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Hydrology and Water Balance of Devils Lake Basin: Part 2 Grid-Based Spatial Surface Water Balance Modeling*

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Abstract

In this part of the study, grid-based spatial water balance approach was used to estimate the annual water balance of Devils Lake basin, hydrologically closed lake located in the Red River of the North basin, northeastern North Dakota. Landsat images from 1991 to 2003 were used in the study. Using spatial precipitation, land-cover and soils data, grid-based surface runoff was estimated based on the Curve Number method. The calibrated upstream runoff inflow for each grid cell was computed using a 10-m digital elevation model. Spatial evapotranspiration was estimated for the study area from remotely-sensed data using a surface energy flux model. The spatial water balance for each grid was constructed using grid geographic information system (GIS). The modeled average change in storage depth was compared to observed values of the lake stage. The grid GIS-based spatial surface water balance predicted the observed values with an average error of prediction of 0.12m. With better understanding of the groundwater contribution to the water balance, the prediction accuracy can be improved. The study ensures the applicability of the technique for surface water budget computation using GIS and remote sensing.

(Key Terms: water balance, Devils Lake, remote sensing, GIS, evapotranspiration, runoff, land use/land cover)

Introduction

In this part of the study, a grid-based spatial surface water balance model was constructed using geographic information system (GIS) to estimate the different components of the hydrologic cycle for the Devils Lake basin. A GIS provides a framework for storing and manipulating spatial data and facilitates the modeling on control volumes of various sizes and shapes. Remotely-sensed data from Landsat images were used to derive land-cover classes and also compute spatial evapotranspiration using surface energy balance approach. Dataset used for both parts of the study is reported in Part I of this study.

Remote Sensing Application

The most promising applications of remote sensing data in hydrologic modeling are the areal measurement of hydrometeorological variables such as precipitation, land surface temperature, land-cover classes, and vegetation and basin characteristics. Land-cover determination using remote sensing is widely used for large watersheds and when land-cover (actual distribution of

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physical features of land) information is required at times of the year when such data is critical. Although remote sensing cannot be used directly to quantify runoff, it can be used to determine watershed geometry, drainage network and also hydrologic input parameters such as soil moisture or delineated land-use classes that are used to define runoff coefficients.

Land-cover information is used in watershed modeling to estimate the value of surface roughness or friction as it affects the velocity of the overland flow of water. It may also be used to determine the amount of rainfall infiltration on a surface. The pixel format of digital remote sensing data makes it suitable to merge it with GIS. GIS allows for the combination of remotely-sensed data with other spatial data forms such as topography, soils maps and hydrologic variables such as rainfall distribution and soil moisture.

METHODOLOGY

The components of the surface water balance and techniques used to estimate each component of the water budget is discussed.

Water balance

An annual spatial water balance per pixel is given by equation (1):

$$P + GW_{in} + Q_{in} = Q_{out} + ET + GW_{out} \pm \Delta Storage \qquad (1)$$

Where P is precipitation, GW_{in} is groundwater recharge, Q_{in} is discharge entering the cell from upstream cells, Q_{out} is discharge leaving a cell, ET is evapotranspiration , GW_{out} is groundwater outflow, and $\Delta Storage$ is change in storage from previous year. All units are in length or volume.

Precipitation

Precipitation volume over the basin was determined using the Thiessen polygon method from a network of seven rain gages. Thiessen polygons (Figure 2 of part 1) were constructed using grid GIS and spatially distributed rainfall volumes for each grid were computed.

Runoff

Spatially distributed excess precipitation was estimated using the U.S. Department of Agriculture-Natural Resources Conservation Service (USDA- NRCS) Curve Number (CN) technique. The rainfall-runoff equation used by the NRCS for estimating depth of direct runoff from storm rainfall (USDA, 1986) is given by

$$Q = \frac{(P - 0.2S)^2}{P + 0.8S} \qquad (P > 0.2S) \qquad (2)$$

S is related to curve number (CN) by

$$\mathrm{S} = \frac{25400}{\mathrm{CN}} - 254 \qquad (3)$$

where Q is actual direct runoff (mm); S is watershed storage (mm); P is total rainfall (mm) ($P \geq Q$). CN is a dimensionless parameter with values ranging from 1(minimum runoff) to 100 (maximum runoff).

CN is determined based on the following factors: hydrologic soil group, land-use, land treatment, and hydrologic conditions. The NRCS runoff equation is widely used in estimating direct runoff because of its simplicity and flexibility.

In USDA-NRCS-CN technique, soils are classified into four hydrologic soil groups (HSGs) (A, B, C, and D) according to their minimum infiltration rate, which is obtained for a bare soil after prolonged wetting. Soils with HSG of A are sandy with less runoff potential and soils with HSG of D are clayey with high runoff potential. Figure 1 shows the hydrologic soils group of the basin.

To assess the runoff response of the basin as a result of land-cover change using the CN technique, a soil GIS coverage showing HSG was obtained from the State Soil geographic (STATSGO) database. The vector coverage of the HSG was converted to 30-m grid using GIS for spatial overlay of the data with that of the land-cover information. Since the STATSGO database has a scale of 1:250,000 and the soil map units identified in the database can have more than one HSG, county level soil survey maps were consulted to improve the accuracy of assigning HSGs.

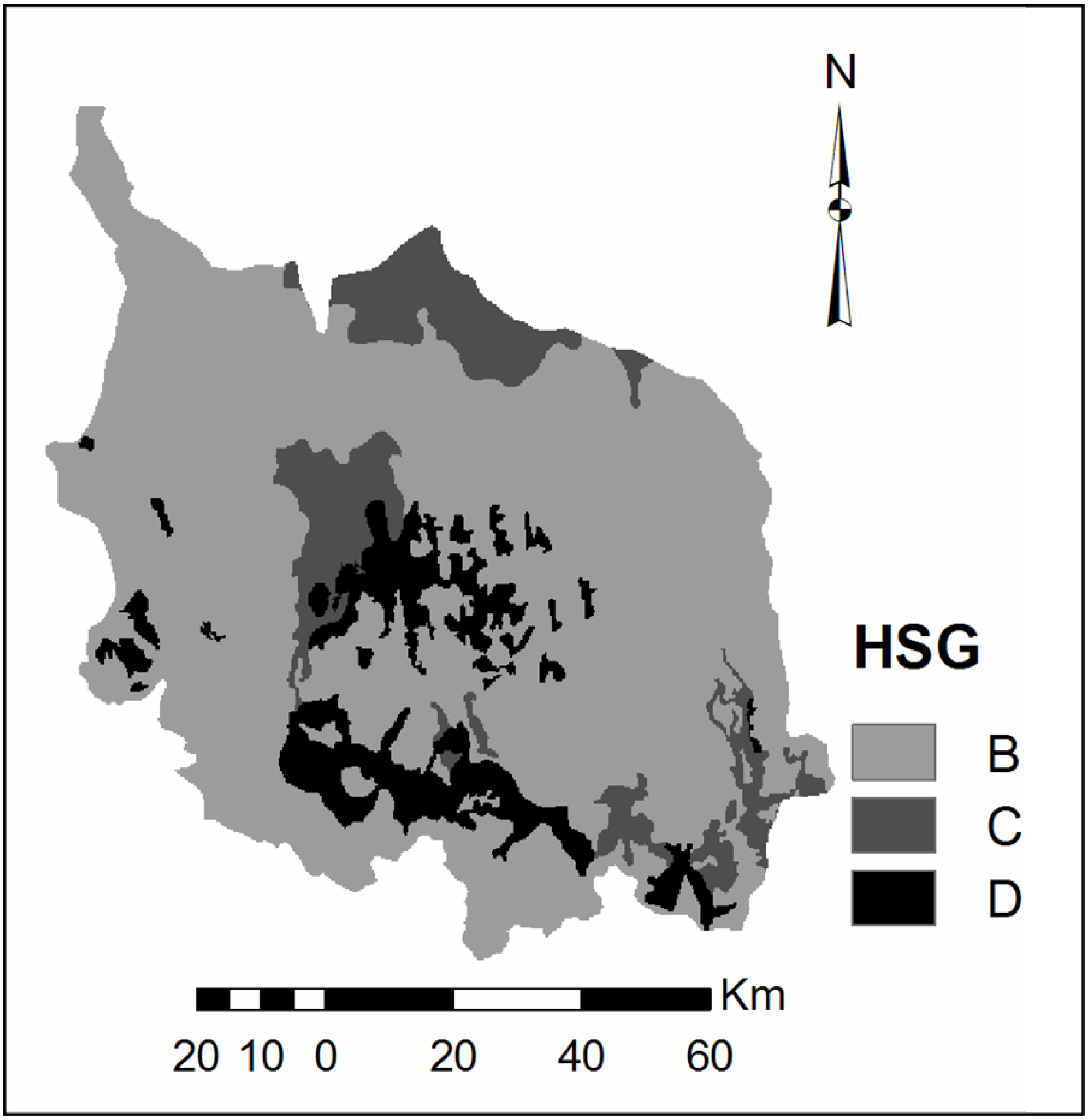

Figure 1 Hydrologic soils group (HSG) of the basin.

Land-cover for each respective year was derived from Landsat images using the procedure discussed in Melesse and Jordan (2002) and Melesse et al. (2003). Figure 2 shows the flow chart for mapping of the land-cover.
Once the spatially distributed excess precipitation was estimated, upstream inflow of runoff to each cell was computed using the flow accumulation script of grid GIS tools (ESRI, 2000). This estimate was used to compute the net runoff for each cell (Figure 3).

Calibration was done using the Elmore Coulee sub-basin and discharge data from nine isolated storms in 1995, 1996, 1998 and 2001. The calibrating sub-basin covers the drainage area flowing to Morrison Lake.

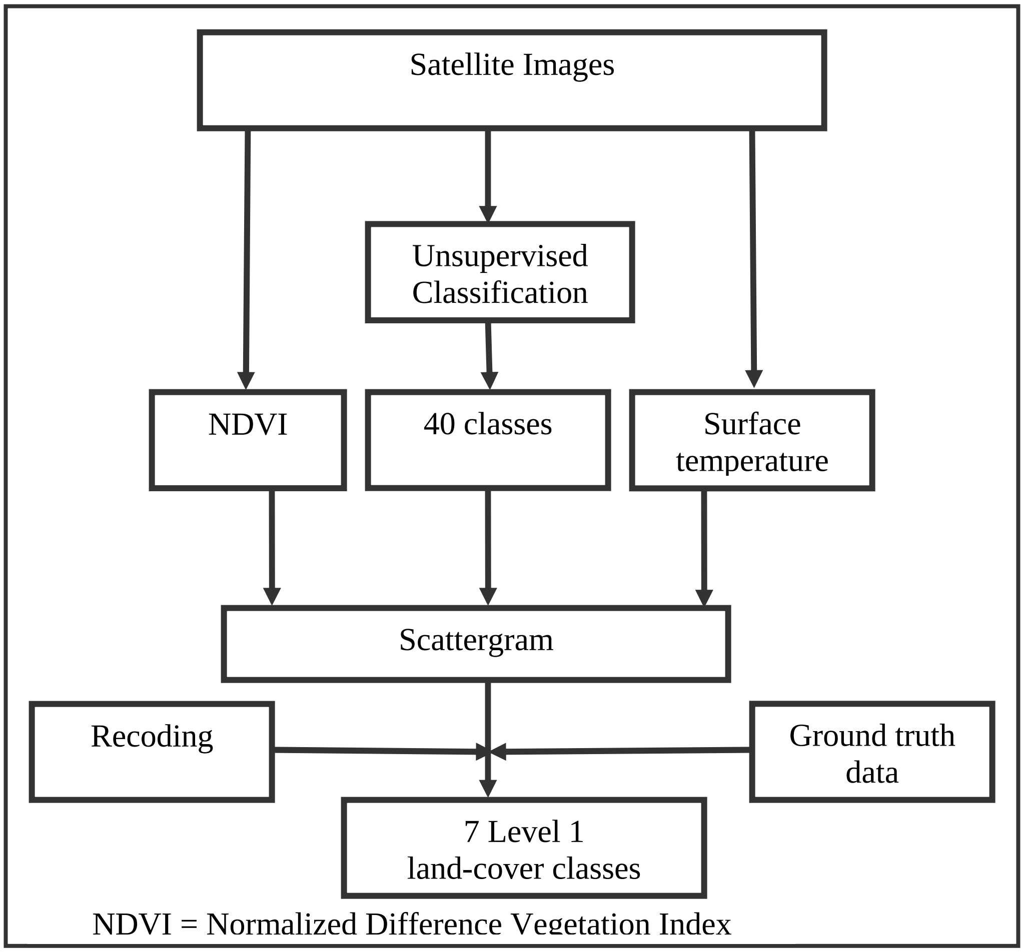

Figure 2 Flow Chart for Land-Cover Classification Using NDVI and Surface Temperature.

Evapotranspiration (ET)

Remote sensing based ET estimations using the surface energy budget are proving to be the most recently accepted technique for areal ET estimation (Morse et al., 2000). Surface Energy Balance Algorithms for Land (SEBAL) is one of such models utilizing Landsat and images from other sensors with a thermal infrared band to solve equation (4) and hence generate an areal map of ET (Bastiaanssen et al., 1998a; Bastiaanssen et al., 1998b and Morse et al., 2000).

SEBAL requires weather data such as solar radiation, wind speed, precipitation, air temperature, and relative humidity in addition to satellite imagery with visible, near infrared and thermal bands. SEBAL uses the model routine of Earth Resources and Data analysis System (ERDAS) Imagine, image processing software, in order to solve the different components of the energy budget equations. Figure 4 shows the evapotranspiration computation flowchart using the surface energy flux balance approach.

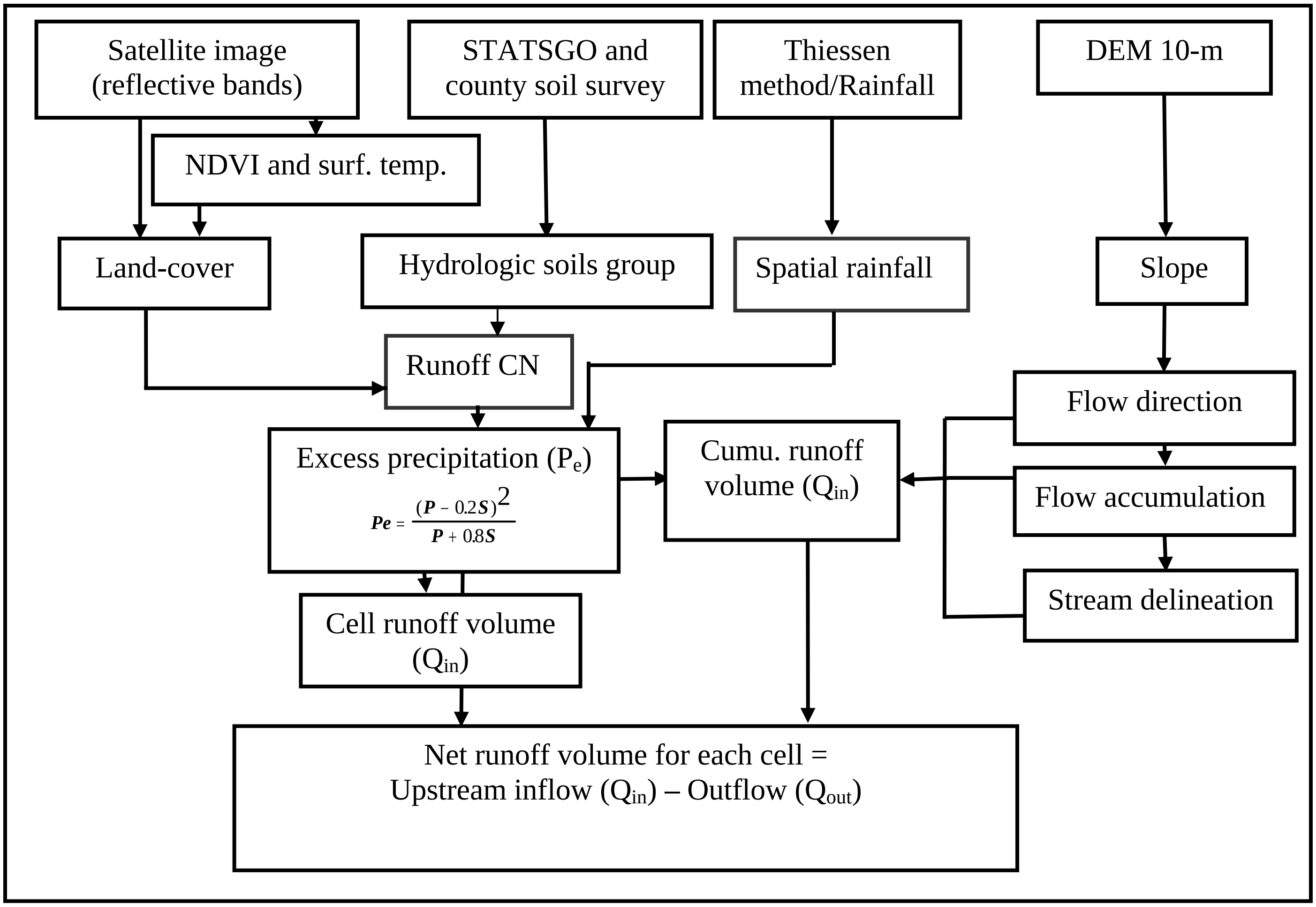

Figure 3 Flow Chart for Computing Grid-Based Spatial Net Runoff.

In the absence of horizontally advective energy, the surface energy budget of land surface satisfying the law of conservation of energy can be expressed as,

$$LE = R_n - H - G \qquad (\text{w/m}^2) \qquad (4)$$

where R_n is net radiation at the surface, LE is latent heat or moisture flux (ET in energy units), H is sensible heat flux to the air, and G is soil heat flux. Energy flux models solve equation (4) by estimating the different components separately. Latent heat (LE) was computed as residual using the energy balance equation and converted to ET values using latent heat of vaporization. The detailed description of the SEBAL model and computation of the model parameters is indicated in Bastiaanssen (1995), Bastiaanssen et al. (1998a) and (1998b) and Bastiaanssen (2000).

The adaptation of SEBAL for wetlands is reported in Oberg (2004), Oberg and Melesse (2006) and Oberg and Melesse (2004). Remote sensing-based ET estimates for each year of study were derived from an instantaneous ET at the time of the Landsat pass using four Landsat images per season (June, July, August and September). The instantaneous ET was extrapolated to daily and monthly values using the average reference ET (ET_r) at the time of Landsat pass. Using the monthly ET values, seasonal and yearly ET values were estimated. Reference ET is computed using the procedure described in FAO-56 (Allen, 1995; Allen et al., 1998).

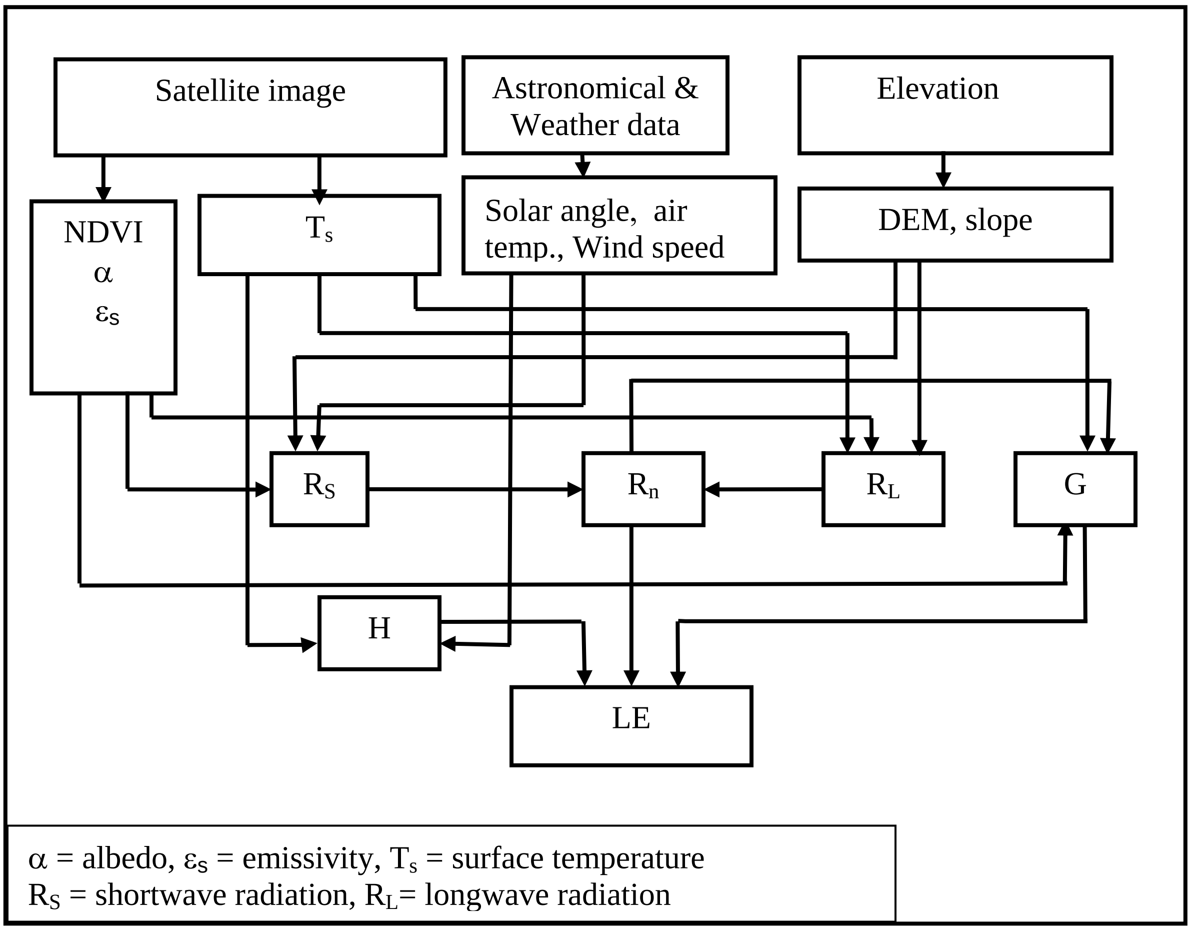

Figure 4 Flow Chart Showing Spatial Evapotranspiration Mapping Using Remote Sensing.

Storage

Once the components of the water budget are estimated for each grid, storage on a spatial basis was computed for each grid (Figure 5).

RESULTS AND DISCUSSION

Spatially distributed precipitation, runoff and evapotranspiration were computed for each year of study. Results show that in addition to the spatial variation, the annual variation of these hydrologic variables is also higher.

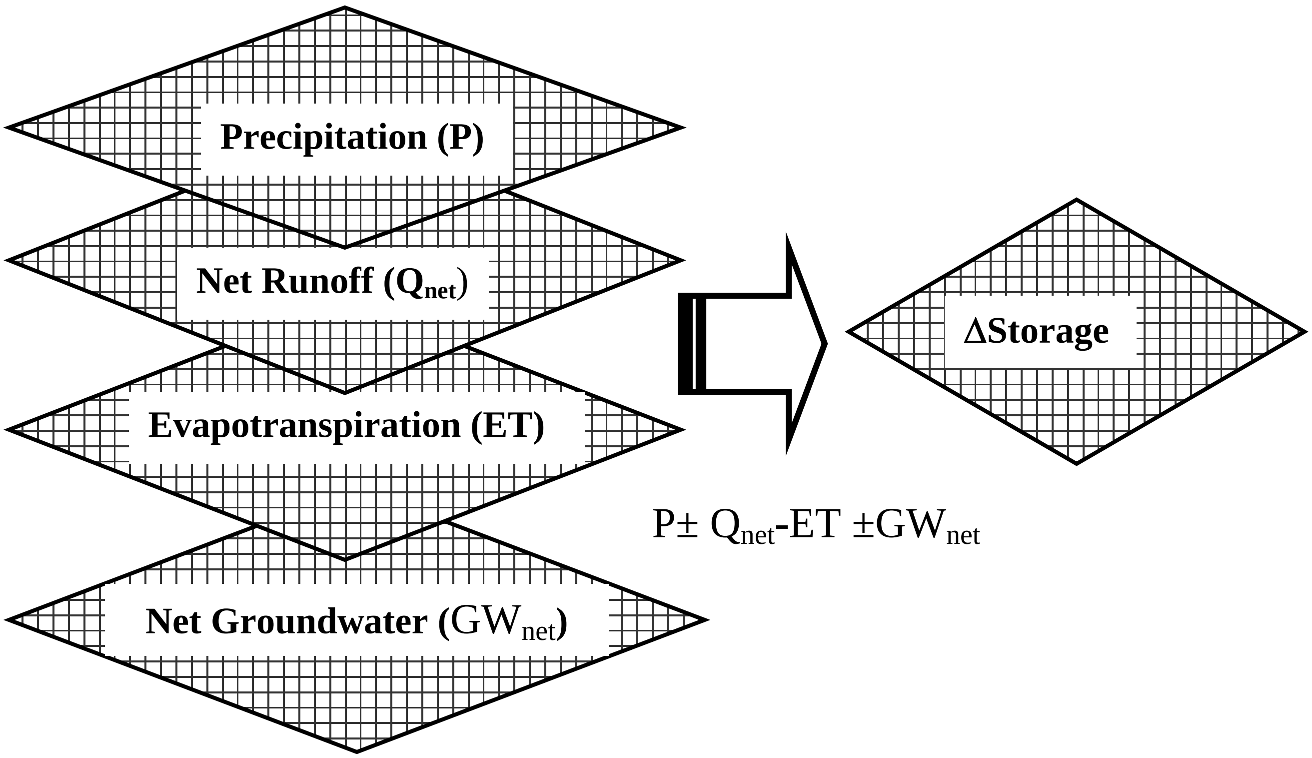

Figure 5 Flow Chart for Spatial Storage Computation.

Runoff estimation

Spatially distributed runoff at the pixel level was estimated and calibrated using gauged data from Edmore Coulee sub-basin (Figures 6). This sub-basin comprises watershed in the upper basin of Morrison Lake. Figure 6a shows daily discharge from the Edmore Coulee gauging station and precipitation from the Langdon rain gage station for the 10 year period (1993-2002). The calibrating sub-basin has a drainage area of 978 km^2 with discharge peaks in spring from snowmelt and also in summer from rainfall (Figure 6a). Nine isolated storms (1995, 1996, 1998 and 2001) were selected for the purpose of runoff calibration (Table 1 and Figures 6b-6e). Runoff depths from the CN technique were estimated and compared to the observed values at the Edmore Coulee gauging station. Uncalibrated data overestimated the runoff depth. The runoff curve numbers were adjusted to reflect actual runoff.

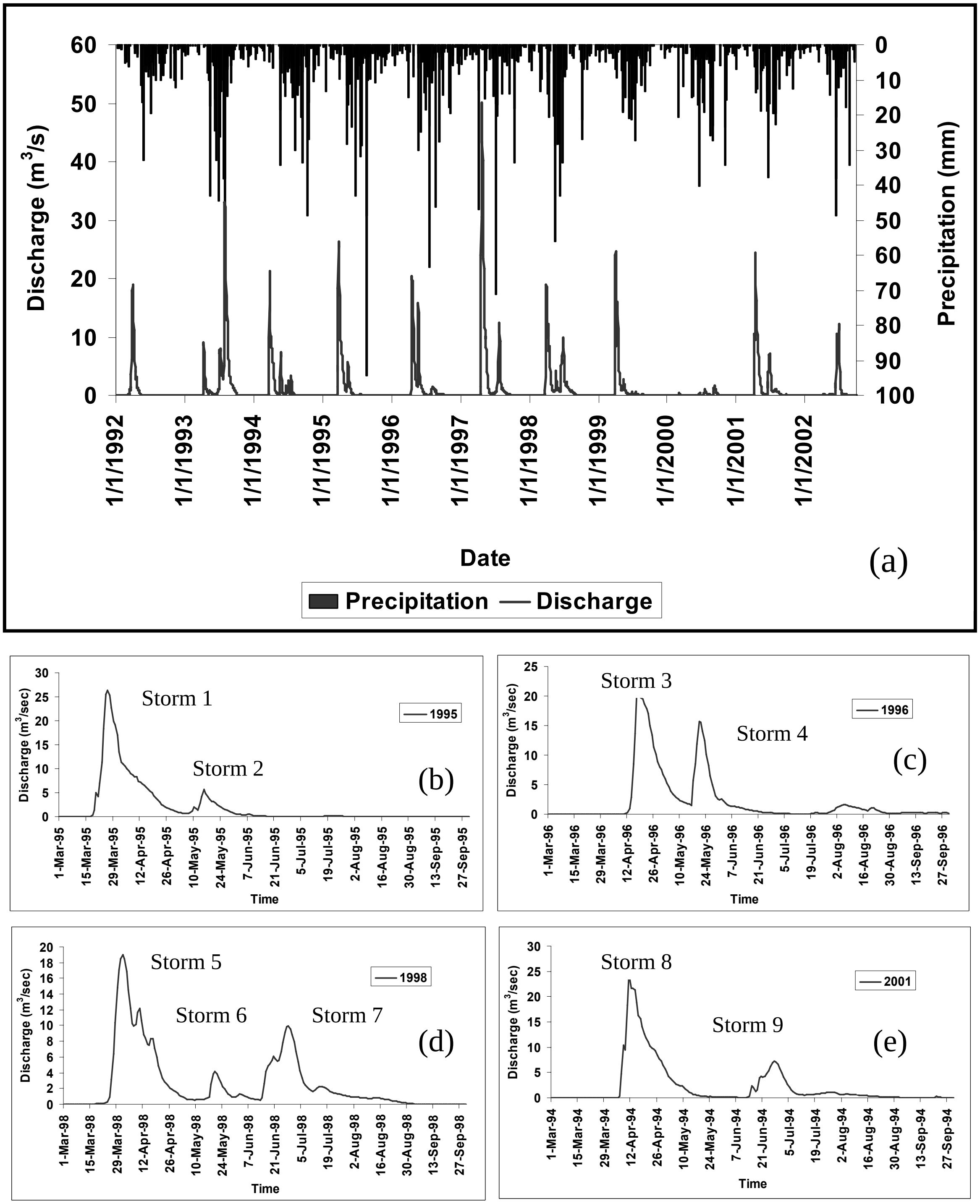

Figure 6 Daily Discharge and Precipitation of Edmore Coulee Sub-Basin (A) 1993-2002 (B) 1995 (C) 1996 (D) 1998 (E) 2001

Table 1. Runoff Calibration Storms and Runoff Depth

		Runoff depth (mm)		
Storm #	**Date**	**Observed**	**NRCS-CN**	**Calibrated**
1	3/20/1995	34.0	44	37.8
2	5/15/1995	5.5	8.9	6.4
3	4/15/1996	35.3	28.3	39.4
4	5/20/1996	12.3	8.6	8.1
5	3/25/1998	27.9	36.3	32.7
6	5/20/1998	4.3	11.1	8.1
7	6/15/1998	17.3	22.3	20.3
8	4/10/2001	30.6	27.2	25.5
9	6/10/2001	8.7	12.3	9.9

Evapotranspiration

A separate study was conducted at the Glacial Ridge wetland restoration site in Minnesota, 185 km east of Devils Lake basin, to monitor changes in ET from 2000-2003 using SEBAL approach using Landsat TM and ETM+ sensors. The study found the technique to predict the observed ET values with an average error of -4.3% (Oberg, 2004; Oberg and Melesse, 2006).

The annual storages for each grid cell were computed using grid GIS (Figure 7). The computed change in the average storage volume for the basin was compared to the observed change in the lake volume for each respective year. Comparison of the predicted and observed change in storage shows little agreement which can be attributed to (1) the observed values were taken from a point gauging station measured to the nearest cm, and (2) the complex hydrologic processes of the basin. This can be seen in the years 1997 and 2003, where the precipitation volumes were 472 and 481 mm, and the change in the lake's stage were 1.29 and 0.04 m, respectively. Table 2 shows a comparison of change in observed and modeled lake level during the years of this study. Results show the modeled change in lake storage under-predicts the observed values for 1994 and 1997, suggesting higher lake levels might be resulting from various hydrologic processes in addition to the processes and hydometeorological data discussed in this Part I of the study. Modeled values from 1991, 2000 and 2003 showed an over-prediction of the observed values. The average error of prediction was 0.12 m.

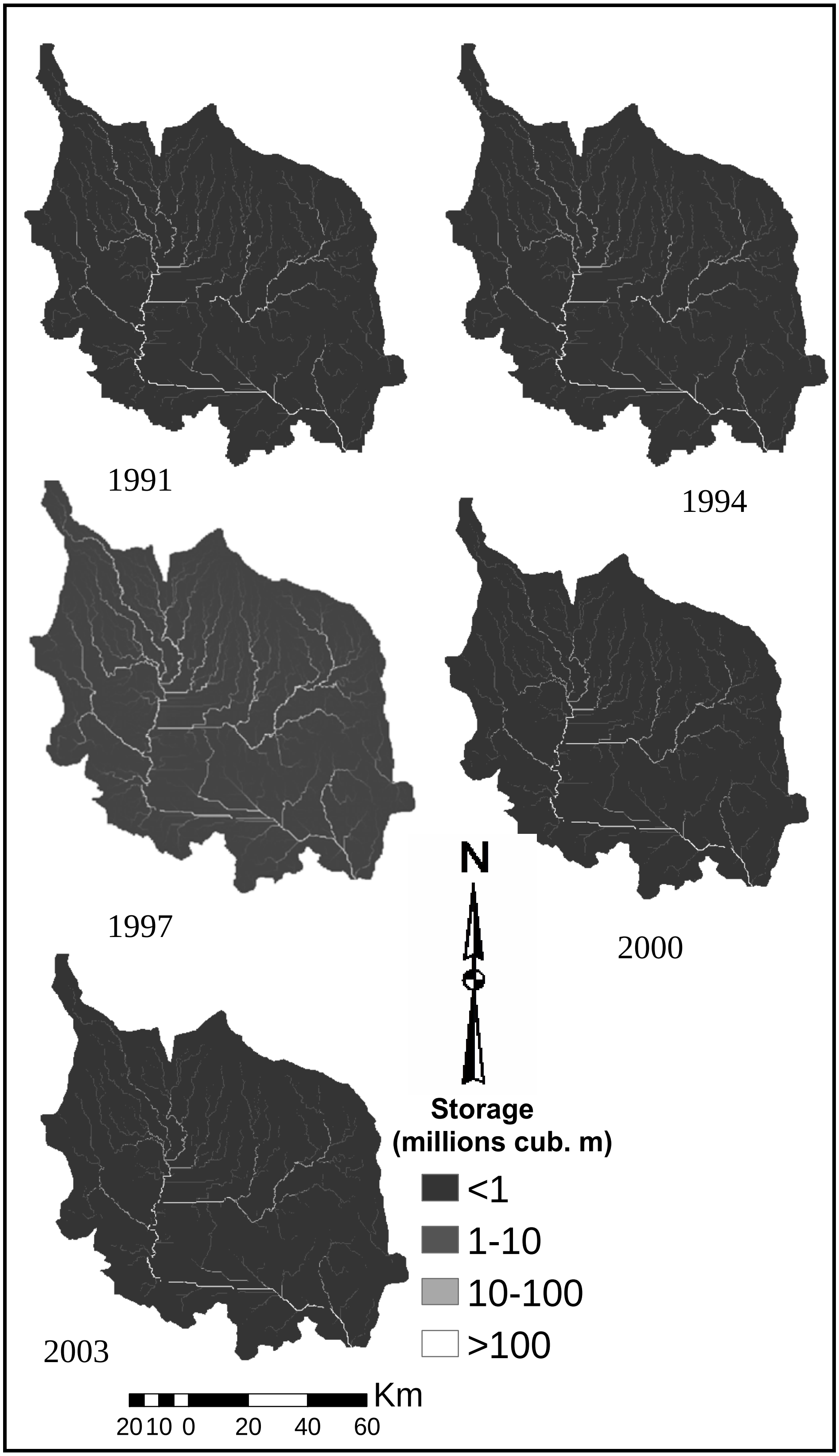

Figure 7 Spatial Map of Estimated Storage (A) 1991 (B) 1994 (C) 1997 (D) 2000 (E) 2003.

Table 2. Observed and Predicted Change in Lake Storage.

Year	∆ depth of lake Observed (m amsl)	Predicted (m amsl)	Error (m amsl)
1991	-0.27	0.37	-0.64
1994	1.52	0.66	0.86
1997	1.29	0.34	0.95
2000	0.06	0.35	-0.29
2003	0.01	0.27	-0.26
Ave	**0.52**	**0.40**	**0.12**

Conclusion

Remotely-sensed data from Landsat TM and ETM+ sensors were used in the study to estimate the spatial water balance of the Devils Lake basin. Components of the surface water budget (precipitation, surface runoff, and evapotranspiration) were computed at the pixel level to estimate the change in surface water storage. The methodology employed estimates the observed lake rise with an average error of 0.12 m.

The grid GIS-based surface water balance estimation was comparable to the observed stage of the lake. The high errors of prediction can be attributed to the complex nature of the runoff response of the basin, underestimation of the groundwater contribution as indicated by prior studies, and the precision of the observed lake stage record. Observed lake stage was measured at a location near the City of Devils Lake. The authors suggest a monthly water balance approach aggregated to seasonal and yearly estimates may improve the results.

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