1. Introduction
The lumped terrestrial water budget is \( S_l = P - ET - Q \), where \( S_l \) is the time change in total soil moisture, \( P \) precipitation, \( ET \) evapotranspiration, and \( Q \) total runoff (surface + base flow and groundwater + discharge). To determine the four components of water budget above, the potential options are:

- (i) direct measurement
- (ii) land surface modeling
- (iii) remote sensing (RS)

Recently, the combined use of RS data product and hydrological models becomes increasingly popular and important. On one hand, the remote sensing, especially satellite sensors, can provide large scale land surface observations in a frequent basis with a relatively low cost. On the other hand, water budget estimation combining both RS and land surface modeling is expected to be able to accommodate the many specific features of the two, like the nonlinearity, non-Gaussianity, non-stationarity, computational complexity, physical consistency.

Data assimilation is a technique which combines the model predictions and observations. In this work we propose to use a non-linear, probabilistic technique referred to as the Particle Filter (PF). This Bayesian approach permits the assimilation of observations into complex non-linear models at a reasonable computational cost without imposing linearity assumption on observation equations and non-stationarity assumption on measurement error.

2.1 Hydrological Model
The hydrological model is the Variable Infiltration Capacity (VIC) macro scale hydrological model (Lins et al) developed in University of Washington and Princeton University. This model is forced with meteorological inputs (e.g. precipitation, air temperature, etc.), and both momentum and energy fluxes are computed. The size of a model grid-cell usually ranges from 10 to 500km.

2.2 Study Area and Remotely Sensed Observations
The study is carried out over the Red-Arkanas river basin, shown as the shaded area in Fig 2.3, which covers ~645,000 km

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3. Results and Findings

3.1 Assimilation Parameters
Other than the meteorological forcing fields listed in the table in the previous section, the assimilation procedure (PF) requires error parameters that describe the error behavior of the data both in the forcing fields and satellite observations. Therefore, the summer period of 2003 was set as the calibration period to derive these parameters by comparing the observations against the values from the benchmark simulation. Errors in \( T_l \) and ET (latent heat) are modeled by the copula approach. The major parameter which describes the dependency structure of copula model is the Kendall's \( \tau \). The higher \( \tau \) is, the higher the monotonic dependence between the benchmark and observations. Fig 3.1 and Fig 3.2 are the maps of \( \tau \) from VIC and MODIS derived observations. Note that both the scale are different from Fig 3.1.

3.2 Assimilation Results
Figure 3.4 summarises the results in the benchmark, open-loop, and assimilation experiments by the time series of basin averaged top 10 cm soil moisture, precipitation, ET, and total runoff. The difference between experiments is not very large at the basin average level. The most significant difference between open-loop and assimilation runs happens in the top soil moisture, which is clearly due to the assimilation of ET. The assimilation helps during both the period of excessive and inadequate moisture (Jul 12 – Aug 23 – Aug 30).

3.3 Assimilation Potentials
The TRMM rainfall, with bias corrected by ground observations, can drive the land surface model to produce reasonably good estimates of the water budget at regional scale.

The assimilation of TRMM microwave \( T_l \) helps identify and compensate small rainfall events missing in TRMM by using the feedback from both model and satellite observations. The mismatch between TRMM and MODIS derived \( T_l \) in the far western part of the basin, where the rainfall was not large (the circled area). This highest amount of rainfall picked up by the PF resulted in a wetter and better soil moisture estimation (right column). Heavily rained eastern part where the major storm occurred, the bias is not alleviated. MODIS observations brings slightly higher latent heat (ET) in the assimilation run (Fig 3.5), but the gap between MODIS and VIC is still large (MODIS indicates much higher estimates constantly).

A map of the assimilation impact in top soil moisture is drawn in Fig 3.6, as a measure of the "strength" of assimilating \( T_l \). This impact is computed as a temporal difference between the model run with assimilation \( S_{l,assim} \) and the model run without assimilation \( S_{l,open} \). A relatively high value of assimilation impact occurs at the low vegetation western part (the circled area) and gradually diminishes towards the east. This result suggests strong dependence of assimilation impact on vegetation cover (Fig 3.3).

3.4 Conclusions

4. Conclusions

- The TRMM rainfall, with bias corrected by ground observations, can drive the land surface model to produce reasonably good estimates of the water budget at regional scale.
- The assimilation of TRMM microwave \( T_l \) helps identify and compensate small rainfall events missing in TRMM by using the feedback from both model and satellite observations.
- Satellite \( T_l \) observations can be well assimilated in poorly vegetated regions and with moderate periods of rainfall.
- Ground rainfall data are used for bias corrections but these data may not be available elsewhere.
- Assimilation of satellite derived ET (latent heat) still suffers from the lack of information on top soil moisture and the model is prone to overestimate any information from two different parameterizations in VIC and SEBS.
- \( T_l \) assimilations are difficult and ineffective over heavily vegetated areas or very wet periods.