(NASA-TM-110500) REGIONAL SCALE
HYDROLOGY WITH A NEW LAND SURFACE
PROCESSES MODEL (NASA. Marshall
Space Flight Center) 7 p

N95-22111

Unclas

G3/43 0039780

REGIONAL-SCALE HYDROLOGY
WITH A NEW LAND SURFACE PROCESSES MODEL

Charles A. Laymon[1] and William L. Crosson

Institute for Global Change Research and Education[2]
Huntsville, Alabama

1. INTRODUCTION

Until recently there has been little attention given to the derivation of regional-scale hydrologic budgets. Most hydrologic analyses have focused on either surface water budgets at watershed scales or atmospheric moisture and energy budgets at global scales. The models used in these analyses are inadequate for application at regional scales. Parameterizations in conventional watershed models are too detailed to be practical for regional scale applications; the converse is true of general circulation models (GCMs). Numerous experiments are demonstrating the value of remote sensing data in capturing the spatial heterogeneity of land surface processes necessary in regional-scale modeling. The Convection and Precipitation/ Electrification (CaPE) Experiment provided an opportunity to develop procedures for regional-scale hydrologic budgets utilizing remote sensing data. This paper describes an offshoot of the CaPE experiment, the CaPE Hydrometeorology Project (CHymP), and the development of a new land surface processes model for regional scale application.

2. PROJECT SUMMARY

The CaPE experiment was a multi-agency field program conducted in east-central Florida between July 8 and August 18, 1991 (Figure 1). The focus of the experiment was to study the development of mesoscale meteorological conditions and consequent storm characteristics and to develop improved techniques for performing short period forecasts of convection initiation, downbursts, and tornadoes (Williams et al., 1992). This experiment resulted in a diverse data set from ground stations, radiosondes,

surface radar, and aircraft and satellite remote sensors. The availability of such data spawned additional research projects, including CHymP involving scientists from NASA's Marshall Space Flight Center and the University of Oklahoma.

The objective of CHymP was to develop a measurement and modeling strategy for estimation of components of the land and atmospheric water budgets on daily and longer time scales over a 20,000 km^2 study area. Targeting spatial scales of between 10 and 100 km, CHymP is similar in scale to recent experiments like the Boreal Ecosystem/Atmosphere Study (BOREAS), the Susquehana River Basin Experiment (SRBEX), Hydrological Atmospheric Pilot Experiment-Modisation du Bilan Hydrique (HAPEX-MOBILHY) and HAPEX-Sahel, but represents a very different environment. It was our intent to help bridge the gap in knowledge related to problems of modeling the hydrologic cycle at scales larger than individual watersheds, but smaller than continental scale or atmospheric models.
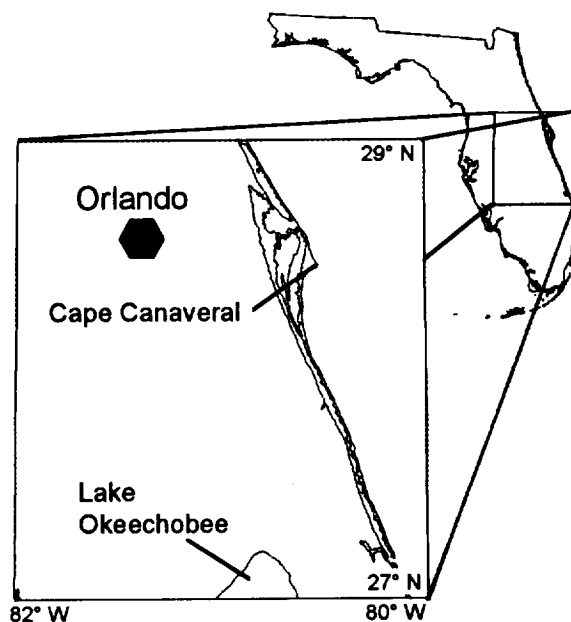

Figure 1. Map showing the location of the CaPE Experiment area (box) in east-central Florida.

---

[1] *Corresponding author address:* Charles A. Laymon, NASA/ES44, Marshall Space Flight Center, Huntsville, AL 35812; Email: charles.laymon@msfc.nasa.gov

Data used in CHymP include station data, map data, and image data. These were obtained from many sources including supervised field measurements, unsupervised temporary and permanent gaging stations, surface radars, radiosondes, aircraft-based instruments, and aircraft and satellite remote sensing instruments. Data sets were supplied in many disparate formats by universities and various state and federal agencies. Data were quality-controlled and preprocessed using spreadsheet software and a geographic information system (GIS) with image processing capabilities. Utilities were developed through this project to provide additional required functionality to manipulate data not already accommodated by existing software.

3. SURFACE WATER BUDGET

The CHymP study area spans 2 degrees of latitude by 2 degrees of longitude in east-central Florida (Figure 1). The study area spans the centrally located north-south-trending watershed divide and comprises the headwaters of the Upper St. Johns River, and the Kissimmee, Oklawaha, and Peace River basins. Mean elevation along the divide is about 45 m asl and relief is very low resulting in poorly defined drainage and numerous ponds, lakes and swamps. Canals and ditches are prevalent in some areas to make land suitable for agriculture.

A simple first-order estimate of daily area-average evapotranspiration (ET) was made for the study area to validate the results of our land surface processes model. The estimate was determined by computing the deficit between rainfall and the sum of runoff and the change in groundwater storage.

A budget was derived for the 40-day period of the experiment for the entire study area. In addition, a surface water budget was derived for a 7-day period for a smaller area used for initial testing of the model. About 80% of the study area is composed of seven discrete watersheds that are gaged by the US Geological Survey. Daily rainfall was derived from about 120 gaging stations within the study area that recorded at daily or higher frequencies. After gridding these data, the total daily volume of rain falling within each of the seven principal watersheds was determined using a GIS. Total daily volume of rainfall for the experiment area is the sum of the volume in each of the seven gaged watersheds. Ground water storage was determined from 14 wells scattered throughout the CaPE experimental area that terminated in the surficial aquifer. Changes in the water levels were corrected for soil porosity, thereby converting fluctuations in water level to water equivalent depth.

Estimated values of daily ET ranged from 15.4 mm to -1.3 mm/day with a 40-day mean of 4.6

mm/day. The structure of the daily ET time series is similar to the structure of the total daily rainfall volume. This high amplitude fluctuation is unrealistic for ET. The least-squares regression for the time series is probably a better estimate of ET for the period of the experiment. The regression curve ranges from 4.3 mm/day to 4.7 mm/day with a mean of 4.5 mm/day (Table 1). The regression standard error of estimate is 4.40, i.e., there is a 64% probability that estimated ET lies within 0.1 and 8.9 mm/day as determined by the water balance method. An examination of the residuals reveals that 39.4% of the variance in estimated daily ET can be attributed to the observed temporal structure of daily rainfall volume. These results compare remarkably well with daily pan evaporation data for the CaPE experiment from eight National Weather Service stations, which ranged from 3.9 mm/day to 8.2 mm/day with a mean of 6.0 mm/day. The regression has a positive slope of .03 and ranges from 5.4 mm/day to 6.5 mm/day (Table 1).

Table 1. Estimates of evapotranspiration using three different methods.

Method	ET (mm/day)
Surface Water Balance	
CHymP Domain (40 day mean)	4.5
Small Test Domain (7 day mean)	5.1
Pan Evaporation	
CHymP Domain (40 day mean)	6.0
SHEELS	
Small Test Domain (7 day mean)	5.7

4. LAND SURFACE PROCESSES MODEL

One of the principal goals of this project was to develop an improved model to study mesoscale hydrologic cycle components and their sensitivity to changing surface conditions. The Marshall Land Surface Processes Model (MLSPM) is a new contribution to the study of large-scale hydrologic processes and parameterizations. The space/time domain targetted for application of this model is between the basin scale applicable to watershed models and global scale where soil-vegetation-atmosphere transfer schemes (SVATS) are commonly coupled with atmospheric models.

The physics of the Marshall LSP Model are based on those of the Biosphere-Atmosphere Transfer

Scheme (BATS) (Dickinson et al., 1986). Thus, the Marshall Model has inherited that model's physical treatment of vegetation properties. The model uses a single canopy layer, but allows for fractional coverage of the ground by vegetation (Figure 2). The soil is divided into three layers, the upper two of which contain roots. The nested soil layer approach of BATS has been converted to a superposed layer configuration in the Marshall Model to facilitate easier computation of water mass balances and implementation of the Soil Conservation Services digital State Soil Geographic (STATSGO) data (see below). Other modifications from BATS include a simplification of the radiation scheme to utilize measured radiative fluxes, a more refined treatment of soil thermal and hydraulic properties, inclusion of a water table and a combined soil/vegetation albedo (Crosson et al., 1993; Smith et al., 1993, and Laymon et al., 1994). Future versions of the Marshall Model will account for and vadose zone water fluxes thereby offering the potential to study and develop parameterization schemes for a range of scales from large catchment to mesoscale.

The Marshall LSP Model represents an integral approach to land surface modeling, bringing together the key biophysical components of the soil, vegetation canopy and atmospheric surface layer. Its uniqueness lies in its treatment of surface variability of vegetation properties obtained from high resolution remote sensing and its use of soil properties obtained from the STATSGO database. Landcover information is obtained from remotely sensed landcover classification images. Table 2 lists the data requirements of the Marshall Model and the sources of these data used in CHymP and alternative data sources.
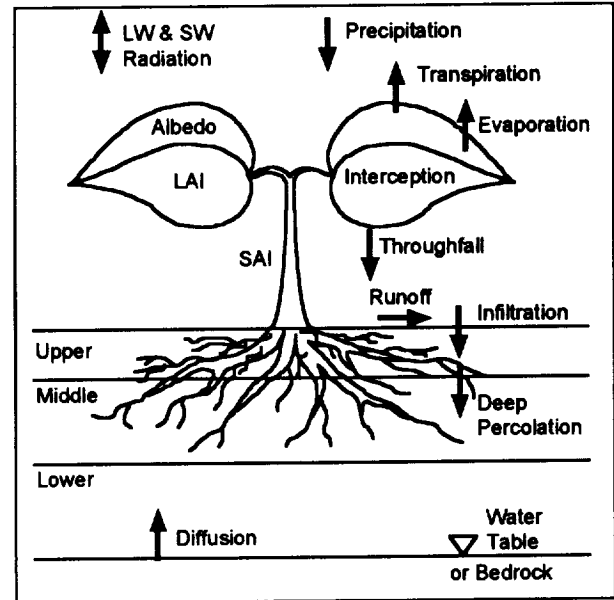

Figure 2. Diagram showing the fluxes simulated in the Marshall Land Surface Processes Model.

Table 2. Marshall Land Surface Processes Model data requirements and the sources of data used in CHymP.

MARSHALL LSP MODEL DATA REQUIREMENTS	CHymP DATA SOURCES	ANCILLARY SOURCES
Atmospheric Inputs:		
T, RH, pressure, wind, radiation fluxes	Flux stations, PAMs	NWS stations, remote sensing, model analyses
Precipitation	Raingage network, radars	Model analyses
Vegetation/Soil/Topographic Inputs:		
LAI, canopy height, % vegetation cover, surface emissivity	Landcover classification (Landsat-TM)	VIS and thermal remote sensing
Soil density, porosity, hydraulic conductivity, suction, wilting point, organic matter content	SCS STATSGO data, flux stations	
Slope, aspect	Digital elevation data	
Verification/Constraint Variables:		
Latent, sensible and ground heat fluxes, soil temperature, soil moisture	Flux stations	Model output
Surface temperature, albedo, NDVI	Flux stations, PAMs, MAMS	AVHRR, SPOT, Landsat-TM
Stream discharge	USGS gages	
Groundwater	USGS groundwater wells	

5. IMPLEMENTION OF STATSGO DATA

Many surface water and energy balance models require information about soil properties and their spatial variablity over the modeling domain. Most modeling activities of this type are performed over time scales for which soil properties are invariant. Thus, soil properties can be defined once for each layer of each soil type. Most water and energy balance models accommodate one to a few soil layers. In the cases of multiple layers, these may be superposed or nested. Although soils are relatively invariable even on annual time scales, they are highly variable spatially, in both the lateral and vertical dimensions.

The STATSGO data base (SCS, 1991) has recently become available in digital format with intercounty variances removed, thereby providing a new source of soil information for environmental modelers. Data are available by state. Each state is divided into delineated map units which comprise up to 21 components for which there are no delineations. Instead, the percentage of each component within the map unit is given. Components are subdivided into soil layers. Thus, each map unit can have multiple components and each component can have multiple layers. Soil attribute information is available for components and layers. Much of the attribute information is descriptive in nature, i.e., categorical, making it difficult to use for modeling without supplimenting these data with established relationships between the descriptive classes and the soil property of interest. There is, however, sufficient quantitative information for the data to be useful. Because the data are the result of aggregation of larger scale data, variability of most properties is accounted for by providing a high and low value for the range expressed by each property.

Our modeling requirements call for three superposed soil layers, an upper, middle and lower layer. A single value for each soil type-dependent property is required for each of these layers. For a few model-insensitive variables, a single value for the entire soil profile is required. A few of the variables of interest can be obtained directly from the data base. Other variables of interest are not explicitly contained within the data base, but can be derived from other attribute data that are contained in the data base. To derive a single value of a property for a map unit, the mean of the high and low value is determined for each layer of each property of interest. The layer mean is weighted by the layer thickness to determine the layer-weighted average for the soil horizon. The thickness-weighted mean is then area weighted by the percentage of each map unit associated with each component. Thus, values for each layer are layer thickness- and area-weighted profile averages. Derivation of several model variables from STATSGO data require special explanation.

5.1 Soil Depth

During pedogenesis soils become differentiated into distinct and not-so-distinct layers, or horizons. These layers are a reflection of different physical properties that result from processes that occur at varying degrees at different depths within the soil. Depth is defined from the surface, whereas thickness is defined as the difference between the lower and upper depths of bounding surfaces.

The upper layer thickness of the model is the surface layer, usually between 8 and 25 cm thick, where root density is greatest and evaporation occurs. This layer has the greatest impact on infiltration capacity. The upper layer for each map unit is the area-weighted thickness of layer 1 of each component.

The middle layer thickness lies between the upper and lower layers and is the layer where transpiration occurs from deep rooting vegetation. Most SCS soil profile descriptions are limited to a depth of 60 to 80 inches (150-200 cm). The relative abundance of roots is usually described in a county soil survey, but has been eliminated from the STATSGO data set. Land cover and vegetation information is, however, a part of the STATSGO data set and can be used to estimate the lower boundary of the root layer. In addition, the data base contains information on water table, pan, and bedrock depths that may also be used to restrict the thickness of this layer.

The depth of the lower layer is somewhat arbitrarily defined as the depth to bedrock or the ground water table if they occur within a depth of 6 m, otherwise a limit of about 4 m is probably adequate. Ground water data in the CHymP area indicated that the water table was at least 3 to 6 m deep.

5.2 Clapp-Hornberger b Parameter

The moisture characteristic curve relates the volumetric water content of a soil, or its wetness, to soil suction potential and is define as

$$\psi = \psi_s W^{-b} \tag{1}$$

where ψ is soil suction, ψ_s is the saturated soil suction, W is the soil wetness equal to θ/θ_s where θ_s is the saturated water content which is equivalent to porosity. In the Marshall Model, b is a soil type-dependent parameter. Clapp and Hornberger (1978)

identified a strong relationship (r = .98) between b and the clay content of soils.

The clay content of the soil fraction less than 2 mm diameter is provided in the STATSGO data base. For each soil layer, the data base provides a high and low value for the range of weight percent clay measured for the layer. The clay content of the root layer is the area- and thickness-weighted average for the profile. By substituting the clay content for x in the regression equation, the b parameter can be estimated for the upper and root layers, although the Marshall Model currently uses only a single value of b for the entire soil profile.

The very low clay content of the organic-rich soils in the CHymP domain result in erroneously low b values for these soils. We can rewrite the moisture characteristic equation to solve for the fractional water content, θ:

$$\theta = \left(\psi_s \Big/ \psi \theta_s^{-b} \right)^{\frac{1}{b}} \tag{2}$$

The soil wetness can then be determined for each soil at field capacity ($\psi = 0.3$ bar or 3000 mm) and the wilting point ($\psi = 15$ bars or 150000 mm). The difference between $\psi_{0.3}$ and ψ_{15} should be equivalent to the available water capacity. Since available water capacity is provided in the STATSGO data base for each layer, it is possible to compare calculated versus measured values to assess the validity of the calculated porosity and b parameter values. In fact, the calculated available water capacity is about .25 to 4 times lower than area- and thickness-weighted layer average values from the data base. This means that either porosity and/or the b parameter is/are too small.

Porosity is determined with moist bulk density rather than dry bulk density. This would result in an underestimate of porosity. The moist bulk density values, however, do not appear to be significantly elevated by a component of water and the resulting porosity values are close to expected values for the soil textures in question.

The low clay fraction of the organic-rich soils is most certainly not a good estimator of the moisture characteristics because the low clay content is offset by high organic content. Clay adsorbs water but organic matter adsorbs as well as absorbs water. At low suction, the wetness of organic-rich soils should more closely resemble that of clay-rich soils rather than sandy soils. In contrast, at high suction much of the water absorbed by organic matter should be available to plants making these soils more closely resemble sandy soils than clayey soils.

Experimenting with various values of b for the organic-rich soils revealed that the smallest difference between calculated and measured available water capacity occurs with b values of 1.5 to 2 times greater than those determined using the regression equation and clay content. The smallest disparity between calculated and meaured available water capacity was found if b values obtained from the regression equation were used for calculated wetness at both $\psi_{0.3}$ and ψ_{15} for the sandy soils and at ψ_{15} for the organic-rich soils, but a value of 2b was used to calculate wetness at $\psi_{0.3}$ for the organic-rich soils. With these values for b, the calculated and measured available water capacity agreed to within 8%.

6. IMPLEMENTATION OF LANDCOVER DATA

A landcover classification derived from Landsat-TM and degraded to 90 m resolution was used to characterize the spatial distribution of landcover types. Of the 22 remote sensing-derived landcover classes, 19 occur within the study domain. The 19 classes were aggregated into ten classes and landcover type-dependent parameters were assigned to each of the ten classes for modeling.

A small portion of the CaPE experiment area measuring 35 km x 50 km was used in an initial test of the model using both the STATSGO and landcover data sets to define the spatial distribution of soil and vegetation properties, respectively. The smaller test area contained nine classes of each data set. As expected, there was a fairly high degree of spatial covariance between these data sets.

The land surface model was run in a one-dimensional mode at 1 km resolution for a seven day period and the spatial distribution of surface fluxes examined. For example, the daily mean latent heat flux for the seven day period ranges from 100 to 240 W/m². The lowest values correspond to swampy areas and areas covered with evergreen shrubs. In contrast, the highest values are associated with short grasses and deciduous forests. Modeled surface runoff was highest over the wetland areas and lowest over the shrub- and grass-covered regions.

Sensitivity studies showed latent heat flux to be insensitive to whether soils were spatially variable or simply defined as the dominant type--sand. Latent heat flux was more sensitive to specification of vegetation type. Defining the entire region as grassland, the dominant vegetation, produced significantly lower latent heat flux than if vegetation was spatially variable (Figure 3). Likewise, surface runoff was more sensitive to landcover type than to soil type (Figure 4). Spatially-averaged ET for the seven day period was 5.7 mm/day. This result compares remarkably well with the ET estimates using the water balance method and pan evaporation (Table 1). These tests demonstrated that the model is sensitive to spatial

heterogeneity and incorporation of land surface heterogenity can result in improved simulations.
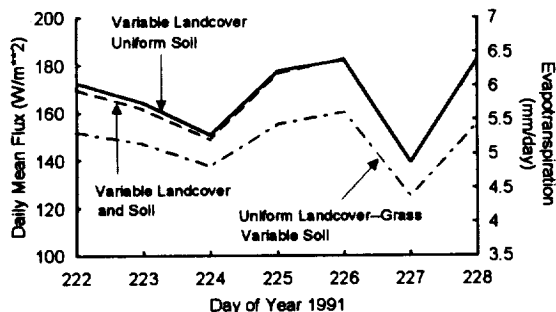

Figure 3. Chart showing the effects of land surface heterogeneity on latent heat flux and ET.
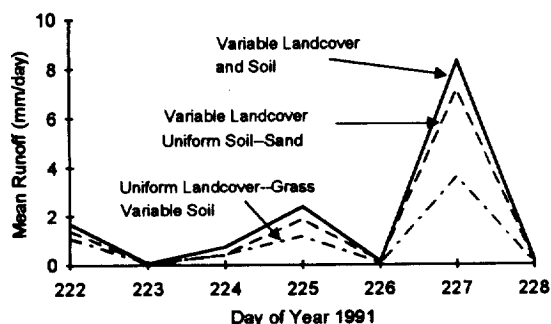

Figure 4. Chart showing the effects of land surface heterogeneity on surface runoff.

7. SUMMARY

Through the CaPE Hydrometeorology Project, we have developed an understanding of some of the unique data quality issues involved in assimilating data of disparate types for regional-scale hydrologic modeling within a GIS framework. Among others, the issues addressed here include the development of adequate validation of the surface water budget, implementation of the STATSGO soil data set, and implementation of a remote sensing-derived landcover data set to account for surface heterogeneity. A model of land surface processes has been developed and used in studies of the sensitivity of surface fluxes and runoff to soil and landcover characterization. Results of these experiments have raised many questions about how to treat the scale-dependence of land surface-atmosphere interactions on spatial and temporal variability. In light of these questions, additional modifications are being considered for the Marshall Land Surface Processes Model. It is anticipated that these techniques can be tested and applied in conjunction with GCIP activities over regional scales.

8. ACKNOWLEDGEMENTS

9. REFERENCES

Clapp, R. B., and G. M. Hornberger, 1978: Empirical equaitons for some soil hydraulic properties, *Water Resources Research*, 14, 601-604.

Crosson, W.L., E.A. Smith and H.J. Cooper, 1993. Estimation of surface heat and moisture fluxes over a prairie grassland. Part IV: Impact of satellite remote sensing of slow canopy variables on performance of a hybrid biosphere model. *J. Geophys. Res.*, 98, 4979-4999.

Dickinson, R.E., A. Henderson-Sellers, P.J. Kennedy and M.F. Wilson, 1986: Biosphere Atmosphere Transfer Scheme (BATS) for the NCAR Community Climate Model. NCAR/TN- 275+STR.

Laymon, C.A., W.L. Crosson and S.J. Goodman, 1994. Simulator for Hydrology and Energy Exchange at the Land Surface and its development through the CaPE Hydrometeorology Project, Abstr., *EOS, Transactions of the American Geophysical Union*, 75, p. 173.

Smith, E.A., W.L. Crosson, H.J. Cooper and H.-Y. Weng, 1993. Estimation of surface heat and moisture fluxes over a prairie grassland. Part III: Design of a hybrid physical/remote sensing biosphere model. *J. Geophys. Res.*, 98, 4951-4978.

Soil Conservation Service, 1991: State Soil Geographic data base (STATSGO): Data users guide, U. S. Department of Agriculture, Soil Conservation Service Misc. Publ. No. 1492, 88.

US Geological Survey, 1992: Water resources data, Florida, Water year 1991. U. S. Geological Survey, 1A, 430pp.

Williams, S. F, K. Caesar and K. Southwick, 1992: The Convection and Precipitation/ Electrification (CaPE) Experiment. Operations summary and data inventory. NCAR/OFPS, 425 pp.