12 Standing Back Looking Forward: Role of Satellite Remote Sensing in the Prediction of Ungauged Basins

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INTRODUCTION AND STATEMENT OF THE PROBLEM

The number of ungauged basins or under-gauged basins is continually on the increase. The main reason for this is lack of resources, both financial and personnel-based. The problem is greater in developing countries where the problem of inadequacy of water resources requires periodic monitoring for societal needs.

In an ungauged catchment, in addition to lack of observations of streamflow (Q), there may not be observations of precipitation (P, which is obtained using raingauges from a neighbouring catchment and/or radar rainfall data) and evapotranspiration (ET). Hence in a simple water balance:

$$\Delta S = P - Q - ET \tag{1}$$

the lack of direct observations of the change in storage (ΔS) implies that in order to reduce the uncertainty estimates of Q, the uncertainty of ΔS, ET and P need to be reduced. Two methods, viz. hydrological models and indirect observations via satellite remote sensing, can help in reducing uncertainty in the solution of the above equation.

Estimates of precipitation, soil moisture/storage change and evapotranspiration can be accomplished using various satellite sensors (see Table 12.1) and the change in storage can be estimated using soil moisture microwave sensors.

CAPABILITIES OF SATELLITE DATA

Land surface modelling has faced limitations in the past due to the lack of spatially distributed data on land surface characteristics as well as variables in water and energy budgets, namely surface temperature and soil moisture. Soil moisture is a crucial component of both the water and energy budget. The absence of spatially distributed observations of soil moisture makes it very difficult for distributed hydrological model validation especially with respect to the water budget. Comparison of the model and the observed streamflow does not ensure distributed water budget validation for the hydrological model. There could be errors in the infiltration and the evaporation which may balance each other and thereby attain water balance but the individual components (infiltration and evaporation) as well as soil moisture could be incorrect. It is therefore imperative to use other data sets to ensure the spatially distributed validity of these models as well as validity of the individual components of the water and energy budgets.

Table 12.1 *Hydrological variables and the satellite sensors that estimate them, with an index of the various satellite and sensor acronyms.*

Hydrological variable	Satellite sensor (spatial resolution)
Vegetation	MODIS (1 km); AVHRR (1–8 km); TM (400 m)
Surface temperature	AIRS/AMSU (15 km); MODIS; AVHRR; ASTER (90 m)
Topography	SRTM (30 m)
Water level	TOPEX (~1 km); ERS-1/2 (~1 km)
Terrestrial water storage	GRACE (1000 km)
Soil moisture	SSM/I (25 km); AMSR (50 km); TRMM (50 km); RADARSAT (10 km)
Atmospheric profiles	AIRS/AMSU
Clouds	GOES; CLOUDSAT (500 m)
Precipitation	TRMM (10 km); GOES
Radiation	GOES (1 km); AIRS/AMSU
Snow	AMSR, MODIS, AVHRR

Index of sensor acronyms	
AIRS/AMSU	Advanced InfraRed Sounder/Advanced Microwave Sounding Unit
AMSR	Advanced Microwave Sounding Radiometer
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
AVHRR	Advanced Very High Resolution Radiometer
CLOUDSAT	Cloud Satellite
ERS	European Remote Sensor
GOES	Geostationary Observation Earth Satellite
GRACE	Gravity Recovery and Climate Experiment
MODIS	Moderate Resolution Imaging Spectroradiometer
RADARSAT	Radar Satellite
SRTM	Shuttle Radar Topography Mission
SSM/I	Special Sensor Microwave Imager
TM	Thematic Mapper
TRMM	Tropical Rainfall Measurement Mission

Satellite observed surface temperature satisfies our requirement of being spatially distributed and having connections to both the water and the energy budgets. Surface temperature influences evapotranspiration (due to the dependence of the saturation vapour pressure on the surface temperature), hence the energy budget. Evapotranspiration is connected to the water budget as it determines the soil moisture content.

Comparison of surface temperature does not ensure that the model simulations of surface soil moisture are correct. There are various reasons for errors in the modelled soil moisture. The primary reason is the errors in the forcing inputs of precipitation and incoming solar radiation. Therefore, we need to compensate for these errors in the input forcings by assimilating the readily available spatially distributed satellite observed surface temperatures. The assimilated surface temperatures will be used to adjust the model-computed surface soil moisture. This adjustment will be carried out such that the new assimilated surface temperature balances the energy balance equation.

A NEW WAY: DATA ASSIMILATION USING SATELLITE OBSERVATIONS

The subject of assimilation of soil moisture data, or assimilation of meteorological data in order to estimate soil moisture more accurately, is a relatively new area of study

(McLaughlin, 1995). Previous studies (Entekhabi *et al*., 1994; Lakshmi *et al*., 1997) have demonstrated the use of microwave satellite data in estimating soil moisture. The assimilation of soil moisture from low-level atmospheric variables using a mesoscale model (Bouttier *et al*., 1993a,b) has shown that the assimilated soil moisture estimates help in the initialization of atmospheric models. Satellite estimates of surface skin temperature are used to adjust for the soil moisture (McNider *et al.*, 1994; Ottle & Vijal-Madjar, 1994) and estimate with greater accuracy the surface fluxes and surface temperature. Other studies (Blyth, 1993) carry out assimilation by nudging the forecast model evaporation fraction using the satellite data and hydrological model computed evaporative fraction. The results are reductions in the predicted 2-m air temperature and vapour pressure after carrying out these assimilations. Another way in which satellite data has been used is for parameterization of hydrological models. In this regard, microwave satellite data is especially helpful (van den Hurk *et al*., 1997).

Figure 12.1 outlines the philosophy and rationale for carrying out the integration of satellite *in situ* data sets and the model output. *In situ* data are point based, as are the prognostic equations in most of the hydrological models. However, both these quantities are reasonably continuous in time. On the other hand, satellites observe the same region on the land surface periodically (twice a day for polar-orbiting satellites) and present a spatially averaged (over each spatial pixel) view of the land surface. The integration of the temporal continuity (model output and *in situ* data), along with the spatial continuity of the satellite data, offers an advantage to using either one of the approaches by itself.

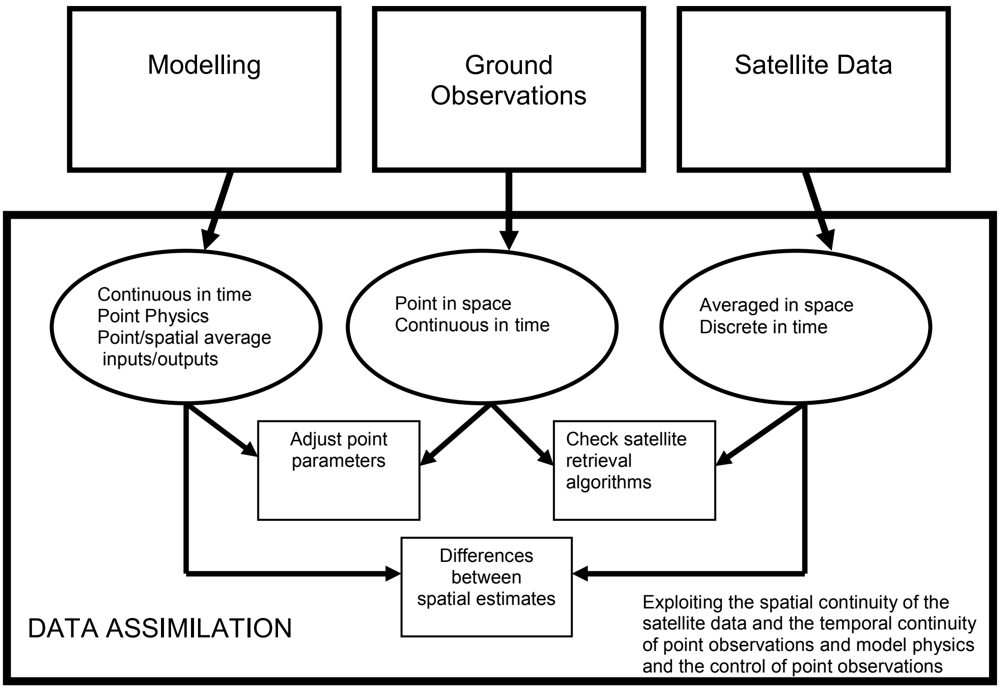

Fig. 12.1 *Representation of the characteristics of models, in situ ground observations and remote sensing data.*

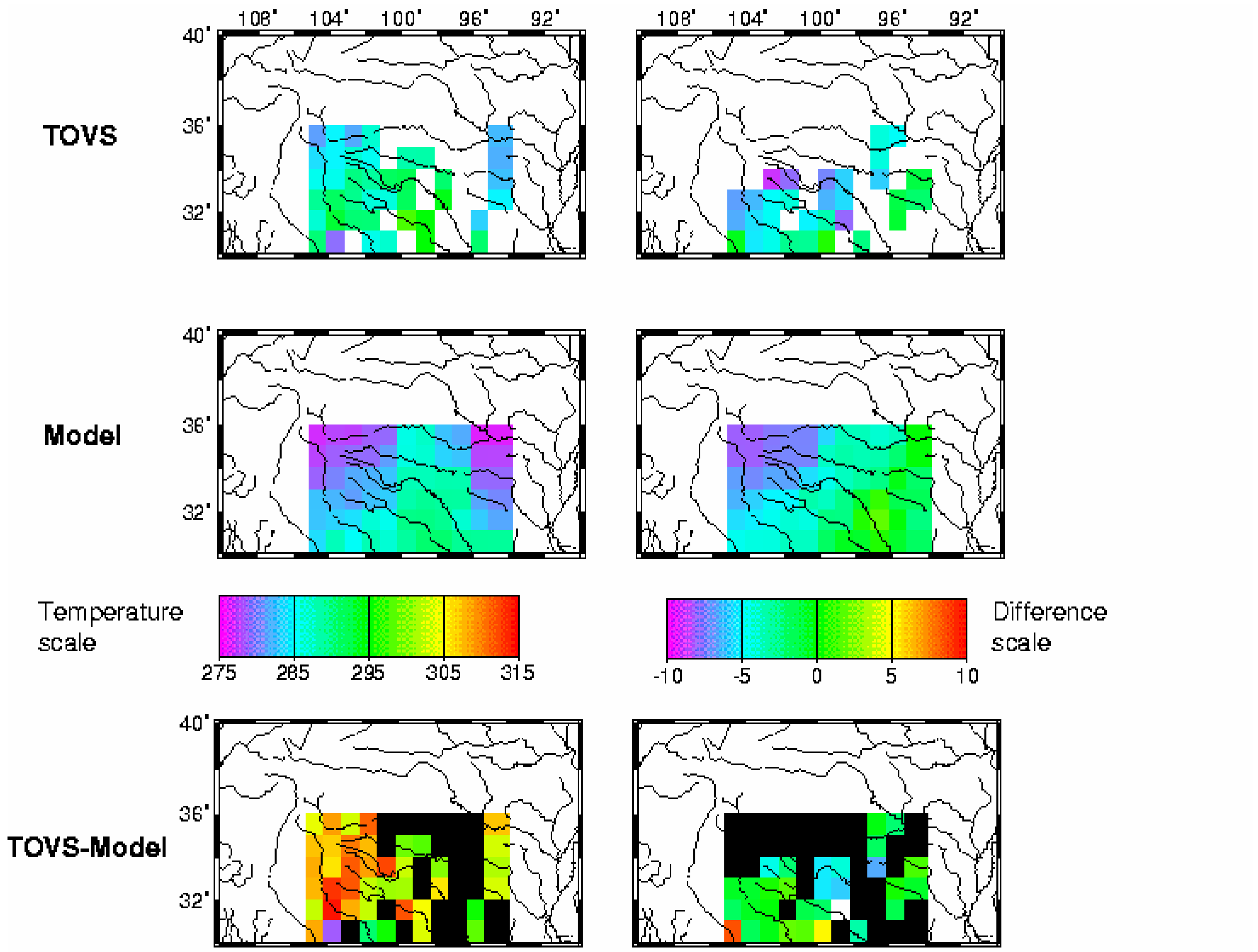

***Fig. 12.2** Comparison of NOAA-10 TOVS derived surface temperatures at 07:30 h and 19:30 h on 31 March 1988 with the hydrological model computed values over the Red-Arkansas basin. All values are in degrees Kelvin.*

In this chapter we compare the model computed surface temperature to the satellite observed surface temperatures and discuss the sources and reasons for these differences. The satellite surface temperatures used in this study are derived from the Tiros Operational Vertical Sounder (TOVS; Susskind *et al.*, 1997). The effect of assimilation on removing the errors caused by incorrect input forcings will be studied. We will carry out spatially distributed comparisons over a large area in the Southern Great Plains of the USA (roughly 5° × 10°) and a time period of one year (August 1987–July 1988), between the assimilated and the un-assimilated cases. The implications of the technique in the context of using it in land surface models within global climate models will be discussed with regard to the feasibility.

The assimilation of surface temperature is carried out using a nudging technique (Lakshmi, 2000). The hydrological model produces values of surface temperature and soil moisture. This surface temperature is compared to the corresponding satellite

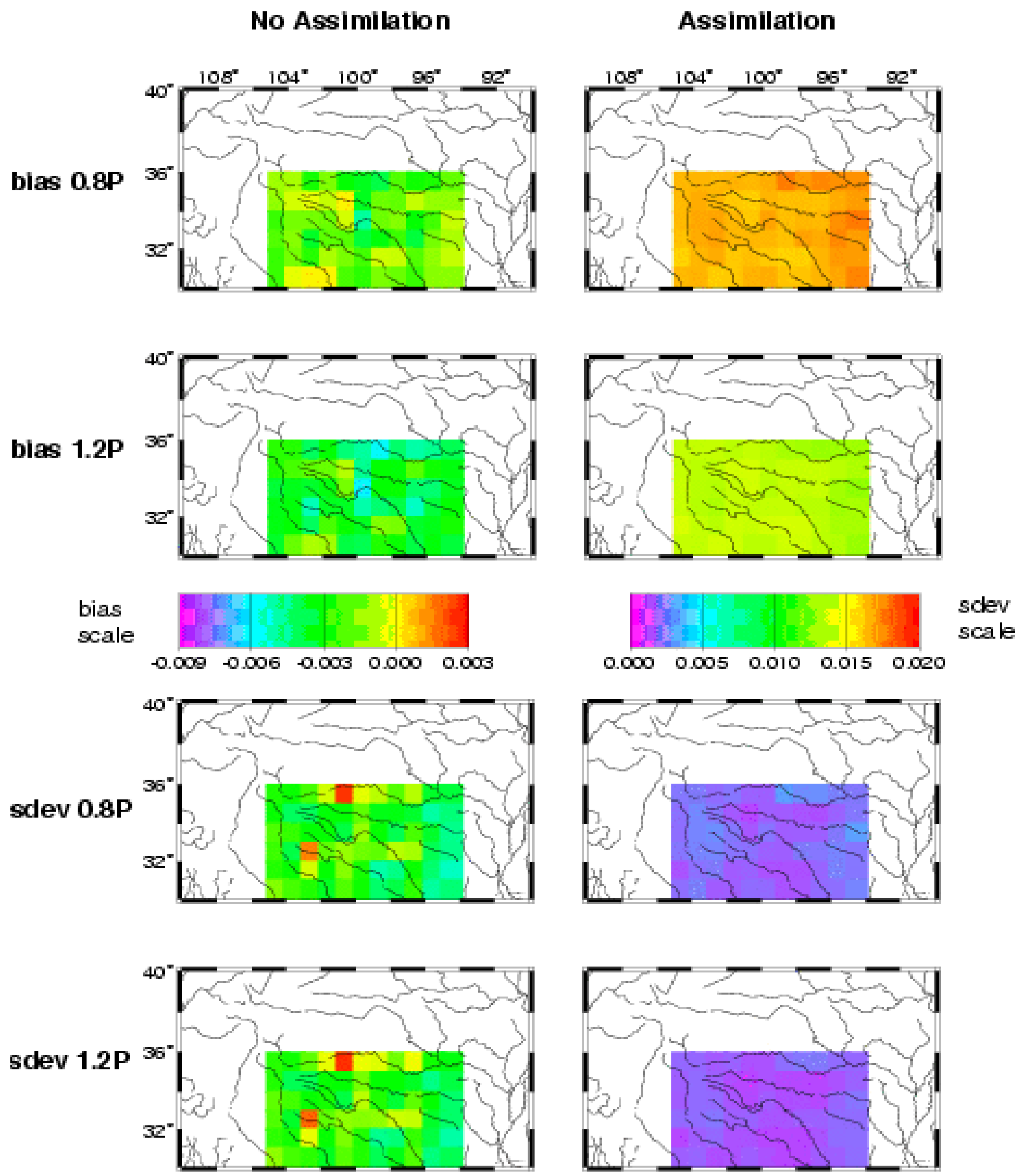

Fig. 12.3 *Difference between volumetric soil moisture for the top 1-cm layer for the rainfall input decreased by 20% (0.8P) and the normal (1.0P) with and without surface temperature assimilation. The difference is indicated by the bias (average difference over the one year period; bias) and the standard deviation (sdev). The case for increase in rainfall by 20% is indicated by 1.2P.*

observed value at the time of satellite overpass. (Incidentally, in this study there are at most two overpasses over a particular area in one day. However, in the time period, 1989 to present, there are up to four overpasses in one day). Figure 12.2 displays the satellite and model output of surface temperature for one day corresponding to the

07:30 h and 19:30 h overpasses. After the comparison of the model derived and the satellite observed surface temperatures, the model surface temperature is "adjusted" to a value midway between the two. (A more realistic method would be to weight the two values using the error characteristics of the two estimates). This merged surface temperature is used to "recalculate" the soil moisture.

This nudging algorithm is used to correct the effects of the precipitation input bias of +/– 20% (increased and decreased precipitation). The comparison of the biased precipitation computed soil moisture with the "observations" (corresponding to no change in the precipitation) shows that assimilation of surface temperature from the 07:30 h and 19:30 h surface temperatures from the TOVS improves both the bias and the standard deviation of the estimates (Fig. 12.3).

TAKING STOCK: THE NEXT STEPS

There are numerous challenges to the problem of prediction of ungauged basins. It is obvious that modelling or data (ground or satellite) alone cannot address these questions. This chapter presents one methodology for integration of hydrological model and satellite data to achieve better estimates of soil moisture under uncertain precipitation input. This method of satellite data integration also overcomes inaccuracies in model physics as well as parameter errors to achieve an observation-consistent solution for the hydrological states.

The problem of prediction in ungauged basins is a challenging task. However, with challenge comes opportunity for innovative science and progress. We need to use this opportunity to test our knowledge and advance the boundaries of hydrological knowledge. At the heart of the matter is the estimation of the availability of water resources for societal needs such as human consumption, agriculture, power production, navigation, fisheries and wildlife and recreation. Indeed, estimation of the various components of the hydrological cycle would serve to obtain better seasonal forecasts. As traditional methods for estimating water resources (with the use of ground observations) become obsolete and expensive to maintain, non-traditional methods of using satellite data along with modelling and data assimilation becomes a reality.

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