buffer that can modulate flooding (Trabucco et al. 2008). Particularly when one considers snow in the vegetation canopy, there is a major additional effect on the surface energy budget through the change in the albedo of the land surface; this affects the weather, and integrated over time this can affect the climate system as a whole (Lundberg and Halldin 2001; Sturm et al. 2017). Warming air temperatures will set off a positive feedback, known as the snow albedo feedback, wherein warmer temperatures cause snow to fall as rain (or to melt earlier), which in turn results in less sunlight reflected and that leads to warmer air temperatures (Letcher and Minder 2015).

7.2 Precipitation Partitioning Models

A computer model is little more than a collection of equations integrated forward in time numerically. These equations relate state variables, e.g., the amount of water stored in the canopy, with input forcing, e.g., the precipitation rate and air temperature, to calculate the fluxes, e.g., throughfall, stemflow, and evaporation. The most common such equation is the simple mass balance for the canopy (Eq. 7.1)

$$\frac{\mathrm{d}W_\mathrm{c}}{\mathrm{d}t} = f_\mathrm{veg}(P - E - S - D) \tag{7.1}$$

where W_c is the intercepted water in the canopy [kg m^{-2}], t is the time [s], P is the precipitation rate [kg m^{-2} s^{-1}], f_veg is the fraction of land covered by the vegetation canopy, E is the canopy evaporation rate [kg m^{-2} s^{-1}], S is the stemflow flux [kg m^{-2} s^{-1}], and D is the drip throughfall from the canopy [kg m^{-2} s^{-1}]. For the fraction of land beneath canopy gaps, this "gap throughfall" is equivalent to P. This seemingly simple equation is at the heart of precipitation partitioning, how much water falls to the surface as drip, throughfall, and stemflow, and how much is "lost" to evaporation. Note that each one of those parameters and fluxes has one, or in some cases many, equation associated with them. For example, the evaporation rate is often computed based on a Penman–Monteith (Penman 1948; Monteith 1965) combination equation which couples the moisture and energy budget after making some simplifying assumptions (Eq. 7.2), though simpler methods exist based on radiation (Priestley and Taylor 1972), or temperature (Thornthwaite 1948). However, evaporation can also be computed through numerical integration over the separate energy and moisture components.

$$E_\mathrm{p} = \frac{\Delta(R_\mathrm{n} - G) + \rho_\mathrm{a} c_\mathrm{p}(e_\mathrm{s} - e_\mathrm{a})/r_\mathrm{a}}{\Delta + \gamma} \tag{7.2}$$

E_p is the potential evaporation, Δ is the slope of the saturation vapor pressure curve, R_n is the net radiation, G is the ground (or stem or leaf) heat flux, ρ_a is the density of air, c_p is the specific heat of air, e_s is the saturated vapor pressure of air, e_a is the actual vapor pressure of the air, r_a is the aerodynamic resistance to turbulent fluxes, and γ is the psychrometric constant (66 Pa K^{-1}).

This deceptively simple mass balance equation can be solved by a variety of approaches. In field-based studies, it is not uncommon to combine the measurement of some of these components to derive the others; indeed, evaporation is often simply calculated from observed precipitation and interception loss (Friesen et al. 2015). In more theoretical approaches, an estimate of average evaporation rates over a storm can be combined in an analytical solution for total evaporative losses (Gash 1979). For more predictive, applied models, a numerical solution is typically used as in the pioneering work of Rutter et al. (1971). These are the types of models explored here; however, many developments in analytical model frameworks, such as variable storage capacity (Bulcock and Jewitt 2012), or the impact of epiphytes (Van Stan et al. 2016) are important and their inclusion in predictive models needs to be better explored.

Here, we present an overview of the canopy interception component of common models of the land surface and provide some examples showing how the canopy interception model affects our estimate of precipitation partitioning, including changes in that partitioning in a future climate.

7.3 Model Overviews

There are a very large number of modeling systems in various states of operational usage around the world. Here, we focus primarily on widely used hydrology, snow, and land surface models. The hydrology models are often used in water resource planning and streamflow prediction, the snow models are commonly integrated into another land surface model, or they are used for specific snow-related applications (e.g., avalanche prediction or ecosystem studies), while the land surface models often provide the lower boundary condition in atmospheric models, both for the climate system and for weather prediction. There are a few cases of overlap, e.g., the National Water Model (Cosgrove 2017) uses the Noah-MP land surface model (Niu et al. 2011) and as such it is not discussed under hydrology models, though it used for hydrologic applications.

One thing that most if not all models have in common is the value they gain from remotely sensed vegetation properties. To apply any model globally, or even regionally anywhere in the globe, one must have a way of describing what is unique about that location for the model. The most commonly prescribed parameters are soil classifications to describe soil hydrology, which is very poorly constrained (Gutmann and Small 2005), topography, which is relatively well known, and vegetation (Gutman and Ignatov 1998). Vegetation is typically described based on very broad classifications of plant functional types, e.g., evergreen needleleaf, broadleaf deciduous, or grassland, and such broad classifications are available globally (Fig. 7.1), typically derived from the seasonal time series of a remotely sensed vegetation index such as the Normalized Difference Vegetation Index (NDVI; Tucker 1979) (Fig. 7.2), or more recently, the Enhanced Vegetation Index (EVI; Huete et al. 2002). While such broad classifications may seem like a poor representation of the world to a researcher focused on evaluating the difference between an Aspen (*Populus tremuloides*), an Oak (*Quercus*), and a Maple (*Acer*), these are the classifications currently supported by available datasets, and arguably the classifications for which models can presently be parameterized. Along with the plant functional type maps they enable, these vegetation indices are also used to

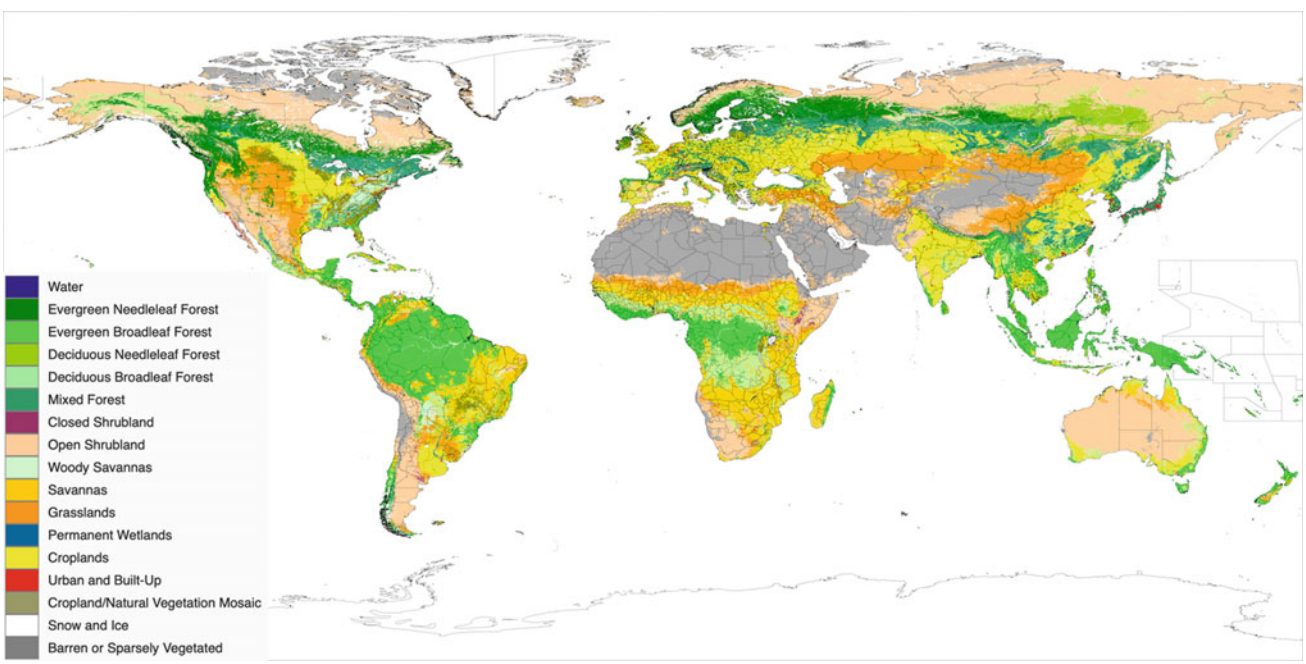


Fig. 7.1 Global land cover map derived from the NASA MODIS sensor in the International Geosphere-Biosphere Programme (IGBP) class definitions, such classes are widely used in land surface models as the primary method of distinguishing different vegetation types. Creative Commons License: https://commons.wikimedia.org/wiki/File:Land_cover_IGBP.png

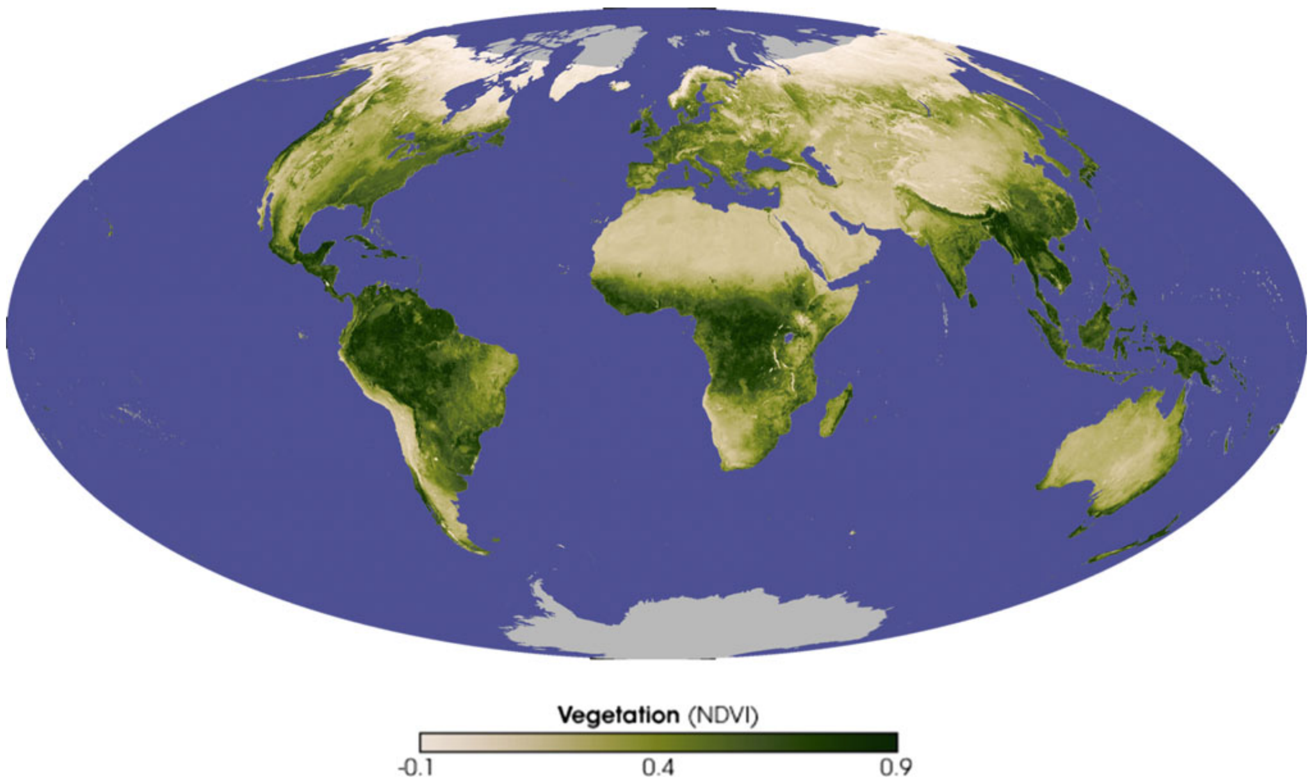


Fig. 7.2 Global map of the normalized difference vegetation index widely used to measure vegetation abundance, e.g., leaf area index or vegetation fractional cover for parameters in global land surface models. Creative Commons License: https://commons.wikimedia.org/wiki/File:Globalndvi_tmo_200711_lrg.jpg

estimate the abundance of different plant types through a simple time mean, a climatological annual cycle, or as a transient evolution of the surface. While these vegetation index datasets and plant functional types are widely used, little consideration is given to understanding the uncertainty in these datasets themselves (Hartley et al. 2017).

In reviewing the section headings and list of models below, one may note that modelers have an affinity for acronyms; one has to admire the ingenuity and creativity that has gone into such a large collection of names. Although the following sections cannot document all details of all canopy models, these sections attempt to highlight many of the key features of a variety of models.

7.3.1 Hydrology Models

Hydrology models typically focus on the prediction of streamflow for either streamflow forecasting and flood applications or water resource management. These models can be global in nature, as is the case for the Global Flood Alert System (GFAS; http://gfas.internationalfloodnetwork.org/gfas-web/), continental such as the US National Water Model (NWM; Cosgrove 2017) (https://water.noaa.gov/about/nwm), regional, as many applications of the Variable Infiltration Capacity (VIC) model that is often used for regional water resource management applications, or local as many implementations of the Sacramento Soil Moisture Accounting model (Sac-SMA) used by the River Forecast Centers (RFCs) in the US National Weather Service.

7.3.1.1 Variable Infiltration Capacity (VIC) Model

The Variable Infiltration Capacity (VIC) model (Liang et al. 1994) is widely used in water resource and hydrologic applications, including climate change impact studies (Brekke et al. 2009), and long-term surface monitoring in continental domain models (Mitchell 2004) for, e.g., drought monitoring (Shukla and Wood 2008). VIC represents vegetation heterogeneity within a grid cell using multiple independent land cover tiles. VIC uses the Penman–Monteith combination equation to estimate potential evaporation rate. This potential evaporation is then modified by the amount of water in the canopy (Eq. 7.3). This formulation permits evaporation to occur at the maximum potential rate limited only by atmospheric demand when the canopy is saturated, and this rate decreases as the amount of water in the canopy, and thus the exposed surface area of water, decreases.

$$E_c = \left(\frac{W_i}{W_{im}}\right)^{\frac{2}{3}} * E_p * \frac{r_w}{r_w + r_o} \tag{7.3}$$

where E_c is the canopy evaporation, W_i is the intercepted canopy water, W_{im} is the maximum intercepted canopy water content for the given vegetation type, E_p is the potential evaporation rate, r_w is the aerodynamic resistance to evaporation between leaves in a canopy and the air above the canopy, and r_o is the architectural resistance specific to each vegetation type. W_{im} for rain is 0.2 * the Leaf Area Index (LAI) after (Dickinson 1984). In some models, the stem area index (SAI) can be included in this relationship.

Canopy snow in VIC is treated explicitly, with the canopy interception rate of snow being equal to the precipitation rate scaled by a vegetation efficiency parameter of 0.6 (Storck et al. 2002) up to a maximum interception capacity given by the product of the LAI, the ratio of observed interception capacity and LAI, and a leaf area ratio as a function of temperature. Snowmelt in the canopy is calculated directly from a modified energy balance, and rain on snow in the canopy is also intercepted according to the water holding capacity of the snow in the canopy. Unloading of snow from the canopy is computed relative to drip of excess meltwater using a ratio of 0.4 (Storck et al. 2002). For a recent comprehensive review of canopy snow processes in VIC, see Andreadis et al. (2009).

7.3.1.2 Precipitation Runoff Modeling System (PRMS)

The Precipitation Runoff Modeling System (PRMS; Leavesley et al. 1983) is a popular hydrology model developed by the United States Geological Survey (USGS). It is used to produce streamflow forecasts and has been used to evaluate climate impacts on hydrology (Markstrom et al. 2012). For rain, PRMS computes available canopy storage as the difference between the maximum storage capacity and the currently stored water. Any precipitation in excess of this available storage is partitioned into throughfall (Markstrom et al. 2015). The spatial discretization of PRMS permits divisions of the area to be modeled into Hydrologic Representative Units (HRUs), with no expectation that HRUs follow a grid, and the precipitation partitioning calculation is tracked for each HRU independently based on the vegetation cover density and type in each HRU. Like VIC, evaporation from the canopy is based on a background potential evaporation rate; however, PRMS provides multiple methods to estimate that background evaporation rate or potential evaporation can be provided as an input forcing dataset. Snow interception and rain interception are treated discretely in PRMS, but only one can be present in the canopy at a time, and the maximum interception capacity is simply defined for each. Snow sublimation from the canopy is treated as a fraction of the potential evaporation rate.

7.3.1.3 Regional Hydro-Ecologic Simulation System (RHESSys)

The Regional Hydro-Ecologic Simulation System (RHESSys; Tague and Band 2009) is an eco-hydrology model, primarily used in research applications, and is often applied for the hydrologic implications of land cover change studies. RHESSys also maintains a detailed biogeochemical state and can be used to dynamically change the vegetation as it runs. RHESSys can include multiple canopy layers in each horizontal patch, and, like PRMS, horizontal patches are not constrained to be on a grid. As a result, RHESSys can simulate the extinction of incoming radiation, precipitation, and wind through multiple canopy layers and different layers can have different properties, thus permitting the explicit simulation of a vegetation overstory and understory. As with PRMS, RHESSys follows a simple relationship that permits the canopy to collect any additional rain up to the maximum storage capacity. RHESSys differs in that it permits throughfall from one canopy layer to be intercepted by lower layers, with the effect cascading down through as many layers as are specified. Snow is treated in the same way, but with a different maximum interception capacity. Evaporation from the canopy is assumed to occur at the potential rate; however, RHESSys computes a new potential rate for each layer in the canopy based on changes in radiation extinction through the canopy (following Beer's Law), and reductions in wind speed through the canopy, in addition, sunlit and shaded portions of the canopy are treated independently.

7.3.2 Land Surface Models

Land surface models are primarily used in atmospheric models to provide the lower boundary condition for both weather and climate simulations. As such, these models often focus much more heavily on processes that affect land–atmosphere interactions. So, while hydrology models such as RHESSys and PRMS often use a daily time step, most land surface models use an hourly or sub-hourly time step to explicitly resolve the diurnal cycle. When run coupled to an atmospheric model, they may even be integrated into sub-minute intervals.

7.3.2.1 Community Land Model (CLM)

The Community Land Model (CLM; Lawrence et al. 2019) provides the lower boundary condition for the Community Earth System Model (CESM; Hurrell et al. 2013). CLM has a long history focusing on biogeochemical fluxes, e.g., carbon, as well as the hydrologic cycle. This focus is evident in that a paper describing improvements to the canopy model in CLM does not mention interception, focusing instead on gross primary production and transpiration (Bonan et al. 2011). That is not to say that CLM has a simplistic canopy representation, merely to illustrate that the development focus of most models is not on canopy interception. The treatment of canopy effects on net evaporation is discussed in detail in other publications (Lawrence et al. 2007), and version 5 includes significant advances in the canopy hydrology representation, in particular, version 5 now tracks canopy snow and liquid water independently and incorporates a canopy snow unloading term as a function of wind speed. The interception of rain and snow occurs at the precipitation rate scaled by a function of leaf and stem area. "Drip" of both snow and liquid from the canopy occurs to remove any canopy water stores in excess of the maximum interception capacity, with different capacity factors for rain and snow. One of the more interesting additions in CLM's treatment of snow in the canopy is the ability to unload snow as a function of wind speed (Eq. 7.4) and temperature (Eq. 7.5).

$$q_{\mathrm{u,w}} = \frac{uW_{\mathrm{cs}}}{1.56 * 10^5\,\mathrm{m}} \tag{7.4}$$

$$q_{\mathrm{u,t}} = \max(0, \frac{W_{\mathrm{cs}}(T - 270\,\mathrm{K})}{1.87 * 10^5\,\mathrm{K\,s}}) \tag{7.5}$$

where $q_{\mathrm{u,w}}$ is the unloading due to wind, u is the wind speed, W_{cs} is the canopy snow, $q_{\mathrm{u,t}}$ is the unloading due to temperature, T is the air temperature, and all other values are constants with units. All subject to the constraint that the unloading flux may not exceed the canopy snow content. In addition, the wetted fractions of the canopy (including rain and snow separately) are used when estimating canopy albedo and evapotranspiration fluxes.

7.3.2.2 Noah Multi-physics (Noah-MP)

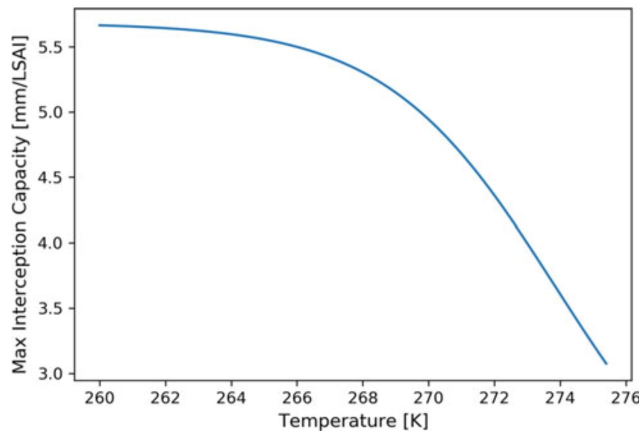
The Noah Multi-Physics (Noah-MP; Niu et al. 2011) model is an important LSM to consider because it currently forms the basis of the United States National Water Model (NWM) and it provides the lower boundary condition for the Weather Research and Forecasting model (WRF; Skamarock and Klemp 2008). The National Water Model provides real-time forecasts of streamflow and other hydrologic variables for the United States National Oceanic and Atmospheric Administration (NOAA). WRF is perhaps the most widely used weather and regional climate model in the world.

The canopy interception model in Noah-MP treats liquid and frozen water separately, and permits both to be present simultaneously with conversions handled explicitly. Noah-MP also tracks unloading of snow from the canopy, though now explicit representation of drip from liquid water is mentioned in the canonical reference (Niu and Yang 2004). The interception of snow in Noah-MP is calculated as a function of the remaining storage capacity of the canopy, and the snowfall rate (Eq. 7.6), and the maximum interception capacity is itself calculated as function of both the combined Leaf and Stem Area (LSAI) as well as the density of fresh snow (Eqs. 7.7 and 7.8). The interception capacity for rain is simply ten percent of SLAI.

$$R_{\mathrm{load}} = (M_{\mathrm{ice,max}} - M_{\mathrm{ice}})\left(1 - e^{\frac{-P_{\mathrm{S}}\Delta t}{M_{\mathrm{ice,max}}}}\right)/\Delta t \tag{7.6}$$

$$M_{\mathrm{ice,max}} = \alpha(0.27 + \frac{46}{\rho_{\mathrm{s}}})\mathrm{LSAI} \tag{7.7}$$

Fig. 7.3 Maximum canopy snow interception per unit of leaf and stem area in the Noah-MP land surface model as a function of air temperature



$$\rho_s = 67.92 + 51.25e^{(T_{air} - 273.16)/2.59} \quad (7.8)$$

where R_{load} is the total snow interception rate, $M_{ice,max}$ is the maximum canopy snow interception capacity, M_{ice} is the current intercepted snow mass, P_s is the snowfall rate, ρ_s is the density of fresh snow, ρ is a constant (approximately 6), LSAI is the combined leaf and stem area index, and T_{air} is the air temperature. The combination of these equations means that new snow density increases with increases in air temperature near freezing; however, the maximum interception capacity actually decreases with increases in air temperature (Fig. 7.3). This has important implications for any climate change analysis as increases in temperature will be expected to decrease canopy snow interception, and thus associated evaporation and sublimation. Noah-MP also includes a wind and temperature modification to snow unloading from the tree canopy as in CLM, though it also includes no effect of wind on the interception of snow or rain.

7.3.3 Other Models

We have necessarily described just a few of the many hydrology and land surface models that exist. The reader is referred to the literature for a description of, for example, the Hydrology Tiled ECMWF Scheme for Surface Exchanges over Land (H-TESSEL; Balsamo et al. 2009), Interaction Soil–Biosphere–Atmosphere (ISBA; Noilhan and Mahfouf 1996), ORganizing Carbon and Hydrology in Dynamic EcosystEms (ORCHIDEE; Krinner et al. 2005), Simple Biosphere model (SiB; Sellers et al. 1986), Joint UK Land Environment Simulator (JULES; Best et al. 2011), the Community Atmosphere Biosphere Land Exchange (CABLE; Wang et al. 2011), and the Structure for Unifying Multiple Modeling Alternatives (SUMMA; Clark et al. 2015a, b) models.

7.4 Future Model Improvements

Perhaps, the most important needs in developing better models of interception are centered on the parameters used in these models. While there are many different approaches to representing the fraction of water that is concentrated in stemflow, the volume of water intercepted, the canopy drip rate, etc., all of these approaches have parameters within them that vary dramatically in field studies, often by an order of magnitude (see Chaps. 2–4). While the experimentalist can simply document these variations, the modeler is required to put something into their model. In most cases, this results in a simple average value from whatever field studies the modeler is able to find in the literature. In reality, it is likely that a stochastic approach to modifying parameters in space and time might represent a more realistic spatiotemporal variability. However, when judging a model based on its predictions, it is very often the average values that will do the best by the common mean squared error metric. This does not make these values correct. Importantly, many different modeling groups have used data from the same, relatively small, set of field experiments (e.g., FIFE and BOREAS), as such these semi-independent models are in reality being constrained to match the same limited set of data, and as such cannot be used to represent independent samples for, e.g., uncertainty quantification (Clark et al. 2016; Abramowitz et al. 2019). There is an important need in the community for a much larger sample of observational studies to be collated for future model development and testing of canopy interception processes. There will also be a substantial benefit in a wider review of the literature to incorporate additional processes such as stemflow (Zhang et al. 2015). For example, functions exist relating rainwater unloading as a function of wind speed (Hormann et al. 1996) that could be added to models in the future. Because some of these land surface models are developed in an open environment, it is possible for the canopy interception community to coordinate with the developers and add such improved formulations and parameters directly to the source code and parameter files.

In streamflow modeling, often the individual parameters of interest are intrinsically impossible to measure (e.g., related to widely distributed transfers of water deep in the soil); as a result, many model parameters are instead calibrated based on a goodness of fit metric to some holistic behavior of the system, e.g., observed streamflow. A similar approach might be taken to improving estimates of landscape-scale effects of canopy interception on water resources, land surface albedo, and evaporative processes, though such macroscale calibration runs into significant problems due to the compensating effects of multiple parameters, as such it must be heavily guided by theoretical understanding and, when possible, distributed measurement as from satellite-based sensors.

Improving parameters can focus on several aspects. Experimentalists and theorists can work to explain the source of the variability such that a model can incorporate additional processes to predict the correct parameter. Modeling efforts also benefit from better spatial measurements of the parameters more directly, e.g., through better remotely sensed products. For example, past work (Gutmann and Small 2010) has attempted to use Earth's surface skin temperature measurements over time, in comparison to model predictions, to modify the soil parameters and thus improve evapotranspiration estimates in a model. This worked reasonably well in areas without dense vegetation cover; however, in areas with dense canopies, the thermal properties of the surface might be better related to the canopy structure and water status, including intercepted rainwater and vegetation drought stress. Indeed, the NASA ECOSTRESS sensor is designed to exploit precisely this relationship by using very high-resolution and high radiometric precision to better monitor vegetation water stress characteristics. Similarly, remotely sensed snow-covered area can be used to estimate when snow is present in the forest canopy, and this could be used to improve canopy snow interception characteristics including interception efficiency and melt rates or mechanical unloading parameters. Novel remote sensing products such a vegetation optical depth (Rodríguez-Fernández et al. 2018) may provide additional useful canopy structure information on global scales.

While more direct measures of properties via remote sensing estimates may have the best chance of improving models in the short term, without a reliable understanding of these parameters and the causes for their variations, it becomes impossible to predict how they will change in the future. This is important for studies that attempt to predict the effect of, e.g., forest thinning, wildfires, changing forest species distributions, or global climate changes that can both alter the forest and the weather conditions in which the forest is operating. Such understanding and capability require a quantifiable mechanistic model of the forest canopy behavior, most likely beyond what the current state of the art in dynamic vegetation models (see: Fisher et al. 2017) are capable of.

7.5 Example Macroscale Applications

In this section, we step away from the details of model parameterizations and instead examine the results of these models. We illustrate how one model (VIC) portrays the partitioning of evapotranspiration into the transpiration, bare soil evaporation, and canopy evaporation components across the Contiguous United States (CONUS). We then compare the estimates of canopy evaporation in VIC with those in CLM, and finally we examine the changes in the canopy water storage term in a climate change scenario using the Noah-MP land surface model within the Weather Research and Forecasting (WRF) regional climate model.

7.5.1 Modeled Evapotranspiration Partitioning

When looking at standard output of the VIC hydrology model (Liang et al. 1994), it is clear that canopy evaporation will only be important in some seasons and regions. Figure 7.4 shows the partitioning of total evapotranspiration predicted by VIC over the CONUS domain. In this example, VIC was run using a gridded daily observation dataset (Maurer et al. 2002)

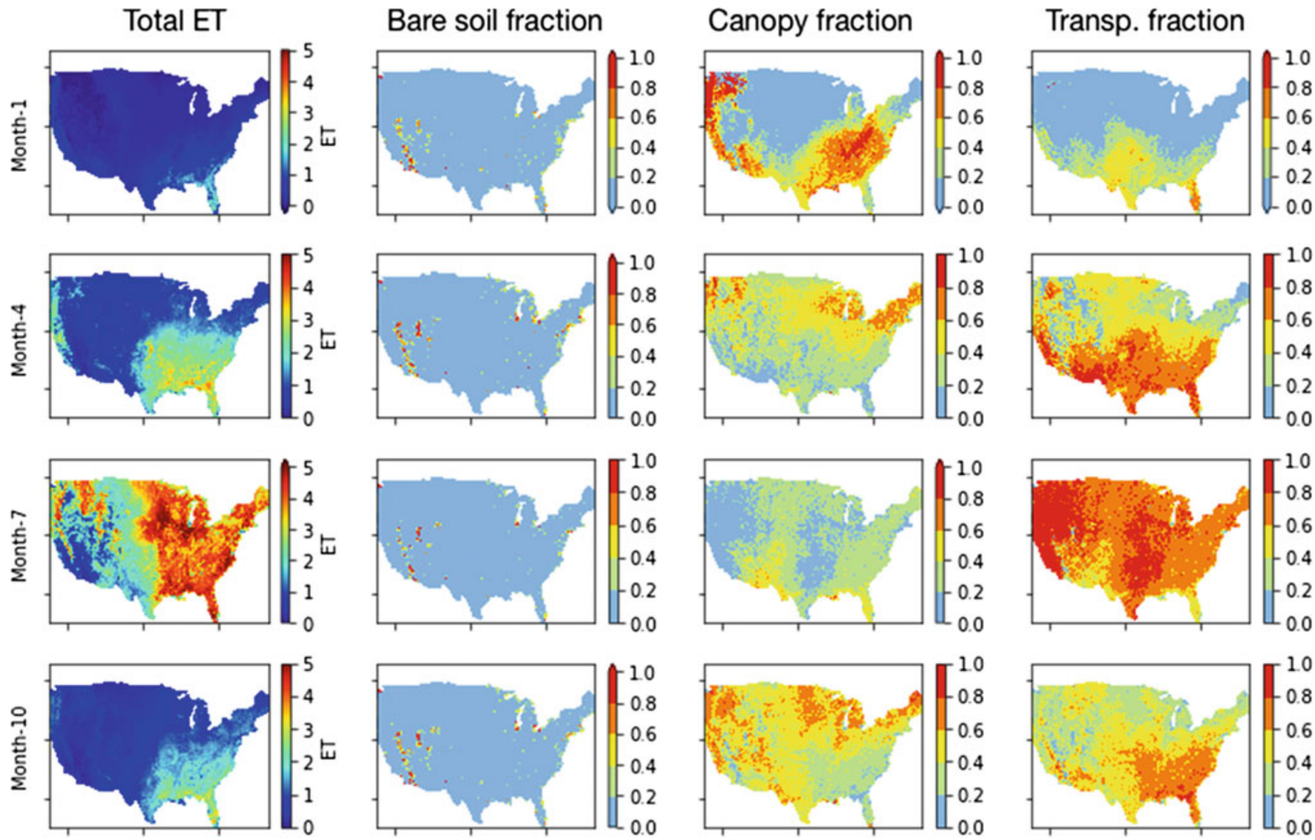


Fig. 7.4 The seasonal evolution of evapotranspiration (ET) in mm/day in the VIC model (left) and the fractional contribution of bare soil evaporation (center left), intercepted canopy evaporation and sublimation (center right), and vegetation transpiration (right)

of precipitation and temperature as input to the model. Many months and regions are dominated by transpiration and some by bare soil evaporation in isolated cases. Evaporation from the canopy is relatively more important in winter, at least where vegetation is abundant and substantial precipitation is present. Transpiration is dominant in summer when more energy is available, and plants are considered more active. While it is likely that evaporation from the canopy in the summer is a larger total flux, it is worth emphasizing that sublimation of snow from the canopy in the winter is a much larger fraction of ET at the time, and measurements of snow interception are much less common, this is almost certainly a topical area ripe for future work. However, it should go without saying that these are simply model results, and a focused evaluation of this partitioning through, e.g., eddy covariance and isotopic measurements would yield exciting comparison points for any model.

7.5.2 Model-to-Model Variability

It is useful to look across models to get some sense of how confident any single model's representation of total canopy evaporation may be. Here, we present a brief discussion of the canopy evaporation predicted by two widely used models, VIC and CLM, over a region with a lot of evapotranspiration, the Tennessee River Basin in the Southeast United States. In this region, canopy interception is clearly an important process throughout the year (Fig. 7.4). When looking at the regional climatology of annual total canopy evaporation predicted by these models (Fig. 7.5), we see very large differences in mean annual canopy evaporation (by a factor of 2) in just the average canopy evaporation [mm year^{-1}]. Over this river basin, VIC estimates canopy evaporation totals in excess of 400 mm year^{-1}, while CLM typically estimates less than 200 mm year^{-1}. A few of the key differences in these models are described in the sections above, but these differences alone do not immediately point to an obvious reason for the differences in total canopy evaporation. It is likely that it is not so much the model structure that is controlling this difference, but the model parameters, in particular, the assumed total canopy water holding capacity. This

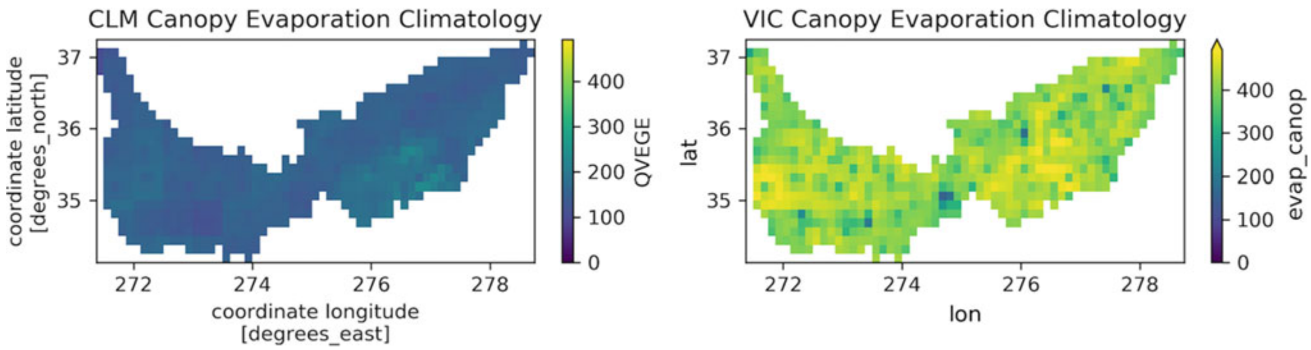


Fig. 7.5 Mean annual canopy evaporation in two different models, CLM (left) and VIC (right) over the Tennessee River Basin. Note that axis and colorbar labels are in the native nomenclature of the two modeling systems and both represent latitude, longitude, and canopy evaporation in mm per year

is a key variable in both models, has a wide range of estimated values in the literature, and exerts a strong control on the total evaporation because it controls the point at which precipitation ceases to be intercepted and it is permitted to pass to the land surface below. Better estimates of how this parameter, canopy water holding capacity, can be included in models likely to significantly improve models that are used in a wide variety of applications and should be a focus of future work.

7.5.3 Climate Change

Stepping back to the full CONUS domain once more, we next look at the role of models in climate change applications through an example projection using the Noah-MP model embedded in the WRF regional climate model. Noah-MP was used to simulate the land surface in a 13-year simulation of the WRF model for the period 2001–2013. In this simulation, the ERA-interim reanalysis (Dee et al. 2011) dataset was used as the observed atmospheric state on the boundaries of the model, and WRF simulated the weather internal to the domain throughout this time period in a convection-permitting mode (Liu

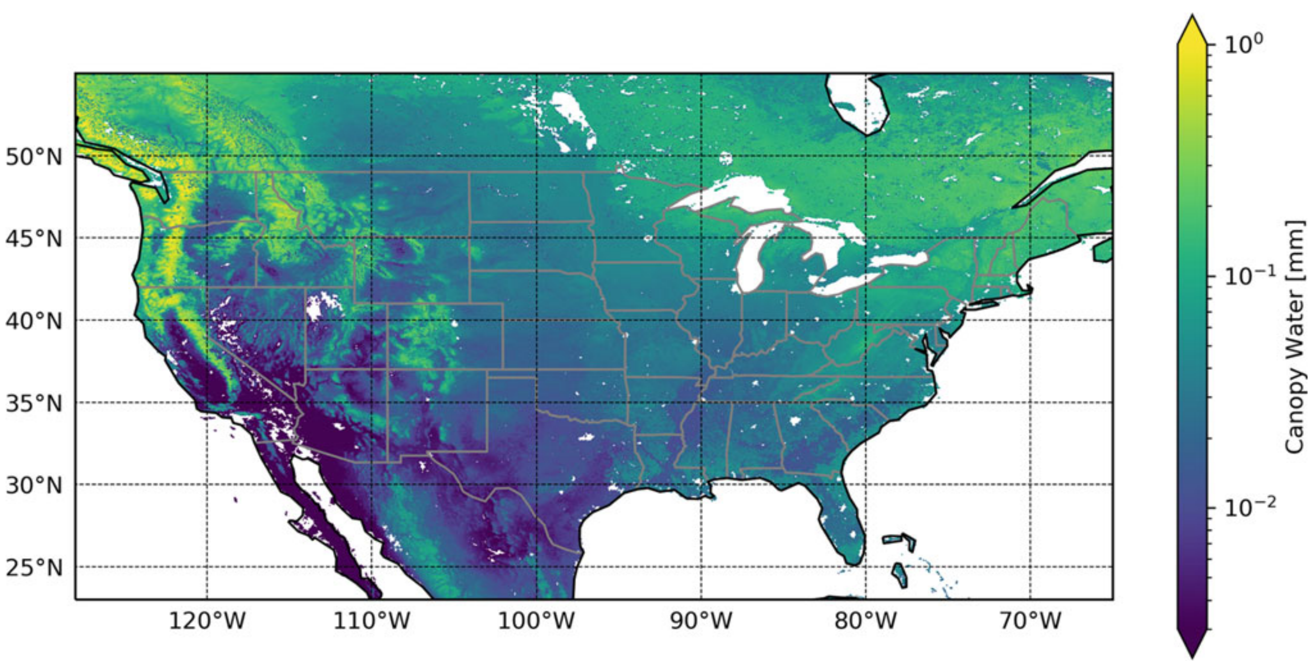


Fig. 7.6 Mean annual canopy water content in the Noah-MP land surface model over much of North America, focused on the United States. Note that white areas correspond to regions that the model treats as lacking any vegetation, e.g., oceans, lakes, bare soil, and dense urban areas

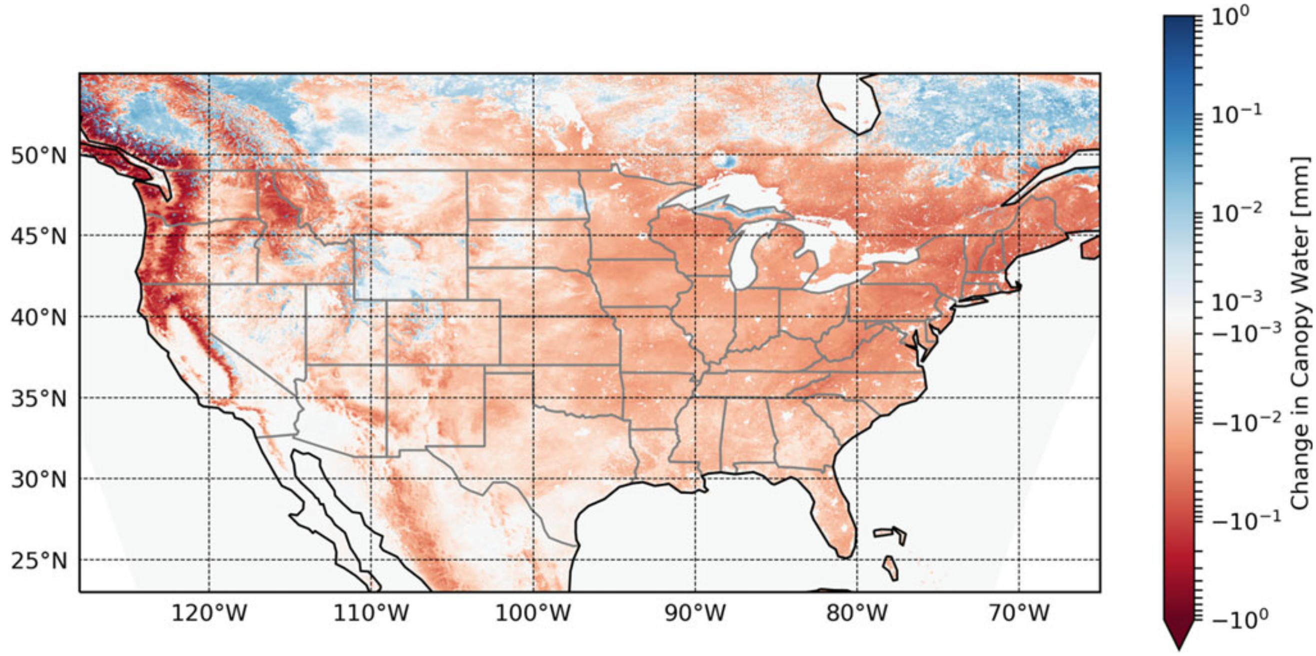


Fig. 7.7 Fractional change in canopy water content in a future warmer climate simulation. Note the positive and negative log scale, blue indicates increases in the average amount of water stored in the vegetation canopy, and red indicates decreases

et al. 2016). As such, WRF provided the precipitation, temperature, humidity, radiation, and other input variables to Noah-MP as a coupled system (e.g., Noah-MP's evapotranspiration was provided back to WRF to provide humidity flux from the surface). To provide a baseline for the reader, the average canopy water content [mm] over the course of the year in the current climate is presented in Fig. 7.6. The absolute values are small in part because this includes many times with no water in the canopy at all. There are relatively substantial spatial variations in the water stored in the canopy (climatologically) in the current climate, with differences tied both to land cover type (forest, grass, or crop, see, e.g., patterns in the Southeastern US) and climate (see, e.g., the Pacific Northwest compared to the desert Southwest, though there also are not a lot of trees where it does not rain much).

Because this baseline is derived from a regional climate model, it is possible to compare it to a future warmer climate by running that regional climate model with a warmer atmosphere. In this case, the same weather events are used to minimize problems due to chaotic variability, and the WRF boundary conditions are simply perturbed using the mean climate change signal for temperature, moisture, pressure, and wind fields in what is termed a Pseudo-Global Warming (PGW) experiment for the same 13 years. The predicted change in water stored in the canopy in the PGW future climate reveals striking patterns of increases and decreases in canopy water content (Fig. 7.7). The decreases in canopy water content may cause decreases in evaporative losses or may be caused by increases in evaporative losses. Even without changes in evaporation, these changes are consistent with the general expectation that precipitation events will increase in intensity, but may decrease in frequency. However, this is only a useful evaluation in almost entirely rain-dominated settings.

There appear to be large regions with increases in average canopy water content, particularly across much of Canada, and to a lesser extent in parts of the mountainous western United States. This could correspond to warmer temperatures causing what were light snow events to have more moisture, and thus more total snowfall available for the interception in these regions. However, the relationship between air temperature and snow interception capacity noted for Noah-MP (Fig. 7.3) suggests that, in this model, it is not warmer, stickier snow causing the increase. The strong decrease in canopy water content in the coastal ranges of the west coast likely correspond to significant shifts from snow to rain, and smaller maximum canopy water holding capacities for liquid water compared to snow, as well as possible shifts in the maximum intercepted snow capacity associated with warmer temperatures.

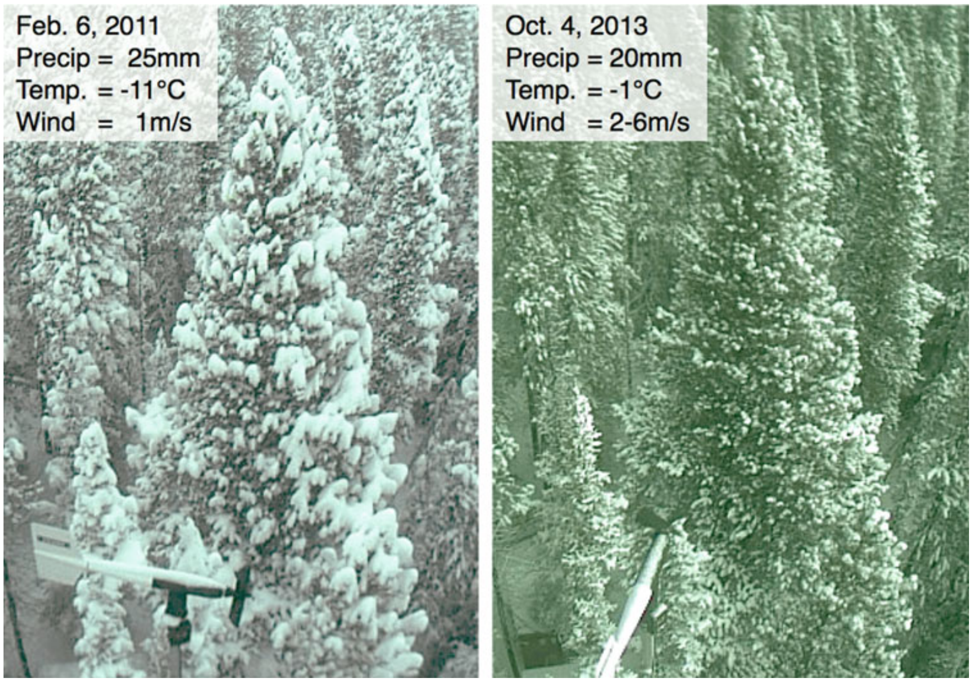


Fig. 7.8 Observed canopy interception of snow during two snowstorms with modest differences in total precipitation as photographed from by the Phenocam on the Niwot Ridge Ameriflux tower

Given the variability noted earlier between different model depictions of canopy water processes (e.g., Fig. 7.5), we might question how confident we can be in these predicted changes. Clearly, significant work is also warranted on the sensitivity of vegetation partitioning of precipitation to climatological factors such as temperature, precipitation phase, and intensity, and, though not discussed here, even wind, radiation, and humidity. As an example, Fig. 7.8 illustrates how different environmental conditions can change the amount of intercepted snow in a tree canopy. This figure shows that two different events with similar magnitude snowfall (25 and 20 mm) can have substantially different amounts of intercepted snow in the canopy. In this case, the low temperature on the left might be expected to decrease the amount of snow intercepted as warmer snow typically sticks to branches, but the higher wind speeds on the right may have dominated this effect by blowing snow out of the tree canopy. It is also possible that some rain was mixed in the snowstorm on the right, although temperatures rarely exceeded 0 °C throughout this event, and snow will not transition to rain until well above 0 °C because it is the cooler temperature at higher elevations in the atmosphere that control precipitation phase. The effect of wind on snowfall interception is not parameterized in most models in part because there are very few observations to quantify the relationship.

7.6 Concluding Thoughts

While much progress remains to be made in the modeling of precipitation partitioning, there are many reasons to be optimistic. The state of the science has advanced dramatically in recent years, as evident from the other chapters in this book, and measurement advances both in the field and from space promise to fill in the gaps in the state of knowledge. For example, recent studies have developed methods to estimate leaf traits in more detail from remotely sensed data (Moreno-Martínez et al. 2018). Measurements in a wide variety of vegetation canopies and climates are critical to advancing what are often global modeling endeavors (e.g., for climate and weather applications), and perhaps more importantly, documenting and cataloging these measurements to make them accessible for integration into models, or as the big data building blocks for new ways of looking at the field. In addition, a review of the parameters used in those models by the observational community can help either guide future observations to provide the information needed in models, or begin a conversation with the modeling community to fundamentally change the way those models work in the first place.

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