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An Overview of Rainfall-Runoff Model Types

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An Overview of Rainfall-Runoff Model Types

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Notice

Abstract

This report explores rainfall-runoff models, their generation methods, and the categories under which they fall. Runoff plays an important role in the hydrological cycle by returning excess precipitation to the oceans and controlling how much water flows into stream systems. Modeling runoff can help to understand, control, and monitor the quality and quantity of water resources. A few categories of rainfall-runoff models are described by the model structure and spatial processes within the model. Both control the way models calculate runoff. Model structure is based on the governing equations a model uses to determine runoff; categories can be generalized into empirical, conceptual, and physical structures. Spatial processes within a model are the interpretation of the catchment characteristics to be modeled. This category separates models into lumped, semi-distributed, and distributed models, which is a generalization because many models overlap and contain elements from each of the categories. A discussion about comparing different runoff models and observed runoff values is presented as well. This report aims to inform modelers about various rainfall-runoff models and their strengths and weaknesses.

Foreword

The U.S. Environmental Protection Agency (EPA) is charged by Congress with protecting the Nation's land, air, and water resources. Under a mandate of national environmental laws, the Agency strives to formulate and implement actions leading to a compatible balance between human activities and the ability of natural systems to support and nurture life. To meet this mandate, EPA's research program is providing data and technical support for solving environmental problems today and building a science knowledge base necessary to manage our ecological resources wisely, understand how pollutants affect our health, and prevent or reduce environmental risks in the future.

The National Exposure Research Laboratory (NERL) Computational Exposure Division (CED) develops and evaluates data, decision-support tools, and models to be applied to media-specific or receptor-specific problem areas. CED uses modeling-based approaches to characterize exposures, evaluate fate and transport, and support environmental diagnostics/forensics with input from multiple data sources. It also develops media- and receptor-specific models, process models, and decision support tools for use both within and outside of EPA.

The goal of the Hydrologic Micro Services (HMS) project is to develop an ecosystem of inter-operable water quantity and quality modeling components. Components are light-weight and can be integrated to rapidly compose work flows to address water quantity and quality related questions. Each component may have multiple implementations ranging from macro (coarse) to micro (detailed) levels of modeling the physical processes. The components leverage existing internet-based data sources and sensors. They can be integrated into a work flow in two ways: calling a web service or downloading component libraries. For light-weight components, it is generally more efficient to call a web service, however, it is more efficient to have local copies of components if the component requires large amounts of input/output data.

Elaine Hubal, Acting Division Director for CED

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Acronyms and Abbreviations

DEM	Digital Elevation Model
DMIP	Distributed Model Intercomparison Project
GLDAS	Global Land Data Assimilation System
HBV	Hydrologiska Byråns Vattenbalansavdelning
HRU	Hydraulic Response Units
HSPF	Hydrological Simulation Program- Fortran
KINEROS	Kinematic Runoff and Erosion Model
MIKESHE	MIKE System Hydrologique European
NASA	National Aeronautics and Space Administration
NLDAS	North American Land Data Assimilation System
NWIS	National Water Information System
NWSRFS	National Weather Service River Forecast System
ORD	Office of Research and Development
PIHM	Penn State Integrated Hydrologic Modeling System
SCS	Soil Conservation Service
SMR	Soil Moisture Routing Model
SWAT	Soil and Water Assessment Tool
TOPMODEL	Topography based Hydrological Model
US EPA	United States Environmental Protection Agency
USGS	United States Geological Survey
VELMA	Visualizing Ecosystem Land Management Assessments
VIC	Variable Infiltration Capacity Model

1. Introduction

The hydrological cycle has many interconnected components, with runoff connecting precipitation to bodies of water. Surface runoff is precipitation that does not infiltrate into the soil and runs across the land surface into surface waters (streams, rivers, lakes or other reservoirs) (Perlman, 2016). Surface runoff varies by time and location, with about one-third of the precipitation that falls on land turning into runoff; the other two-thirds is evaporated, transpired, or infiltrated into the soil (Perlman, 2016). By returning excess precipitation to the oceans and controlling how much water flows into stream systems, runoff is important in balancing the hydrological cycle. The water balance equation governs the hydrological cycle by describing the flow of water into and out of a system for a specific period of time (shown in Equation 1, Fig. 1).

$$Q_s = P - ET - \Delta SM - \Delta GW \tag{1}$$

Equation 1. Where P is precipitation, Q_s is surface runoff, ET is evapotranspiration, ΔSM is change in soil moisture, and ΔGW is the change in groundwater storage.

The amount of surface runoff is influenced by soil properties, land cover, hillslope, vegetation, and storm properties such as rainfall duration, amount, and intensity. Runoff is generated by a combination of two mechanisms, saturation excess and infiltration excess (Yang et al., 2015). Saturation excess occurs when the soil becomes fully saturated with water, exceeding the water holding capacity of the soil; when the surplus rainfall can no longer be held in the soil, the water is directed to another location through overland flow (Johnson et al., 2003). Infiltration excess occurs when rainfall intensity exceeds the maximum rate that water can infiltrate into the soil, and water must flow over land to a different area (Yang et al., 2015). Excess rainwater flowing over land picks up debris and chemicals along the flow path. The debris may include sediments, organic matter, nutrients, pesticides, and other materials which impact the quality of receiving surface water (Huffman et al., 2011). Surface runoff is therefore an important area of interest for monitoring water resources, as well as solving water quality and quantity problems such as flood forecasting and ecological and biological relationships in the water environment (Kokkonen et al., 2001). Runoff is also the main driver in contaminant transport due to excess nutrients and pesticides from agricultural lands being washed into waterways by rain events. High runoff rates, along with unmanaged drainage systems, cause flooding and erosion that damage vegetation and manmade structures (Huffman et al., 2011). Sediment transport by runoff can change stream morphology and alter stream biodiversity. When runoff reaches the stream, along with the transported sediment, it is added to the natural baseflow of the stream. Baseflow supplies stream channels with water in the absence of runoff or precipitation events, creating a persistent habitat for aquatic life that responds slowly to precipitation events. The sustained baseflow is fed by the subsurface flow of water through groundwater seepage and moisture in the soil (shown in Fig. 1) (Beven, 2012; UCAR., 2010). Streamflow is a combination of direct precipitation, runoff, and baseflow. Since most of the damaging effects to streams are caused by surface runoff, modeling runoff is essential for preventing and managing its damaging effects.

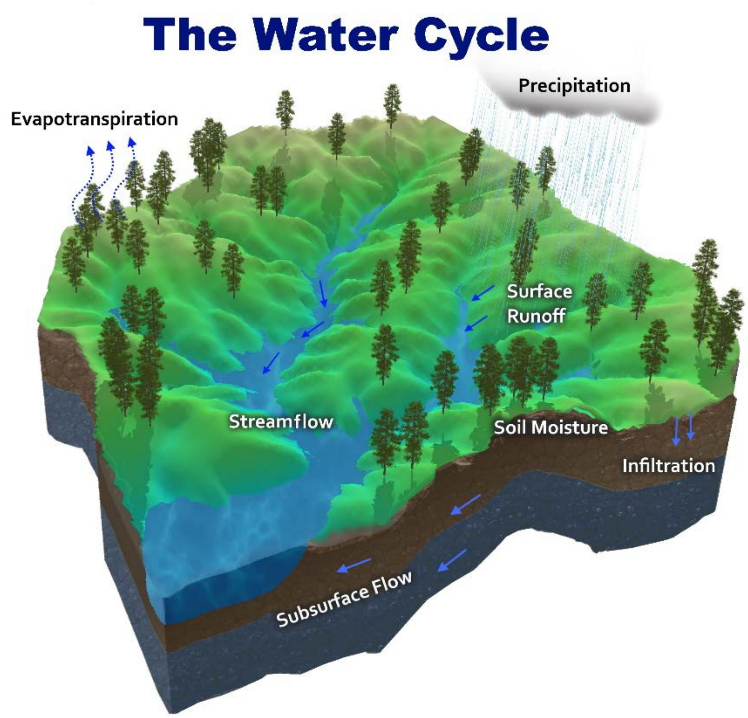


Figure 1. A simplified diagram of the hydrological cycle governed by the water balance equation (Brewster, 2017; ESRI, 2015).

1.1 History of Runoff Prediction

Early hydrologists calculated surface runoff with limited data and simple computational techniques. The first widely used runoff method was the Rational Method published by Thomas Mulvaney in 1851, which used rainfall intensity, drainage area, and a runoff coefficient to determine the peak discharge in a drainage basin (Beven, 2012; Xu, 2002). The coefficient determining the relationship between the amount of rainfall and runoff was studied heavily and led to a graphical technique for estimating the amount of runoff. The graphical technique uses a sequence of graphs showing antecedent precipitation, week of the year, soil water retention index, and precipitation in the past six hours to calculate the amount of runoff (Beven, 2012). This technique is still used in the conceptual model, National Weather Service River Forecasting System (NWSRFS) (NOAA, 2017). More recently, the unit hydrograph concept was introduced to conceptualize a catchment's response to a storm event based on the superposition principle (Beven, 2012; Todini, 1988; Xu, 2002). The unit hydrograph made it possible to separate baseflow and storm event runoff from streamflow (Figure 2). With increased computing power and a deeper understanding of hydrological processes, runoff models have become more sophisticated.

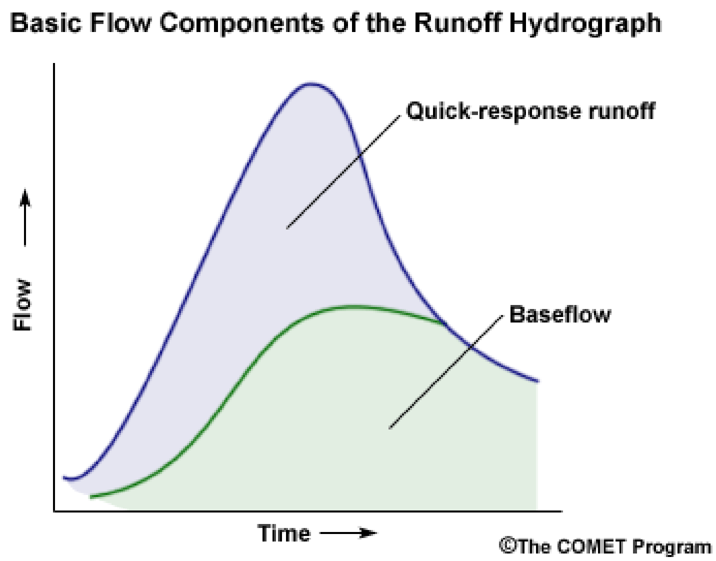


Figure 2. The unit hydrograph separation into quick response runoff from a storm event and baseflow. Image from (UCAR., 2010)

1.2 Runoff Modeling

Modeling runoff helps gain a better understanding of hydrologic phenomena and how changes affect the hydrological cycle (Xu, 2002). Runoff models visualize what occurs in water systems due to changes in pervious surfaces, vegetation, and meteorological events. Devi et al. (2015) defines a runoff model as a set of equations that aid in the estimation of the amount of rainfall that turns into runoff as a function of various parameters used to describe the watershed. Modeling surface runoff can be difficult, for the calculation is complex and involves many interconnected variables. General components of a model include inputs, governing equations, boundary conditions or parameters, model processes, and outputs (Singh, 1995). Surface runoff modeling is used to understand catchment yields and responses, estimate water availability, changes over time, and forecasting (Vaze, 2012). HSPF[1] is a hydrologic model that uses runoff as part of its functionality to predict sediment loads, nutrients, pesticides, toxic chemicals, and other water quality concentrations for management purposes (Bicknell et al., 2005). Although there are many ways to classify models, not all models fit into a single category because they are developed for a variety of purposes (Singh, 1995). In this report we classify models as one of three general types as shown in Table 1; each type calculates runoff differently. The categories are empirical, conceptual, and physical, as arranged by the model structure (See Table 1, in Section 2). Researchers use different ways to classify and divide models based on spatial resolution, input/output type, model simplicity, etc. Another classification based on the spatial interpretation of the model's catchment area is described in this report. This separates models into lumped, semi-distributed, and distributed models, as shown in Table 2 (Section 3). Choosing a rainfall-runoff model is based on the purpose for modeling such as understanding and answering specific questions about the hydrological process; assessing the frequency of runoff events; or estimating runoff yield for management purposes (Vaze, 2012). Identifying the

[1] Hydrological Simulation Program-Fortran (Bicknell et al., 2005) https://www.epa.gov/exposure-assessment-models/hspf

priorities of modeling and the limitations of data availability, time, and budget for models help to narrow the choices and ensure that the model is the best for the intended purpose.

2. Model Structure

A model's structure determines how runoff is calculated. Some are easily used with few variables, while others require a vast number of interconnecting variables. Model structure varies from simple to complex, based on the governing equations. Models are listed below in order of increasing complexity, with empirical models being the simplest and physical mechanistic models the most complicated. Physical and conceptual models need thorough understanding of the physics involved in the movement of surface water in the hydrological cycle (Srinivasulu, 2008). Many models overlap within this classification of model structure (Pechlivanidis et al., 2011). These hybrid models combine the strengths of multiple model structures, but are usually labeled as one of the three structures described in this report. The three structural categories of runoff models, with strengths and weaknesses for each are displayed in Table 1.

Table 1. Comparison of the basic structure for rainfall-runoff models

	Empirical	**Conceptual**	**Physical**
Method	Non-linear relationship between inputs and outputs, black box concept	Simplified equations that represent water storage in catchment	Physical laws and equations based on real hydrologic responses
Strengths	Small number of parameters needed, can be more accurate, fast run time	Easy to calibrate, simple model structure	Incorporates spatial and temporal variability, very fine scale
Weaknesses	No connection between physical catchment, input data distortion	Does not consider spatial variability within catchment	Large number of parameters and calibration needed, site specific
Best Use	In ungauged watersheds, runoff is the only output needed	When computational time or data are limited.	Have great data availability on a small scale
Examples	Curve Number, Artificial Neural Networks[a]	HSPF[b], TOPMODEL[a], HBV[a], Stanford[a]	MIKE-SHE[a], KINEROS[c], VIC[a], PRMS[d]

a] Devi et al. (2015)
[b] Johnson et al. (2003)
[c] Woolhiser et al. (1990)
[d] Singh (1995)

2.1 Empirical models

Empirical models, sometimes called data-driven models, use non-linear statistical relationships between inputs and outputs as shown in Figure 3. They are observation-oriented and depend heavily on input accuracy (Kokkonen et al., 2001). For simple rainfall-runoff regression models, inputs are rainfall and historical runoff, with outputs of runoff at a specific location. The general governing equation for empirical models is a function of inputs as shown:

$$Q = f(X, Y) \tag{2}$$

Equation 2. Where Q is the runoff output and X, Y are input datasets of rainfall and historic runoff.

Most empirical models are black box models, meaning very little is known about the internal processes that control how runoff results are determined (Beven, 2012; Granata et al., 2016). The function used to transform rainfall to runoff is either an unknown procedure (as in machine learning) or without any reference to the physical processes (as in the curve number method.)

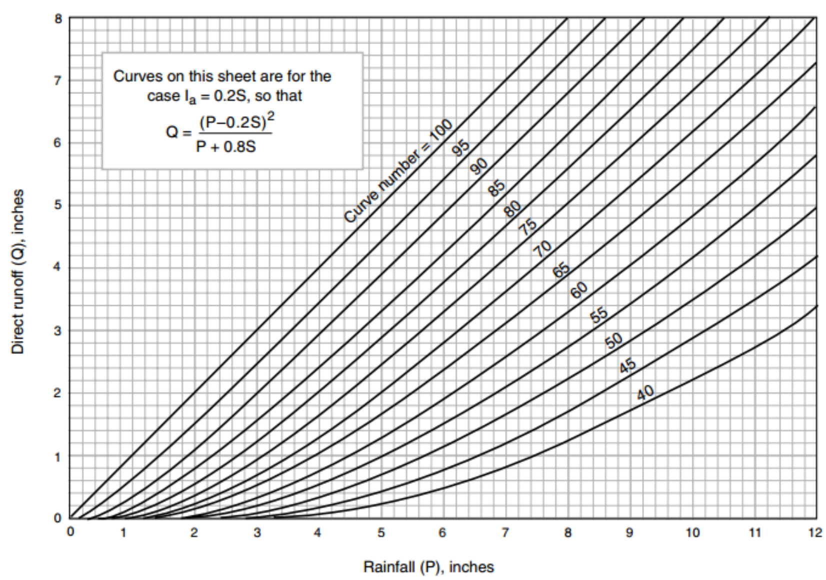


Figure 3. A visualization of the empirical Curve Number method shows the relationship between rainfall inputs and runoff outputs where I_a is initial abstraction, S is the retention parameter, P is precipitation, and Q is runoff. Image from (USDA, 1986)

Empirical runoff models are best used when other outputs are not needed; for example: the distribution of runoff values between upstream and downstream areas cannot be calculated with this model type. Ungauged watersheds are also best modeled by an empirical method due to lack of specific information about the watershed (Pechlivanidis et al., 2011). Empirical models can yield accurate simulations in many situations including long time steps and recreating past runoff values (Vaze, 2012; Xu, 2002). Very few parameters are needed, making data-driven models easy to use. Parameters in empirical models lack physical significance because there are no realistic watershed components within the model. Simplicity of implementation, faster computational times, and cost effectiveness are reasons for empirical models to be chosen for modeling (Dawson & Wilby, 2001). Since they are data-driven, input data are a main source of error because input data distortion produces serious ramifications in the modeled output. Some empirical models are more biased toward certain magnitudes of flow (Srinivasulu, 2008). One downfall of the empirical process is that it may lead to different conclusions than accepted theoretical analysis would suggest (Beven, 2012). This, in turn leads to the assumption that one method is wrong when there may actually be multiple ways of arriving at the answer.

Some examples of empirical models are the SCS-Curve Number used in SWAT[2] (USDA, 1986), regression equations, and machine learning used by Artificial and Deep Neural Networks. The popular curve number method assumes the ratio of actual runoff to potential runoff is equal to the ratio of actual to potential retention, but there is no physical justification for this assumption; details in Appendix 1 (Beven, 2012). Regression equations find the functional relationship between inputs and outputs (Devi et al., 2015). Machine learning techniques use data-driven artificial neural networks that train themselves to learn behaviors of the rainfall-runoff relationship. Machine learning used in Neural Networks makes output predictions based on statistics learned from the training period. Machine learning can be over-trained on specific inputs which cause the model to lose its ability to discern one catchment from another (Dawson & Wilby, 2001).

2.2 Conceptual Models

Conceptual models interpret runoff processes by connecting simplified components in the overall hydrological process. They are based on reservoir storages and simplified equations of the physical hydrological process, which provide a conceptual idea of the behaviors in a catchment (Devi et al., 2015; Vaze, 2012). Conceptual models represent the water balance equation with the conversion of rainfall to runoff, evapotranspiration, and groundwater, as shown in Figure 4 (Vaze, 2012). Each component in the water balance equation is estimated by mathematical equations that distribute the precipitation input data. The general governing equations for conceptual models are versions of the water balance equation which control surface water and storage fluctuations shown below.

$$\frac{dS}{dt} = P - ET - Q_s \pm GW \tag{3}$$

Equation 3. Where dS/dt is the change in reservoir storage, P is precipitation, ET is evapotranspiration, Q_s is surface runoff, and GW is groundwater.

[2] Soil and Water Assessment Tool (Neitsch et al., 2009) http://swat.tamu.edu/

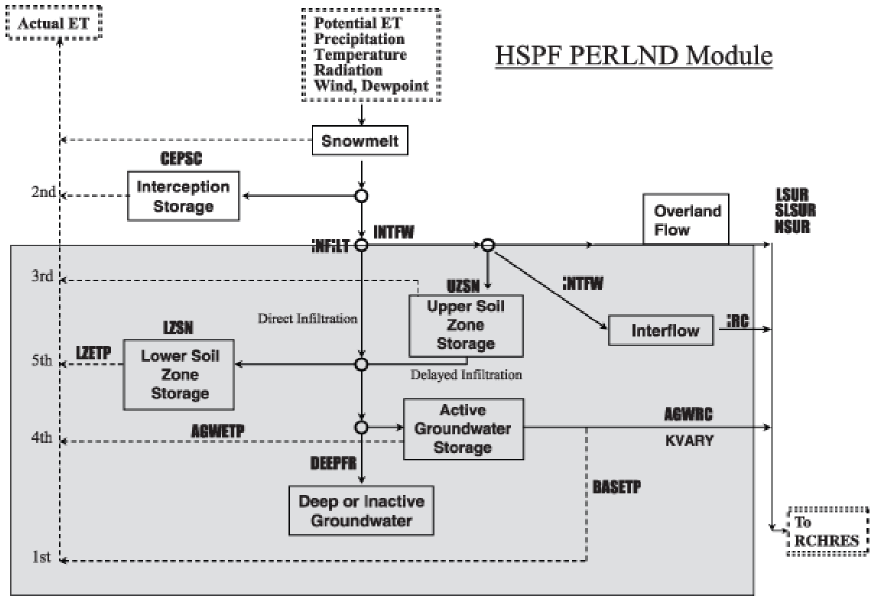


Figure 4. The conceptual model HSPF schematic shows the Pervious Land segment module (PERLND) as an assembly of multiple storage processes following the water balance equation. Image from (Atkins et al., 2005)

Hydrological components and water storages in soil or groundwater reservoirs are idealized in the model process (Devi et al., 2015). Models simulate the exchange in water among the atmosphere, hydrological components, and storage reservoirs, based on a water balance equation. Conceptual models vary in complexity depending on the sophistication of the balance equations used to represent hydrological components (Beven, 2012; Pechlivanidis et al., 2011). Because of this variation, these models need a range of parameters and meteorological input data. Conceptual models have gained popularity in the modeling community because they are easy to use and calibrate. With some, there is a likelihood that a previously calibrated model can be used for a different catchment (Vaze, 2012). Spatial variability is generally not considered due to the simplicity of the model. Lack of physical meaning in governing equations and parameters is also a limitation. Conceptual models are best used when computation time is limited and catchment characteristics are not analyzed in detail. TOPMODEL[3], HBV[4], NWSRFS[5], and HSPF are some examples of conceptual models.

2.3 Physical Models

Physical models, also called process-based or mechanistic models, are based on the understanding of the physics related to the hydrological processes (Vaze, 2012). Physically-based equations govern the model to represent multiple parts of real hydrologic responses in the catchment. The general physics laws and principles used include water balance equations,

[3] Topography based Hydrological Model (Beven & Kirkby, 1979; Beven et al., 1984) Source code for TOPMODEL written in R can be found at: https://idea.isnew.info/r.topmodel.html
[4] Hydrologiska Byråns Vattenbalansavdelning (Bergström, 1992) http://www.geo.uzh.ch/en/units/h2k/Services/HBV-Model.html
[5] National Weather Service River Forecast System (Burnash et al., 1973) http://www.nws.noaa.gov/iao/iao_hydroSoftDoc.php

conservation of mass and energy, momentum, and kinematics. St. Venant, Boussinesq's, Darcy, and Richard's are some of the equations adopted by physical models (Pechlivanidis et al., 2011). The semi-discrete form of the St. Venant Equation below is used in the Penn State Integrated Hydrological Modeling System (Qu, 2004):

$$\left(\frac{\partial h}{\partial t} = P_o - I - E_o - Q_{oc} + \sum_{j=1}^{3} Q_s{}^{ij}\right)_i \tag{4}$$

Equation 4. Where ∂h/∂t is water depth at time t, Q_s^{ij} is the surface flow from element i to j, P_o is the precipitation, I is infiltration, E_o is evaporation, and Q_{oc} is the interaction between overland flow and channel routing.

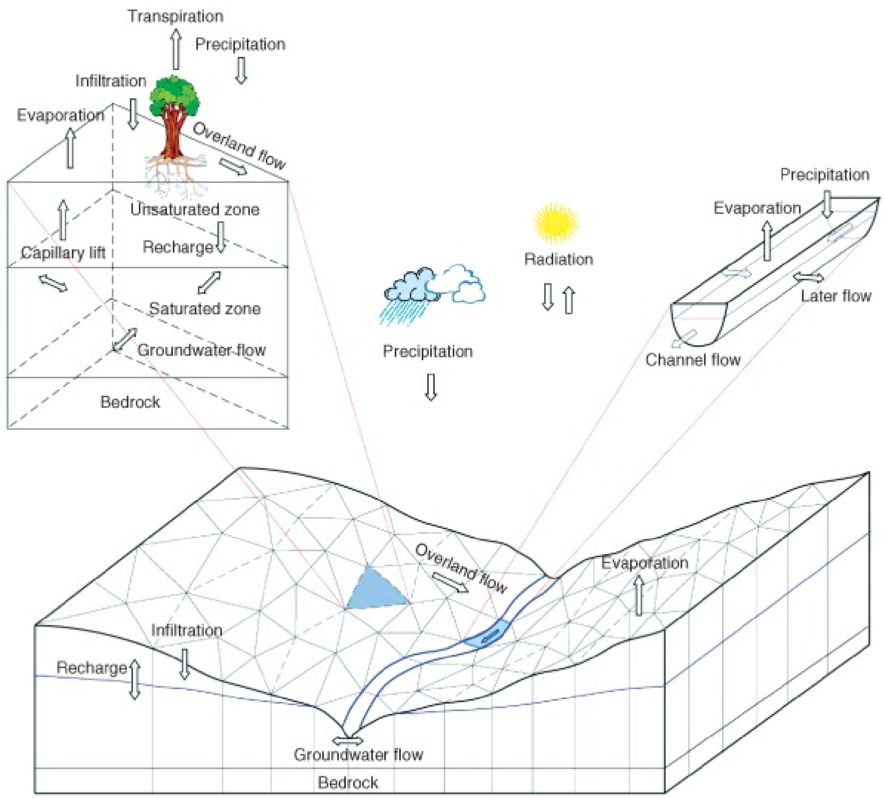


Figure 5.The model structure of the physically-based Penn State Integrated Hydrologic Modeling System (PIHM). It shows physical movement of water through each Triangular Irregular Network via overland flow, evapotranspiration, infiltration, recharge, and groundwater. Image from Qu (2004).

Spatial and temporal variations within the catchment are incorporated into physical models. A physical model has a logical structure similar to the real-world system. The greatest strength of a physical model is the connection between model parameters and physical catchment characteristics which make it more realistic. They are best used when precise data are available, physical properties of the hydrological processes are accurately understood, and applied on fine scales due to computational time. A large number of physical and process parameters are needed to calibrate the model. Physical parameters are physical properties of the catchment and can be measured; process parameters, on the other hand, cannot be measured, but represent physical properties including average water storage capacity (Pechlivanidis et al., 2011). Physical models are site- or catchment-specific. The large amounts of data required to run them limit their usage (Uhlenbrook et al., 2004). Most physical models give a three-dimensional view of the water exchange within the soil, surface, and air, as shown in Figure 5. These models can also be used to simulate groundwater movement, and the catchment's interactions with sediments, nutrients, and chemicals. Examples of physical models include VELMA[6], VIC[7], MIKE SHE[8], PIHM[9], KINEROS [10](Singh, 1995).

3. Spatial Processes

The spatial processes in runoff models provide a means of representing the catchment for modeling. They are based on input data and how runoff is generated and routed over the catchment. Variability in geology, soils, vegetation, and topography affect the relationship between rainfall and runoff within a catchment and should be considered in modeling (Beven, 2012). The spatial structure of catchment processes in rainfall-runoff models can be categorized as lumped, semi-distributed, and fully distributed (See Table 2). Lumped models do not consider spatial variability within the catchment; semi-distributed models reflect some spatial variability; and fully distributed models process spatial variability by grid cells. Semi-distributed models take spatial variability into consideration at smaller scales than lumped models, but do not calculate runoff at every grid cell. Rainfall-runoff models cover a wide spectrum of spatial processes because there are many ways of representing a catchment. Spatial interpretation in a lumped model, a semi-distributed model, and a distributed model is shown in Figure 6. The spatial processes within rainfall-runoff models and the output produced can determine the type of model needed.

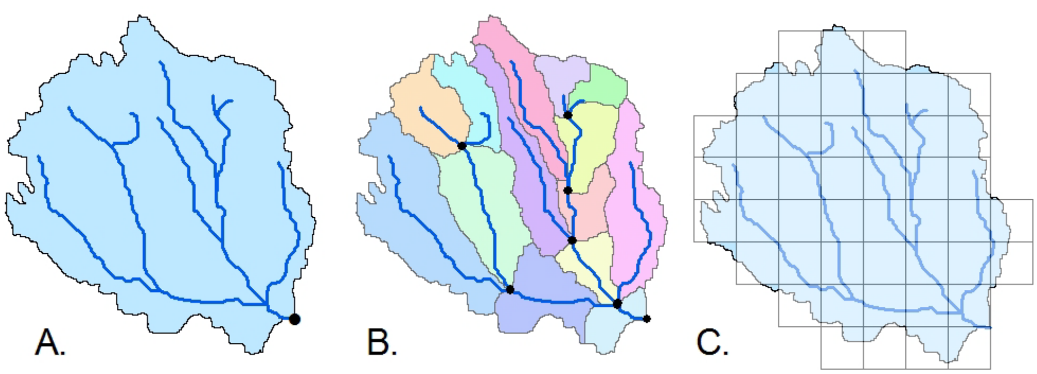


Figure 6. Visualization of the spatial structure in runoff models. A: Lumped model, B: Semi-Distributed model by sub-catchment, C: Distributed model by grid cell. Runoff is calculated for each sub-catchment at the pour point represented by the black dots in Fig. 6B. Distributed models calculate runoff for each grid cell, while lumped

[6] Visualizing Ecosystem Land Management Assessments (Abdelnour et al., 2011; McKane et al., 2014) https://www.epa.gov/water-research/visualizing-ecosystem-land-management-assessments-velma-model-20
[7] Variable Infiltration Capacity Model (Liang et al., 1994) http://www.hydro.washington.edu/Lettenmaier/Models/VIC/index-old.shtml
[8] MIKE System Hydrologique European (Abbott et al., 1986) https://www.mikepoweredbydhi.com/products/mike-she
[9] Penn State Integrated Hydrologic Modeling System (Qu, 2004) http://www.pihm.psu.edu/
[10] Kinematic Runoff and Erosion Model (Woolhiser et al., 1990) http://www.tucson.ars.ag.gov/kineros/

models calculate one runoff value for the entire catchment at the river outlet point represented by the black dot in Fig. 6A. Image created using ArcGIS software (ESRI, 2015).

Table 2. Comparison of the spatial structures in rainfall-runoff models

	Lumped	**Semi-Distributed**	**Distributed**
Method	Spatial variability is disregarded; entire catchment is modeled as one unit	Series of lumped and distributed parameters	Spatial variability is accounted for
Inputs	All averaged data by catchment	Both averaged and specific data by sub-catchment	All specific data by cell
Strengths	Fast computational time, good at simulating average conditions	Represents important features in catchment	Physically related to hydrological processes
Weaknesses	A lot of assumptions, loss of spatial resolution, not ideal for large areas	Averages data into sub-catchment areas, loss of spatial resolution	Data intense, long computational time
Examples	Empirical and conceptual models, machine learning	Conceptual and some physical models, TOPMODEL[a], SWAT[b]	Physically distributed models, MIKESHE[c], VELMA[d]

[a] Devi et al. (2015)
[b] Beven (2012)
[c] Singh (1995)
[d] McKane et al. (2014)

3.1 Lumped Models

Lumped models treat the catchment area as a single homogenous unit. Spatial variability of catchment parameters is disregarded in lumped models (Moradkhani & Sorooshian, 2008; Singh, 1995). Averaged values over the catchment are used such as mean soil storage and uniform precipitation amounts (Beven, 2012; Rinsema, 2014). The catchment characteristics are set as equal for the entire area and often cause over-or under-parameterization (Rinsema, 2014). A single runoff output value is calculated at the river outlet point of the catchment area in these models (shown in Figure 6A).

A lumped model is designed to simulate total runoff and streamflow at the outlet point, not specific flows within a catchment. For this reason, lumped models adequately simulate average runoff conditions with fast computational times. Average and annual runoff conditions produced by lumped models are used for regulatory purposes that look at long-term conditions. Lumped models include a lot of assumptions about the hydrological processes. Because of these assumptions, lumped models have a tendency to over-or under-estimate runoff values (UCAR., 2010). They do not consider changes within a watershed, or if the changes affect the runoff process (Uhlenbrook et al., 2004). Land use changes may alter the runoff process in specified areas, but a lumped model averages these over the entire catchment. Inputs in a lumped model are all lumped or "averaged" data. Such data are relatively easy to attain or create by averaging data across the study area. All data including input, output, and parameters are constant over space and time in a lumped model. By assuming homogeneity over the catchment, lumped models lose spatial resolution of the data. For example, rainfall and runoff patterns vary over space and time but, in lumped models they are considered stationary. *"There is spatial variability in rainfall across a catchment which is not captured"* when used in a lumped model (Vaze, 2012, p.21). Empirical and conceptual models are usually run spatially as lumped. Due to the many assumptions and averaged conditions that lumped models incorporate, they do not represent large watersheds and catchments accurately (Moradkhani & Sorooshian, 2008).

3.2 Semi-distributed Models

Semi-distributed models are variations of lumped models, with features of distributed models. They can consist of a series of lumped parameters applied in a quasi-spatially distributed manner. The model process divides the catchment into smaller areas, with different parameters for each (Rinsema, 2014). Sub-areas represent important features in a catchment and combine advantages of lumped and distributed models (Pechlivanidis et al., 2011). Semi-distributed models are classified by their inputs; if inputs include lumped and distributed input parameters, the model is considered semi-distributed. Most models are semi-distributed because of data availability, and range in the spectrum between lumped and distributed models. A semi-distributed model can have data that are separated within the catchment but homogenous within the sub-area (Beven, 2012). Sub-areas can be divided in many ways; by slope, soil group, vegetation zones, or a combination called Hydraulic Response Units (HRUs) in which the region within the HRU responds to rainfall the same way, based on overlaying maps of land cover, soil group, and elevation (Beven, 2012; Devi et al., 2015). Semi-distributed models calculate runoff at the pour point for each sub-catchment shown as black dots in Figure 6B.

Semi-distributed models consider spatial variability and land use characteristics without an overwhelming model structure (Kokkonen et al., 2001). The benefits of a semi-distributed model are fast computational time and the ability to use less data and fewer parameters than a distributed model (Pechlivanidis et al., 2011). A drawback is manipulation of input data. For example, spatially-distributed rainfall data must be averaged within the sub-area, or rain gauge data at specific locations must be distributed to the area using the Thiessen Polygon method. Conceptual and physical models can be run in a semi-distributed manner depending on input data. TOPMODEL is a semi-distributed conceptual model which uses land surface slope and soil characteristics to sub-divide the catchment. Models like SWAT use hydraulic response units to further divide a catchment.

3.3 Distributed Models

Distributed runoff models are the most complex because they account for spatial heterogeneity in inputs and parameters. Fully distributed models separate the model process by small elements or grid cells. They are also structured like a physically-based model which makes them more relatable to the actual hydrologic process. Spatially distributed models have influenced management practices by providing detailed data for small elements. See Bouadi et al. (2017) for more information about improving nitrogen management with a spatially distributed model. Each small element (or cell) has a distinct hydrological response and is calculated separately, but incorporates interactions with bordering cells (Rinsema, 2014). By calculating runoff for every grid cell, the model provides detailed runoff information at various points within the catchment (see Figure 6C). Distributed models route the calculated runoff from each cell to the nearest cell or stream, based on physical equations used to determine flow path and natural time lags. The distributed runoff model used in NASA's Global and North American Land Data Assimilation System provides calculations on a grid cell (see Appendix 2). This comprehensive information, helps to understand pollutant and sediment transport within a watershed along with capturing spatial and temporal variability of the hydrological process (Knapp, 1991). Distributed models study impacts of basin change on runoff values (Singh, 1995). This type of spatial process is physically-related to the natural hydrological cycle which is why many physical models are processed in a distributed way. Distributed models are data-intensive, with all input data distributed spatially and temporally. Inputs needed for a typical distributed model are Digital Elevation Models (DEM); land use imagery from satellites; gridded precipitation; soil characteristics and how they change over time; topography; and watershed characteristics such as dimensions and boundaries.

Drawbacks of distributed models are their demands for distributed data and calibrated parameters for every grid cell. If the data are not fully distributed, estimations using weighted averages are used to extrapolate data. Distributed models are also limited spatially by model resolution or by input grid size. Another weakness of distributed models is the computational time needed to run one simulation which can vary from one minute to several hours, depending on input data, catchment size and computational constraints (Vaze, 2012). Such difficulties, when compared to lumped models, is why distributed models are not widely used (Rinsema, 2014).

4. Comparison

There are many different types of models, with some working better in certain situations than others. Phase 2 of the Distributed Model Intercomparison Project in 2012 (DMIP2) compared lumped and distributed model simulations of the water balance equation. Key findings were that distributed models provided an improved hydrograph compared to lumped models, and distributed models simulate streamflow at interior points well (Smith et al., 2012). Both DMIP1 in 2004 and DMIP2 in 2012 concluded that calibrated models outperformed uncalibrated models (Reed et al., 2004; Smith et al., 2012). The Project showed that models that combine conceptual rainfall-runoff modeling and physical distributions perform better. A more detailed comparison was made by Johnson et al., 2003 in the Irondequoit Creek basin in New York. Johnson et al. (2003) compared a semi-distributed conceptual model, HSPF, to a distributed physical model, Soil Moisture Routing Model (SMR). Overall hydrographs of this comparison had minimal differences, but SMR was more accurate in summer periods when saturation excess was a major factor in runoff generation, and HSPF was more accurate during the winter when an energy balance was essential due to different runoff mechanisms. Results of rainfall-runoff model comparisons may be contradictory and hard to interpret because models differ in so many aspects (Andréassian et al., 2004). Models are usually created to answer specific questions and thus cannot be compared in a general way.

4.1 Observed Data

Comparing model runoff simulations to real-world runoff is a challenge. Observed runoff data are derived from detected stream discharge data by dividing discharge by upstream contributing catchment area (Fekete, 2002). Stream discharge incorporates surface runoff, interflow, and baseflow. The United States Geological Survey has vast networks of sensors to collect instantaneous stream discharge values which can be found on the USGS National Water Information System (NWIS) webpage. The challenging aspect is that observed discharge data cannot be directly compared to modeled runoff values because modeled runoff does consider subsurface interactions and discharge data does not give information about spatial distribution of runoff within the catchment (Fekete, 2002). Observed data can be used when several modules of a watershed model are compiled to simulate discharge in a stream system. Srinivasulu (2008) noted that hydrographs displaying discharge are influenced by many factors and that a single technique for simulating discharge is not as effective as separating the hydrograph into modules. Baseflow, throughflow, and overland flow are some of the modules that, together, simulate a stream discharge value (See Figure 7).

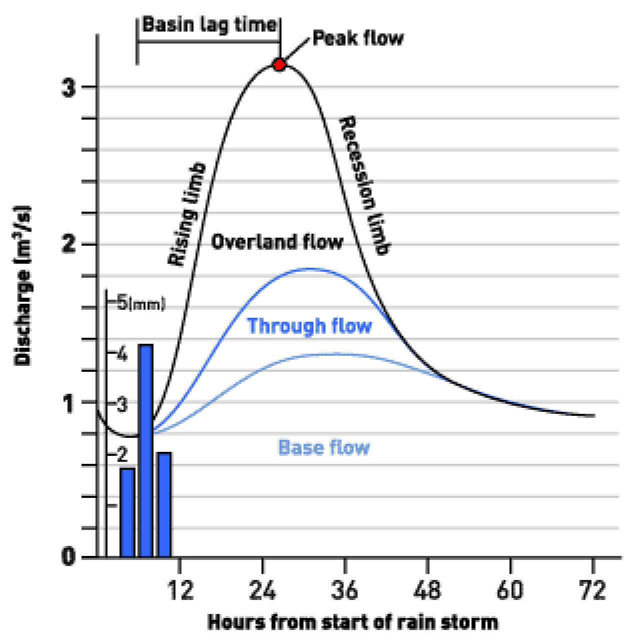


Figure 7. Shows a hydrograph of observed discharge data separated into model components of Baseflow, Throughflow, and Overland flow.

4.2 Calibration and Uncertainty

For rainfall-runoff models to efficiently simulate runoff in a catchment, calibration to the specific catchment is required. Calibrated parameters are adjusted to fit observed data for better output (Beven, 2012). There are several ways to calibrate a rainfall-runoff model. The manual trial-and-error method uses observed historical data to adjust each model parameter, and parameters are then compared visually to determine if another trial should be executed (Singh, 1995). Manual calibration is time-consuming and experience is needed to obtain a good calibration (Xu, 2002); difficulty in knowing when the "best" fit has been obtained is another weakness (Singh, 1995). Automatic-optimization algorithms are computer-based methods designed to speed up calibration time. These algorithms calibrate rainfall-runoff models quickly, with confidence intervals to minimize differences between modeled and observed data (Xu, 2002). Goodness-of-fit calibration techniques create a numerical relationship between observed and simulated output to put a value on correctness. Least squares methods and maximum likelihood methods are examples of goodness-of-fit techniques (Pechlivanidis et al., 2011). Using a calibration method is essential for obtaining the most reliable runoff data.

A runoff model is a simplification of a physical process; therefore, all models are uncertain to some degree. Rainfall-runoff model uncertainty can come from the observed data, natural uncertainties, parameter estimation, calibration, or model assumptions. Input data are a major source of uncertainty for rainfall-runoff models because they rely heavily on input data and physically based parameters (Pechlivanidis et al., 2011). As a result of the imbalance of model parameters and observed measurements, the equifinality problem creates different optimal parameter sets that lead to good model performances without having parameters with physical numerical meaning (Lee et al., 2012). Parameters connect the model to the physical catchment but the number of catchment specific parameters does not indicate a good and accurate model. Viney et al. (2009) commented that, *"With a larger number of parameters, there is a greater possibility that some parameters become too site specific"* (p. 3432). Models with many parameters have less chance of finding the best parameter than models with fewer parameters (Rinsema, 2014). Bashar (2005) concluded that simple models involving fewer parameters forecasted discharge in the Nile River Basin better than models using more parameters and complex mathematical computations. Although simple models with few parameters can have better performances and less calibration time, they may also undermine physical characteristics. Model selection is also tied to uncertainty in model results due to the assumptions and simplifications each model incorporates (Vaze, 2012). Melsen et al. (2016) determined that model performance is mainly limited by the model structure, not by parameters.

5. Discussion

Surface runoff, a major process in the hydrological cycle, connects precipitation to surface reservoirs. Changes in vegetation, soil moisture, meteorological components, and surface conditions alter runoff (Chahine, 1992). Some models are better at considering these changes by computing runoff in a distributed spatial process. Simulations of surface runoff can help us understand how changes in the environment affect runoff and the hydrological cycle. Our classification of rainfall-runoff models by model structure and spatial processes shows different types of rainfall-runoff models and ways in which we distinguish models. The structure of a rainfall-runoff model is determined by the complexity of governing equations used for calculating runoff. Spatial processes in models are determined by how the catchment is interpreted: as lumped, semi-distributed, or fully distributed. Many models contain more than one element from each category and cover the spectrum between categories (Rinsema, 2014). Rainfall-runoff models must be chosen according to the project objective, data availability, size of the study, output needed, and simplicity desired. If a watershed or catchment of interest has high infiltration rates (and thus little overland flow), a model that only calculates overland flow and neglects subsurface flow is not suitable (Knapp, 1991). For example: TOPMODEL considers a single overland flow generation mechanism of saturation flow and cannot perform well in semi-arid regions where saturation overland flow rarely occurs (Jiang et al., 2015). Data availability may also limit the model selection. For this reason, simpler models are widely used because fine-scale catchment characteristics are unknown or too expensive to investigate (Rinsema, 2014). Each model type has limitations that may make it unsuitable for a specific project. Reviewing data requirements, physical meaning, user friendliness, and spatial resolution are all necessary to determine which model type should be selected.

Appendix 1

SCS Weighted Curve Number

The SCS Weighted Curve Number method was developed by the United States Department of Agriculture. The SCS Weighted Curve Number is a calculation method for surface runoff. The purpose of the curve number is to describe average conditions for design purposes. The curve number was originally developed for agricultural watersheds with a land slope of 5% and an initial abstraction of rainfall of 20% due to infiltration. The initial abstractions consist of interception loss, surface storage, and infiltration prior to runoff.

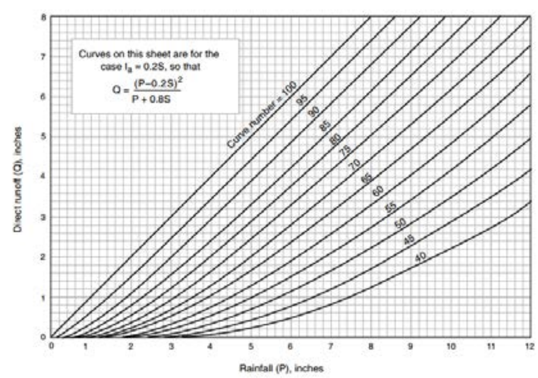
Table 3. An Example of Corresponding Curve numbers

Cover Description	Hydrologic Condition	Curve numbers for hydrologic soil group			
		A	B	C	D
Urban	Industrial	81	88	91	93
Pasture	Poor	68	79	86	89
	Fair	49	69	79	84
	Good	39	61	74	80
Woods	Poor	45	66	77	83
	Fair	36	60	73	79
	Good	30	55	70	77

The curve number is determined by inputs of the hydrologic soil group, land cover type, and hydrologic condition (Table 3). Four soil groups are defined as A, B, C, and D according to the infiltration rates. Cover types are determined by photographs and land use maps, ranging from developed surfaces to agricultural and forest areas. The table above is an example of the curve numbers associated with a few land cover types. The weighted curve number method computes the weighted average of all the curve numbers in the area of interest to provide one curve number for runoff calculation.

Once the curve number is determined an equation using the amount of rainfall and initial abstractions calculates the amount of rainfall translated into surface runoff. The curve number method assumes the ratio of actual runoff to potential runoff is equal to the ratio of actual to potential retention. This is a purely empirical process for determining runoff. There is no temporal resolution within the curve number calculation in order to consider rainfall duration and intensity.

Application of the SCS Weighted Curve Number: Ungauged areas, within other models such as the Soil and Water Assessment Tool (SWAT).



Reference: USDA. (1986). *Urban Hydrology for Small Watersheds TR-55*. Natural Resources Conservation Service: Retrieved from https://www.nrcs.usda.gov/Internet/FSE_DOCUMENTS/stelprdb1044171.pdf.

Appendix 2

Land Data Assimilation Systems Surface Runoff (non-infiltrating)

The Land Data Assimilation Systems (LDAS) are datasets of meteorological and land surface data provided by NASA's web services. LDAS has two products: one for North America (NLDAS) and the other a global resolution (GLDAS). The land surface model within LDAS is Noah-2.8. The Noah model was developed by the National Centers for Environmental Prediction (NCEP), Oregon State University (Dept. of Atmospheric Sciences), The Air Force, and Hydrologic Research Lab (NWS). Noah was established for use in the NCEP mesoscale Eta model.

Noah uses an infiltration-excess based surface runoff scheme with a gravitational drainage subsurface runoff scheme which can be found in more detail in Schaake et al. (1996). Noah is a spatially distributed model where runoff is computed for each grid cell. NLDAS is on a 0.125-degree grid of North America with an hourly time step. GLDAS is on a 0.25-degree grid covering the Earth between 90 degrees north and 60 degrees south. GLDAS data are given every three hours and takes a least a month for data processing.

Application of Noah: Coupled in global circulation models and weather predictors like Weather Research Forecasting model (WRF).

Reference: Schaake, J. C., Koren, V. I., Duan, Q. Y., Mitchell, K., & Chen, F. (1996). Simple water balance model for estimating runoff at different spatial and temporal scales. *Journal of Geophysical Research-Atmospheres*, *101*(D3), 7461-7475. doi: Doi 10.1029/95jd02892**https://disc.gsfc.nasa.gov/information/tools?title=Hydrology%20Data%20Rods**

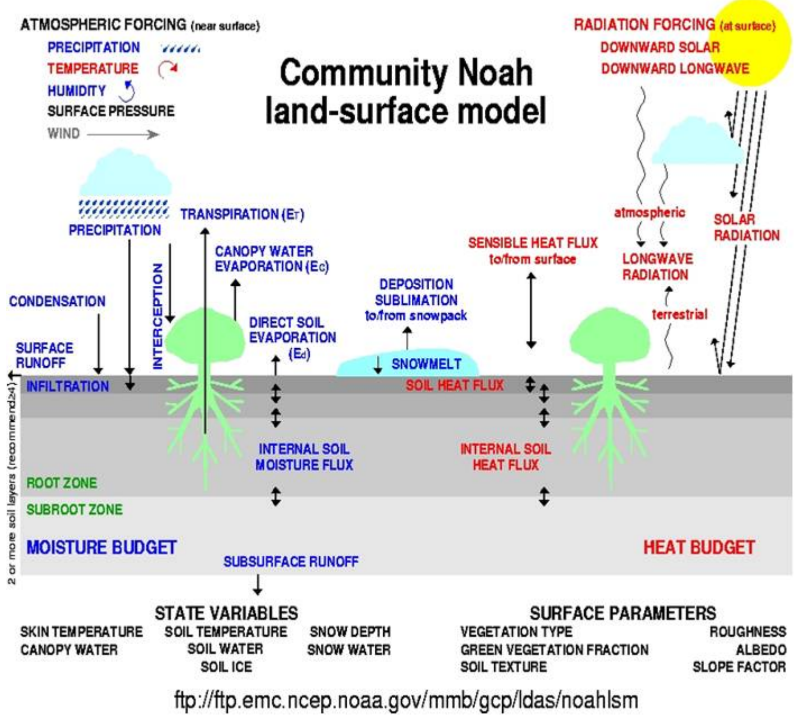


Figure 8.The Community Noah land-surface model schematic

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