The Integrated Precipitation and Hydrology Experiment - Hydrologic Applications for the Southeast US (IPHEX-H4SE)

Part I: High-Resolution Landscape Attributes Datasets

http://iphex.pratt.duke.edu

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Data Availability: http://iphex.pratt.duke.edu

Disclaimer: This purpose of this report is to provide background information on the generation of IPHEX-H4SE data sets. Results are presented for the first five years. The same methods were used for subsequent updating of data sets. This report will be submitted also to peer-review after extensive internal review. Comments and suggestions are welcome.

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Abstract

Quality-controlled datasets at high spatial and temporal resolution (1km×1km, hourly) for a five-year period (2007-2011) were developed for the IPHEx-H4SE project (Integrated Precipitation and Hydrology Experiment – Hydrologic Applications for the Southeast US), to support a common platform for the intercomparison and evaluation of hydrological models using various QPE (Quantitative Precipitation Estimation) products in an operational setting in coordination with the Intense Observing Period of the IPHEx field campaign in April-July 2014 (IPHEX2014). The data sets span four major river basins in the Southeast US with headwaters in the Southern Appalachians: the Upper Tennessee, the Savannah, the Catawba-Sandee, and the Yadkin-Peedee. Quality control and post processing were conducted to correct and improve the hydrometeorological forcing data sets. In this manuscript, we present the procedures and methodology to develop land surface broadband albedo, broadband emissivity, leaf area index (LAI), and fractional vegetation coverage (CV) at high tempo-spatial resolution based on the MODIS (Moderate Resolution Imaging Spectroradiometer) products. Quality control, gap filling and temporal filtering were performed to correct and improve the landscape attributes derived from MODIS products mainly due to cloud or snow or foggy contamination and limitations of retrieval algorithms. The datasets were utilized to specify land attributes in a distributed hydrological model (3D-LSHM) in the Pigeon River Basin, a headwater basin of one of the four major river basins in the Southeast of interest in the IPHEx-H4SE project. Results from five-year continuous simulations from 2007 to 2011 are used illustrate the importance of the quality landscape attributes affect the regional water partitioning at basin scale and thus the overall the hydrologic regime.
1. Introduction

In anticipation of NASA’s Global Precipitation Measurement (GPM) ground-validation activities in the Southeast United States, specifically the Integrated Precipitation and Hydrology Experiment (IPHEx, http://iphex.pratt.duke.edu/), a quality-controlled digital repository of comprehensive high-resolution data has been developed for Hydrologic Modeling/Forecasting in the Southeast (IPHEx-H4SE). The data sets provide common control forcing and landscape attributes to facilitate multi-scale, multi-purpose hydrologic modeling activities ranging from flash-flood forecasting to basin-scale water resource assessments in support of multi-model Operational Hydrologic Forecasting during IPHEX2014, the Intense Observing Period of the IPHEx field campaign planned in April-July 2014. The objective of this project is to establish a comprehensive data base that will serve as the foundation of the Precipitation Measurement Mission (PMM) Hydrology Working Group and HMT-SEPS common platform for transparent and robust testing and evaluation of various configurations of hydrologic and atmospheric models, the replication of operational forecasting applications under the same conditions, and thus the rigorous establishment of a state-of-the-science baseline in satellite-based Quantitative Precipitation Estimate (QPE) prior and after the GPM launch.

In the first phase of the project, the goal is to generate quality hydrometeorological forcing data sets at high spatial and temporal resolution (1km×1km, hourly time step) for the five-year time period 2007-2011 with a focus on four major river basins in the Southeast US, with headwaters in the Southern Appalachians: Upper Tennessee River Basin (56,573 km²), Savannah River Basin (27,110 km²), Santee River Basin (39,862 km²) and Yadkin-Pee Dee River Basin (46,310 km²), as shown in Figure 1. Overall, the databases include soil hydraulic parameters derived from the State Soil Geographic (STATSGO) database, landscape attributes datasets derived from...
the Moderate Resolution Imaging Spectroradiometer (MODIS) products, atmospheric forcing data derived from the North American Regional Reanalysis (NARR), and precipitation generated from NCEP/EMC 4KM Gridded Data (GRIB) Stage IV datasets. All the datasets were firstly extracted from original data sources, re-projected to UTM17N (WGS84) and bi-linearly interpolated to the domain grid system at 1km×1km resolution. Then, corrections and adjustments were applied to improve these datasets, aiming to provide five-year “historical” best estimates, which are essential for many applications such as hydrological hindcast/forecast, evaluating model skills and uncertainty, evaluating the accuracy of current radar-based QPE products especially in mountainous regions through hydrological verifications, and testing impacts of hydrometeorology regimes any others. In this paper, we will focus on the development of landscape attributes datasets. The development of atmospheric forcing datasets is provided in EPL-IPHEX-H4SE-2.

Space-time varying landscape attributes such as broadband albedo, broadband emissivity, leaf area index (LAI), and fractional vegetation coverage (CV) are crucial parameters affecting water and energy fluxes exchange at the soil-vegetation-atmosphere interface. These landscape attributes provide spatial-temporal varying patterns of land surface properties including vegetation states describing phenological dynamics. Previous studies demonstrated that the seasonality of latent heat flux and surface temperature are affected strongly by the vegetation states, and that the difference in latent heat fluxes between numerical experiments with fixed annual mean values and realistic seasonally varying vegetation characteristics was proportional to the difference in LAI (Lawrence and Slingo, 2004a; Lawrence and Slingo, 2004b). Yildiz and Barros (2007) showed that fractional vegetation coverage and albedo were the governing hydrological parameters in their hydrologic sensitivity study using an uncalibrated model. Land
surface albedo is an important indicator of landcover change (e.g. deforestation and forest restoration) resulting in impacts on regional energy balance at climate scale (Dickinson and Kennedy, 1992; Dirmeyer and Shukla, 1994; Garratt, 1993; Liu, 2011), and of land surface disturbances (e.g. wildfire burning) at shorter time scales (Jin et al., 2012). Cedilnik et al. (2012) found that using daily albedo instead of climatologically based monthly albedo in a NWP model could significantly reduce the model biases in surface net radiation. Land surface broadband emissivity is also a key parameter playing an important role in energy budget in land surface hydrologic model, and usually is assumed to be consistent or fixed values depending on landcover (Dickinson et al., 1993; Sellers et al., 1996). However, Jin and Liang (2006) demonstrated that evident changes in soil an skin temperature, sensible and latent heat fluxes were found using time-varying satellite-derived broadband emissivity compared to the results using fixed emissivity in a community land surface model coupled NCAR community atmosphere models (CAM2–CLM2).

In the IPHEx-H4SE project, the spatial-temporal varying landscape attributes, including LAI, CV, land surface broadband emissivity and albedo were derived from the Moderate Resolution Imaging Spectroradiometer (MODIS) products (Table 1). The unstable reliability of MODIS land products due to cloud contamination, or missing data due to persistent presence of cloud or snow, and uncertainty in retrieval algorithm are well documented (Gao et al., 2008; Roman et al., 2009; Williamson et al., 2013; Yang et al., 2007; Yuan et al., 2011). Here, we conducted independent quality control, gap filling and temporal filtering for MODIS products, to generate spatially and temporally consistent landscape attribute datasets of high quality for hydrological applications. All the improved landscape attributes datasets are available to PMM hydrologists and potential participants at the website of IPHEx (http://iphex.pratt.duke.edu/).
Headwater catchments of the UTRB, a basin featuring the most complex terrain of the four drainage basins of interest in this project (the UTRB, the SVRB, the SRB, and the YPDRB), are located at the Southern Appalachian Mountains in NC. One of these headwater basins, the Pigeon River Basin (shown in Figure 1), will be the testbed for the hydrological simulation experiments in this study. The hydrological verification has been conducted in three sub basins that are equipped with USGS stream gauge, but not limited by dam operation in the Pigeon River Basin (see report EPL-IPHEX-H4SE-3). These include the Cataloochee Creek Basin (CCB), the West Fork Pigeon River Basin (WFPRB) and the East Fork Pigeon River Basin (EFPRB). The impact of quality landscape attributes on water flux simulations will be illustrated by analyzing the water balance/budget over the five year period (2007-2011) in the Pigeon River Basin, using the landscape attributes before and after adjustment/improvement.

The organization of this manuscript is as follows: Section 2 describes the methodology for developing the landscape attributes datasets from MODIS products, and the procedure for post processing and improving the datasets. Section 3 presents the results of the derived datasets and analyzes the statistical seasonal characteristics of these landscape attributes with respect to land cover. The comparison of derived land surface broadband albedo with observations at AmeriFlux tower is also provided. Section 4 presents hydrological application experiments over the Pigeon River basin using the 3D-LSHM driven by both the raw and the adjusted landscape attributes datasets. The analysis of regional water budget at five-year time scale is also included. The summary and discussion are provided in Section 5.
2. Methodology and Procedures

MODIS land products provide 8-day LAI and spectral emissivities which were used to construct hourly LAI, CV and broadband emissivity within the IPHEx-H4SE domain at 1km in a consistent projection system (UTM17N). There is no available hourly product of land surface broadband albedo, thus it was derived from MODIS BRDF parameters to generate a consistent hourly land surface albedo for hydrological applications. Figure 2 illustrates the sequence of procedures for generating landscape attributes datasets from MODIS products. Generally, the original MODIS products were re-projected and composited to the study area using the MODIS Reprojection Tool (MRT), interpolated to basin grids using the nearest-neighbor or bi-linearly method depending on the resolution of MODIS products, and then interpolated into hourly time steps. Quality-control and temporal filtering of the landscape attributes data were performed to reduce the discontinuities or to correct for cloud contamination. The details about the procedure are discussed in detail next.

a) LAI and CV

The leaf area index (LAI) is a key parameter influencing energy fluxes exchange at vegetation-atmosphere interface, and also water fluxes by affecting hydrologic processes such as intercepting rainfall and releasing throughfall and stemflow (Galdos et al., 2012; Marin et al., 2000; Park and Cameron, 2008). The combined Terra and Aqua MODIS version of the 8-day Leaf Area Index and FPAR product (MCD15A2, Collection 5) was used to extract and generate LAI data over the southeast US at IPHEx-H4SE basin domain. Due to the cloud contamination, post-process filtering combining quality control has to be applied to generate LAI of high quality (Gao et al., 2008; Yuan et al., 2011). In this project, we use a software package, TIMESAT (Eklundha and Jönnsonb, 2012; Jonsson and Eklundh, 2004), to perform temporal filtering and to
reduce the discontinuity caused by cloud contamination combining quality control data. The TIMESAT is a tool utilized for analyzing time series of satellite-derived product and extracting vegetation phonologic characteristics, and has been widely applied for post-processing and then generating high-quality satellite products (Eklundh et al., 2009; Heumann et al., 2007; Yuan et al., 2011). The Savitzky-Golay (SG) filter method implemented in the TIMESAT was used to conduct the adaptive temporal filtering for MODIS LAI, by fitting a quadratic polynomial function using the time series data in a moving window.

The Fractional vegetation coverage (CV) then was estimated from LAI, based on an empirical relationship with LAI (Choudhury, 1987; French et al., 2003):

\[
CV = 1 - \exp(-0.5 \times LAI)
\]  
(2.1)

Many other methods estimate CV based on NDVI (Baret et al., 1995; Carlson and Ripley, 1997; Gutman and Ignatov, 1998), such as the semi-empirical relationship proposed by Carlson and Ripley (1997),

\[
CV = \left( \frac{NDVI - NDVI_0}{NDVI_s - NDVI_0} \right)^2
\]  
(2.2)

where \( NDVI_s \) and \( NDVI_0 \) represent the values of NDVI for fully covered vegetation and bare soil, respectively. Because NDVI is more indicative of greenness than adult vegetation canopy structure, density and coverage, NDVI product also suffer from problems of contamination by background soil and easy saturation for dense vegetation. Therefore the CV estimated here is produced by LAI based on equation (2.1). Other CV products estimated from NDVI can be also provided upon request, or independently generated by interested users. Comparing the time...
series and also spatial distribution of these CV products can help deciding the best method for specific applications.

b) Land Surface Emissivity

Land surface emissivity plays an important role in the surface radiation budget, and has a strong impact on energy balance especially at climate time scales (seasonal to interannual). The MODIS/Terra 8-Day Land Surface Temperature and Emissivity (LST/E) product on a latitude/longitude–based (0.05°) climate modeling grid (CMG) system (MOD11C2, Collection 5) consists of spectral emissivities. However, the land surface broadband emissivity is required for hydrological applications to describe the integral emitting properties of surface over the full electromagnetic spectrum (mainly concentrated at long-wavelength infrared).

Previously, the linear relationship between the broadband emissivity and MODIS spectral emissivities was established through regression analysis by Jin and Liang (2006), using emissivity at MODIS band 29 (8.400–8.700 μm), band 31(10.780–11.280 μm) and band 32 (11.770–12.270 μm):

\[ \varepsilon_b = 0.0139 \times \varepsilon_{29} + 0.4606 \times \varepsilon_{31} + 0.5256 \times \varepsilon_{32} \]  

(2.3)

This relationship (2.3) almost fully covers the wavelength of 8–12 μm and accounts for soils and minerals background information, and was used to generate land surface broadband emissivity in this project.

The TIMESAT software was also used for temporal filtering to improve the emissivity data. The method for detecting spikes/outliers and assigning weights to the LAI data relies on the Seasonal Trend Decomposition using Loess (STL) algorithm, which first decomposes the time series into
trends, seasonality and remainder components and then assigns the weights accordingly. On the other hand, experimental tests demonstrated that the median filtering method was the most efficient approach to detect emissivity outliers, resulting in very similar weights as the STL-decomposition method. Thus the median filtering was selected for detecting spikes in the emissivity data, while other parameters were derived using the same approach as for the LAI data (e.g. fitting method is Savitzky-Golay, seasonality parameter, etc). Because emissivity data are governed by landcover, soil moisture content and vegetation characteristics, the upper envelope is not necessarily the true value. The STL-decomposition method is more favorable for fitting to the upper envelope of data, for instance, in the case of LAI.

c) Land Surface Albedo

The MODIS albedo product (MCD43B3) provides both the directional hemispherical reflectance (black-sky albedo) at the local solar noon (a specified solar zenith angle) and the bihemispherical reflectance (white-sky albedo). Then the blue-sky (actual) albedo at local solar noon can be calculated using the MCD43B3 product given the aerosol optical depth. However, the instantaneous actual albedo at time other than the local solar noon cannot be obtained from the MCD43B3 product, since the actual albedo depends on instantaneous solar zenith angle (Liu et al., 2009; Schaaf et al., 2002). Thus, the MODIS BRDF/Albedo Model Parameters product (MCD43B1), which provides spectral-band and also broadband BRDF model parameters every 8 days with 16 days acquisition interval, is used in this project to estimate the diurnal cycle of actual albedo as a function of solar zenith angle, as suggested by Schaaf et al. (2002). Relying on the Ross-Thick/Li-Sparse-Reciprocal (RTLSR) kernel-driven BRDF model, the directional hemispherical reflectance (black-sky albedo) given any solar illumination geometry condition and the bihemispherical reflectance (white-sky albedo) can be derived by calculating the
weighted sum of an isotropic parameter and two kernels describing viewing and illumination geometry (Roman et al., 2009; Schaaf et al., 2002).

\[
\alpha_{bs}(\theta, \lambda) = f_{iso}(\lambda)(g_{0iso} + g_{1iso}\theta^2 + g_{2iso}\theta^3) \\
+ f_{vol}(\lambda)(g_{0vol} + g_{1vol}\theta^2 + g_{2vol}\theta^3) \\
+ f_{geo}(\lambda)(g_{0geo} + g_{1geo}\theta^2 + g_{2geo}\theta^3)
\]  

(2.4)

where \(\alpha_{bs}(\theta, \lambda)\) is the black-sky albedo; \(g_{jk}\) are coefficients and \(\theta\) is the solar zenith angle. \(f_{iso}(\lambda)\) is the isotropic scattering component, \(f_{vol}(\lambda)\) is the parameter for the Ross-Thick volume scattering kernel, and, \(f_{geo}(\lambda)\) is the parameter for the Li-Sparse-Reciprocal geometric scattering kernel. These BRDF model parameters were extracted from the product MCD43B1. The \(g_{jk}\) coefficients for the \(\alpha_{bs}(\theta, \lambda)\) are provided in Schaaf et al.(2002), in which the integrated coefficients over all the solar zenith angle for the white-sky albedo \(\alpha_{ws}(\theta, \lambda)\) are also presented.

\[
\alpha_{ws}(\theta, \lambda) = f_{iso}(\lambda) + 0.189184f_{vol}(\lambda) - 1.377622f_{geo}(\lambda)
\]  

(2.5)

The actual albedo of the land surface then is the weighted average of black-sky albedo (BSA) \(\alpha_{bs}(\theta, \lambda)\) and white-sky albedo (WSA) \(\alpha_{ws}(\theta, \lambda)\). The weighting coefficient is the fraction of diffuse skylight which depends on solar zenith angle, optical depth, local aerosol type etc. (Schaaf et al., 2002).

\[
\alpha(\theta, \lambda) = \left[1 - S(\theta, \tau(\lambda))\right]\alpha_{bs}(\theta, \lambda) + S(\theta, \tau(\lambda))\alpha_{ws}(\theta, \lambda)
\]  

(2.6)

where \(S(\theta, \tau(\lambda))\) is fraction of diffuse skylight which depends on solar zenith angle \(\theta\) and optical depth \(\tau(\lambda)\). Solar zenith angle was calculated according to the Sun position at local time. The fraction of diffuse skylight was obtained from a lookup table which was established with the
help of the 6S (Second Simulation of a Satellite Signal in the Solar Spectrum) code including situations up to 90° solar zenith angle (0° to 89° with a 1 degree step), 50 optical depths (0 to 1.0 with 0.02 step), 10 bands (7 MODIS land bands and 3 broad bands) and 2 aerosol model types (continental and maritime). The aerosol optical depths (at 550 nm) were obtained from the MODIS Level 3 Atmosphere Daily Product (MOD08_D3). Whereas the simple linear interpolation was used to generate hourly emissivity, LAI and CV, the same method cannot be applied to generate hourly albedo. In this case, the hourly solar zenith angle should be calculated first and then the fraction of diffuse skylight was estimated according to the optical depth and solar zenith angle. Furthermore, hourly albedo were produced by Eq. (2.6) using the BSA and WSA derived from the 8-day BRDF model parameters.

3. Results and Analysis

3.1 LAI and CV

The adaptive temporal filtering was performed for LAI using TIMESAT software (Eklundha and Jönssonb, 2012; Jonsson and Eklundh, 2004), using an adaptive Savitzky-Golay filtering method based on least-squares fits to the upper envelope of the time series of data. Figure 4 and Figure 5 show the time series of LAI and CV before and after temporal filtering at locations of towers in the southeast US (shown in Figure 1), including six Ameriflux towers and a Duke Environmental Physics Laboratory tower (DKEPL) installed at Purchase Knob in the Southern Appalachian Mountains by the second author’s research group. The landcover for these towers is listed in Table 2. However, no measurements of LAI and CV are available for validation proper. We show the comparison of time series to illustrate how the adaptive filtering method can

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1 [http://www-modis.bu.edu/brdf/userguide/tools.html](http://www-modis.bu.edu/brdf/userguide/tools.html)
significantly reduce the discontinuity in LAI and thus CV, improving the data quality. It can be seen from Figure 4 and Figure 5 that the filtered LAI preserve the inter- and intra-annual variability and capture the growing season. Consequently, the CV derived using the filtered LAI is a true representative of the vegetation coverage than the CV directly calculated using unfiltered LAI. The LAI and CV at the DKEPL-tower (bottom rows in Figure 4 and Figure 5) show the largest improvement compared to other towers, reducing the fog and low level cloud banks contamination during the warm season, a quite normal characteristic in the Smoky Mountains. Generally, the most frequent contaminations occurred during the summer time (shown by the downward peaks from Jun. to Oct. in the figures), especially in 2009 (the third column in each row in the figures) which witness frequent storm events during the Atlantic hurricane season. For example, MODIS can hardly capture cloud-free data over the southeast US even within an 8-day period around Sep.16 in 2009, and thus suffer from severe cloud contaminations in the LAI product, as shown in the top-middle figures in Figure 6 and Figure 7. As can be seen in the top panel in both Figure 6 and Figure 7, the spatial LAI/CV on 10-day before and after Sep.16 (left and right figures in the top row) exhibit reasonable values and distributions over the southeast US, but the LAI/CV on Sep. 16 show very small values (large area in red color) due to cloud contamination. This contamination is effectively removed by the adaptive Savitzky-Golay filtering, as shown by the middle figure in bottom panel in Figure 6 and Figure 7.

Figure 8 presents the time series of the average of filtered LAI and CV for all the pixels of same landcover types over the southeast US region for the five years 2007-2011 from left to right. The barren or sparsely vegetated (BA) type is mainly concentrated over the coastland, showing small LAI/CV all year around. Mixed forest (MF) and deciduous broadleaf forest (DBF) show close
values and similar variability. Figure 9 and Figure 10 provide the PDF of LAI and CV respectively, separated by four seasons for each landcover type. The statistics associated with the PDF figures of LAI and CV are given in Table 3 and Table 4. It can be seen from Figure 9 and Figure 10, the mixed forest (MF), evergreen broadleaf forest (ENF) and deciduous broadleaf forest (DBF) present large variability, especially in the growing season (MAM) and the dormant season (SON), indicating the varying phenologic characteristics of broadleaf forests. Compared to the large variability in the growing or dormant season, all the forest type in the blooming season (JJA) show much less variation. Note the PDF shapes in the growing season are very similar to the shape in the dormant season for almost all the landcover types, but having very different PDF shapes in the blooming season (JJA). This is quite important for data merging techniques such as data assimilation, in which the prior PDFs of land surface parameters usually are assumed independently on seasons. In addition, the dynamic temporal-spatial heterogeneity of vegetation is essential for modeling energy and water fluxes, since apparently landcover-determined values of vegetation characteristics cannot represent the true landscape attributes in reality. Closed shrubland (CS) and woody savanna (WSA) show less variation in LAI than open shrubland (OS) and savanna (SA) respectively (Figure 9), although the mean for these types are quite similar. The PDF shapes of LAI for both grassland (GA) and cropland (CP) have long tails (Figure 9), positively skewing to the upper side with larger means than medians in four seasons (shown in Table 3), indicating large diversities of vegetation existing in the same type of GA and CP. But the long tails are just shown in the PDF of CV for GA and CP in MAM and SON (Figure 10). While in JJA, the PDF of CV for GA and CP present two peaks at both end sides, demonstrating the nonlinear relationship between LAI and CV. Generally, the intra-annual variation of CV is larger than LAI, which is also illustrated in the spatial distribution examples of
LAI (Figure 11) and CV (Figure 12). Figure 11 and Figure 12 clearly demonstrate the temporal-spatial heterogeneity over the region. The northeast-to-southwest patterns of alternating large and low values are attributed to the vegetation zones as shown in landcover map (Figure 3). As shown in Figure 11, the mixed zones of woody savanna and croplands close to the coastlands show low LAI all year around and for all the years, in contrast to the adjacent mixed forest zone which shows relatively larger LAI all the time. The seasonality of the mixed zones of woody savanna and croplands is shown more clearly in Figure 12. Compared to the forests in the Southern Appalachian Mountains, the northeast-to-southwest mixed forest zones in between the woody savanna zones and close to the coastlands stay with large CV all year around (Figure 12).

Overall, the filtered LAI and CV show reasonable and correct temporal-spatial patterns, presenting dynamic temporal-spatial heterogeneity which should be imposed in hydrological modeling to correctly simulate energy and water fluxes.

### 3.2 Land Surface Emissivity

The land surface broadband emissivities are derived from spectral emissivities at MODIS band 29, 31 and 32. Temporal filtering for the emissivity data was performed used the TIMESAT software, as discussed in Section 2. Figure 13 shows the time series of the land surface broadband emissivity before and after temporal filtering. In contrast to the LAI and CV, which most contamination is negative-biased, the bad quality of land surface emissivity is represented by up and down dramatically noisy variations. The filtered results obviously demonstrate smoother and reasonable changes.

Figure 14 presents the time series of averaged land surface emissivity for different landcover types. As can be seen from the figure, the land surface emissivity of most of the landcover types
have similar inter- and intra-annual variability, except for the barren or sparsely vegetated (BA) and Urban and built-up (UB) type which present larger variation and smaller minimum values. Figure 15 shows the PDF of land surface emissivity for each landcover and each season, about which the statistics are provided in Table 5. Not like LAI or CV, the PDF of emissivity remain similar for all the landcover types and seasons, although the variation changes in a similar way, i.e. small variation in JJA but large variation in other seasons. The spatial distributions of emissivity in different seasons are provided in Figure 16. Previous study has demonstrated that the land surface emissivity depends on surface characteristics (i.e. landcover type, vegetation density and structure), soil moisture and soil organic content (Jin and Liang, 2006). Combing with Figure 11 and Figure 12, we can see from Figure 16, the overall emissivity increase as LAI and vegetation coverage, such as that the emissivity is low in Feb. and then increase to larger values though Apr., Jun. to Aug. and Oct., then again decrease in Dec.. The dependence of emissivity on vegetation demonstrated here is consistent with previous studies (Jin and Liang, 2006; Vandegriend and Owe, 1993). The urban regions always stay at high values, which although is altered by wet (e.g. June 1 in 2009 and 2010) or dry conditions (e.g. June 1 in 2008 and 2011), or subsequently by the surface moist, vegetation and temperature conditions in the urban areas.

In summary, the land surface emissivity is landcover-dependent and presents small seasonal variations. The small tempo-spatial variability of land surface emissivity is partially due to spatial heterogeneity at 1km resolution and partially due to the climatologic characteristics of the surface over the southeast US.
3.3 Land Surface Albedo

The albedo measurements at towers were obtained based on the reflected global solar radiation divided by the incoming global solar radiation, and then were used to validating retrieved albedo from MODIS. However, the point-to-pixel comparison of tower observation with MODIS retrieved albedo is largely limited by the spatial heterogeneity and the uncertainty induced by scale mismatches (Cescatti et al., 2012; Liu et al., 2009; Roman et al., 2011). Román et al. (2009) proposed a methodology for assessing the landscape heterogeneity and the spatial representativeness of albedo observations at AmeriFlux forest sites based on variogram functions calculated from ETM+(Enhanced Thematic Mapper Plus) images, to evaluate if the tower observed albedo can represent the spatial variability of the surrounding landscape extending to the spatial scales of MODIS products. This method has been applied by many studies on evaluating albedo products (Cescatti et al., 2012; Roman et al., 2013). Román et al. (2009) concluded in their study that the US-ChR tower is the only tower spatially representative of its surrounding landscape in the Southeast US. Figure 17 shows the ETM+ images over the tower US-ChR, demonstrating a very similar spatial distribution of landscapes, i.e. low heterogeneity, across the Oak Ridge Forest (Roman et al., 2009). Therefore, we will validate the MODIS retrieved albedo against the observation at tower US-ChR, without further evaluating the spatial representativeness at this tower.

Figure 18 shows the comparison of monthly mean diurnal cycle of land surface albedo between estimation from MODIS and observation at US-ChR. Basically the retrieved albedo agree well with the observation at the tower except for the later afternoon, with a little bit underestimation mainly during the winter time (Jan., and Oct. to Dec.). The derived albedo exhibit quite symmetric diurnal cycle resulted from the assumption of symmetry with respect to the local solar
noon in the theoretical retrieving algorithm (Liu et al., 2009), whereas the observed albedo shows asymmetry characteristic as shown in the figure. Previous studies have investigated the diurnal asymmetry characteristic of albedo in the fields of grassland or cropland (Minnis et al., 1997; Song, 1998), and found that albedo in the early morning usually is larger than in the afternoon. The diurnal asymmetry of albedo might attributed to the effects of dew, frost, precipitation, evaporation and wind (Minnis et al., 1997), which cause brighter surface, but not accounted for in the MODIS albedo retrieval algorithm. For example, the strong prevailing wind lean the vegetation canopy and turn the back of leaves upward, and then brighten the surface. However, as shown in Figure 18, the observed albedo has larger value in the later afternoon than in the early morning at a deciduous broadleaf forest dominated site US-ChR (Table 2), which can be explained by the different canopy structure of forest from grassland or cropland. Figure 19 shows the validation results of the retrieved land surface albedo at the local solar noon (LSN), demonstrating a good agreement with the observation at the tower US-ChR with small root mean square error (RMSE=0.017), mean absolute error (MAE=0.013) and mean bias error (MBE=-0.007). Since MODIS BRDF parameters are snow-free and cloud-free, to avoid cloudiness condition, the mean of the observed albedo within a 3-hour window centered at the LSN was calculated and compared with MODIS retrieved albedo similarly to the study of Román et al. (2009). The snow conditions were identified by air temperature less than zero Celsius degree observed at the tower. However, it is not possible completely screen out cloud conditions even using 3-hr mean of observation for comparison, which may explained the underestimation of retrieved albedo around May.

Figure 20 presents the time series of the averaged albedo at the LSN for all the pixels of the same landcover type from 2007 to 2011. Although the average of many pixels may reduce the
difference between landcover types, the ENF and DNF still distinguish themselves from other
types by much lower albedo except for BA. As stated above, BA regions are concentrated along
the coastland and thus have very low albedo due to the dark color. The lower albedo of the ENF
and DNF are attributed to the dark needles and also the trapping of light by the needle leaf
canopy. The outmost two types which present very large albedo are grassland (GA) and
cropland (CP). Generally, albedo starts to increase during the growing and blooming season and
then decrease during dormant season, and increase again during winter time. The PDF shapes of
the land surface albedo at LSN (as shown in Figure 21) do not exhibit much discrepancy in
different seasons for a same landcover type, illustrating the diversity of vegetation of same
landcover do not affect the seasonality of albedo very much. The statistics associated with Figure
21 are given in Table 6. Figure 22 shows the spatial distribution of land surface albedo at the
LSN, including the black-sky albedo, white-sky albedo and the blue-sky (actual) albedo on
March 1, June 1, September 1 and December 1 in 2008. It can be clearly seen that, the wetlands
along river networks demonstrate very small albedo, especially the area near the coastlands. The
black-sky albedo heavily depends on solar zenith angle, thus the difference between the black-
sky albedo at the LSN in different months is small due to small difference in the solar zenith
angle. Whereas the white-sky albedo depends on the observed intrinsic properties of the land
surface as indicated by equation (2.5), thus large differences are shown between the white-sky
albedo in months, as shown in the middle column in vertical rows in Figure 22. The final actual
albedo then is the combination of black-sky and white-sky albedo, weighted by the condition of
the diffuse skylight.
4. Hydrological Application

The illustrating hydrological modeling study was conducted in one of the headwater basins of the UTRB, the Pigeon River Basin (shown in Figure 1). Hydrological verification was performed in three sub-basins equipped with USGS stream gauges but not limited by dam operation in the Pigeon River Basin, including the Cataloochee Creek Basin (CCB, 128km$^2$), the West Fork Pigeon River Basin (WFPRB, 71km$^2$) and the East Fork Pigeon River Basin (EFPRB, 131km$^2$). The Pigeon River Basin features topographically complex terrain, characterized by gentle to very steep slopes and dominated by very dense forest (mix forest and deciduous forest). Previous hydrological studies had been conducted in the Pigeon River Basin investigating the predictability of flash flood (Tao and Barros, 2013b) and debris flow initiation (Tao and Barros, 2013a), for particular storm events. In this study, we conducted hydrological simulations at IPHEX-H4SE conventional scale at 1km×1km spatial resolution and hourly temporal resolution over a five year period from 2007 to 2011, using a physically-based fully-distributed hydrological model (3D-LSHM) driven by both raw and the adjusted landscape attributes (LA), in order to characterize the impact of landscape attributes on regional water budget. Raw landscape attributes consist of the original broadband emissivity, LAI and CV datasets without further quality control and adaptive temporal filtering. While the adjusted landscape attributes include the emissivity, LAI and CV after post processing, e.g. quality control and the Savitzky-Golay filtering. The derived broadband albedo is the same dataset in both the raw and adjusted landscape attributes category. The atmospheric forcing datasets developed for the IPHEX-H4SE were derived from the North American Regional Reanalysis (NARR) and had been corrected for elevation and topographic effects. Details about the adjustment of atmospheric forcing datasets are provided in EPL-HYPHEX-H4SE-2. Precipitation data were generated from NCEP/EMC
4KM Gridded Data (GRIB) Stage IV datasets and then downscaled to 1km using various methods (see EPL-IPHEX-H4SE-3). Here, a randomly selected realization among the 50 realizations available of the Precip_StageIV_TF product based on a transient multi-fractal downscaling method is used to illustrate the sensitivity of model simulation to land attributes. Model description and implementation can be found in (Tao and Barros, 2013a; Tao and Barros, 2013b; Yildiz and Barros, 2007; Yildiz and Barros, 2009). One-year spin-up simulations were conducted before the five-year simulation, to reach the model consistency. The comparison of the five-year continuous streamflow simulations against the observations for the three sub-basins (WFPRB, EFPRB and CCB) is shown in report EPL-IPHEX-H4SE-3.

Figure 23 shows the spatial distribution of simulated intercepted rainfall, evaporation and transpiration in the Pigeon River Basin using landscape attributes (LA) before and after the adjustment. As can be seen from the figure, the improvement in LAI and CV (as shown in Figure 6 and Figure 7) causes increase in intercepted rainfall amount and transpiration but decrease in evaporation. Note the cloud contamination generally reduce LAI and then CV, thus the adjustment or improvement for LAI data mainly removed these downward peaks as shown in Figure 4 and Figure 5. Thus, the small LAI and CV before improvement having cloud or foggy contamination result in little canopy-interception capacity, which is quite critical for light rainfall regime. For light rainfall dominated scenario, light rainfall would exceed the interception capacity when using inaccurate vegetation characteristics (i.e. the raw LAI and CV data), and then could reach ground and wet the soil. However, in reality the light rainfall will most likely be retained in the canopy and be evaporated later. For moderate or heavy rainfall dominated scenario, on one hand, more rainfall will be retained in the canopy when using the corrected LAI and then contribute to evaporation, and less rainfall can be infiltrated into ground and contribute
to runoff, soil water content and thus transpiration. On the other hand, the CV after correction is larger thus reducing the bare soil area, which causes decrease in evaporation. In the 3D-LSHM, the evaporation at each pixel comprises the components from bare soil area (1-CV) and also skin reservoir including canopy retention. However, overall the accumulated evaporation using adjusted LA is less than that using raw LA as shown in Figure 23, demonstrating that the decrease in evaporation due to reduced area coverage of bare soil exceeds the increase in canopy retention. Consequently, larger vegetation coverage results in increase in transpiration as shown by the third column in each panel of Figure 23. Nevertheless, the varying changes in intercepted rainfall, evaporation and transpiration also depend on landcover and hydrometeorological regime. For instance, the transpiration is always very small in the urban area in the center and the mixture patch of cropland and woody savannah in the northern part of the basin. Large changes occur in the mix forest and deciduous forest dominated area. Also, the tremendous enchantment in transpiration in 2011 (the third column in e.2 of Figure 23) is due to the extreme wet conditions in that year. In contrast, the year of 2009 shows very small transpiration and experienced severe drought after a very dry year of 2008. In short, the accuracy of landscape attributes directly affects the water partitioning and then the regional water budget in a nonlinearly complex manor. Water balance/budget in the Pigeon River Basin is of vital importance. Figure 24 presents the basin-averaged water components including precipitation (P), runoff(R), evapotranspiration (ET), soil moisture change (ΔSM), leakage (LK) and the water imbalance (Im.= P-(R+ET+ΔSM+LK)) accumulated over the simulation period using both raw and the adjusted LA datasets. As the figure shows, although water balance is closed with very small imbalance fraction (about 4% accumulated for five years) independently of using raw or the adjusted LA, the accumulated ET estimates using the adjusted LA is much larger and the
runoff is smaller compared with the counterpart estimates using the raw LA data. Consequently, the ratio of runoff to precipitation (R/P) is decreased by 4%, and the ratio of ET/P increased by 4%. The increase in ET results from the larger increased amount in transpiration and relative smaller decrease in evaporation (as shown by c in Figure 24).

Note that these five year simulations were conducted without initialization or re-initialization, and therefore errors in the specification of initial soil moisture conditions and groundwater storage as well as rainfall related errors can severely impact the initial conditions for specific events. To alleviating this impact, spin-up simulations for 15 years were conducted. The spin-up consisted in re-running the 5-year simulation three times using the same 5–year forcing. Results that illustrate the impact of initial conditions for the EFPRB watershed are shown in Figure 25: the 5-year NSE (Nash-Sutcliffe efficiency) score for hourly streamflow simulations increases from 0.28 to 0.45. This implies, there are still unaccounted for forcing errors, especially in the rainfall as discussed in EPL-IPHEX-H4SE-3, but there is strong improvement in model performance as indicated by the 61% improvement in NSE. This finding suggests that the atmospheric forcing and land-attributes data sets are reliable, and confirm the importance of initialization of basin storage in basins where surface-subsurface interactions are important (Tao and Barros, 2013b).

5. Summary and Discussion

Dynamical landscape attributes varying in space and time affect regional water and energy budget. However, currently there are no available landscape attributes products at high temporal-spatial resolution for hydrological application. In this study, we develop a quality landscape
attributes datasets, including land surface broadband albedo, broadband emissivity, leaf area index (LAI) and fractional vegetation coverage (CV) at high tempo-spatial resolution (1km×1km, hourly) based on the MODIS (Moderate Resolution Imaging Spectroradiometer) products for a five-year period (2007-2011) over the Southeast US. The landscape attributes datasets, as well as the atmospheric forcing dataset (EPL-HYPHEX-H4SE-2), is developed for the IPHEx-H4SE project and will support the multi-model Operational Hydrologic Forecasting during the Intense Observing Period of the IPHEx field campaign in 2014 (IPHEX2014). All of these datasets are available at the IPHEx website (http://iphex.pratt.duke.edu/).

The derived and improved LAI and CV demonstrate reasonable inter- and intra-annual variability and show better tempo-spatial pattern for each land cover type compared with the raw LAI and CV before quality control and adaptive temporal filtering. The developed land surface broadband emissivity show much smaller tempo-spatial variability compared to LAI and CV, but is also demonstrated dependent on land-cover and seasons. The land surface broadband albedo was derived from MODIS BRDF/Albedo Model Parameters product. The retrieved albedo was compared with the observation at an AmeriFlux tower (US-ChR) which is proved spatially representative of its surrounding landscape. The comparison results reveal that the retrieved albedo agree well with the observation at the tower except for the later afternoon, and show a little bit underestimation mainly during the winter time. The broadband albedo is also depending on land cover and seasons. Diurnal cycle of albedo is found showing much larger variability than the seasonal changes. The land cover types showing generally larger albedo are grassland (GA) and cropland (CP) among others.

Hydrological application was conducted at the Pigeon River basin, one of the headwater basins of the UTRB in the Southern Appalachian Mountains. Both the raw and adjusted
landscape attributes that are corrected for cloud or snow or foggy contamination effects were utilized to drive the distributed hydrological model (3D-LSHM) continuously for the five-year period (2007-2011) at IPHEx-H4SE conventional resolution (1km×1km, hourly). The regional water budget analysis demonstrates that quality landscape attributes affect the water partition at the surface, mainly due to the improvement in LAI and CV. Water balance is closed at very small imbalance fraction (about 4%) for five-year scale in the Pigeon River Basin, no matter using raw or the adjusted LA. However, the ratio of R/P is decreased and the ET/P increased by 3% respectively, when using the adjusted LA compared with that using Raw LA data. Although the fraction is small, the absolute decreased magnitude in runoff (about 200mm) over a drainage area of 1,778 km² of the Pigeon River Basin implies a large change of total water volume about 355,600 km³ in five years, which is a huge number deserved attentions from water resource management aspect. Therefore, tempo-spatially reasonable and corrected landscape attributes datasets for hydrological application is essential and should be incorporated in modeling and forecast activities. Or else, even with perfect Quantitative Precipitation Estimate (QPE) and Quantitative Precipitation Forecast (QPF), the hydrological model cannot resolve the water budget correctly if these forcing datasets are biased or not representative of the real condition of the land surface. This would impede any hydrological study such as the scientific objectives of the IPHEx-H4SE project. Therefore, developing and providing the best hydrometeorological forcing datasets is the prerequisite task at the first stage of the IPHEx-H4SE project.
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Table 1 - Summary of the MODIS Products used in this project.

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2 https://lpdaac.usgs.gov/products/modis_products_table
Table 2 - Landcover of the referred towers locations

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Table 3 – Statistics of LAI for each landcover type and for four seasons

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Table 4 – Statistics of CV for each landcover type and for four seasons

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Table 5 – Statistics of emissivity for each landcover type and for four seasons

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Table 6 – Statistics of albedo at local solar noon (LSN) for each landcover type and for four seasons

| Albedo | ENF  | EBF  | DNF  | DBF  | MF   | CS   | OS   | WSA  | SA   | GA   | CP   | UB   | BA   |
|--------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|
| Mean   | 0.0841 | 0.1367 | 0.0900 | 0.1239 | 0.1113 | 0.1183 | 0.1444 | 0.1294 | 0.1308 | 0.1462 | 0.1540 | 0.1241 | 0.0659 |
| Median | 0.0822 | 0.1353 | 0.0901 | 0.1185 | 0.1119 | 0.1220 | 0.1414 | 0.1287 | 0.1352 | 0.1437 | 0.1492 | 0.1236 | 0.0644 |
| Std.   | 0.0270 | 0.0300 | 0.0089 | 0.0385 | 0.0163 | 0.0304 | 0.0392 | 0.0137 | 0.0314 | 0.0361 | 0.0381 | 0.0196 | 0.0142 |
| Max.X-axis | 0.2 | 0.2 | 0.4 | 0.2 | 0.2 | 0.2 | 0.2 | 0.2 | 0.2 | 0.2 | 0.2 | 0.2 | 0.2 |

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Figure 1 – The four drainage basins of interest in this project (shown on the right), namely Upper Tennessee River Basin (UTRB), Savannah River Basin (SVRB), Santee River Basin (SRB) and Yadkin-Pee Dee River Basin (YPDRB). Headwater catchments of UTRB are located at the Southern Appalachian Mountains in NC. One of these basins, the Pigeon River Basin (shown on the left), will be studied intensively. The hydrological verification will be conducted at three sub basins that are not limited by dam operation in the Pigeon River Basin, including the Cataloochee Creek Basin (CCB), the West Fork Pigeon River Basin (WFPRB) and the East Fork Pigeon River Basin (EFPRB).
Figure 2 - Flowchart for generating quality landscape attributes datasets, including broadband albedo, broadband emissivity, LAI and CV, from MODIS products.
Figure 3 – The MODIS yearly land cover product at 500m (MCD12Q1, Collection V51) (Type2/UMD) from 2007 to 2010.
Figure 5 – Time series of the fractional vegetation coverage (CV) derived using LAI before and after temporal filtering, at six Ameriflux towers US-Akn, US-ChR, US-Dk1, US-Dk2, US-Dk3, US-WBW, and the DKEPL tower from the top to the bottom, respectively.
Figure 6 – Example of the spatial distribution of LAI before (top panel) and after temporal filtering (bottom panel) over the SEUS. Extensive cloud contamination is clearly appearing on Sep.16 (center figure, top row). For comparison, the LAI 10-days before and after Sep.16 are shown on the left and right panel.
Figure 7 – Same as in Fig. 6 but for CV before (top panel) and after temporal filtering (bottom panel) over the SEUS.
Figure 8 – Time series of the averaged LAI and CV for all the pixels of the same landcover type within the SEUS region from 2007 to 2011.
Figure 9 – PDFs of LAI for each landcover type and for four seasons from the top to the bottom, respectively. The dark bar indicates the mean for each case.
Figure 10 – The PDF of CV for each landcover type and for four seasons from the top to the bottom, respectively. The dark bar indicates the mean for each case.
Figure 11 – The spatial distribution of LAI on Feb.1, Apr.1, Jun.1, Aug.1, Oct.1 and Dec.1 (from left to right), in 2007 to 2011 from top to bottom, respectively.
Figure 12 – The spatial distribution of CV on Feb.1, Apr.1, Jun.1, Aug.1, Oct.1 and Dec.1 (from left to right), in 2007 to 2011 from top to bottom, respectively.
Figure 14 – Time series of the averaged land surface emissivity for all the pixels of the same landcover type within the SEUS region from 2007 to 2011.
Figure 15 – PDFs of land surface emissivity for each landcover type and for the four seasons from the top to the bottom, respectively. The dark bar indicates the mean for each case.
Figure 16 – The spatial distribution of land surface broadband emissivity on Feb.1, Apr.1, Jun.1, Aug.1, Oct.1 and Dec.1 (from left to right), in 2007 to 2011 from the top to the bottom, respectively.
Figure 17 - Shortwave reflectance composites centered at the Chestnut Ridge tower for two seasonal periods illustrating conditions of greenness (Upper) and dormancy (Bottom). Adopted from (Roman et al., 2009).
Figure 18 – The monthly mean diurnal cycle of land surface albedo estimated from MODIS BRDF parameters and observed at AmeriFlux tower US-ChR in 2008 to 2010.
Figure 19 – Time series and scatter plots of land surface albedo at the Local Solar Noon (LSN) estimated from MODIS BRDF parameters and observed at AmeriFlux tower US-ChR from 2008 to 2010. The symbols with void color indicate snow conditions.
Figure 20 – Time series of the averaged albedo at the Local Solar Noon (LSN) for all the pixels of the same landcover type within the SEUS region from 2007 to 2011.
Figure 21 – PDFs of land surface albedo at the Local Solar Noon (LSN) for each landcover type and for four seasons from the top to the bottom, respectively. The dark bar indicates the mean for each case.
Figure 22 - Spatial distribution of land surface albedo at noon (EST) on March 1, June 1, September 1, and December 1 over the SEUS.
Figure 23 - Spatial distribution of simulated intercepted rainfall, evaporation and transpiration using landscape attributes before (*.1) and after the adjustment (*.2), accumulated in each year from 2007 to 2011 (a.* to e.*), and the whole five-year period (f.*) over the Pigeon River Basin.
Figure 24 - The time series of cumulative basin-averaged precipitation (P), runoff(R), evapotranspiration (ET), soil moisture change (ΔSM), leakage (LK) and the water imbalance (Im= P-(R+ET+ΔSM+LK)) using raw (a) and the adjusted (b) landscape attributes, accumulated over the five-year period in the Pigeon River Basin. The comparison of transpiration, evaporation, ET and runoff between simulations using raw and adjusted landscape attributes data are shown in (c).
Figure 25 - Continuous 5-year streamflow simulations with the uncalibrated Duke-3DLSHM hydrologic model (1 km², 1 hr resolution in this implementation) forced by a randomly selected realization of Precip_StageIV_TF. The 5-year simulation was conducted with a previous spin-up period of 15 years consisting of repeating the 5-year simulation three times using as initial condition the final condition from the previous simulation. The NSE score is indicated in the scatter plots to the right.