Comparison of Soil Moisture Simulated by HBV96 and Estimated from TRMM Passive Microwave Observations for a Catchment in Southern NSW, Australia

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EXTENDED ABSTRACT

Soil moisture is an important hydrological variable in rainfall-runoff modelling: it significantly influences the partitioning of precipitation between infiltration and runoff and therefore the streamflow of a catchment. Previous studies have shown that the assimilation of *in situ* soil moisture measurements can improve the streamflow prediction (Aubert *et al.* 2003). However, soil moisture obtained from *in situ* measurement is not feasible everywhere due to the limitation of time and investment. Satellites offer an alternative since they can observe large areas over extended periods of time. Among remote sensing technologies, passive microwave observation has its own advantages in monitoring soil water content. In this paper, we compared TRMM-TMI passive microwave soil moisture (PMSM) observations and soil moisture generated by a conceptual rainfall-runoff model (HBV96), to evaluate the relationship between these two soil moisture signals and whether PMSM observations can be used to constrain a conceptual rainfall-runoff model.

The Tarcutta catchment, located within the Murray Darling Basin in eastern Australia, is the study area in this paper. TRMM-TMI PMSM was retrieved using the Land Parameter Retrieval Model and X-band (10.7 GHz) brightness temperature, roughly representing soil moisture of the top 1-cm. HBV96 model covers most of the important runoff generating processes by quite simple and robust structures, and does not require too much input data. The HBV96 was implemented in the freely available Geographical Information System—PCRaster, which enables the model to run on a series of discrete spatial units.

The Nash-Sutcliffe model efficiency reached 0.64 for the calibration period (1 Jan 1998 through 31 Dec 2003) and 0.67 for the validation period (1 Jan 1981 through 31 Dec 1997). The TRMM-TMI PMSM and soil moisture from HBV96 had a similar seasonal pattern. The peaks of rainfall events coincide with the peaks of TRMM-TMI PMSM, but the soil moisture from HBV96 peaks around 58 days later. TRMM-TMI PMSM represents the very top soil (1-cm). At the start of the wet season, the top soil can be expected to wet up before moisture moves down into deeper soil layers, and this would explain the lag time of around 58 days.

It is also observed that PMSM was already decreasing when the value in HBV96 soil moisture "bucket" and baseflow were still increasing. This can not be explained within the scope of this investigation. Future analysis using multi-layer soil water balance models may shed more light on this. However, the influence of lateral heterogeneity should also be considered.

1. INTRODUCTION

Soil moisture plays a critical role in many hydrological processes. Accurate measurements of soil moisture can help to predict runoff, infiltration, evaporation and other important variables. (Cashion *et al.* 2005).

Soil moisture data can be obtained in several ways: *in situ*, through remotely sensed observations, and through modelling. Aubert *et al.* (2003) assimilated *in situ* measurements of soil moisture into the rainfall-runoff model. It was found that the assimilation of soil moisture data is particularly effective during flood events while assimilation of streamflow data is more effective for low flows. Combined assimilation is more adequate for the entire forecasting period. However, *in situ* measurements of soil moisture are often time consuming and require a large investment to sufficiently sample even small catchments (Rawls *et al.* 1982).

Satellites offer an alternative since they can observe large areas over an extended period of time (Jackson 1993). Compared with other remote sensing technologies, passive microwave observations have certain advantages in that: (1) they are available regardless of cloud cover; (2) there is a physical relationship relating emissions to water amounts in the environment; and (3) rather than the land surface only, they provide information on water content of the top soil layer (albeit still only a few cm deep, depending on wavelength).

The major objective of this paper is to compare TRMM-TMI passive microwave soil moisture (PMSM) observations and soil moisture generated by a conceptual rainfall-runoff model (HBV96), to evaluate the relationship between the two soil moisture signals and whether PMSM observations can be used to force a conceptual rainfall-runoff model.

2. DATA AND METHODS

2.1. Study area

The Tarcutta catchment, the study area of this paper, is located in southern New South Wales, and is a tributary of the Murrumbidgee River and located within the Murray Darling Basin (MDB) in eastern Australia (Figure 1). The catchment covers 1640 km^2, has average annual rainfall of 810 mm, of which 98 mm becomes stream flow. A land use map of the Tarcutta catchment was extracted from the MODIS Land Cover Classification products (http://modis-land.gsfc.nasa.gov/landcover.htm). The Tarcutta catchment has three major land cover types, cropland covering 60%, grassland 26%, and forest 13%.

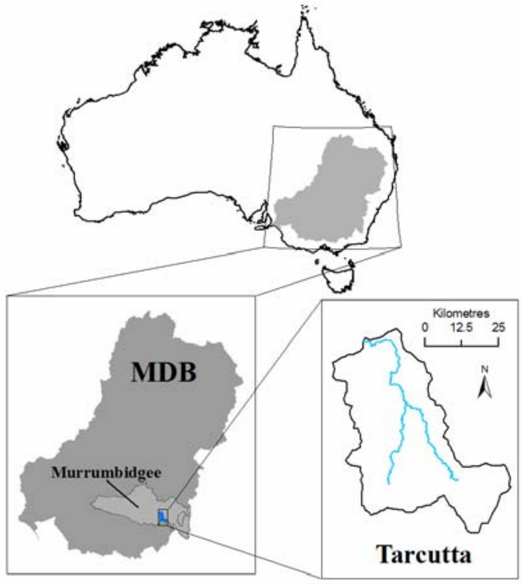

Figure 1. Tarcutta catchment, Australia

2.2. TRMM-TMI Soil Moisture

The Microwave Instrument (TMI) on board NASA's Tropical Rainfall Measuring Mission (TRMM) has provided operational passive microwave measurements at 10.7 GHz (X-band) and eight higher frequencies including the 37 GHz (Ka) band since December 1997 (Kummerow *et al.* 1998). The observations can be ingested into a microwave radiation transfer model to infer soil moisture, as well as a set of atmospheric, soil and vegetation variables, including soil and canopy temperature and vegetation optical depth.

We used the top soil moisture content (m^3 m^{-3}) retrieved using the Land Parameter Retrieval Model (LPRM) (Owe et al., 2001; De Jeu and Owe, 2003; Meesters et al., 2005) and X-band brightness temperature. The retrieved soil moisture roughly represents the top 1-cm at X-band and was re-sampled to the resolution of 25 km prior to this analysis. It has been evaluated against various observational and simulated datasets, generally with good results and with an absolute accuracy of ca. 0.06 m^3 m^{-3} (Owe et al., 2001; de Jeu and Owe, 2003; O'Neill et al., 2006; Wagner et al., 2007).

2.3. HBV96 Model

The HBV-model is named after the abbreviation of Hydrologiska Byråns Vattenbalansavdelning (Hydrological Bureau Waterbalance-section), a former section at the Swedish Meteorological and Hydrological Institute, where the model was originally developed. The original purpose of this model was for runoff simulation and hydrological forecasting, but the scope of applications has increased steadily (Bergström 1995). The HBV96 is the modified version following the basic modelling philosophy as the original HBV model, leading to significant improvements in model performance (Lindström *et al.* 1997).

The advantages of the HBV96 model are that (a) it covers most of the important runoff generating processes by quite simple and robust structures and does not require too extensive input data, (b) it accounts for topographic conditions by defining elevation zones within a basin or sub-basins, and (c) the model was successfully tested in different conditions in more than 40 countries (Krysanova *et al.* 1999).

The HBV96 consists of three major routines: (a) snow accumulation and melt, (b) soil moisture accounting, and (c) runoff response and river routing. Its structure is presented schematically in Figure 2. The Tarcutta catchment has no snow accumulation and melt, so parameters related to snow components are not considered in this paper.

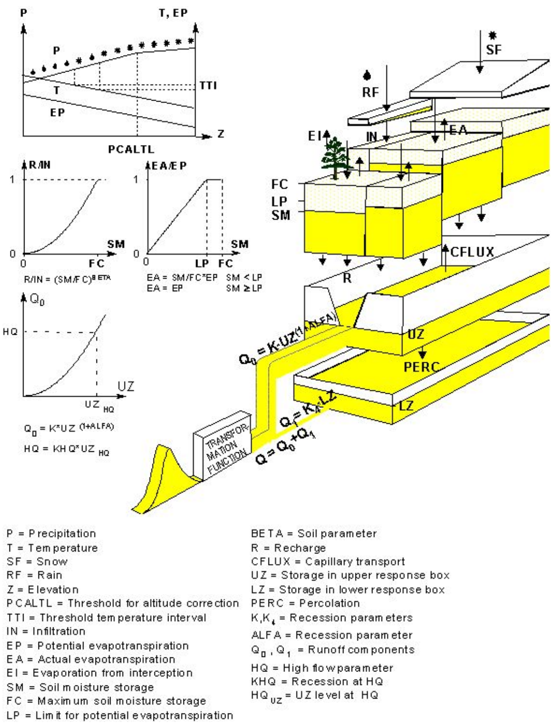

Figure 2. Schematic structure of one subbasin in the HBV-96 model (Lindström et al., 1997)

2.4. Modelling Environment

The HBV96 model was implemented in the freely available modelling environment—PCRaster, which consists of a set of computer tools for storing, manipulating, analysing and retrieving geographical information. The central concept of PCRaster is a discretization of the landscape in space, resulting in cells of information. Each cell can be regarded as a set of attributes defining its properties. It receives and transmits information to and from neighbouring cells. The lateral directions in a landscape are represented by a set of neighbouring cells composing a map; relations in vertical directions, for example between soil layer and groundwater zone, are implemented using several attributes stored in each cell. Operations used in modelling can be regarded as functions that induce a change in the properties of the cells on the basis of the relations within cells and between cells. In our analysis, the grid size of each cell is 100×100 m.

The discharge simulated from HBV96 was compared with the streamflow measured by the gauge station at the outlet of the Tarcutta catchment (station 410047). The calibration period was 1 Jan 1998 through 31 Dec 2003 and the validation period 1 Jan 1981 through 31 Dec 1997. We compared PMSM and HBV96 modeled soil moisture for the 1 Jan 1998 through 31 Dec 2003.

3. RESULTS

Because the PCRaster software did not provide for a parameter optimization function, parameters were fitted visually. Fitted values for the most important parameters are listed in Table 1.

The efficiency criteria used in this paper to evaluate the model behavior is Nash-Sutcliffe model efficiency (NSME) (Nash and Sutcliffe 1970).

$$\text{NSME}=1-\frac{\sum\left(Q_{sim}(t)-Q_{obs}(t)\right)^2}{\sum\left(Q_{obs}(t)-\overline{Q}_{obs}\right)^2} \qquad (1)$$

The NSME obtained for the calibration period was 0.64 (Figure 3). This resulted in a NSME of 0.67 for the validation period (Figure 4). It is noted that the peak flow was not very well reproduced (Figure 3), but this was considered of secondary importance considering the aim of this investigation was to compare soil moisture.

The comparison between average soil moisture for the Tarcutta catchment derived from TRMM-TMI and soil moisture from HBV96 is shown in Figure 5. The soil moisture from TRMM-TMI peaks around the same time as the rainfall events and shows one seasonal pattern. For the purpose of better comparison, the time series of rainfall and soil moisture from TRMM-TMI are smoothed (Figure 6). The soil moisture time series show a similar seasonal pattern, although HBV96 lags TRMM-TMI. The greatest correlation coefficient (0.67) is obtained with a lag time of 58 days (Figure 7) and the root mean square error (RMSE) of 0.047.

Table 1. Relevant parameters in HBV96 model derived from modelling calibration

Soil moisture routine		
FC	430mm (forest) 150mm (grass and crops)	the maximum soil moisture storage (mm)
BETA	6	parameter that determines the relative contribution to runoff from precipitation
LP	0.8	fraction of FC above which actual evaporation equals potential evaporation
Runoff response routine		
KBaseFlow	0.005	recession coefficient of base flow (day^{-1})
KQuickFlow	0.05	recession coefficient of quick flow (day^{-1})
PERC	0.75	maximum percolation from upper to lower zone ($mm.day^{-1}$)
ALPHA	1.2	measure of non-linearity of upper zone
MAXBAS	1	number of days in unit hydrograph

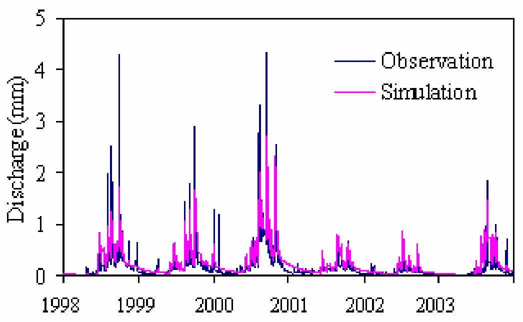

Figure 3. Observed and simulated runoff for the calibration period (1998 through 2003)

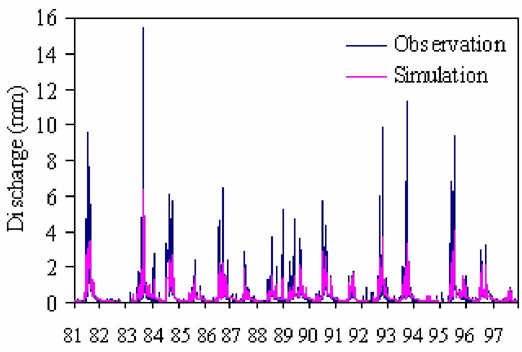

Figure 4. Observed and simulated runoff for the validation period (1981 through 1997)

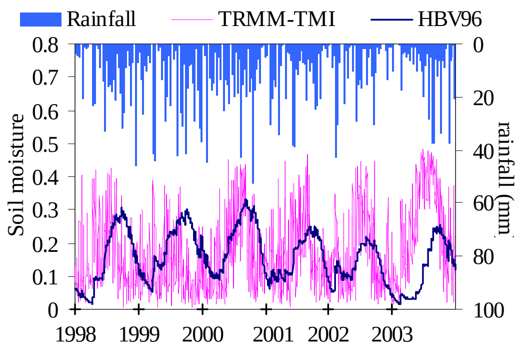

Figure 5. Comparison of soil moisture from TRMM-TMI and HBV96

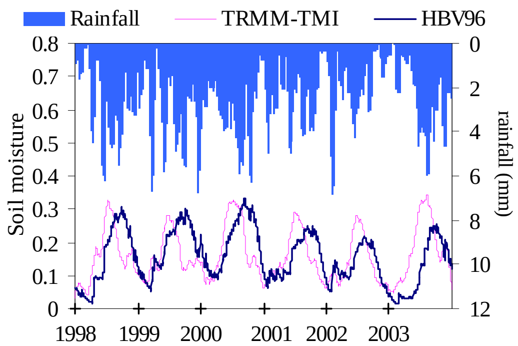

Figure 6. Comparison of soil moisture from smoothed TRMM-TMI and HBV96. The original rainfall and TRMM-TMI were smoothed by taking the average of 40 neighbouring data points in time

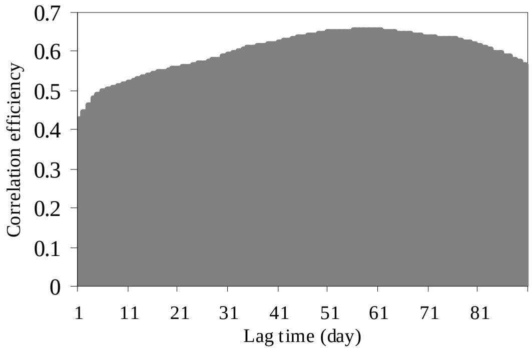

Figure 7. Coefficient of lagged correlation between HBV96 soil moisture and TRMM-TMI soil moisture for different lag times.

4. DISCUSSION

To some extent the lag between PMSM and HBV96 might be expected on conceptual considerations. TRMM-TMI with the low observing frequency of 10.7 GHz (X-band) has a source depth of about 1 cm, and so represents the very top soil only. At the start of the wet season, the top soil can be expected to wet up before moisture moves down into deeper soil layers, while in the dry season, the top soil is expected to dry out first. In other words, the top soil responds immediately with rainfall. Soil moisture simulated by the HBV96 model is the average value of the soil moisture "bucket" of unknown depth. The entire profile is assumed to wet/dry at a constant amount, rather than the surface wetting faster and subsequently drying faster. This could partly explain the lag time of two months.

The lag time of two months was also found by Kwantes (2007) who performed a base flow separation on the daily flow data for the Tarcutta catchment and compared the stream flow and base flow patterns to the PMSM data. It was demonstrated that the rainfall-runoff response (determining how much rainfall becomes stream flow) peaks around the same time as base flow, but that the seasonal PMSM pattern peaked some two months earlier, in line with the results presented here. The fact that soil moisture peaks before rainfall-runoff response is not conceptually consistent if it is assumed that rainfall-runoff response is primarily a function of top soil wetness. However, it would be consistent if rainfall-runoff response is a function of the fractional area of (near-) saturated soil, which would be expected to increase with groundwater level. The strong correlation between base flow (a proxy for groundwater level) and rainfall-runoff response provides some indirect support for this notion.

The results of this study can also be compared with those reported in a very similarly designed study by Alvarado (2006) in a tributary catchment of the Rhine basin in Germany. In Alvarado's study a seasonal pattern in PMSM was found. This pattern was reproduced by HBV96, somewhat unexpectedly, as this model does not represent top soil explicitly.

However, the observation that PMSM is already decreasing when the modeled soil moisture is still increasing (Figure 6) can not be explained within the scope of this analysis. Alvarado (2006) compared the PMSM with the soil moisture of shallow depth simulated by a multi-soil-layered model named Representative Elementary Watershed (REW) model. The soil moisture from the top soil layer did not show the seasonal pattern which was reflected from PMSM and reproduced by HBV96 model; instead it moved between wet and dry conditions depending on rainfall conditions. To some extent, this indicates that the multi-soil-layered model assuming the top soil layer is homogeneous would not help explain the mismatch observed in this analysis.

Further more detailed analysis using other layered soil water balance models may help elucidate the cause of this mismatch. However, it must be kept in mind that the real world is a 3-dimensional and very heterogeneous.

5. CONCLUSION

This investigation in Tarcutta catchment shows that PMSM peaks around the same time as rainfall events, but soil moisture from HBV96 peaks about two months later. PMSM represents the soil moisture of the shallow depth (about 1-cm) while the soil moisture modeled from HBV96 represents the soil moisture "bucket" of unknown depth. The top soil is expected to immediately react upon rainfall events and it takes longer for soil moisture "bucket" to respond, which could explain the lag time of two months.

The lag time of two months was also found in previous studies which revealed that streamflow and baseflow peak simultaneously, but also two months later than PMSM. This indicates the soil moisture modeled from HBV96, streamflow and baseflow are highly correlated. Also, the rainfall-runoff response is a function of the fractional area of (near-) saturated soil rather than the top soil wetness.

The observation that PMSM decreases while modeled soil moisture and base low are still increasing can not be explained within the scope of this investigation. Possibly, future multi-layer soil water balance modeling will shed more light on this. However, the influence of lateral heterogeneity should also be considered.

6. ACKNOWLEGEMENT

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