CHAPTER THREE

3. LITERATURE REVIEW: SOIL MOISTURE ESTIMATION

The soil moisture measurement techniques reviewed in Chapter 2 are unable to individually provide information on both the spatial distribution and temporal variation of soil moisture profiles. Whilst point measurements yield information on the temporal variation of soil moisture content over the soil profile at a specific point, estimation of the spatial variation in soil moisture profiles from these point measurements is problematic. This is a result of the typically low spatial correlation of soil moisture content and the limited area that can be satisfactorily monitored with an acceptable spatial resolution. While remote sensing observations provide information on the spatial distribution of soil moisture content, they do not provide timely information on the temporal variation of soil moisture content, or direct information on soil moisture content of more than the top few centimetres of the soil profile. Hence, this chapter provides a review of techniques for estimating the temporal variation and spatial distribution of soil moisture profiles, thus allowing the development of a soil moisture profile estimation algorithm that is built upon previous work in this area.

3.1 SOIL MOISTURE PROFILE ESTIMATION FROM POINT MEASUREMENTS

While point measurements can give continuous estimates of soil moisture variation over the entire soil profile, these estimates are not always representative of the spatial distribution, with observed correlation lengths varying from 10 to 1000 m (Western *et al.*, 1998). In order to relate point measurements of soil moisture content to the spatial variation in soil moisture content, Grayson and Western (1998) have examined a concept proposed by Vauchaud *et al.* (1985), that particular sites in the field always display mean behaviour while others always represent extreme values. Thus, if several time-stable sites are monitored, some with an extreme wet response, some with an extreme dry response and some with a mean response, information about both the spatially average soil moisture content and the spatial variation of soil moisture content may be obtained (Grayson and Western, 1998). Grayson and Western (1998) have suggested that points representing the mean spatial response are likely to be located in areas that are neither strongly convergent or divergent, are located near the mid-slopes and are in areas that have topographic aspect close to average for the catchment.

The procedure that has been used in the United Stated for making a regional assessment of soil moisture content in the pre-planting season consists of collecting soil cores, and producing a soil water deficit map by contouring from the point measurements of water deficit. The resulting maps show general patterns of variability, but do not provide specific information for individual fields (Jackson *et al.*, 1987).

3.2 SOIL MOISTURE PROFILE ESTIMATION FROM HYDROLOGICAL MODELS

Recent developments in hydrologic models for estimating soil moisture profiles provide an alternative to directly or indirectly measuring soil moisture content in the field (Schmugge *et al.*, 1980). Figure 3.1 is a schematic representation of the physical system and its driving forces.

Published hydrologic models vary in the level of detail they use in representing the physical system and temporal variation of the driving forces. Some of the important differences between published hydrologic models are: (i) the computation of evapotranspiration; (ii) the partitioning between infiltration and runoff; (iii) the temporal definition of evapotranspiration demand and precipitation; (iv) the computation of vertical and lateral redistribution; and (v) the number of soil layers used (Schmugge *et al.*, 1980).

The partitioning of precipitation between runoff and ground storage is governed by two main mechanisms. Firstly, infiltration excess runoff (Hortonian overland flow) occurs when the rainfall intensity exceeds the soil infiltration capacity, which is dependent on the soil moisture content ahead of the wetting front at depth (Entekhabi *et al.*, 1993). Hortonian runoff is predominantly connected with arid and semi-arid regions where vegetation is absent or sparse,

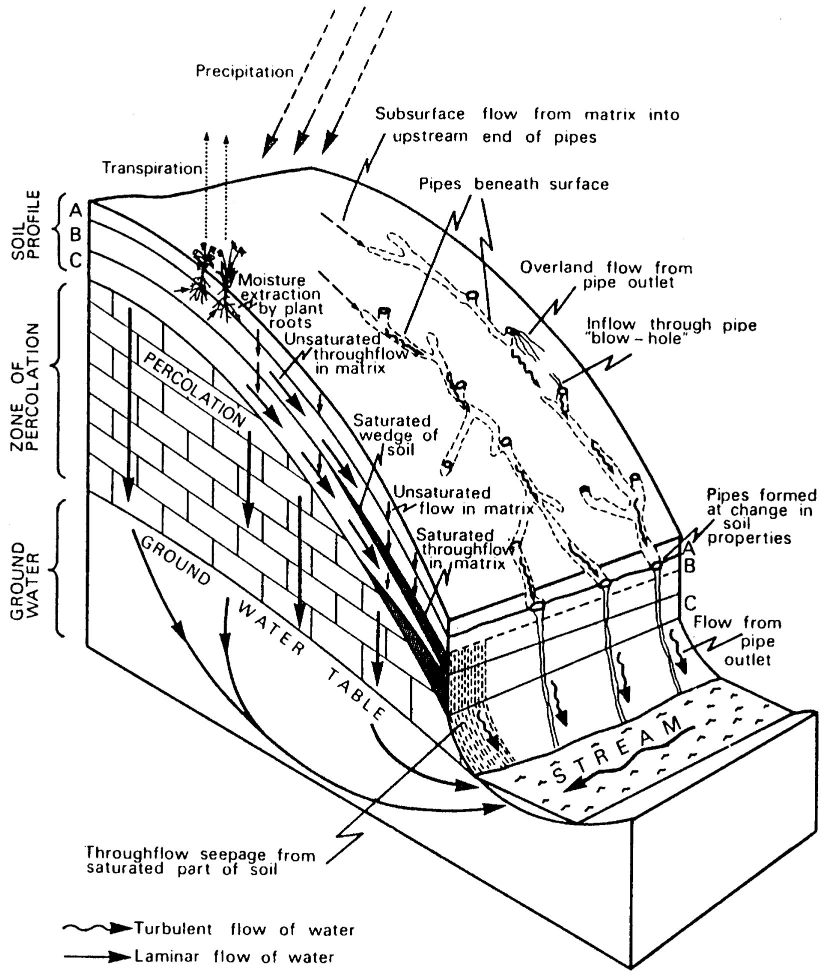

Figure 3.1: Schematic representation of surface and sub-surface hillslope flow components (Kirkby, 1985).

having thin soils with low infiltration capacities (van de Griend and Engman, 1985). Secondly, saturation overland flow (Dunne type flow) and return flow, known as saturation excess, is generated by rainfall on usually narrow saturated areas along valley bottoms, widening somewhat around stream heads (Kirkby, 1985). When these saturated areas exist in isolated locations, it is referred to as the variable source area concept. According to this second mechanism, not all the catchment contributes equally to runoff. The runoff generating zone may be of varying size and represents the groundwater exfiltration areas. Its occurrence depends on the convergence of runoff flow, terrain slope and soil hydraulic conductivity (Mérot *et al.*, 1994). A crucial role for any hydrologic model is the estimation of saturated contributing areas and their variation during a storm (Kirkby, 1985).

Classical hydrologic models cope with the spatial variability problem by dividing the total area into homogeneous sub-units, and applying unsaturated flow models to each sub-unit. The problem with this approach is two-fold. First, assignment of hydrologic parameters to each sub-unit is usually done in a more or less arbitrary way, neglecting the scale dependency of these parameters. Secondly, the interaction between the sub-units is often assessed by addition of the quantities calculated (Feddes *et al.*, 1993).

The principal advantage of hydrologic models is that they can provide timely information on the spatial soil moisture distribution without the necessity of field visits. A general disadvantage of hydrologic models is the error associated with their estimates. These difficulties are mainly related to the fact that soil moisture exhibits large spatial and temporal variations (Engman and Chauhan, 1995; Wigneron *et al.,* 1998), as a result of heterogeneity of soil properties, vegetation, precipitation and evaporation (Rajaram and Georgakakos, 1989; Lin *et al.,* 1994a; Ottlé and Vidal-Madjar, 1994).

Even though hydrologic models have been verified on basin scales with discharge data at various time scales, the estimated soil moisture in the various layers has not been verified against measured soil moisture data (Georgakakos and Baumer, 1996). The value of soil moisture data for model calibration is expected to be high during periods of dry weather and low stream flows, when the soil states become less observable by stream flow measurements (Georgakakos and Baumer, 1996). Western *et al.* (1997a) have illustrated the importance of this by showing that the same runoff hydrographs can be produced from a catchment with saturated hydraulic conductivity values of 100 mm h^{-1} and 2000 mm h^{-1}. By using the two different saturated hydraulic conductivity values, the dominant runoff mechanism was switched from saturation excess to sub-surface flow. The effect of this was vastly different soil moisture distributions with the same runoff hydrograph.

3.3 DATA ASSIMILATION

Data assimilation is the incorporation of observations into a numerical model, with the purpose of providing the model with the best estimate of the current state of the modelled system. Thus, the numerical model must have the capacity to predict dynamic changes occurring in the system, and accept the on line insertion (assimilation) of new observation data distributed heterogeneously in time and space. Theoretically, the use of data assimilation should lead to an estimate of the system states which is better than that which can be achieved from either the numerical model or observations alone (Houser, 1996).

Two major types of data assimilation are currently used. The first is an intermittent process of initialising an explicit prediction model, using the subsequent forecast as a first guess in a static objective analysis step. The second major type of data assimilation is a continuous (repeated) dynamical assimilation where forcing functions are added to the governing model equations to gradually "nudge" the model state towards the observations (Stauffer and Seaman, 1990).

The process of data assimilation was developed initially for meteorological forecasting applications, and has been successfully used to improve numerical weather predictions. Data assimilation has also been used successfully in ocean modelling and rainfall analysis. However, the technique has not been widely used in hydrologic modelling, mostly due to the limited and widely scattered sources of traditional hydrologic data such as raingauges, stream gauges and wells (McLaughlin, 1995).

A wide range of data assimilation techniques have been presented in the literature (see Daley, 1991 and Bennett, 1992). However, most of these techniques have been derived with meteorological (see Daley, 1991) or oceanology (see Bennett, 1992) applications in mind. The most commonly used data assimilation schemes in hydrologic applications (as will be seen in section 3.4.4) are: (i) hard-updating; and (ii) Kalman-filtering.

3.3.1 HARD-UPDATING

The hard-updating assimilation scheme (also known as direct-insertion) directly substitutes the observed system state values (ie. soil moisture content) for the simulated system state values when observations become available. This is illustrated in Figure 3.2a, where the model estimate of the soil moisture profile is

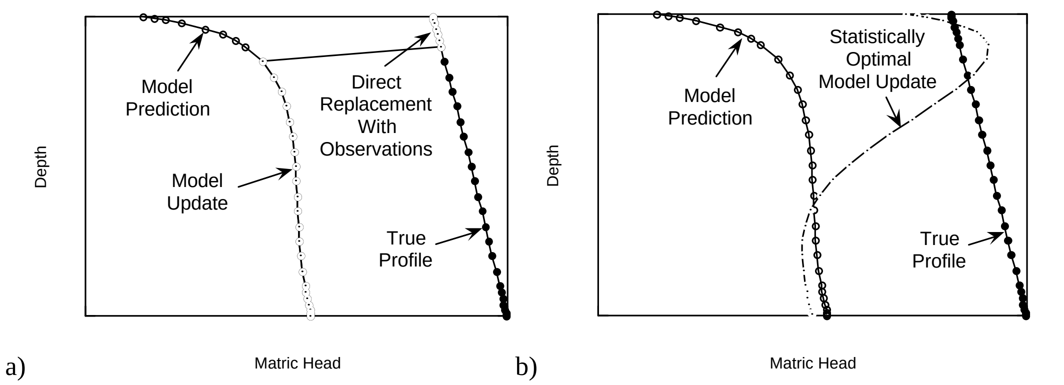

Figure 3.2: Illustration of data assimilation schemes for soil moisture profile estimation. a) Hard-updating; and b) Kalman-filtering.

replaced by the observations of the true soil moisture profile to yield the updated model estimate of the soil moisture profile.

An extension to the hard-updating scheme is the continuous Dirichlet boundary condition. Rather than make a replacement of the observed system state values only at the time of observation, the observed system state is held fixed, or continuously updated by interpolation between successive observations, to reflect the change in system state between observations.

3.3.2 KALMAN-FILTERING

The Kalman-filter assimilation scheme is a linearised statistical approach that provides a statistically optimal update of the system states, based on the relative magnitudes of the covariances of both the model system state estimate and the observations. The principal advantage of this approach is that the Kalman-filter provides a framework within which the entire system is modified, as illustrated in Figure 3.2b, with covariances representing the reliability of the observations and model prediction.

The Kalman-filter algorithm (Kalman, 1960) tracks the conditional mean of a statistically optimal estimate of a state vector **X**, through a series of propagation and update steps (Bras and Rodriguez-Iturbe, 1985). To apply the Kalman-filter, the equations for evolving the system states must be written in the linear state space formulation of (3.1). When these equations are non-linear, the Kalman-filter is called the extended Kalman-filter and is an approximation of the non-linear system that is based on first-order linearisation. The forecasting equations are (Gelb, 1974; Bras and Rodriguez-Iturbe, 1985)

$$\hat{\mathbf{X}}^{n+1/n} = \mathbf{A}^{n} \cdot \hat{\mathbf{X}}^{n/n} + \mathbf{U}^{n} + \left(\mathbf{w}^{n}\right) \tag{3.1}$$

$$\Sigma_{\mathrm{x}}^{n+1/n} = \mathbf{A}^{n} \cdot \Sigma_{\mathrm{x}}^{n/n} \cdot \mathbf{A}^{n^{\mathrm{T}}} + \mathbf{Q}^{n} \qquad (3.2),$$

where $\mathbf{A}$ is the state propagation matrix relating the system states at times n+1 and n, $\mathbf{U}$ is a vector of forcing, $\mathbf{w}$ is the model error, Σ_{x} is the covariance matrix of the system states and $\mathbf{Q}$ is the covariance matrix of the system noise (model error), defined as $E[\mathbf{w}\cdot\mathbf{w}^{\mathrm{T}}]$. The notation $n+1/n$ refers to the system state estimate from a propagation step and n/n refers to the system state estimate from either a propagation or updating step at time n.

The covariance evolution equation consists of two parts: (i) propagation by model dynamics, and (ii) forcing by model error. The first, which is computationally the most demanding step in the Kalman-filter algorithm, expresses how the error covariance matrix is affected by the dynamical processes that are present in the forecast model. The second part of the covariance evolution equation represents, loosely speaking, the cumulative statistical effect of all processes that are external (ie. not accounted for) to the forecast model (Dee, 1991, 1995).

For the update step, the observation vector $\mathbf{Z}$ must be linearly related to the system state vector $\mathbf{X}$ through the matrix $\mathbf{H}$.

$$\mathbf{Z} = \mathbf{H} \cdot \hat{\mathbf{X}} + (\mathbf{v}) \qquad (3.3),$$

where $\mathbf{v}$ accounts for observation and linearisation errors.

Updating of the best estimate of the system state vector $\hat{\mathbf{X}}$ by the observation vector $\mathbf{Z}$ is performed by means of Bayesian statistics. The system state vector and associated covariances are updated by the expressions (Gelb, 1974; Bras and Rodriguez-Iturbe, 1985)

$$\hat{\mathbf{X}}^{n+1/n+1} = \hat{\mathbf{X}}^{\mathbf{n+1/n}} + \mathbf{K}^{n+1}\left(\mathbf{Z}^{n+1} - \mathbf{H}^{n+1} \cdot \hat{\mathbf{X}}^{n+1/n}\right) \qquad (3.4)$$

$$\Sigma_{\mathrm{x}}^{n+1/n+1} = \left(\mathbf{I} - \mathbf{K}^{n+1} \cdot \mathbf{H}^{n+1}\right) \cdot \Sigma_{\mathrm{x}}^{n+1/n} \qquad (3.5),$$

where $\mathbf{I}$ is the identity matrix. The Kalman gain matrix $\mathbf{K}^{n+1}$ weights the observations against the model forecast. Its' weighting is determined by the relative magnitudes of model uncertainty embodied in $\Sigma_{\mathrm{x}}^{n+1/n}$ with respect to the observation covariances $\mathbf{R}^{n+1}$, defined as E[$\mathbf{v} \cdot \mathbf{v}^{\mathrm{T}}$]. The Kalman gain is given by

$$\mathbf{K}^{n+1} = \Sigma_{\mathrm{x}}^{n+1/n} \cdot \mathbf{H}^{n+1^{\mathrm{T}}} \cdot \left(\mathbf{R}^{n+1} + \mathbf{H}^{n+1} \cdot \Sigma_{\mathrm{x}}^{n+1/n} \cdot \mathbf{H}^{n+1^{\mathrm{T}}}\right)^{-1} \qquad (3.6).$$

The key assumptions in the Kalman-filter are that the continuous time error process **w** is a Gaussian white noise stochastic process with mean vector equal to the zero vector and covariance parameter matrix equal to **Q**, and that the discrete-time error sequence **v** is a Gaussian independent sequence with mean equal to zero and variance equal to **R**. The initial state vector $\hat{\mathbf{X}}^{0/0}$ is also assumed Gaussian with mean vector $\hat{\mathbf{X}}^{0/0}$ and covariance matrix $\Sigma_{\mathrm{x}}^{0/0}$.

Given the initial state vector $\hat{\mathbf{X}}^{0/0}$ with covariance matrix $\Sigma_{\mathrm{x}}^{0/0}$, the system states and covariances are propagated (denoted by the time superscript n+1/n) using (3.1) and (3.2) respectively. When a set of observations become available, an update of the system states and covariances is made (denoted by the time superscript n+1/n+1) using (3.4) and (3.5) respectively.

Prior to implementation of the Kalman-filter assimilation algorithm for a particular model, the initial system state covariance matrix $\Sigma_{\mathrm{x}}^{0/0}$, the model error covariance matrix **Q** and the observation error covariance matrix **R** must be identified. Very few methodologies have been proposed and tested for estimation of the covariance matrices (Georgakakos and Smith, 1990). Hence, these covariances are generally chosen ad hoc (Ljung, 1979).

The system state covariance matrix is often initialised using degree-of-belief estimates of the errors in initial states to specify the diagonal elements (variances) of the initial covariance matrix, with the off-diagonal elements (covariances) set to zero (Georgakakos and Smith, 1990).

Model errors result from inaccurate specification of the model structure as a result of: (i) linearisation of the model physics; (ii) estimation errors in the values of model parameters; and (iii) measurement errors in the model input (eg. precipitation and evapotranspiration). This is the most difficult component of the Kalman-filter to identify correctly (Georgakakos and Smith, 1990).

The variance of the observations **R** can be identified reliably in most cases, since it depends on the characteristics of the measuring device (Georgakakos and Smith, 1990).

3.4 SOIL MOISTURE PROFILE ESTIMATION FROM NEAR-SURFACE MEASUREMENTS

The use of near-surface soil moisture measurements for estimating soil moisture content over the soil profile will provide much needed information in hydrological models which lack this type of information, especially those developed for flood forecasting (Su *et al.*, 1994; Kite and Pietroniro, 1996). This is due to the fact that hydrologic models are generally unable to correctly simulate: (i) water exchanges at the soil-atmosphere interface; and (ii) the time evolution of near-surface soil moisture content, due to the highly dynamic nature of the surface zone (Arya *et al.*, 1983). Thus, after periods of low flows, hydrologic models usually experience poor simulations of runoff due to the wrong estimation of soil moisture content (Ottlé and Vidal-Madjar, 1994).

One of the main reasons for hydrologic models failing to provide accurate estimates of soil moisture content is the poor estimation of precipitation and evaporation, due to a high variability in space and time and the fact that they generally originate from only a few meteorological sites (Ottlé and Vidal-Madjar, 1994). Blanchard *et al.* (1981) have noted that such estimates of precipitation are relatively good in areas with wide spread low intensity rainfall. However, in areas subject to frontal convective storms, there is a non-uniform distribution of rainfall. This problem is currently being addressed by investigating methods for estimating both precipitation and evapotranspiration from remote sensing.

Given the current technology, microwave remote sensing can only provide a measurement of the soil moisture for the top few centimetres of the soil profile at most (section 2.4.6), and very few attempts have been made to extrapolate this measurement of soil moisture content to estimate the soil moisture content over the entire soil profile (top one to two metres of the earth's surface). Although a detailed distribution of moisture content in the soil profile is desirable, knowledge of the total amount is often adequate (Arya *et al.,* 1983).

This section reviews the approaches that have been made for estimation of the soil moisture profile from observations of near-surface soil moisture content. These approaches have been classified into four types: (i) regression, (ii) knowledge-based, (iii) inversion and iv) combinations of remotely sensed data with soil water balance (hydrologic) models (Kostov and Jackson, 1993).

3.4.1 REGRESSION APPROACH

The simplest approach to estimating the soil moisture profile from near-surface measurements is to develop a regression equation. Such an approach is usually based on data for typical soil and land use conditions, and generally cannot be extrapolated from one location to another (Ragab, 1995). The reason why simple regression relationships can be used under some conditions to predict the soil moisture profile from measurements in a near-surface layer, is that the laws of physics link all layers of the soil together (Kostov and Jackson, 1993).

One of the earliest studies to relate the complete soil moisture profile to near-surface soil moisture measurements was that of Kondratyev *et al.* (1977). They used a regression approach to obtain a correlation between the soil moisture content of a near-surface layer and the soil moisture content of the layer of interest. Correlations for different thickness near-surface layers were evaluated from passive microwave observations at several wavelengths.

Biswas and Dasgupta (1979) have presented a general form for a regression equation to estimate the soil moisture content at deeper layers from soil moisture measurements in the near-surface soil layer. In formulating their regression equation, the authors gave regard to their observations of typical soil moisture profiles. These observations were: (i) that variation of soil moisture content at a particular depth is more or less linearly related to the variation of soil moisture content near the soil surface; and (ii) that variation of soil moisture content with depth is curvilinear, but approaches linearity with low near-surface soil moisture content. Biswas and Dasgupta (1979) included a parameter in their equation to account for different drying characteristics of bare and vegetated soil. They found that bare soil lost a greater amount of water from the near-surface layer than deeper layers, while vegetated soil lost a greater amount of water from deeper layers than the near-surface layer, as a result of root water uptake for transpiration. Comparisons of this regression equation with field data gave reasonable results, except for a few cases where relative errors were more than 20%. However, it is not clear whether the evaluation was made with the same data used for the calibration or with different data. The authors have noted that this approach is not valid for situations immediately after rainfall or irrigation.

In an attempt to relate passive microwave observations to the soil moisture content in a much thicker soil layer than the microwave sensor can sense, Blanchard *et al.* (1981) used a direct correlation with an **A**ntecedent **P**recipitation **I**ndex (API). Their basis for using such a correlation was that measurements of antecedent soil moisture content can serve as an indicator of the amount of moisture storage available in the soil profile. The API used in this study was a numerical value that represents the soil moisture content present each day in a specific soil layer. The API was modelled for any following day by depleting the API for the previous day by a given depletion constant, and adding an amount equal to the effective rainfall (or infiltration). Thus, the API was estimated from passive microwave observations by an empirical relationship with observed emissivity. As the repeat cycle for passive microwave satellites was anticipated to only be as good as once every three days, it was suggested that the API for intermediate days be estimated from the effective precipitation and depletion constant. The actual soil moisture content over a given soil profile depth was then estimated from a further regression relationship with the API. In this study a K-Band (1.55 cm) radiometer was related to the soil moisture content in a 23 cm layer. The relationship between observed and predicted soil moisture storage over the 23 cm depth was found to have an R^2 of 0.71 and a standard error of 0.76 cm.

Arya *et al.* (1983) used a linear regression approach to estimate soil moisture profile storage from the soil moisture content in the near-surface layer. Using this approach, the authors found that for a given thickness of near-surface layer, the correlation between near-surface soil moisture content decreased as the profile depth increased, and that for a given profile depth the correlation increased as the near-surface layer thickness increased. The results of this study showed that the profile depth over which useful soil moisture information can be determined from near-surface soil moisture measurements using linear regression is shallow. The authors also looked at the correlation of soil moisture content between various soil layers. They concluded that correlations deteriorate as the distance between soil layers increases, indicating that a linear relationship between the soil moisture content of two soil layers may be expected only if the layers are closely spaced. It was also found that mere adjacency was not sufficient to ensure high correlation, as increasing the layer thickness includes soil that is further apart and poorly related. The authors have noted that a useful application of this approach is in determining (for a specified correlation coefficient) the soil profile depth for which soil moisture content can be predicted from measurements in a given near-surface layer.

In a study by Zotova and Geller (1985), soil moisture contents in the 0-20, 0-50 and 0-100 cm layers were evaluated from the soil moisture content in the 0-10 cm layer using **S**oil **I**ndication **F**unctions (SIF). The SIF were essentially regression equations which related the near-surface soil moisture content to that in deeper soil layers, giving regard to soil type, texture and mode of soil moisture functioning of the soil profile. Soil moisture content in the 0-10 cm layer was evaluated from a backscattering regression equation of the form given in (2.31).

Jackson *et al.* (1987) have used a regression approach to produce a soil moisture deficit map, using near-surface soil measurements from passive microwave observations. The procedure they used is outlined below. Firstly, the profile field capacity was estimated using the soil texture relationship of Rawls *et al.* (1982). Secondly, the soil moisture profile was estimated using a regression relationship between the near-surface soil moisture content and the soil moisture profile. Finally, the soil moisture deficit was computed as the field capacity less the soil moisture profile estimate. The results from this study indicated that the soil moisture deficit map produced was similar to that obtained using conventional methods (section 3.1).

The regression approach has also been used by Bruckler *et al.* (1988) to relate the observed backscattering coefficient from active microwave observations, to soil moisture content over the radar penetration depth (see Chapter 4). This methodology relied upon calculating separate regression equations between backscattering coefficient and volumetric soil moisture content, taking into account different soil depths (0-1, 0-2, 0-3, 0-4, 0-5, 0-6, 0-7 and 0-10 cm). In order to evaluate the soil moisture content for a specific layer, Bruckler *et al.* (1988) used the relationship that average soil moisture over the depth of say 0-5 cm is a linear combination of the soil moisture content for 0-1, 1-2, 2-3, 3-4 and 4-5 cm. Writing this in matrix form, the soil moisture for each respective layer was evaluated using a single measurement of backscattering coefficient, in conjunction with the regression equations. Using this approach, it was found that near-surface soil moisture contents and profile shapes were estimated quite well, especially for dry and wet soils. Bruckler *et al.* (1988) found the relationship between observed and estimated soil moisture content for different layers down to the penetration depth to have an R^2 of 0.83, and a maximum error of 10%. However, the regression lines were derived from the same data used for evaluation, through a simulation study.

In a recent study by Srivastava *et al.* (1997), soil moisture profiles to a depth of 20 cm were estimated from remotely sensed near-surface soil moisture content by the regression approach. The study found that this approach was inadequate to extrapolate soil moisture estimates beyond 20 cm depth, and that soil moisture profiles were over-estimated in all cases. It was also found that the correlation between layers deteriorated as the distance between the layers was increased, indicating that a significant linear relationship between the soil moisture content of two soil layers may be expected only if the layers are close.

3.4.2 KNOWLEDGE-BASED APPROACH

The knowledge-based approach uses *a-priori* information on the hydrological behaviour of soils together with near-surface soil moisture content observations, in order to estimate the moisture content of the soil profile.

In the early attempt of Kondratyev *et al.* (1977) to relate the soil moisture profile to that of the near-surface soil moisture content (referred to above), a knowledge-based approach was also used. In this study, the soil moisture content in a one-metre layer was determined using a two-parameter model of the soil moisture profile, based on the correlation between soil moisture profile and that of the minimum soil moisture content. The first model parameter was the soil moisture content of the top 5 to 10 cm soil layer, determined from remote sensing measurements. The second parameter was the lapse rate of the minimum soil moisture profile in the field. Comparison of this model with field measurements showed a mean relative error of 13% and a maximum relative error of 35%.

Among the first studies was that of Jackson (1980), where the soil moisture profile in the prolonged inter-storm period was assumed to be in hydrostatic equilibrium. Under this assumption, the laws of physics specify that all points in the soil profile must have the same hydraulic potential, which is the summation of the matric potential and the gravitational potential (depth below the surface). If the near-surface soil moisture content has been determined by remote sensing, a first order approximation of the entire soil moisture profile may be made through the hydrostatic assumption. Jackson (1980) showed from a simulation study using a soil water transfer model that the accuracy of the predictions increased as the thickness of the near-surface layer increased, up to a near-surface layer thickness of 10 cm. It was also shown that the approach worked best on soils with high conductivities, and that this model is mostly applicable to periods when the surface flux is small (a result of the hydrostatic assumption) such as early morning and late afternoon. For large departures from equilibrium (ie. during precipitation or evaporation events), the hydrostatic profile assumption may not be valid. Furthermore, hydraulic equilibrium implies no flow across any depth, which Arya *et al.* (1983) indicate is highly unlikely, particularly in the near-surface layers. Arya *et al.* (1983) have also noted that it would be difficult to coincide the timing of the remote sensing observations of near-surface soil moisture content with that of hydraulic equilibrium in the soil profile.

Camilo and Schmugge (1983) extended the model of Jackson (1980) to include a root sink term during the inter-storm evaporative period. In this study, it was shown that the matric suction profile will eventually acquire the same shape as the relative root density profile, with the suction at any depth being proportional to the corresponding root density raised to a power that depends on the soil texture. This behaviour was only found for fully grown root systems where the soil moisture distribution was controlled primarily by the water absorption of the roots, which becomes more likely as the soil dries out. Thus, as long as the atmospheric evapotranspiration demand is being satisfied primarily by plant transpiration, the root density profile will control the soil moisture profile at all depths. Camilo and Schmugge (1983) demonstrated that this scheme may provide soil moisture estimates at depths greater than the observation depth of remote sensing satellites, through comparisons with field observations of soil moisture profile storage. For a profile depth of 30 cm, a maximum error of 0.8 cm storage was shown for a crop of corn from a single measurement of 3.8 cm depth.

Reutov and Shutko (1986) have used microwave radiometer data and *a-priori* information on the hydro-physical properties of soils to estimate the soil moisture profile and the net moisture content of the top one metre soil layer. In the approach used by Reutov and Shutko (1986), four main types of vertical soil moisture profiles and corresponding dielectric profiles were identified: (i) linear variation, (ii) piece-wise linear, (iii) exponential variation and (iv) parabolic variation; as shown in Figure 3.3. Corresponding theoretical models that describe the reflectivity for each of the above dielectric profiles were then used to evaluate a set of approximate reflectivity relationships using simulated data. The approximate reflectivity relationships were functions of the near-surface dielectric constant, the gradient of the dielectric profile, and the wavelength. Thus, from brightness temperature observations at two or more wavelengths, the soil moisture profile was estimated. As prior knowledge on the shape of the dielectric profile was required, it was suggested that information on the mean statistical soil moisture profile of the upper 50 or 100 cm of the soil could be used. From the results of a field experiment, it was shown that this method could be used to

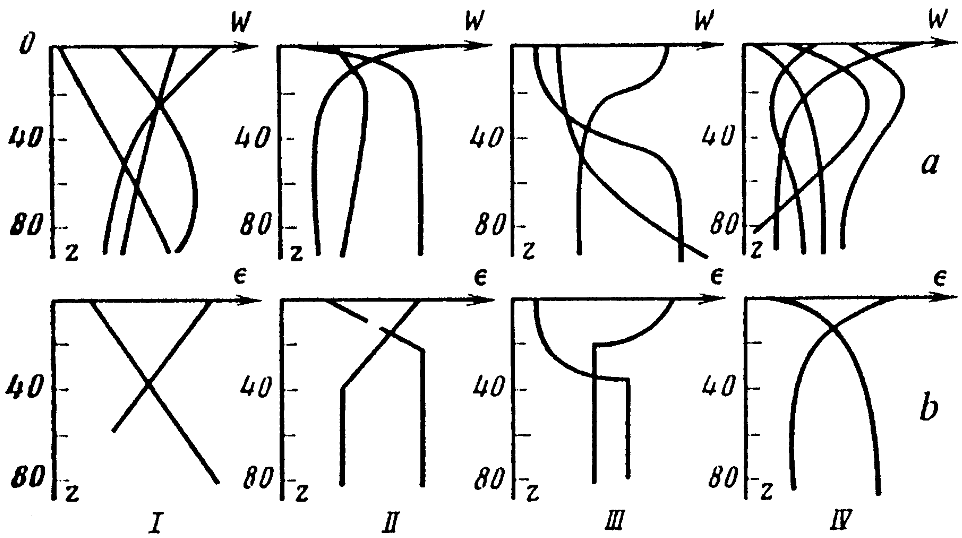

Figure 3.3: a) Basic types of soil moisture profiles of real soils and b) corresponding dielectric profiles: (i) linear variation, (ii) piece-wise linear, (iii) exponential variation and (iv) parabolic variation (Reutov and Shutko, 1986).

estimate the soil moisture profile of the top one metre soil layer and the total soil moisture content of this layer with an error less than 0.05 g cm^{-3} and 0.04 g cm^{-3} respectively.

Based on the method of Reutov and Shutko (1986) for estimating the soil moisture profile, Mkrtchjan *et al.* (1988) have estimated and mapped the water content in the top one metre soil layer in near-real-time over vegetated soil. It was shown that the soil moisture content for the top one metre layer could be determined with an accuracy of 0.05 g cm^{-3}, provided the crop biomass was less than 2 kg m^{-2}.

Jackson *et al.* (1987) have produced a soil moisture deficit map using a knowledge-based approach, in addition to their previously described regression approach. In applying the knowledge-based approach, the soil moisture profile was estimated using the equilibrium method of Jackson (1980) in place of the regression relationship. The results from this study indicated that the equilibrium approach under-estimated the soil moisture profile and hence over-estimated the soil moisture deficit. This was reported to be the result of data collected during a period of predominantly surface evaporation, during which the equilibrium assumption was invalid.

3.4.3 INVERSION APPROACH

As passive microwave brightness temperature models are written as a function of both the soil moisture and temperature profiles, inversion of the brightness temperature equations can be used to yield both the soil moisture and temperature profiles of the soil. The problem with this method is that the inversion is difficult to perform, as the soil moisture and temperature profiles are not independent (Kostov and Jackson, 1993).

Using a stratified model, Njoku and Kong (1977) conducted a study to determine if the soil moisture and temperature profiles could be estimated from brightness temperature observations. In this study, the soil moisture and temperature profiles of the soil were given a specified mathematical form. Using these profiles and the stratified brightness temperature model, brightness temperatures were generated for four observation frequencies. A matrix regression approach was then used to estimate the parameters used to generate the profiles. Good estimates were obtained for all parameters using this approach, especially for the near-surface soil moisture content.

The inversion technique has also been used by Entekhabi *et al.* (1993, 1994) to solve for simultaneous soil moisture and temperature profiles. In this instance, the stratified brightness temperature model of Njoku and Kong (1977) presented in (2.15) and a soil moisture and heat transfer model were used in the framework of the Kalman-filter to successfully estimate the soil moisture profile. The approach used by Entekhabi *et al.* (1993, 1994) is discussed in more detail in the following section.

The depth of soil which influences the backscattering from a soil surface is a function of the wavelength (ie. frequency). Hence, Bolognani *et al.* (1996) have suggested the use of multi-frequency radar observations to provide information on the soil moisture profile. Using C-, L- and P-Band SAR measurements from a field study, Bolognani *et al.* (1996) have shown the possibility of extracting the soil moisture profile to a depth of 10 cm, by inverting the IEM surface scattering model (2.46). However, this approach relies upon an accurate knowledge of the radar observation depth (see Chapter 4) at the different frequencies.

3.4.4 WATER BALANCE APPROACH

The water balance approach uses a soil water balance (hydrologic) model that has been adapted to use remote sensing data as input, in order to produce information on the soil moisture content as well as other components of the water balance. Published soil moisture models vary in the level of detail and input information they require to model the physical system, the boundary conditions and the temporal variations of the driving forces. However, a major difficulty with these models is in providing the data required for input, calibration and evaluation.

Remote sensing observations of near-surface soil moisture content can provide spatial and temporal information on soil moisture content, which can be used as input for models, as independent feedback, or to keep the simulation on track (Kostov and Jackson, 1993). Three ways in which remote sensing observations have been suggested as input into distributed models are: (i) as parametric input data, including soil properties and land cover data such as land use classes; (ii) as data on initial conditions, such as initial catchment wetness; and (iii) as data on hydrological state variables such as soil moisture content (de Troch *et al.*, 1996). Whereas the application of the data of types (i) and (ii) in distributed models is quite straight forward in principle, application of type (iii) data requires new approaches for distributed models (de Troch *et al.*, 1996).

A single near-surface soil moisture measurement every *n* days represents the simplest sensor configuration and the least costly alternative. From this option, the frequency of near-surface soil moisture measurements can be increased, ancillary meteorological data can be used, and sophisticated hydrologic models can be employed. If the data are available on a frequent basis, the change in near-surface soil moisture content provides additional information for assessing the soil moisture profile (Jackson, 1986).

In simulating soil moisture over the entire soil profile using a soil moisture model, large errors in predicting near-surface soil moisture contents are unavoidable because of the highly dynamic nature of the near-surface zone. Thus when measured soil moisture data are available, their use in place of the simulated data should improve the overall estimation of the soil moisture profile. The expectation of improvement however, is based on the assumption that measurement errors are smaller than simulation errors (Arya *et al.*, 1983). Unfortunately, most of the hydrological models developed and evaluated for modelling of soil moisture content have been for bare soils. Furthermore, in most hydrologic models, the soil moisture component is an intermediary component within the water balance equation, and is not assessed using measured soil moisture data (Kite and Pietroniro, 1996).

3.4.4.1 Parametric Input Data

Due to the variability of the water pressure head function and the initial soil moisture profile within a region, accurate modelling of soil moisture content on a regional basis with good precision is difficult. Therefore Bernard *et al.* (1986) proposed a simple two-layer hydrologic model, which considered only evaporation and capillary flow. This model characterised each field by two parameters, the mean soil moisture content of the lower layer and the pseudo-diffusivity of the soil. Evaluation of these two parameters was achieved through calibration of the model with active microwave observations of the near-surface soil moisture content for each of the fields over a number of days.

Given the inherent problem of assigning spatially representative soil hydraulic properties from point measurements in hydrologic models, Feddes *et al.* (1993) have presented a method for determining spatially representative soil properties using remote sensing observations. The approach involved combining large-scale inverse modelling of unsaturated flow with remotely sensed measurements of evaporation and near-surface soil moisture content. After measuring the spatial distribution of soil moisture content and evaporation, Feddes *et al.* (1993) estimated the soil hydraulic properties by inverting the dynamic one-dimensional SVAT model SWATRE (**S**oil **W**ater **A**ctual **TR**anspiration **E**xtended). The inversion of the model was achieved through an indirect inverse method, which was based on the minimisation of the output error. It was concluded from this study that small-scale soil physics can adequately describe large-scale hydrological phenomena, by evaluating effective hydraulic parameters through inverse modelling on the basis of spatial evapotranspiration and near-surface soil moisture data.

The spatial variation of saturated soil hydraulic conductivity has also been estimated from remote sensing observations by Mattikalli *et al.* (1998). In this study, saturated soil hydraulic conductivity was related to 2 days of initial soil moisture drainage.

3.4.4.2 Data on Initial Conditions

Lin *et al.* (1994a) have used both remotely sensed observations of near-surface soil moisture content and stream flow data at the catchment outlet to initialise the hydrologic model of Paniconi and Wood (1993), which solves the three-dimensional Richards equation by the finite element method. It was found in this study that initialising the hydrologic model using stream flow data, led to the simulation of consistently wetter soil moisture content than those observed both in the field and from remote sensing observations. On the other hand, initialising the hydrologic model using remotely sensed near-surface soil moisture content gave a closer simulation to the soil moisture content observed in the field, but the simulated runoff was less than that observed in the field. Thus, there was a problem of being able to simultaneously reproduce the variations of runoff and soil moisture. This may be a result of inadequate identification of the horizontal hydraulic conductivity.

Ragab (1995) proposed a system to estimate the soil moisture profile using a two-layer hydrologic model and remotely sensed near-surface soil moisture data. However, remote sensing data was not used in the study. The proposed system consisted of an initialisation phase and a dynamic phase. The initialisation phase provided the dynamic model with the initial values of soil moisture content in the near-surface and deep soil layers. It was proposed that in the initialisation phase, the near-surface soil moisture content be estimated from either ground measurements or remotely sensed data. It was then proposed that soil moisture content in the deep soil layer be estimated from a relationship with the near-surface soil moisture content. Suggested approaches were to use a regression equation for either wet or dry periods, or in the absence of these relationships that knowledge-based values be assigned. The knowledge-based techniques that were suggested include the field capacity values during the rainy season, the root density relationship of Camillo and Schmugge (1983), and the hydraulic equilibrium profile method of Jackson (1980). Upon initialisation of the hydrologic model, the dynamic phase was commenced. The input into the hydrologic model for this phase consisted of daily values of rainfall and evapotranspiration, as well as three soil parameters. The evapotranspiration was scaled from the potential evapotranspiration by the ratio of available soil moisture to maximum available soil moisture. The soil parameters required were field capacity, wilting point and a pseudo diffusivity factor, which varied according to soil type. The output of the model was daily values of soil moisture content in the near-surface and deep soil layers, and deep drainage. In this study, the hydrologic model was not initialised with remote sensing data, but by assuming that the soil moisture content was at field capacity. Evaluation of the hydrologic model was undertaken by comparing simulated and observed soil moisture content in the near-surface and deep soil layers. The work by Ragab (1995) did not consider using remote sensing observations for updating the hydrologic model.

Giacomelli *et al.* (1995) have compared SAR derived soil moisture distribution with hydrologic simulations, using the distributed model of Famiglietti and Wood (1994a). They report acceptable results when comparing sampled, modelled and SAR derived soil moisture content at the field scale, but also that the spatial patterns of soil moisture predicted by the distributed model and by the SAR images were quite different. They claim that these differences were due to the model structure and its' initial conditions.

3.4.4.3 Data on Hydrological State Variables

One of the first studies to use the soil moisture modelling approach for estimation of the soil moisture profile was that of Jackson *et al.* (1981). In this study near-surface soil moisture observations were used to update soil moisture predictions in the **U**nited **S**tates **D**epartment of **A**griculture **H**ydrograph **L**aboratory (USDAHL) hydrologic model of Holtan *et al.* (1975). The USDAHL model simulated evapotranspiration, infiltration, surface runoff, sub-surface redistribution, lateral flow, percolation and stream flow. The model incorporated the spatial variability of soils, land use, and topography by simulating several zones in the watershed. Each zone was defined with regard to the homogeneity of one of the above factors and utilised two soil layers. Generally, one was taken as the A horizon and the other was a layer to the depth of maximum root penetration, which was sometimes the B horizon. The updating of soil moisture content in the hydrologic model was performed by substituting the current simulation values of both soil layers with the passive microwave observed near-surface soil moisture content (hard-updating), as observations became available. The improvement in performance of this model as a result of assimilation of the soil moisture data was evaluated by comparing simulation of annual runoff values with observations. Simulation of runoff was found to improve when soil moisture data was assimilated into the hydrologic model.

Bernard *et al.* (1981) developed an approach for modelling soil moisture content and estimating evapotranspiration under bare soil conditions. The numerical soil moisture transfer model used was a finite difference representation of the classical Richards equation for one-dimensional isothermal water movement in the unsaturated zone. The model used measurements of near-surface soil moisture content for specifying the surface boundary condition, in order to estimate the surface flux. To test the model, soil moisture profile data was simulated for a 25 day period using a surface flux boundary condition. The flux (Neumann) boundary condition consisted of three rain periods and diurnally varying evaporation, modelled by a sine function with randomly varying amplitude and limited by water availability at the soil surface. Active microwave observations were simulated from the soil moisture profiles, with an observation error added through a random perturbation having a standard deviation of 0.5 dB. The backscattering model used for this was a linear regression model of the form given in (2.31).

A second simulation was then performed having a fixed value (Dirichlet) boundary condition for the top two layers, in order to estimate the evaporation rate previously imposed. The Dirichlet boundary condition was evaluated by linearly interpolating between the remotely sensed soil moisture observations made at either 12, 24 or 72 hours apart. Simulations using a bare surface light clay soil indicated that the procedure would be accurate for estimating cumulative evaporation if the near-surface soil moisture content was measured once every three days. However, it was shown that for sandy soil with higher hydraulic conductivity values, the sampling period must be shorter, particularly for wet conditions. It was also shown that daily evaporation could be determined accurately with twice-daily measurements of near-surface soil moisture content, one in the early morning and one in the early evening. Bernard *et al.* (1981) pointed out that the critical point would be in the monitoring of rainy periods, where large variations of soil moisture content occur within a sampling period. A detailed knowledge of the amount and time of precipitation and special handling of the upper boundary condition after rain would be needed (Bernard *et al.,* 1981).

Prevot *et al.* (1984) followed up on the approach of Bernard *et al.* (1981), using the same soil moisture transfer model with actual active microwave observations of near-surface soil moisture content to prescribe the surface boundary condition. The hydrologic model was initially calibrated against measured soil moisture profiles on 4 days. In prescribing the boundary condition of near-surface soil moisture content for each time step, the near-surface soil moisture content was linearly interpolated between adjacent active microwave observations, which were provided daily. In order to account for microwave penetration into the soil, the active microwave derived soil moisture content from a linear regression equation with backscattering, of the form given in (2.31), was imposed as the average soil moisture content (in terms of matric head) over the first 5 cm of the soil profile.

Prevot *et al.* (1984) ran their model in two modes. In the first mode, only the soil moisture boundary condition was specified, with no information given about surface fluxes, and the evaporation estimated. In the second mode, both near-surface soil moisture content and rainfall information was supplied, and evaporation estimated. In this second mode, if a rainfall event occurred between two consecutive observations, the boundary condition of near-surface soil moisture content was not applied as the rainfall would have affected the soil moisture estimate. Hence, a null surface flux was imposed for the periods between the observations for which it was raining. Starting with an observed soil moisture profile, evaluation of this modelling approach was undertaken for both modes by comparing simulated and observed soil moisture profiles and cumulative evaporation. Prevot *et al.* (1984) found that this modelling approach actually worked better if the rainfall observations were not used (ie. first mode), which they attribute to the structure of the hydrologic model and the near-surface soil moisture measurement frequency.

Arya *et al.* (1983) used a modelling approach that was based on the assumption that under bare field conditions, change in soil moisture profile storage over a period of time equals the net surface flux over the same time (ie. no gravity drainage or lateral flux). If the initial amount of soil moisture storage is known, then one needs only to know the daily gains and losses to determine the daily total amounts. In this study, it was assumed that surface fluxes account for most of the gains and losses in the soil moisture profile storage, and that fluxes across the bottom boundary of the soil profile and lateral flow were negligible. The surface flux was computed using a relationship between the soil hydraulic conductivity and the hydraulic potential gradient. This gradient can be evaluated if moisture data at two closely spaced points are available. However, remote sensing techniques at that time did not provide two point measurements, but rather a single valued average moisture content for a near-surface layer. To resolve this problem, the authors used a regression approach to develop a two or three point moisture profile from the average moisture content for the top 5 cm layer. The basis for this was the high linear correlations they had found between the soil moisture contents of adjacent layers. Comparisons between predictions using this approach and both field and simulated data showed good agreement.

Camilo and Schmugge (1984) have shown that cumulative infiltration, a surrogate variable for change in soil moisture storage, is clearly related to the emissivity measured in passive microwave remote sensing. In this study, a soil moisture and heat transfer model was used to simulate soil moisture and temperature profiles during and after rainfall, and a radiative transfer model was used to estimate the intensity of emitted radiation using these profiles. The purpose of this study was to investigate the relationship between emissivity and soil moisture content, for the purpose of estimating rainfall.

The first known study to consider estimation of the soil moisture profile from near-surface soil moisture observations through Kalman-filtering is that of Milly (1986). In this study, a simple linear reservoir model was used to investigate theoretically the possible advantage of updating a soil moisture model with near-surface observations. Milly (1986) found that updating of the hydrologic model with near-surface observations resulted in a reduction in the model variances, being indicative of improved soil moisture profile estimates. Furthermore, Milly (1986) found that the error reduction achieved by doubling the number of near-surface soil moisture observations was greater than that achieved by reducing the variance of the observations by a factor of 10. Thus, it was suggested that this implied that it is critical to obtain measurements of near-surface soil moisture soon after storms, before redistribution and evaporation have had significant effects, and that measurements on a daily basis would not be excessive.

Bruckler and Witono (1989) used remotely sensed near-surface soil moisture data from active microwave remote sensing as the surface boundary condition for the physically based heat and moisture transport model of Witono and Bruckler (1989). This heat and moisture transport model solved the equations of Philip and de Vries (1957) by a Galerkin finite element method with time integration through an implicit method. Witono and Bruckler (1989) showed that this heat and water transport model described soil temperature and moisture content variation to within 1.5°C and 3.6% v/v respectively, after a calibration phase, using only surface values of temperature and soil moisture content and the true initial conditions. In applying the near-surface soil moisture boundary condition to this model, Bruckler and Witono (1989) successfully used both the average soil moisture content for the top 5 cm layer from a linear regression relationship, and the soil moisture profile for the top 10 cm using the method of Bruckler *et al.* (1988) (section 3.4.1), to solve for evaporation and infiltration from the water budget. In applying the continuous near-surface soil moisture content boundary condition, near-surface soil moisture estimates were made from fitting a cubic spline to active microwave observations with a time interval of 1 to 4 days. In this study, Bruckler and Witono (1989) found that under both evaporation and infiltration phases, use of near-surface soil moisture measurements as boundary conditions provided satisfactory soil moisture estimates only when many input data, correctly located and connected with rainfall sequences, were available. Evaluation of this modelling approach was undertaken by comparing simulated cumulative evaporation and infiltration with observations.

Entekhabi *et al.* (1993, 1994) developed an algorithm to solve the inverse problem for estimating both the soil moisture and temperature profiles using remotely sensed observations of multispectral irradiance. A model of coherent wave radiative transfer (2.15) and a model of coupled heat and moisture diffusion in porous media (Milly and Eagleson, 1980) were combined in a Kalman-filter, in order to estimate the soil moisture and temperature profiles of a one-dimensional soil column. The Kalman-filter used observations of low frequency passive microwave (vertical and horizontal polarisation) and thermal infra-red emitted radiation. Since the focus was on methodology, the profile estimation algorithm was tested on a synthetic situation where soil moisture and temperature profiles were simulated using the physically based model of Milly and Eagleson (1980) for a period consisting solely of evaporation. The synthetic microwave and thermal infra-red observations were then generated by processing the resulting dielectric and temperature profiles through the radiative transfer model of Njoku and Kong (1977). Starting from a poor initial guess of the soil moisture and temperature profile, the synthetic passive microwave and thermal infra-red observations from the "true" soil moisture and temperature profiles were used to update the system state equations each hour. After approximately four days of updating each hour, Entekhabi *et al.* (1993, 1994) found that the Kalman-filter estimate of the soil moisture profile coincided with the true profile.

Ottlé and Vidal-Madjar (1994) used a water balance model to evaluate stream flow, with remote sensing measurements of near-surface soil moisture content to correct for imperfect model parameterisations of the processes, and to correct for the imprecise knowledge of spatial variation of precipitation and failure to take into account irrigation. The hydrologic model used was that of Ottlé *et al.* (1989), which was based on the one-dimensional two-layer hydrologic model of Bernard *et al.* (1986). The hydrologic model simulated water flows by means of three mechanisms on a 5 km square grid. The first was the production function, which subdivided rainfall into storage within the first layer, surface runoff, evaporation, and infiltration into the second layer. The second mechanism calculated the surface transport by routing the runoff from each grid-point to the closest river mesh following the drainage directions. Finally, the third mechanism calculated the infiltration into the water table, the underground transfers and the water flows coming back up to the surface layer, which were only allowed in the river meshes. Calculations were done with a time step of one day. The main difference between the hydrologic models of Bernard *et al.* (1986) and Ottlé *et al.* (1989) was in how the surface fluxes were evaluated. With the hydrologic model of Ottlé *et al.* (1989), runoff appeared for bare soil surfaces as soon as the first layer was saturated, while for vegetated areas, runoff only occurred after the bulk layer had filled up. In specifying the actual evaporation rate, total evaporation was taken as the sum of the contributions from the vegetation and that for bare soil. The fractional vegetation cover was estimated from the NDVI, which is a function of the measured reflectances in the visible and near infra-red wavelengths. Actual bare soil evaporation and evapotranspiration were estimated from regression relationships with the potential evapotranspiration rate. As clear sky images became available, near-surface soil moisture content was determined and the near-surface layer of the water balance model updated. In determining the near-surface soil moisture observations for updating the hydrologic model, Ottlé and Vidal-Madjar (1994) inverted a SVAT model using observations from a thermal infra-red sensor. By updating the near-surface soil moisture content from remote sensing observations, Ottlé and Vidal-Madjar (1994) found an improvement in the simulated stream flow. They also found that a two-layer model performed better than a single-layer model, as it reacted more quickly to rainfall.

Saha (1995) used remote sensing observations in the visible, near infra-red, mid infra-red and thermal infra-red bands to estimate the soil moisture profile from a SVAT model. This model required vegetation canopy surface temperature, surface albedo, land cover, soil texture, rooting depth, vegetation height, and daily meteorological data, such as incident short wave radiation, maximum and minimum air temperatures, relative humidity and wind speed. In this study, the soil surface temperature data was obtained from analysis of the thermal infra-red band; the surface albedo was obtained from analysis of the visible, near infra-red, and mid infra-red bands; the land cover and soil texture data was obtained from a supervised classification using visible wave-bands; and the aerodynamic resistance factor, vegetation height, and rooting depth were derived from the vegetation classes using ground observed values. Using the above data and the SVAT model, the soil moisture profile was estimated.

Georgakakos and Baumer (1996) used monthly data and a two-layer large scale (basin average) conceptual hydrologic model in conjunction with the Kalman-filter to update the modelled soil moisture content with near-surface soil moisture measurements. Initial model parameters were estimated from a calibration to 20 years of stream flow data. The model was then run for the following 20 years of data, with a time varying model parameter vector to account for model structure errors. Remotely sensed soil moisture "observations" for model updating were simulated from field measured soil moisture content in the top 10 cm, with observations at least twice a month. The model updating was performed with various levels of observation noise. Results showed that even when the observations carried substantial measurement errors, estimation of soil moisture profiles and total soil moisture storage was possible with an error that was smaller than that achieved without the use of remotely sensed data.

Houser *et al.* (1998) investigated the feasibility of updating the three-layer hydrologic model TOPLATS (Famiglietti and Wood, 1994a) with remote sensing observations, using several alternative assimilation procedures. The assimilation schemes investigated were: (i) hard-updating; (ii) statistical correction; (iii) Newtonian nudging; and (iv) statistical interpolation. With hard-updating, no data were assimilated outside the region where observations were available, and advection of information to deeper layers and outside the observed area was solely through the model physics in subsequent time steps. In the statistical correction scheme, the mean and standard deviation of the near-surface soil moisture states in the model were adjusted to match the mean and standard deviation of the observations. As with hard-updating, advection of the information to deeper soil layers was accomplished solely through the model physics. However, updating of the model near-surface soil moisture content outside the observed region was performed. Newtonian nudging relaxed the model state towards the observed state by adding an artificial tendency term which was a function of the difference between the observed and modelled states, weighted by the distance (horizontally and vertically) from the observation and time since the observation (Houser *et al.*, 1998). The Newtonian nudging technique is a special and typically pathological case of the Kalman-filter (Bennett, 1992).

Houser *et al.* (1998) found that even after a comprehensive multi-objective parameter calibration, the hydrologic model over-estimated near-surface soil moisture content and was unable to achieve observed post-storm dry-down. All of the above data assimilation schemes were found to significantly and similarly improve the simulation of near-surface soil moisture content, with the exception of hard-updating, which was unable to impose an entire watershed correction (as a result of limited near-surface soil moisture content observations). However, the statistical interpolation approach resulted in an undesirable linear streaking feature that extended outwards from the observed area. It was also noted that nudging had the advantage of providing smoother temporal adjustments, which is a characteristic that would limit its application in real time. None of the schemes produced time series that matched the soil moisture profile observations. However, Newtonian nudging made the largest impact on the soil moisture profile due to an explicit nudging in the deep soil layers, while statistical interpolation had a relatively strong modification of the soil moisture content in the deep soil layers.

3.5 THE SOIL MOISTURE PROFILE ESTIMATION ALGORITHM

The review of soil moisture profile estimation from remote sensing of near-surface soil moisture has shown that previous studies have either: (i) used remote sensing observations to estimate the soil moisture profile at the time of observation (ie. regression approach, knowledge-based approach and inversion approach); or (ii) assimilated the near-surface soil moisture observations into a hydrologic model (ie. water balance approach), with the purpose of improving the forecast of either runoff or evapotranspiration, and in a few studies (often one-dimensional), soil moisture. As there is no current passive microwave satellite suitable for remote sensing of near surface soil moisture and all current generation active microwave remote sensing satellites have a standard repeat time generally in excess of 1 month, it is necessary to use the water balance approach in order to estimate the spatial distribution of soil moisture profiles during the inter-observation period.

The water balance approach requires both an initialisation phase, and a dynamic phase (Ragab, 1995). In the initialisation phase, the initial system states (ie. soil moisture content) are assigned some feasible value, preferably close to the true value, for initiation of the water balance calculations. Once the hydrologic model is initialised, the dynamic phase is commenced. In the dynamic phase, the system states are forecast using the best estimate of soil parameters and atmospheric forcing. As near-surface soil moisture observations become available, these are assimilated into the system to yield an updated (hopefully improved) estimate of the system states.

A significant difference between the study presented in this thesis and many of those presented in the literature review, is the objective. The objective of this thesis was to make improved estimates of the spatial distribution and temporal variation of soil moisture profiles, with the ultimate goal of being able to perform this in near-real-time. With the exception of only a few studies, all previous studies using the water balance approach have assimilated near-surface soil moisture observations with the objective of improving evapotranspiration or runoff predictions, or have only investigated the estimation of soil moisture profiles for a one-dimensional soil column, often using synthetic data.

3.5.1 INITIALISATION PHASE

Ragab (1995) has suggested that the hydrologic model be initialised with soil moisture profile estimates from: (i) the hydraulic equilibrium method of Jackson (1980); (ii) the relative root density profile method of Camillo and Schmugge (1983); or (iii) assigned the field capacity soil moisture if it is a rainy period. Other options for model initialisation that were not mentioned by Ragab (1995) are: (i) interpolation of in-situ soil moisture profiles using a bi-cubic spline and near-surface soil moisture observations as ancillary data; (ii) the soil moisture lapse rate model of Kondratyev *et al.* (1977); (iii) a uniform soil moisture profile using the near-surface soil moisture content; and (iv) the residual soil moisture content under extended drying periods.

3.5.2 DYNAMIC PHASE

The dynamic phase consists of both forecasting and updating steps. During the inter-observation period, the system states of the hydrologic model are forecast by forcing the model with meteorological data. When near-surface soil moisture observations are available, the system states of the model are updated to reflect the near-surface soil moisture observations, so as to account for initialisation, model structure, parameter, and atmospheric forcing inadequacies.

3.5.2.1 Forecasting

Forecasting of the model is a relatively straightforward step. Using the initial system states from the initialisation phase and the best estimate of soil parameters, the hydrologic model is run forward in time to predict the spatial distribution and temporal variation in soil moisture profiles. In order to force the model, estimates of actual evapotranspiration and precipitation are required.

Potential evapotranspiration is less spatially variable than actual evapotranspiration and precipitation. Hence, in an operational system, potential evaporation could be estimated from standard meteorological data collected from routine monitoring stations. Actual evapotranspiration may then be estimated from the potential evapotranspiration as a function of moisture availability, estimated from the hydrologic model.

Accounting for the spatial variability in precipitation is more difficult. Interpolating between raingauges often misses the small-scale variability of rainfall that is particularly evident in convective thunderstorms. However, there is a current move towards using ground-based radar to determine the spatial variability in rainfall, and point measurements to correct for the poor rainfall rate estimates from the radar (eg. Krajewski, 1987; Seo, 1998).

It is these inadequacies in estimating the atmospheric forcing, along with model structure and parameter errors, which result in poor estimates of the spatial distribution and temporal variation of soil moisture profiles. Updating of the hydrologic model through the process of assimilating observations of near-surface soil moisture should alleviate these problems.

3.5.2.2 Updating

The present literature review on soil moisture profile estimation has shown that updating of the hydrologic model has generally been applied in three ways: (i) hard-updating (direct-insertion) of simulated soil moisture content with observations (eg. Jackson *et al.*, 1981; Ottlé and Vidal-Madjar, 1994; Houser *et al.*, 1998); (ii) specifying a continuous fixed value (Dirichlet) boundary condition in the top soil layers by interpolating between observations (eg. Bernard *et al.*, 1981; Prevot *et al.*, 1984; Bruckler and Witono, 1989); and (iii) using the Kalman-filter to provide a statistically optimal update of the system states, based on the relative covariances of the observations and the system states in the hydrologic model simulations (eg. Milly, 1986; Entekhabi *et al.*, 1993, 1994; Georgakakos and Baumer, 1996; Houser *et al.*, 1998).

Apart from Houser *et al.* (1998), no other study has been found to compare the relative advantages and disadvantages of different assimilation techniques. Furthermore, no known study has made a direct comparison of the three most frequently used assimilation techniques outlined above. However, Bruckler and Witono (1989) found that under both evaporation and infiltration phases, use of near-surface soil moisture as boundary conditions provided satisfactory water balance calculations *only when* many input data, correctly located and connected with rainfall sequences, were available. This suggests that use of the Dirichlet boundary condition for current generation active microwave satellites, which have a typical repeat time that exceeds 1 month would be ineffective.

3.5.2.3 Evaluation

An essential component of any modelling endeavour is an adequate evaluation process. In evaluating the estimation of soil moisture profiles, it is necessary that comparisons of model simulated soil moisture content be compared with field measured soil moisture content. Good comparisons of model simulated catchment runoff or evapotranspiration do not necessarily mean that there would be a good comparison with model simulated soil moisture content. Hence, estimation of soil moisture profiles has been evaluated in this study by comparing the soil moisture profile estimates with field measured soil moisture profiles.

3.6 CHAPTER SUMMARY

This chapter has reviewed the methods previously used for estimating the spatial distribution and temporal variation of soil moisture profiles. While the spatial distribution of soil moisture profiles may be estimated from point measurements, these estimates are rather poor as a result of a low spatial correlation for soil moisture content. Hence, the spatial distribution of the soil moisture profiles is often estimated from hydrologic models. This estimate is also often poor, as a result of model errors and a misrepresentation of the atmospheric forcing. It has also been shown that the spatial distribution of soil moisture profiles has been estimated from remotely sensed near-surface soil moisture measurements in four ways: (i) regression; (ii) knowledge based; (iii) inversion; and (iv) assimilation of near-surface soil moisture observations into a water balance (hydrologic) model.

Due to the low temporal resolution of current active microwave remote sensing data, it is necessary to apply the water balance approach for estimation of the soil moisture profiles during the inter-observation periods. Based on the review of soil moisture profile estimation techniques presented in this chapter, the soil moisture profile estimation algorithm that is tested in this thesis, is presented. This algorithm uses the water balance approach, which forecasts the soil moisture profiles using a hydrologic model and standard meteorologic data, and updates the model forecasts through the process of data assimilation when near-surface soil moisture observations are available. The point measurements of soil moisture are used for calibration of the hydrologic model and ongoing evaluation of the soil moisture profile estimation.