Spatial distribution of global runoff and its storage in river channels

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Spatial distribution of global runoff and its storage in river channels

Abstract
The present dissertation attempts to improve our current understanding of some of the key elements of the surface runoff and its horizontal transfers in rivers. The dissertation presents an intensive analysis of the uncertainties in water balance calculations and the impact of uncertainties in the input data and the formulation of the water balance calculations on the runoff estimate. A simple technique is presented to combine observed river discharge and simulated runoff to derive accurate estimates of the spatially distributed runoff. Such composite runoff estimates are valuable for numerous earth science and water resource studies.

The dissertation also discusses the representation of river networks for flow simulations. The performance of simulated river networks is analyzed with respect to resolution which provides guidance for the design of simulated river networks. New relationships are developed between river discharge and the riverbed geometry. These relationships provide the basis for the design of flow routing schemes incorporating the complete hydraulic dynamics of the riverine flow in the flow simulations.

The dissertation demonstrates the use the composite runoff in a simulated river network context and the application of the relationships relating river discharge to flow properties to estimate the volume and surface of waters stored in rivers. The estimates agree well with previous estimates published in the scientific literature, but provide more insight into the spatial distribution of river water storage.

Keywords
Hydrology
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Spatial Distribution of Global Runoff and its Storage in River Channels

BY

BALÁZS M. FEKETE

Master of Science, Technical University of Budapest, 1984

DISSERTATION

Submitted to the University of New Hampshire in partial fulfillment of the requirements for the degree of

Doctor of Philosophy in Earth Sciences

May 2001
This dissertation has been examined and approved.

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May 16, 2001
Date
Dedication

To My Father

In fulfillment of the over 150 years of family heritage demanding that male descendents earn a doctoral degree.
Acknowledgments

First of all, I would like to express my thanks to Charlie Vörösmarty for inviting me to be a part of his team and encouraging me to continue learning and pursuing my interests. Over the years, he initiated exciting research projects and brought together a dynamic research group with such excellent colleagues as Richard Lammers.

Although I already dedicated this dissertation to my father who, besides putting pressure on me to earn a doctoral degree was influential in building my curiosity in the world around me. He and my late sister (who passed away so young) were instrumental in orienting me toward and generating enthusiasm in the engineering and earth sciences.

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ABSTRACT

Spatial Distribution of Global Runoff and its Storage in River Channels

by

Balázs M. Fekete
University of New Hampshire, May, 2001

The present dissertation attempts to improve our current understanding of some of the key elements of the surface runoff and its horizontal transfers in rivers. The dissertation presents an intensive analysis of the uncertainties in water balance calculations and the impact of uncertainties in the input data and the formulation of the water balance calculations on the runoff estimate. A simple technique is presented to combine observed river discharge and simulated runoff to derive accurate estimates of the spatially distributed runoff. Such composite runoff estimates are valuable for numerous earth science and water resource studies.

The dissertation also discusses the representation of river networks for flow simulations. The performance of simulated river networks is analyzed with respect to resolution which provides guidance for the design of simulated river networks. New relationships are developed between river discharge and the riverbed geometry. These relationships provide the basis for the design of flow routing schemes incorporating the complete hydraulic dynamics of the riverine flow in the flow simulations.

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INTRODUCTION

Water resources are among the most significantly disturbed natural resources. Despite the importance to human society, they have been neglected elements of the global change question (Vörösmarty, 1997). Global change studies tend to focus on changes in the atmosphere, although hydrologic processes are already significantly altered by human activities. Water is becoming the most important environmental question (Vörösmarty et al., 2000c; Falkenmark, 1991) and limiting natural resource. Although water resources are getting increasing attention only a few steps have been made to assess the available water resources and estimate its human disturbance. Current assessments of water resource components (Korzoun et al., 1978), such as annual runoff, water storage in rivers, lakes and ground-water are based on the extrapolation of observed discharge hydrographs and river bed surveys to non-measured river basins or tributaries. Current estimates are generally imprecise (Postel et al., 1996). For example, annual runoff estimates range from 33,500 km³ to 47,000 km³ (L’Vovich and White, 1990).

Besides the direct importance of the water to human society, the water cycle is a crucial element of the atmospheric processes. Atmospheric scientists traditionally did not pay much attention to runoff and its horizontal transfers over the landscape. They considered runoff as a surplus of water leaving the domain of their interest, but this is changing as atmospheric scientists are recognizing the potential of closing the water budget on discharge gauged watersheds (Gutowski et al., 1997; Hagemann and Dümenil, 1998). River discharge – which is an aggregated signal of the terrestrial runoff – is the most accurately measured component of the water cycle (Fekete et al., 1999; Hagemann and Dümenil, 1998) and therefore it can serve as an important constraint for Global Circulation Models.
The estimates of the contemporary water resources can be improved by collecting and assembling state of the art global data sets and using more sophisticated spatial data analysis and modeling tools. Combining different data sets and simulations helps to find inconsistencies among data sets and to potentially identify errors. Spatial data analysis and modeling can improve not only the current estimates but offer the capability of analyzing the spatial and temporal distribution of continental water resources.

By assembling improved data sets on the water resources components the following questions can be answered:

- What is the spatial and temporal distribution of runoff on the continental land mass?
- How is the continental runoff transferred horizontally on the landscape? What are the delays and what is the distribution of the residence times of the continental runoff? What are the natural and human factors controlling the timing of the continental runoff delays?
- How do human activities, such as damming, irrigation, etc. affect these fluxes?
- What are the discharge fluxes to oceans? What are the impacts of the continental runoff delays on the temporal distribution of discharge fluxes to oceans?

The spatial distribution of runoff is essential information for water resource assessment and closing the water budget in soil vegetation atmosphere transfer (SVAT) schemes. The understanding of the typical time delays (both natural and human induced) in the horizontal water transfers is critical for linking the river discharge observation and SVAT schemes. The river discharge fluxes to oceans also affect significantly the coastal ecosystems.

The present dissertation work focuses on the first question and addresses some elements of the riverine water transport. It presents a series of sensitivity analyses demonstrating the limitations of the water balance calculation due to uncertainties in the land surface characterization (e.g. land use, soil categories and the corresponding parameterization of
land cover and soil types), and potential errors in the forcing data (e.g. air temperature, precipitation, etc.).

The dissertation demonstrates the importance of validating water balance analysis against measured discharge and presents a technique to blend simulated runoff with observed discharge. Such data sets can provide the most accurate estimate of the continental runoff since it preserves the details of the spatial and temporal distribution of the water balance model simulated runoff but constrained by measured discharge.

The dissertation also attempts to estimate the total water volume in rivers by applying a simple relationship between river discharge and river-bed geometry. This analysis is an important first step in assessing the residency times and the potential time delays in riverine water transport. The presented experiments give some guidance about the potential limitation of simulated gridded networks and the achievable improvements from using finer resolution networks.

The dissertation is organized in three chapters. The first is a brief introduction to the GIS terms and concepts applied in the present dissertation. It gives a short description of the special features of the Global Hydrological Archive and Analysis System (GHAAS) developed at UNH. Most of the GHAAS package was actually developed by the author prior to and throughout the course of his Ph.D. research.

The second chapter of the dissertation discusses the runoff generation processes and the uncertainties in water balance calculations. This chapter presents the sensitivity analysis of the water balance calculations, and demonstrates the impact of uncertainties in the input forcings. This chapter briefly describes the procedure of combining observed discharge and simulated runoff. This technique was developed by the author of this dissertation and his advisor in a joint research with the Global Runoff Data Center, Koblenz, Germany. The detailed documentation of this work was published by GRDC as a technical report (Fekete et al., 1999). A shortened version of the report was submitted to Global Biogeochemical Cycles, and at the time of writing passed the first round of the review process (Fekete et al., 1999).
The third chapter discusses the representation of river networks and the formulation of an idealized river-bed geometry and its use to assess the volume of water stored in rivers and the flow characteristics such as depth, width and mean velocity. This chapter analyzes the impact of resolution on the performance of the simulated river network and on the large scale pattern of river surfaces and volumes. The analysis of the spatial distribution of river networks was carried out by applying a network rescaling algorithm (Fekete et al., 2001b) developed by the author and the primary advisor of this dissertation. This algorithm was recently accepted by Water Resource Research for publication. The linkage of the river network and the idealized river bed geometry is demonstrated by using the composite runoff fields, presented in chapter 2 in a simple flow-accumulation scheme.

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Chapter 1

GIS Representation of the Hydrological Data

Hydrological studies by nature require spatial analysis. Geographical Information Systems evolving in the last 20 years have offered the necessary tools to represent spatial features numerically. The present chapter briefly summarizes the GIS concepts used throughout the dissertation and some of the special features offered by the Global Hydrological Archive and Analysis System (GHAAS) developed by the Water System Analysis Group (primarily by the author of the present dissertation).

1.1 Surface Data

GIS technology offers different approaches to represent surfaces numerically (such as irregular triangular networks, contour lines, regular grids). One of the most popular techniques is the grid representation, which divides the domain of interest into equally sized rectangular areas and assigns values to the individual cells. Such a mesh is often called grid and the individual rectangles are referred as a grid cell.

In the present dissertation, surface grids are used to represent climate variables and other components of the hydrological cycle, such as air temperature, precipitation, runoff and soil moisture or land surface characteristics such as elevation or surface slope. However, the
grid representation of surfaces has numerous limitations, most notably the limited scaling capability, but the simplicity of using grids out-weights the limitations in most applications.

Traditional GIS software packages often handle single layer grids only. Bundling of several surface layers is often convenient. For instance, time series of gridded precipitation can be conveniently handled as one multilayer data set, where the individual layers represent time steps. GHAAS was designed to manage and manipulate multilayer gridded data. All of the grid manipulation functions implemented in GHAAS apply the function to all layers in the data set speeding up many multilayer analyses.

1.2 Categorical Data

Categorical information such as land use or soil types can be represented by a polygon as vector coverage where the bounding outlines of the regions with uniform categories are stored as a series of vertex coordinates, or regular grids similar to the ones used to represent surfaces. The GHAAS software has the basic functionality to handle polygon data, but mostly for display purposes. Vector representation of categorical information is typically more scalable than the grid representation, but the simplicity of the grid manipulation particularly the overlay operations again out-weight the potential advantages of using vector coverage in many applications. Therefore the grid representation of the categorical data is the primary means in GHAAS for performing spatial analysis.

Unlike most GIS software, GHAAS strictly distinguishes surface and categorical grids. The rational to do so is the fundamental difference in the meaning of the grid values in the surface and the categorical data sets. This difference is most apparent when the gridded data has to be resampled at a different resolution. While the preferable method of resampling continuous grids is typically a distance weighted averaging, the same kind of averaging is meaningless on categorical grids. Furthermore categorical grids in GHAAS can have any number of attributes associated with the distinct grid values. For instance, different land-
use categorizations can be treated as one data set, where the individual grid values can be mapped to different land-use categorization schemes.

1.3 River Networks

The most important element of GHAAS is its unique representation of rivers. Conceptually, river networks can be represented either as vectors (series of vertices) or flow direction grids. Similarly to the representation of categorical information, vector representation of rivers is potentially more scalable, but lacks the linkage between the river and the it surrounding tributaries. Some sort of combination of vectors (representing the rivers) and corresponding polygons delineating the tributaries would solve this problem, but this approach is rarely used due to the complexity of performing overlay manipulations with such data sets. A gridded approach, where the individual grid cells represent a flow direction to one of the four or eight neighboring grid cells, offers a simpler solution. Such a network grid is capable of representing not only the rivers themselves, but the connectivity of the land mass.

The gridded network representation in GHAAS (figure 1-1) differs from traditional gridded networks by maintaining a separate topological table for each grid cell which contains network derived information about the individual grid cells such as catchment area, distance to ocean, basin identifier, etc. However, this approach adds significant overhead to the data set, but reduces the need to do network searching when these derived attributes are needed. Furthermore, the topological sorting of the cell records (i.e. the cells are sorted by catchment area) simplifies the development of flow routing schemes. Since the grid cells with larger tributaries are preceded by the cells with smaller tributaries, a flow routing scheme can rely on the assumption that by advancing from the bottom to the top of the cell table all the inputs from the upstream cells were already collected.

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Figure 1-1: RiverGIS as part of the GHAAS package offers special tools. Simulated Topological Network in RiverGIS view window. RiverGIS as part of the GHAAS package offers special tools to manipulate gridded networks. This figure shows the North American portion of STN-30p simulated topological network at 30' resolution. The catchment area of the Missouri river is highlighted and the STN-30p derived attributes are displayed in the RiverGIS query window on the left.
1.4 Point Data and the Corresponding Inter-station Regions

The fourth important data type in the present dissertation is the point data. Point data are often representing objects which are related to the nearby passing river networks (such as discharge gauging stations or reservoirs). The GHAAS package allows the co-registration of such related point data sets to a gridded network where the co-registration not only moves the individual point objects to the best fitting neighboring network grid cells but also allows the delineation of attributes derived from the gridded network, such as upstream area, downstream distance to ocean, and station topology given as the identifier of the next downstream station.

GHAAS also allows the delineation of the inter-station regions (the catchment area between upstream and downstream gauging stations) of each individual stations. The delineated tributaries are represented as categorical grids where grid values are the unique identifiers of the station. The resulting categorical grid inherits all the station attributes from the original point data set. Figure 1-2 shows the inter-station regions of the Danube basin.
Chapter 2

Spatial Distribution of Runoff

As the First Symposium in Scale Problems in Hydrology in 1982 pointed out the main problem in hydrology is not the horizontal routing of water, but how much water to route (Beven, 1995) (i.e. how to estimate runoff). Spatially distributed runoff is not measured directly. River discharge, which is a spatially and temporally integrated signal of the runoff, is monitored routinely. Spatially-distributed runoff estimates can be derived from land surface hydrology models, which rely on either climate data or atmospheric model outputs such as precipitation, air temperature, radiation, vapor pressure, wind speed (Vörösmarty et al., 1989) and from atmospheric vapor budget calculations (Browning and Gurney, 1999). When observed climate forcings are used, potentially large errors in their geographic specificity can arise. This problem is widely recognized in the climate research community (Willmott and Rowe, 1985) where such errors can then propagate through the water budget calculations (Vörösmarty et al., 1998) and thereby considerably compromise the accuracy of the computed water budgets.

Section 2.1 of the present chapter discusses the basis of the water balance calculation, the available data sets and presents and analysis of the key uncertainties affecting the potential accuracy of estimating runoff from climate forcings. Due to its special importance, the uncertainties and the impact of precipitation as an input for water balance calculations are discussed in a separate section 2.2. Section 2.3 describes the method developed in joint research with the Global Runoff Data Center, Koblenz, Germany to develop composite runoff fields combining the observed discharge with simulated water balance runoff. Such
composite fields represent our best estimate of the continental runoff since they are benchmarked to the very accurate measured discharge and yet preserve the spatial distribution of the water balance model runoff.

2.1 Water Balance Calculation

Water balance calculations based on climate input data and proper land surface characterization can provide spatially distributed runoff, which is important information in most hydrological studies. Section 2.1.1 gives an overview of the basic concepts of the water balance calculations. Section 2.1.2 briefly summarizes the global data sets available today for hydrological studies. Section 2.1.3 describes one particular implementation of the water balance calculations. This model was developed by Vorosmarty et al. (1989) and provided the basis for all of the water balance analysis in the present dissertation. Section 2.1.4 discusses the uncertainties in WBM due to the different formulation of the water balance calculations. Section 2.1.5 demonstrates the impact of uncertainties in the input climate variables (except precipitation which is discussed in section 2.2) on the water budget estimates.

2.1.1 Basic Concepts of the Water Balance Calculations

The first soil moisture budget was given by Thornthwaite (1948) as

\[ R = P - E - \frac{\partial W}{\partial t} \]  

(2.1)

where

- \( \frac{\partial W}{\partial t} \) - change in soil moisture \([L/T]\)
- \( P \) - rate of precipitation \([L/T]\)
- \( E \) - rate of evapotranspiration \([L/T]\)
- \( R \) - rate of surplus water (runoff and/or recharge) \([L/T]\)
He proposed a relatively simple procedure for estimating land-surface evaporation (Thornthwaite, 1948; Thornthwaite and Mather, 1955). He introduced the concept of potential evapotranspiration (PET) as an upper limit to evapotranspiration in given atmospheric conditions when the evapotranspiration is not limited by water stress. Thornthwaite formulated the soil moisture budget given by equation 2.1, and expressed evapotranspiration as a function of available soil moisture and the rates of precipitation and potential evapotranspiration (Willmott and Rowe, 1985):

\[
E = \begin{cases} 
  P + \beta(W, W^*) [E_0(T, h) - P], & P < E_0(T, h) \\
  E_0(T, h), & P \geq E_0(T, h)
\end{cases}
\]  

(2.2)

where

- \( T \) - daily average air temperature [°C]
- \( h \) - duration of the daylight [hour]
- \( E_0, (T, h) \) - potential evapotranspiration [mm/day]
- \( W, W^* \) - soil moisture and soil moisture storage capacity [mm]
- \( \beta, (W, W^*) \) - function that relates actual to potential evaporation or, more specifically \([(E - P) / (E_0 - P)]\) to \( W/W^* \)

Numerous methods have been proposed to calculate potential evapotranspiration since Thornthwaite published his concept. Federer et al. (1996) gave a summary of the most frequently used methods. Vörösmarty et al. (1998) studied the impact of the choice of PET method on water-balance estimates (Vörösmarty et al., 1998) and concluded that it had more importance in wet regions, where evapotranspiration is not limited by the availability of water (i.e. \( E = E_0 \)), than in dry regions where the soil moisture \( W \) approaches the wilting point \( W_0 \), the \( \beta, (W, W^*) \) function approaches 0:

\[
\lim_{W \to W_0} \beta(W, W^*) = 0
\]  

(2.3)
and the evaporation becomes limited by the precipitation (i.e. $E = P$). Applying different PET methods on 679 US watersheds Federer et al. (1996) found Hamon’s formula (Hamon, 1963) gives the least bias among the “reference crop” methods which are designed to represent a generic land-cover (typically a short, complete green plant cover, employed in experimental plot studies with dry leaf surfaces and “well-watered” soil).

Vörösmarty et al. (1998, 1989) applied a variant of the Thornthwaite soil moisture budget as a Water Balance Model (WBM) at continental and global scales. They expressed soil-moisture change ($\frac{\partial W}{\partial t}$) as a function of the soil-moisture ($W$), the soil’s water holding capacity ($W_c$), potential evaporation ($E_0$), precipitation ($P_a$) available for soil recharge as rainfall and any snow-melt:

$$\frac{\partial W}{\partial t} = \begin{cases} g(W)(E_0 - P_a); & P_a < E_0 \\ P_a - E_0; & 0 < P_a - E_0 < W_c - W \\ W_c - W; & W_c - W < P_a - E_0 \end{cases}$$

(2.4)

where $g(W)$ is a unitless soil drying function given as

$$g(W) = \frac{1 - e^{\frac{-P_a}{W_c}}}{1 - e^{-\alpha}}$$

(2.5)

with $\alpha$ an empirical constant. Evaporation becomes:

$$E = \begin{cases} P_a - \frac{\partial W}{\partial t}; & P_a < E_0 \\ E_0; & E_0 \leq P_a \end{cases}$$

(2.6)

Recent modifications to WBM use quasi-daily time steps to reduce the temporal aggregation bias arising from the use of monthly climatic variables. Monthly precipitation is divided into daily wetting events by applying a probability function based on Rastetter et al. (1992). Precipitation is considered snow when the monthly temperature is below -1 [$^\circ$C].
Snow-melt is a prescribed function of temperature and elevation as given by Vörösmarty et al. (1989, 1998). Runoff is formed either as snow-melt or when the surplus from the difference between precipitation and evaporation \((P - E)\) exceeds soil moisture deficit \((W_c - W)\).

WBM maintains a simple runoff retention pool \((D_r)\) to represent the runoff delay caused by water transport through ground-water before it enters river channels. The runoff retention pool dynamics is expressed with the following differential equation:

\[
\frac{dD_r}{dt} = (1 - \gamma) R - \beta D_r
\]

where \(R\) is the soil moisture budget runoff from equation 2.1 and \(\gamma\) and \(\beta\) are empirical constants. The river runoff \((R_r)\) then becomes:

\[
R_r = \gamma R + \beta D_r
\]

2.1.2 Global Datasets Available for Water Balance Studies

Global land-surface characterization data sets assembled in the late 1980s and early 1990s (e.g. ETOPO5 Global Elevation Data Set (Edwards, 1989), Olson’s land use characterization (Olson, 1991) and FAO Soil characteristics (FAO/UNESCO, 1986)) had coarse resolutions and were often inaccurate representations of the ecosystem components. The typical spatial resolution was in the range of 5-10' to 2-5°. These data sets were developed mostly to satisfy the needs of Global Circulation Models, which tended to operate at coarse spatial resolutions. Newer land surface data sets are spatially much more resolved (e.g. GTOPO30, HYDRO1k and GLOBE digital elevation data sets (Gesch et al., 1999; USGS EROS Data Center, 1996; USGS EROS Data Center, 1998b), Global Land Cover Characteristics Data Base (USGS EROS Data Center, 1998a)). The spatial resolution of these new data sets, typically around 1 km or 30", were developed to satisfy the needs of the earth ecosystem modeling community.
Climate data sets (such as gridded air temperature and precipitation fields) developed in the early 1990s had similar coarse resolution as the land surface characterization data sets. The temporal resolutions were also limited to long-term mean monthly values (Leemans and Cramer, 1991; Legates and Willmott, 1990a; Legates and Willmott, 1990b). Recently released climate data sets still maintain the relatively coarse 30' to 2° resolution but they provide monthly mean time series for various time periods (New et al., 1998a; New et al., 1998b; Willmott, 1999; Huffman et al., 1995; Rudolf et al., 1994). Appendix A summarizes the global data sets available at the Water Systems Analysis Group, University of New Hampshire. These data sets provided the basis for most of the water balance experiment in the present dissertation.

2.1.3 Water Balance Model

In the present dissertation, UNH's water balance model (WBM) was used. This formulation of the water balance calculations was originally developed by Vörösmarty et al. (1998, 1989) and was applied successfully in regional (Vörösmarty et al., 1998, 1996, 1989) and global scale (Fekete et al. 2001a, 1999) studies. The current version of the water balance model is highly modularized and can be configured to use a variety of components performing certain elements of the water balance calculations. One of the most significant components is the calculation of potential evaporation (Vörösmarty et al., 1998; Federer et al., 1996).

WBM can be configured with a number of potential evapotranspiration functions ranging from the simple reference crop type formulas (such as Thornthwaite (1948), Hamon (1963) Turc (1961) and Jensen and Haise (Federer et al., 1996)) to more sophisticated cover dependent formulas (Federer et al., 1996) (such as Penman's method (Penman, 1948), Priestley and Taylor (1971), McNaughton and Black (1973), Penman-Montieth (Monteith, 1973) and Shuttleworth and Wallace (1991)).

The original concept of potential evapotranspiration was to define PET as an atmospheric water vapor deficit or demand as a function of atmospheric variables only. The
reference crop type formulas satisfy this criteria since they typically require only the air
temperature solar radiation and vapor pressure at the most. Cover dependent PET methods
recognize the impact of the canopy and incorporate some land cover dependent resistance
in the PET calculation. Penman-Monteith method (Monteith, 1973) introduces canopy
resistance to account for the failure of the surface to be effectively saturated. Shuttleworth-
Wallace method takes into account the evaporation from soil and from the canopy and the
transpiration of the leaves (Shuttleworth, 1991). Shuttleworth and Wallace introduced five
resistance terms:

- resistance to movement of water vapor out of the leaves
- resistance from the surface of the leaves to the source height of the canopy
- resistance to movement of the water vapor from inside the soil to the surface of the
  soil
- resistance from the ground surface to the effective source height, and
- resistance to movement from the source height to the atmosphere.

The last resistance term is common for the soil evaporation and the canopy evapotranspi-
ration and it is controlled by aerological variables.

2.1.4 Structural Sensitivity Analysis of WBM

WBM calculations have two main sources of uncertainty, the first is the effect of the in-
ternal configuration and parameterization, the second is the external uncertainty in the
input data. In this section only the internal structural uncertainties are demonstrated,
and the uncertainties in the input data are discussed in separate section. The structural
uncertainties of WBM were assessed through sensitivity analysis. WBM configured with
Shuttleworth-Wallace PET function using the CRU climate data set served as the baseline
for this sensitivity analysis. The CRU data holding had all the climate variables WBM would use with the most complex PET configurations. The following structural uncertainties were tested:

- sensitivity to the choice of potential evaporation function
- sensitivity to land use parameterization
- sensitivity to rooting depth

Meaningful graphical representation of the differences between more than two spatial data set is difficult in the two-dimensional figure space. The spatial integration helps to reduce the number of dimensions to be presented, but potentially hides significant differences between spatial data sets. In the following sections, the results of various water balance model results are integrated over latitudinal bands (reducing one dimension of the spatial data sets), so the differences among more than two data set can be visualized in single plots. While this integration helps to summarize major differences, it may hide significant differences in the underlying spatial patterns.

**Sensitivity to the Choice of Potential Evapotranspiration Functions**

The sensitivity to the choice of potential evaporation function was tested by running WBM with three cover independent (i.e. reference crop type) and three cover dependent PET functions. The tested PET functions and their data needs are summarized in table 2.1

Figure 2-1 shows the latitudinal profile of the continental mean annual runoff (i.e. the annual runoff averaged by latitudinal bands). The six different function show more consistent behavior in the mid-latitudes, while there are widening disparities in the tropics and the high latitudes. The cover dependent functions clearly have a tendency to produce less runoff in the tropics. Similar trends can be seen on figure 2-2a which shows the spatial distribution of the range of runoff using the different PET functions, however looking at
Table 2.1: Summary of the tested potential evaporation functions and their data needs.

<table>
<thead>
<tr>
<th>PET Function</th>
<th>Input Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Thornthwaite</td>
<td>air temperature</td>
</tr>
<tr>
<td>Harnon</td>
<td>air temperature</td>
</tr>
<tr>
<td>Jensen and Haise</td>
<td>air temperature, solar radiation</td>
</tr>
<tr>
<td>Priestley and Taylor</td>
<td>air temperature, solar radiation, vapor pressure</td>
</tr>
<tr>
<td>Penman and Montieth</td>
<td>air temperature (mean, minimum and maximum), solar radiation, vapor pressure, wind speed</td>
</tr>
<tr>
<td>Shuttleworth and Wallace</td>
<td>air temperature (mean, minimum and maximum), solar radiation, vapor pressure, wind speed</td>
</tr>
</tbody>
</table>

The relative range expressed shows a different picture (Figure 2-2b). The relative range of differences caused by the use of different PET functions is actually higher in dry regions. In both the absolute and relative range, there is an apparent high consistency in those regions where WBM does not produce any runoff regardless of the choice of PET function, but this high consistency should be attributed to WBM insensitivity to produce runoff in dry regions, which experience occasional but rapid and often intensive rain events.

**Sensitivity to Land-surface Parameterization**

Land-surface characterization has an impact only on the cover dependent potential evaporation functions. As mentioned earlier current configurations of WBM has parameter sets for eight characteristic cover types (conifer forest, broad-leaf forest, savannah / shrub-land, grassland, tundra / non-forested wetland, cultivation, desert, open water). The most important parameters are leaf area index, canopy height, albedo and surface roughness. These parameters were assigned to the major cover types based on literature recommendation and normally they are not tuned. In the present dissertation, instead of testing the impact of changing the individual parameters, WBM calculations were performed using uniform land cover characterization. Figure 2-3 shows the latitudinal profile of the mean annual runoff using uniform land cover types and figure 2-4 shows the absolute and relative ranges of the
Comparison of Runoff Climatologies

![Runoff Climatologies Graph](image)

Figure 2-1: Latitudinal profiles of different mean annual runoff estimates applying different PET methods in WBM calculations.

annual runoff fields using seven typical cover types. This analysis was a very unrealistic application of the water balance model. The intention with this test was to assess the impact of the land surface parameterization of the Shuttleworth-Wallace potential evaporation function on the water balance calculation and cannot be interpreted as an assessment of the impact of the land-surface characteristics on the evapotranspiration processes itself.

The results shown in figure 2-3 and 2-4 show significantly less sensitivity to the land surface parameterization than the choice of the PET function. This finding explains why relatively simple reference crop type potential evaporation functions can be used successfully in water balance calculations. Apparently the simple functions are able to capture the most important driving factors of the evapotranspiration processes, but the large differences between the different PET functions still suggest, that the proper representation of the evapotranspiration processes is key to successful water balance calculation. The more sophisticated cover dependent methods presumably represent the physical and biological processes more accurately. Furthermore, the land use characterization plays important role in the feedback between the land-surface and atmosphere interaction, which further adds to the potential importance of accurate land cover representation, but which was neglected in
Figure 2-2: Absolute and relative ranges of mean annual runoff using different potential evaporation functions. The absolute range is expressed as the difference between the highest $R_{\text{max}}$ and the lowest $R_{\text{min}}$ runoff estimates from the different models. The relative ranges are expressed as $\frac{R_{\text{max}}-R_{\text{min}}}{R_{\text{max}}+R_{\text{min}}}$. 

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Comparison of Runoff Climatologies

Figure 2-3: Latitudinal profiles of different mean annual runoff estimates applying different land-use.

the present analysis.

Sensitivity to Rooting Depth

The rooting depth is recognized as one of the most important factors affecting the water balance calculations. Current versions of WBM assigns rooting depth based on the land use and soil type. In order to test WBM sensitivity, the rooting depth was uniformly increased and decreased by 50%. Figure 2-5 shows the latitudinal profiles of the resulting mean annual runoff. The impact of the change in rooting depth is far less significant than the choice of PET function or the land-use cover and affects only those regions, where the soil is rarely saturated (therefore it acts as a storage pool).

2.1.5 WBM Sensitivity to Climate Variables

Climate variables available for water balance studies are subject to uncertainties which vary by variables. These uncertainties in the individual variables affect the water balance
Figure 2-4: Absolute and relative ranges of mean annual runoff using different spatially uniform land-use.
Comparison of Runoff Climatologies

Figure 2-5: Latitudinal profiles of different mean annual runoff estimates applying different rooting depth.

calculations differently. A series of WBM model runs were performed considering either alternative input data sets when it was available or arbitrary altered the input data in order to assess the impact of these uncertainties. The variables tested in the present work were air temperature, cloud cover and wind speed. The arbitrarily alteration of vapor pressure in a consistent manner with other input variables is not trivial, therefore the testing of this variable was left out from the present sensitivity analysis.

Air Temperature

Air temperature is one of the most accurately measured atmospheric variables, furthermore, it changes less rapidly than some of the other climate variables (especially precipitation) and therefore it is easier to interpolate from neighboring observation stations. As a result of these conveniences, the different air temperature data products such as CRU and Willmott-Matsuure show good consistency (figure 2-6a) and the resulting WBM runoff have very little differences (figure 2-6b).

The CRU data set offers the opportunity to compare climatologies from different time
Figure 2-6: Latitudinal profiles of different mean annual runoff estimates using different input air temperature fields.
Comparison of Runoff Climatologies

Figure 2-7: Latitudinal profiles of different mean annual runoff estimates using mean monthly climatologies of air temperature from CRU for the 1901-95 (control), 1901-60, 1960-90 and 1986-95.

periods since this data set is available as a time series for 1901-95. Furthermore the developers of these data sets demonstrated marked temperature increase from 1960 to 1990, so it is very appealing to test the climatologies derived for different periods to see if the impact of differences in the temperature fields would result from differences in the water balance results. Besides the 1901-95 period (which was used as control), three additional climatologies were calculated for 1901-60, 1960-95 and 1986-95 periods. Figure 2-7 shows the latitudinal profiles of the resulting WBM runoff. The longitudinal profile of the different runoff estimates are almost identical. This result suggests that change in the temperature according to the CRU data set was not enough to change the runoff regime, therefore any detected change in discharge regimes must be the result of changes in other input forcings, most probably in the precipitation.
Uncertainties in Cloud cover and Wind Speed

Due to the lack of alternative data sets, the WBM sensitivity to cloud cover and wind speed was assessed by increasing and decreasing the original CRU data arbitrarily. Figure 2-8a shows the effect of ±20 % change in cloud coverage on the runoff estimate. Since the cloud coverage cannot exceed 100 % the original values from CRU were increased by a maximum of 20 % but only up to 100 % cloud cover. The differences in the WBM estimated runoff are quite substantial particularly in the tropics and less severe in the mid and high latitudes. This result suggest that, the inclusion of cloud (or solar radiation) in the calculation of the evapotranspiration is important.

Figure 2-8b shows the water balance sensitivity to ±50 % change in wind speed. The latitudinal profiles of the resulting WBM runoff fields are almost identical despite of the radical alteration of the input data sets. The water balance model is practically insensitive to the wind speed.

2.2 Testing Different Precipitation Data in a Water Balance Model Context

Precipitation is the only measured variable which is a direct input to the water balance calculations (equation 2.1). Unfortunately, precipitation measurements are much more prone to error than air temperature measurements. Not only is the appropriate sampling of the spatially heterogeneous precipitation surfaces difficult, but the observation itself has an unknown error due to gauge under-catch. As a result of these difficulties, the various precipitation data sets derived from different data sources often show marked differences. Six precipitation data products (CRU, Willmott-Matsuura standard and gauge corrected, GPCC, GPCP and NCEP) were tested. The differences in the precipitation data products are discusses in Appendix B.
Figure 2-8: Latitudinal profiles of different mean annual runoff estimates applying altered cloud (panel a) and wind fields (panel b). The original data were uniformly increased and decreased by ±20 % and 50 % respectively. The sensitivity in the cloud coverage is significant. The sensitivity to wind is less significant despite of the substantial alteration of the wind data.
In this analysis UNH's water balance model (WBM) (Vörösmarty et al., 1998, 1992, 1989) configured with Shuttleworth and Wallace (1985) potential evaporation function was used. This is one of the most data intensive PET functions, which considers all elements (evaporation from soil and leaves and transpiration from the plant) by calculating resistance terms from the different evaporating surfaces. The availability of vapor pressure, cloud coverage and wind speed from the CRU data set made it possible to use such a complex PET calculation scheme at the global scale.

The land surface characterization was based on the Terrestrial Ecosystem Model (TEM) (Melillo et al., 1993) land use classification, which was translated to seven major land surface categories (conifer forest, broad-leaf forest, savannah, grassland, tundra, desert, open water). These major land-use categories were found to have distinct evaporation characteristics (Federer et al., 1996; Vörösmarty et al., 1998). Dominant soil textures were from FAO soil maps (FAO/UNESCO, 1986). The combination of the major land-use categories and the soil texture was used to determine rooting depth (Vörösmarty et al., 1998). Soil texture was also used to parameterize soil properties such as porosity, maximum capacity and wilting point.

Water balance model calculations were made using long-term mean monthly input climate forcing (maximum, minimum and mean air temperature, vapor pressure, cloud coverage and wind speed) and varying input precipitation. As it was stated earlier, all the climate forcings were long-term monthly averages from the CRU 95 year time series. The precipitation was varied in order to assess the impact of the differences in the tested precipitation data sets on the resulting runoff (figure 2-9).

Figure 2-10 shows the comparison of observed and simulated WBM runoff averaged over the inter-station regions of the selected 663 discharge gauging stations and the observed runoff. However, the observed and simulated runoff widely differs in many regions and consistent patterns where WBM over or underestimates the runoff can be found. WBM runoff appears to be too high in the wet tropics except when using GPCC. We have to note
Figure 2-9: Mean annual runoff estimates using CRU, GPCC, GPCP, NCEP, WMcor and WMstd mean monthly precipitation.

that earlier global applications of the WBM with simpler PET functions and Willmott-Matsuura gauge corrected precipitation resulted in less runoff, which actually matched quite well the observed runoff (Fekete et al., 2001a, 1999). Therefore the WBM configuration can play an important role in “tuning” the simulated runoff to match the observations.

WBM runoff in higher latitudes is consistently lower than the observed runoff in most cases. GPCP and Willmott-Matsuura gauge corrected data product seem to do better at the higher latitudes. NCEP is the only data set which consistently overestimates the precipitation in the higher latitude. This is consistent with earlier water balance calculations.
Figure 2-10: Relative runoff error (simulated $R_{wbr}$ vs. observed $R_{obs}$ runoff) expressed as
\[
\frac{R_{obs} - R_{wbr}}{R_{wbr} + R_{obs}}
\]
using different PET functions and Willmott-Matsuura gauge corrected precipitation data
(Fekete et al. 2001a, 1999). Apparently, the impact of using different PET function in the
colder regions is less significant.

Figure 2-11 shows the latitudinal profile of the six water balance model runs. The
latitudinal profiles largely have the same pattern as the precipitation profiles in figure B-3
but the spread between the different data sets appears to be increased.

Figure 2-12 shows clearly an increase in the relative range of the spatial distribution

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Figure 2-11: Latitudinal profiles of the mean annual water balance model runoff using CRU, GPCC, GPCP, NCEP and Willmott-Matsuura mean monthly precipitation.

of runoff. The apparent insensitivity of WBM in the dry regions has to be noted. WBM does relatively poorly in extremely dry regions where rapid rain events has the ability to produce substantial runoff despite the overall water stress. In these regions WBM tends to not to produce any runoff regardless of the differences in precipitation. The largest relative sensitivity to precipitation occurs in semi-arid regions, where the differences in precipitation could cause widely different runoff due to the highly non-linearity of the evaporation processes. In wet regions, where the precipitation exceeds the potential evaporation, the precipitation differences translate to the same amount of runoff difference, but since runoff is always less than the precipitation, this absolute difference translates to higher relative differences.

Figure 2-13 shows the increase in the relative runoff differences compared to the relative precipitation differences (figure B-12a and b). The increase is more significant in dry regions. Our finding highlights the importance to improving the precipitation monitoring in dry regions where the current precipitation estimates are less reliable. These are the regions where accurate water balance estimates could be vital for sustainable development.
Figure 2-12: Absolute and relative range of the mean annual runoff calculated from the CRU, GPCC, GPCP WMcor and WMstd precipitation data sets.

Figure 2-13: Distribution of the absolute and relative ranges of mean annual runoff using the CRU, GPCC, WMcor, WMstd and GPCP precipitation data inputs.
2.3 Creating Composite Runoff Fields

One important way to validate components of hydrological models is to compare predicted and observed runoff, the latter computed as river discharge at gauging station divided by upstream contributing catchment area. Discharge can be measured more accurately than other components of the land-based energy and water cycles with perhaps the exception of temperature (Krahe and Grabs, 1996). Discharge measurements have an accuracy on the order of 10-20% (Dingman, 1994; Rantz, 1982), which is much higher than what typically can be achieved for precipitation (Hagemann and Dümenil, 1998). The routine availability of such information could contribute to the validation and improvement of climate, terrestrial ecosystem and water resource models which often show marked discrepancies between observed and modeled runoff. Atmospheric scientists (Gutowski et al., 1997; Rudolf, 1998) and ecosystem modelers (Dirmeyer et al., 1999; Costa and Foley, 1997), and water resource assessments (Vörösmarty et al., 2000c) are beginning to adopt river discharge data for calibrating and validating their models.

Even though discharge is an accurate measure of integrated terrestrial runoff, it typically offers little information on the spatial distribution of runoff within a watershed unless the river basins are highly instrumented. Disaggregation of the river discharge signal is necessary when spatially-distributed runoff information is needed. Early works of Baumgartner and Reichel (1975) and Korzoun et al (1978) estimated global runoff using manual techniques to develop such runoff fields on an annual basis.

A collaboration between the University of New Hampshire and the World Meteorological Organization's Global Runoff Data Centre (GRDC, Koblenz, Germany) seeks to develop automated procedures for routinely producing high spatial resolution runoff fields that are based on atmospheric drivers and observational discharge networks. The primary product of this initial joint effort is a set of monthly mean composite runoff fields (UNH/GRDC Composite Runoff Fields V1.0) on a 30' global grid. The intermediate data sets, such as the simulated river network and the co-registered discharge gauging stations data, are also

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2.3.1 Simple Method of Combining Observed Discharge with Water Balance Model Runoff

Creating observed runoff fields from observed discharge is ambiguous. As stated earlier, observed discharge is an aggregate signal of terrestrial runoff and spatial disaggregation of discharge requires additional knowledge about the spatial distribution of runoff and the potential time delays along flow pathways. Lacking this information, the only possibility is to assume a uniform spatial distribution and no time delays, i.e. distribute the observed inter-station runoff uniformly over the inter-station areas (Figure 2-14).

As stated above, simulated runoff represents the best potential method of estimating the spatial and temporal pattern of continental runoff, but it is often inherently biased...
due to inaccuracies in the climate forcings (precipitation in particular). The combination of the two sources of information (observed discharge and simulated runoff) to estimate continental runoff has the possibility of yielding the most reliable assessment at present.

One method to combine water-balance runoff and discharge gauging station data is to use tributaries and inter-station regions of the individual gauging stations in the context of a topological network, and to calculate mean modeled runoff for the defined regions. The simulated mean runoff can be compared to observed runoff over the same domains to calculate a set of correction coefficients for each distinct inter-station area. Assuming there is no substantial year-to-year water storage, the correction coefficients can be calculated on an annual basis to eliminate the impact of travel time delays.

This procedure can be formalized as follows. The mean observed inter-station runoff for inter-station region $i$ can be expressed as:

$$\bar{R}_{oi} = \frac{\bar{Q}_{oi}}{A_{si}} \quad (2.9)$$

where

- $\bar{R}_{oi}$ - Mean annual observed inter-station runoff $[L/T]$  
- $\bar{Q}_{oi}$ - Mean annual inter-station discharge $[L^3/T]$  
- $A_{si}$ - Inter-station area $[L^2]$

The mean water balance runoff in the inter-station region $i$ becomes:

$$\bar{R}_{w} = \int A_{si} R_{wbm} dA \quad (2.10)$$

where

- $\bar{R}_{w}$ - Mean annual water balance runoff $[L/T]$  
- $\bar{R}_{wbm}$ - Local annual water balance runoff $[L/T]$
Water balance runoff correction coefficient $\xi_{si}$ for inter-station area $A_{si}$ can be calculated as:

$$\xi_{si} = \frac{R_{oi}}{R_{wbi}} \tag{2.11}$$

The corrected runoff then becomes:

$$R_c = \xi_{si} R_{wbm} \tag{2.12}$$

The water balance runoff correction coefficient ($\xi_{si}$) can be calculated on an annual basis (i.e. as a time series of annual correction coefficients) or on a long-term annual mean basis. The runoff correction coefficients were calculated for only those inter-station regions where both the observed and the WBM predicted annual runoff was positive.

The runoff correction coefficient ($\xi_{si}$) can be viewed as a measure of WBM error. Figure 2-15 shows interesting pattern in terms of water balance error. When the runoff correction coefficient $\xi_{si} < 1$ WBM over-estimates runoff when $\xi_{si} > 1$ represents under-estimation of runoff. According to figure 2-15 WBM has a tendency to over-estimate runoff in the tropics with the exception of some portions of the Amazon, while it under-estimates runoff in most of the Arctic basins such as the Ob, Yenisei, Lena, Mackenzie, etc. This is inherent from the precipitation data.

The annual composite runoff field is shown on figure 2-16.

### 2.3.2 The Distribution of Contemporary Global Runoff

One important application of the composite runoff fields (Figure 2-16) is a digital geography of spatially-distributed terrestrial runoff. Various statistics and summaries by regions such as continents and receiving water bodies can be calculated (Table 2.2, 2.3).
Figure 2-15: Mean annual runoff correction coefficients. Values < 1.0 indicate underestimate and > 1.0 indicate overestimate by WBM.
Table 2.2: Distribution of terrestrial runoff [mm/yr] by continents and receiving water bodies. The geography is defined in Vörösmarty et al. (2000b).

<table>
<thead>
<tr>
<th></th>
<th>Africa</th>
<th>Asia</th>
<th>Australasia</th>
<th>Europe</th>
<th>North America</th>
<th>South America</th>
<th>By Oceans</th>
</tr>
</thead>
<tbody>
<tr>
<td>Arctic Ocean</td>
<td>191</td>
<td></td>
<td></td>
<td>384</td>
<td>115</td>
<td>191</td>
<td></td>
</tr>
<tr>
<td>Atlantic Ocean</td>
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<td></td>
<td>286</td>
<td>673</td>
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<td>238</td>
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<td></td>
<td>348</td>
<td>657</td>
<td>496</td>
<td></td>
</tr>
<tr>
<td>Endorheic Basins</td>
<td>67</td>
<td>26</td>
<td>0</td>
<td>165</td>
<td>26</td>
<td>97</td>
<td>58</td>
</tr>
<tr>
<td>By Continents</td>
<td>150</td>
<td>298</td>
<td>154</td>
<td>275</td>
<td>263</td>
<td>655</td>
<td>299</td>
</tr>
</tbody>
</table>
Table 2.3: Distribution of discharge [km$^3$/yr] by continents and receiving water bodies.

<table>
<thead>
<tr>
<th></th>
<th>Africa</th>
<th>Asia</th>
<th>Australasia</th>
<th>Europe</th>
<th>North America</th>
<th>South America</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Arctic Ocean</td>
<td>2143</td>
<td></td>
<td></td>
<td>633</td>
<td>492</td>
<td></td>
<td>3268</td>
</tr>
<tr>
<td>Atlantic Ocean</td>
<td>2935</td>
<td>1099</td>
<td></td>
<td>3609</td>
<td></td>
<td>10864</td>
<td>18506</td>
</tr>
<tr>
<td>Black, Mediterranean Seas</td>
<td>352</td>
<td>123</td>
<td></td>
<td>730</td>
<td></td>
<td>1204</td>
<td>4868</td>
</tr>
<tr>
<td>Indian Ocean</td>
<td>1019</td>
<td>3638</td>
<td></td>
<td>201</td>
<td></td>
<td></td>
<td>4886</td>
</tr>
<tr>
<td>Pacific Ocean</td>
<td>6778</td>
<td>1118</td>
<td></td>
<td></td>
<td>1781</td>
<td>799</td>
<td>10479</td>
</tr>
<tr>
<td>Endorheic Basins</td>
<td>211</td>
<td>410</td>
<td>0</td>
<td>311</td>
<td>9</td>
<td>52</td>
<td>993</td>
</tr>
<tr>
<td>Total</td>
<td>4517</td>
<td>13091</td>
<td>1320</td>
<td>2772</td>
<td>5892</td>
<td>11715</td>
<td>39319</td>
</tr>
</tbody>
</table>
We compared the UNH/GRDC composite fields to estimates made by Baumgartner and Reichel (1975), Korzoun et al. (1978) and GRDC (Grabs et al., 1996). There is good general agreement over individual continents, but there also can be sizable disparities (Table 2.4). Runoff in Korzoun et al. and the UNH/GRDC composite show best agreement in relatively wet continents and less agreement in dry areas. For Australasia there is a very large disparity. We think this is partly due to inconsistencies in the delineation of Australasia in the different studies. Unfortunately, the early studies do not provide enough information to reconstruct exactly their definition of Australasia. The agreement of UNH/GRDC with GRDC (Grabs et al., 1996) estimates is also best in wetter regions and poorest in dry regions. Since the GRDC estimates assume similar runoff in the monitored and un-monitored portions of the continental land-mass, the GRDC estimate has a tendency to over-estimate dry continents like Africa.

Figure 2-17 shows the latitudinal runoff means for the land mass from UNH/GRDC and
Table 2.4: Comparison of continental runoff [mm/yr] estimates between Korzoun et al (1978), GRDC (1996) and this study.

<table>
<thead>
<tr>
<th></th>
<th>Korzoun et al. (1978)</th>
<th>GRDC (1996)</th>
<th>UNH/GRDC (this study)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Africa</td>
<td>153</td>
<td>283</td>
<td>150</td>
</tr>
<tr>
<td>Asia</td>
<td>324</td>
<td>288</td>
<td>298</td>
</tr>
<tr>
<td>Australasia</td>
<td>280</td>
<td>N/A</td>
<td>154</td>
</tr>
<tr>
<td>Europe</td>
<td>283</td>
<td>233</td>
<td>275</td>
</tr>
<tr>
<td>North America</td>
<td>339</td>
<td>170</td>
<td>263</td>
</tr>
<tr>
<td>South America</td>
<td>685</td>
<td>771</td>
<td>655</td>
</tr>
<tr>
<td>Total</td>
<td>315</td>
<td>771</td>
<td>299</td>
</tr>
</tbody>
</table>

Baumgartner and Reichel (1975). The degree of agreement is generally quite good at the global scale and major features of runoff generation are apparent, for example the similar placement of the inter-Tropical Convergence Zone, the desert belt, and the Polar front. Significant differences occur only below 30° South. We have to note that Baumgartner and Reichel (1975) provide runoff over land below 55° South despite the absence of any meaningful land mass, except Antarctica.

Calculating mean runoff by successively including river basins ranked by area (Figure 2-18) shows the progression toward global mean. Mean runoff calculated from the top 25 river basins (representing 40% of the continental land mass, and 56% of the actively flowing portion of the land mass) is already within 5% agreement of the global mean runoff of 299 mm/yr (Table 2.4).

Comparing discharge to oceans (Table 2.5) according to Korzoun et al. (1978), Baumgartner and Reichel (1975) and the composite runoff field derived summaries, the latter tends to be lower than the first two estimates. Some differences might be due to a different delineation of ocean catchments. Furthermore, Korzoun’s estimate includes ground-water flow to ocean, which could be significant in some regions. In general, both Korzoun et al. and Baumgartner and Reichel’s estimate of the continental total discharge flux to ocean is higher than that of the composite runoff fields derived in this study.

The global river discharge estimates published in the scientific literature vary consider-
Figure 2-17: Latitudinal mean runoff comparison for the land mass from Baumgartner et al. and this study.

Figure 2-18: Mean annual runoff calculated by successively including river basins ranked by area (i.e. rank #1 represents mean annual runoff calculated by considering the Amazon only, rank #2 considers both the Amazon and the Nile and so on).
Table 2.5: Comparison of continental discharge to oceans [km³/yr] estimates between Korzoun et al. (1978), Baumgartner et al. (1975) and this study.

<table>
<thead>
<tr>
<th></th>
<th>Korzoun et al.</th>
<th>Baumgartner and Reichel</th>
<th>UNH/GRDC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Arctic Ocean</td>
<td>5200</td>
<td>2600</td>
<td>3268</td>
</tr>
<tr>
<td>Atlantic Ocean</td>
<td>20800</td>
<td>19300</td>
<td>19711</td>
</tr>
<tr>
<td>Indian Ocean</td>
<td>6100</td>
<td>5600</td>
<td>4862</td>
</tr>
<tr>
<td>Pacific Ocean</td>
<td>14800</td>
<td>12200</td>
<td>10479</td>
</tr>
<tr>
<td>Total</td>
<td>46900</td>
<td>39700</td>
<td>38320</td>
</tr>
</tbody>
</table>

ably (38,800 (L’Vovich and White, 1990); 39,700 (Baumgartner and Reichel, 1975); 40,700 (Postel et al., 1996); 42,700 (Grabs et al., 1996), 46,900 (Korzoun et al., 1978) km³/yr). These differences are partly due to the differences in the set of discharge gauging stations used for the analysis (e.g. GRDC used 198 stations with a total of 52.3×10⁶ km² catchment area measuring 18,000 km³ discharge, while the 298 most downstream stations out of the 663 considered in this study represents 67×10⁶ km² catchment area monitoring 20,700 km³/yr discharge).

Beside differences in the set of discharge gauging stations represented in the various continental discharge estimates further differences in the final results arise from differences in how the measured runoff was extrapolated to un-monitored regions. The simplest approach is to assume similar runoff on the monitored and un-monitored portion of the continental land mass. Considering the 133×10⁶ km² of total area of the non-glaciarized land-mass this assumption would result in (20,700 [km³/yr]×133 [10⁶km²] ÷ 67 [10⁶km²]) = 41,000 km³/yr annual discharge. Although this approach could be reasonable for some parts of the globe, it fails to recognize the fact that large portions of the un-monitored regions are actually dry (and there is no river water to monitor). If we proportionally reduce this estimate to represent the actively-discharging area of the land mass (i.e. assume identical runoff on the un-monitored but actively discharging land mass), we get (41,000 [km³/yr] ×93 [10⁶km²] / 133 [10⁶km²]) = 28,700 km³/yr annual discharge. This estimate is much lower than any
other estimate published, suggesting that the un-monitored but actively flowing portion of the continental land-mass is probably wetter than the monitored average.

The composite runoff fields developed within the present study capture a higher wetness for the un-monitored land mass (722 mm/yr). The global total discharge estimate of 39,319 km$^3$/yr agrees best with earlier estimates made by Baumgartner (1975), and L'Vovich (1990).

### 2.3.3 Spatial Coverage of Monitored Discharge

Considering the discharges by region (Table 2.3) and at the non-nested (most downstream) gauging stations within those regions, the percentage of monitored discharge can be assessed (Table 2.6).

This information by itself can be misleading in terms of the monitoring station coverage, but still it is useful to understand how well the discharge from the continental land mass is monitored in different regions. Using the most downstream station may create the false impression of good data coverage. A good example is South America and particularly the Amazon, which is not an exceptionally well monitored river system, but since the last discharge gauging station at Obidos monitors much of the discharge to ocean from the Amazon basin, and the Amazon delivers a significant fraction of the continental discharge to ocean, South America has an apparently high percentage of monitored discharge.
2.3.4 Considering Global Continental Discharge Estimates

The global and the continental river discharge estimates published in the scientific literature vary considerably (36,400 (Korzoun et al., 1978); 38,800 (L'Vovich and White, 1990); 39,700 (Baumgartner and Reichel, 1975); 40,700 (Postel et al., 1996); 42,700 (Grabs et al., 1996) km\(^3\)/yr). These differences are partly due to the differences in the set of discharge gauging stations used for the analysis (e.g. GRDC used 198 stations with a total of 52.3 \times 10^6 km\(^2\) catchment area measuring 18,000 km\(^3\)/yr discharge, while this report was based on 298 stations with 67 \times 10^6 km\(^2\) catchment area monitoring 20,700 km\(^3\)/yr discharge).

Beside the differences in selecting discharge gauging stations, the assumption in extrapolating the measured runoff to un-monitored regions may vary. The simplest approach is to assume similar runoff on the monitored and non-monitored portion of the continental land mass. Considering the 133 \times 10^6 km\(^2\) of total area of the non-glaciarized land-mass this assumption would result in (20,700 [km\(^3\)/yr] \times 133 \times 10^6 [km\(^2\)] / 67 \times 10^6 [km\(^2\)] = 41,000 km\(^3\)/yr annual discharge. Although this approach could be reasonable for some parts of the globe, it fails to recognize the fact that a large portion of the un-monitored regions are actually dry (and there is no river water to monitor). A next approach considers the 93 \times 10^6 km\(^2\) of actively flowing continental land-mass and assumes the same average runoff as on the observed portion yielding (20,700 [km\(^3\)/yr] \times 93 \times 10^6 [km\(^2\)] / 67 \times 10^6 [km\(^2\)] = 28,700 km\(^3\)/yr annual discharge. This estimate is much lower than any current other estimate published, but the only possibility to increase this number is to assume higher mean runoff on the un-monitored but flowing regions than the observed in the monitored river basins. This finding suggests that the un-monitored but actively flowing portion of the continental land-mass is probably wetter than the monitored average. It is unlikely however that those regions are significantly wetter than the monitored land-mass, therefore lower global river discharge estimates are likely to be more accurate.

The composite runoff fields developed within the present study capture the higher wetness by applying Water Balance Model runoff estimates in the un-monitored regions. The
global total discharge estimate of 39,319 km³/yr agrees with several earlier estimates like Baumgartner (Baumgartner and Reichel, 1975), and L’Vovich (L’Vovich and White, 1990).
Chapter 3

Characterization of River Channels

Runoff generated over the land surface moves horizontally on the surface (sheet flow) under the surface (ground-water flow) and in channels (river flow). Typically the first two forms of the horizontal water transport have limited capacity to deliver water. As a result of the high efficiency in transporting water, river flow is the dominant means of horizontal water transport globally. This chapter discusses our current ability to represent river networks and their properties (e.g. channel width, depth, mean velocity, etc) and our limitations to assess these properties accurately. Section 1.3 discusses the spatial distribution of the rivers and their representation using gridded networks. Section 3.2 focuses on the possible approximation of the riverbed geometry and the corresponding synthetic rating function by using idealized cross-sections and a combination of theoretical and empirical relationships relating flow characteristics (bankfull flow, riverbed slope). Section 3.3 applies the developed synthetic rating function to spatially distributed discharge derived from the composite runoff (discussed in section 2.3) by accumulating along simulated river networks at different resolutions. The impact of network resolution on the total river volume and surface calculations is analyzed and an estimate of the continental distribution of river water surface and volume is presented.
3.1 Simulated River Networks

Gridded networks are often used in large-scale hydrological modeling, since they represent both the rivers themselves and the connectivity of the land mass. In section 1.3, some of special capabilities of the simulated topological networks developed at the University of New Hampshire were discussed. In this section the properties of gridded networks at various resolution are demonstrated.

3.1.1 The Impact of Resolution on Gridded Network Performance

The testing of the impact of resolution on gridded network performance requires a set of comparable networks at different resolution. Since the development of gridded networks is often difficult and time consuming, such data sets were rarely available in the past. The author of the present dissertation and his primary advisor developed an algorithm which allows the rescaling of fine resolution networks to coarser resolutions. Appendix D describes the Network Scaling Algorithm (NSA) and its improved variant with basin enhancement (NSA-BA) in details.

The NSA and NSA-BE allows us to derive comparable networks over the same domains at different resolutions to study the impact of resolution on network-derived basin characteristics such as stream order, catchment area, mainstem length, and other geomorphometric properties. Such analysis can give a better understanding of how to optimize networks for particular applications.

Deriving 2.5, -5, -10, -15 and 30 Minute Networks from HYDRO1k

Simulated topological networks at five resolutions (2.5, -5, -10, -15 and 30 minute) were derived from HYDRO1k using NSA-BE with Pfafstetter-encoded subbasins supplied as part of HYDRO1k. The 2.5 minute network served as a reference data set for the comparison of network performance at different resolutions.
Figure 3-1: Comparison of gridded network performance in terms of drainage-area representation. Panels a through d show the regridding error (i.e., regridding the 2.5 minute subbasin grid at different resolutions), while panels e through h show the total NSA-BE rescaling error.

A subbasin partitioning with drainage area of approximately 5000 km\(^2\) (with corresponding basin outlets) was derived from the 2.5 minute network. The 5000 km\(^2\) threshold is well below the minimum catchment area that can be represented well by a 30 minute network (Vörösmarty et al., 2000b), but still larger than the average cell area at this resolution, ensuring that basin outlets will not fall into the same grid cell. Network-derived attributes at subbasin outlet points were computed based on the 2.5 minute network to serve as a basis for assessing NSA-BE performance at four spatial resolutions. The basin outlets were geo-registered to the 5, 10, 15 and 30 minute resolution using the 3x3 kernel search for the cell with the best-fitting drainage area. Network attributes were then derived from the coarser-resolution networks. Figure 3-1 shows the performance (in terms of resolving drainage area) of the different networks derived from HYDRO1k, with error in drainage area clearly increasing as resolution decreases.
Comparison of Gridded Networks at Different Resolutions

The network statistics for the five European gridded networks at 2.5, 5, 10, 15 and 30 minute resolutions are presented in Table 1. Some of the statistics such as average cell area, average cell length and number of cells are predictable by simply considering the grid resolution. The number of Strahler stream segments follows the same logarithmic trend as the number of cells. The average number of cells per basin does not decrease at the same rate as the number of cells in the whole network because the coarser-resolution networks tend to preserve the larger basins while the smaller basins are integrated into the large basins as the resolution is degraded.

Basin shape indices were calculated at the basin outlets using the 5000 km$^2$ subbasin partitioning. The shape index (Vörösmarty et al., 2000a) is defined as

$$S = \frac{L}{\sqrt{A}}$$  \hspace{1cm} (3.1)

where

$S$ - shape index

$L$ - mainstem length [ km]

$A$ - basin area [ km$^2$]

Figure 3-2 shows the shape index error as a function of number of grid cells. The shape index error increases dramatically under 300 grid cells and has an increasing negative bias at coarser resolutions (Figure 3-2). This negative bias indicates that regridding to coarser resolutions tends to result in more rounded basins. A review of the data sets reveals that this tendency toward more rounded basins is not due to the changing outline of the basins, but is instead a function of decreasing mainstem length at coarser resolutions.
Table 3.1: Grid Comparisons

<table>
<thead>
<tr>
<th>Resolution</th>
<th>Mean Cell Area [km²]</th>
<th>Mean. Cell Length [km]</th>
<th>Number of Cells</th>
<th>Number of Stream Segments</th>
<th>Number of Basins</th>
<th>Mean Number of cells per basin</th>
<th>Highest Order</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.5 minute</td>
<td>14</td>
<td>4</td>
<td>1 205 647</td>
<td>818 075</td>
<td>11 571</td>
<td>104.2</td>
<td>9</td>
</tr>
<tr>
<td>5 minute</td>
<td>55</td>
<td>9</td>
<td>301 437</td>
<td>207 144</td>
<td>3 835</td>
<td>78.6</td>
<td>8</td>
</tr>
<tr>
<td>10 minute</td>
<td>221</td>
<td>17</td>
<td>75 355</td>
<td>52 530</td>
<td>1 452</td>
<td>51.9</td>
<td>7</td>
</tr>
<tr>
<td>15 minute</td>
<td>497</td>
<td>25</td>
<td>33 467</td>
<td>23 614</td>
<td>838</td>
<td>39.9</td>
<td>7</td>
</tr>
<tr>
<td>30 minute</td>
<td>1994</td>
<td>50</td>
<td>8 360</td>
<td>5 986</td>
<td>327</td>
<td>25.6</td>
<td>6</td>
</tr>
</tbody>
</table>
Figure 3-2: Basin shape index error (defined as basin shape index at the regridded resolution minus basin shape index at 2.5 minute resolution) by drainage area at 5, 10, 15, and 30 minute resolutions.
Network Performance at Different Resolutions

Designing gridded networks for particular applications needs to strike a balance between the higher accuracy of fine-resolution networks versus the increasing difficulties of developing and using those networks in associated flow-routing schemes. The first step in assessing network performance of gridded networks at different resolutions was to identify 88 basins with drainage area greater than 25,000 km² for each resolution. The 25,000 km² basin size was found to be the minimum that could be represented in a 30 minute network (Vörösmarty et al., 2000b), which was the coarsest resolution in our experiment.

We now assess the fidelity of simulated river networks by comparing the maximum lengths of the 88 basins at 5, 10, 15, and 30 minute resolutions (Figure 3-3). As expected, the regression lines show a systematic decreases in the maximum lengths at coarser resolutions (Figure 3-4). This systematic length decrease explains the increasing negative bias in the basin shape index described in section 3.1.1. The intercept terms of the regression lines are negligible compared to the maximum basin lengths. The slope terms of the regression lines, however, show an important linear trend in the decrease of the maximum length at coarser resolution (Figure 3-4). This decrease is due to the inability of the coarser-resolution networks to represent the sinuosity of the real rivers.

When slopes of the maximum-length regression lines at different resolutions as a function of the resolution differences (i.e., the cell size ratio) (Figure 3-4) are plotted, a log-linear relationship between cell size ratio and stream length ratio is apparent. This relationship can be expressed as

\[
\frac{L_f}{L_c} = 1.024 - 0.077 \ln \left( \frac{\Delta L_f}{\Delta L_c} \right)
\]

(3.2)

where
Figure 3-3: Comparison of the maximum river length at 2.5 minute vs. 5, 10, 15 and 30 minute resolutions. Only those basins where the drainage area estimate at 2.5 minute resolution and the regridded resolution agreed within ±10 % error were included in the comparison. This criteria was applied to ensure that the compared basins have reasonably similar representation at all resolutions and that the differences in the morphometric characteristics are due to the resolution differences only, and are not affected by the errors introduced through rescaling. Linear regression coefficients including the intercept \( (b_0) \), slope \( (b_1) \) and correlation coefficient \( (R^2) \) are shown.
Figure 3-4: Maximum river length ratio as a function of cell size ratio. The slope term in the linear regression of maximum river length (Figure 3-3) can be viewed as the ratio of the fine- and the coarse-resolution maximum river lengths. Relating these maximum length ratios to the logarithm of the corresponding cell size ratios shows a linear trend. This relationship can be used to predict the shortening of river lengths due to decreasing grid resolution.
\( L_f \) - Stream length [km] at fine resolution
\( L_c \) - Stream length [km] at coarse resolution
\( \Delta L_f \) - Cell size [km] at fine resolution
\( \Delta L_c \) - Cell size [km] at coarse resolution

Equation 3.2 can be used to predict the decrease in stream length for coarser-resolution networks or adjust the stream lengths calculated at a coarser-resolution network. We constructed the width function of the Danube basin from the original HYDRO1k network and the 5 minute regridded network (Figure 3-5). The width function is either normalized (Rinaldo et al., 1995) or non-normalized (Veneziano et al., 2000). In this paper we use the width function \( W(L) \) from Veneziano et al. (2000), defined such that \( W(L)dL \) is the drainage area increase for a drainage area located between distance \( L \) and \( L + dL \) from basin mouth. The width functions of the Danube at different resolutions show that the 5 minute network without length correction is systematically shorter than the 1 km network (Figure 3-5a). By applying the length correction computed from equation 3.2, the coarser-resolution network can be adjusted to match the width function derived from the fine-resolution network (Figure 3-5b).

We applied the correction coefficient to the 5, 10, 15 and 30 minute networks in order to compare the width function of the 88 basins in Europe at different resolutions. Figure 3-6 shows the width functions for different resolutions of the larger European basins. The ability of the width function to replicate the finer scales becomes limited for smaller drainage-area basins. However, this result is expected given the increased error in the shape index at coarser resolutions (Figure 3-2).

3.1.2 A Priori Estimation of Error Characteristics

The rounding error discussed in section D.2.3 offers a means to assess the expected accuracy of a gridded network at a given resolution. Two equations derived in the appendix E relate the desired area accuracy \( (\epsilon_A) \), mean length accuracy \( (\epsilon_L) \), and the smallest area \( (A) \)
expected to be represented at that accuracy to the minimum number of grid cells (n) needed to maintain those accuracies as $n = \frac{1}{2\epsilon_A}$ and $n = \frac{1}{4\epsilon_L^2 S_m}$, respectively. The $S_m$ term in the length accuracy equation is the mean length shape index of the basin, which is similar to the shape index (equation 3.1). $S_m$, however, relates the mean river length to the square root of the basin area instead of mainstem length. The mean river length is typically half of the mainstem length and, therefore, the mean length shape index is also half of the traditional shape index. While the values of the traditional shape index span 1.0 to 3.6 (Vörösmarty et al., 2000a), the mean length shape index ($S_m$) varies between 0.5 and 2.0.

Based on the area accuracy equation, if the desired area accuracy is $\epsilon_A = 0.1$, then $\Delta A = 0.2A$ and at least 5 grid cells are needed to maintain 10% accuracy. This corresponds well with the 10,000 to 25,000 km$^2$ minimum basin size that can be represented in 30 minute networks (~2000 km$^2$ average grid cell size) (Vörösmarty et al., 2000b; Lammers et al., 2001). Similarly, if the desired length accuracy is $\epsilon_L = 0.1$ and we assume $S_m = 0.5$ as a worst case scenario, the length accuracy equation yields $n = 1/\epsilon_L^2$. Therefore, to maintain

Figure 3-5: Width function of the Danube basin at 1 km and 5 minute resolution a) without length correction and b) with length correction.
Figure 3-6: Width functions of major European rivers with the length correction at 2.5, 10 and 30 minute resolutions. Solid line shows 2.5, dotted line is 10, and dot-dashed line the 30 minute resolution.
10% accuracy, a minimum of 100 grid cells is required. This estimate does not take into account the cell-length variation in gridded networks and any additional error contained within a gridded network. Considering these uncertainties, a minimum of 200-300 grid cells may be required to represent the underlying river topology, which is consistent with our finding that the shape error dramatically increases below 300 grid cells (Figure 3-2). This result is important in applying gridded networks in flow-routing schemes, since the failure to maintain the geomorphometric characteristics of river basins may result in substantial flow-routing errors.

3.2 Cross-sectional Geometry

Typically, river cross-sections have very irregular shapes and may vary rapidly along particular reaches. Despite this heterogeneity, careful analysis of cross-sections and the corresponding rating curves (relating stage-height or flow width to discharge) reveals surprisingly regular patterns. Bjerklie and Dingman (University of New Hampshire, Earth Sciences Department, personal communications, 2001) analyzed numerous US Geological Survey cross-sections and compared them to regular geometric shapes (i.e. triangle, trapezoid, parabola of different order, semi-ellipse). They found that second and third order parabolas provide good approximations to the tendencies of natural cross-sections. Once a riverbed geometry is chosen classical flow hydraulic equations can be applied to estimate the river flow properties (i.e. mean velocity, depth and width). We do this, testing synthetic rating curves to actual functions, as guidance in developing globally-applicable hydraulic rules.

3.2.1 Synthetic Rating Function

Synthetic rating curves can be derived from the classical flow equations like Chezy or Manning (Dingman, 1994), which relate flow depth and slope to mean velocity. A generalized formulation of the Chezy and Manning equations was given by Dingman (1994) as:
\[ \bar{u} = c \, R^d \left( \frac{dH}{dl} \right)^e \]  

(3.3)

where

- \( \bar{u} \) - the mean velocity \([L/T]\) in the cross-section;
- \( R \) - hydraulic radius of the cross-section expressed as the ratio of the cross-sectional area \((A)\) and the wetted \((P)\) perimeter \(R = A/P\);
- \( \frac{dH}{dl} \) - is the energy slope, which is often approximated by the riverbed slope \((dZ/dl)\);
- \( c \) - smoothness coefficient, which is related to the roughness coefficient of Manning by \( n = 1/c \);
- \( d \) - the exponent of the hydraulic radius, which is 1/2 according to Chezy and 2/3 according to Manning;
- \( e \) - the exponent of the energy slope, which is 1/2 according to both Chezy and Manning.

Discharge \((Q)\) can be calculated as the product of the mean velocity \(\bar{u}\) and the cross-sectional area \((A)\)

\[ Q = \bar{u} \, A. \]

By substituting \(\bar{u}\) with equation 3.7, the discharge can be expressed as:

\[ Q = c \, R^d \left( \frac{dH}{dl} \right)^e \, A \]

(3.4)

Approximating the cross-section by a \(b\)th order parabola \((y = a \, w^b)\), the cross-sectional area can be expressed as:

\[ A = yw - \int_0^w w^b \, dw = yw - \left[ \frac{a}{b+1} w^{b+1} \right]_0^w = \frac{b}{b+1} yw \]

(3.5)

The natural river-beds typically are relatively shallow (i.e. the depth/width ratio is small).
therefore the hydraulic radius can be approximated by the average depth ($\bar{y}$), which can be expressed as:

$$\bar{y} = \frac{A}{w} = \frac{b}{b + 1} y$$  \hspace{1cm} (3.6)

Substituting the cross-sectional area equation 3.5 and the mean depth as hydraulic radius in equation 3.4 yields:

$$Q = c \left( \frac{b}{b + 1} \right)^{1+d} y^{1+d} w \left( \frac{dH}{dl} \right)^e$$  \hspace{1cm} (3.7)

In equation 3.7 width ($w$) can be expressed as $w = (y/a)^{1/b}$, which yields:

$$Q = \frac{c}{a^b} \left( \frac{b}{b + 1} \right)^{1+d} y^{1+d+\frac{1}{b}} \left( \frac{dH}{dl} \right)^e$$  \hspace{1cm} (3.8)

One of the numerical advantages of using a parabola as an idealized cross-section profile is this capability to derive an explicit formula, which relates flow depth ($y$) to discharge ($Q$). Furthermore, the parabola has only one parameter ($a$) to be specified (once the order ($b$) is decided).

Equation 3.8 is effectively a synthetic rating curve for flow depth $y$ since it relates that flow depth to discharge, but it still needs an energy slope ($dH/dl$) to be specified. The energy slope is often approximated by the riverbed slope ($dZ/dl$). Unfortunately, the riverbed slope is at least as difficult to specify as the energy slope. One way to eliminate the energy/riverbed slope from equation 3.8 is to assume that riverbed slope ($dZ/dl$) at the mean flow is proportional to the depth/width ratio ($y_{mean}$, $w_{mean}$ flow depth and width at mean flow):

$$\frac{y_{mean}}{w_{mean}} = k \left( \frac{dZ}{dl} \right)^e$$  \hspace{1cm} (3.9)
This assumption will make the river depth depend only on discharge and expand and contract its width as the slope changes. Since, the depth/width ratio of a parabola can be given as \( \frac{y}{w} = a^\frac{1}{b}y^{1-\frac{1}{b}} \) the riverbed slope becomes:

\[
\left( \frac{dZ}{dt} \right)^e = \frac{a^\frac{1}{b}}{k} y^{1-\frac{1}{b}} \text{mean}
\]  

(3.10)

Substituting equation 3.10 in equation 3.8 yields:

\[
Q = \frac{c}{k} \left( \frac{b}{b+1} \right)^{1+d} y^{1-\frac{1}{b}} y^{1+d+\frac{1}{b}} \text{mean} y^{1+d+\frac{1}{b}}
\]  

(3.11)

Equation 3.11 is a true synthetic rating function since it relates flow depth \((y)\) to discharge \((Q)\) with no other variable. In this equation the only parameter to be determined is \(k\) since the \(c\) smoothness coefficient can be specified from literature, \(d\) hydraulic radius power is either 1/2 (Chezy) or 2/3 (Manning) and \(b\) (the order of the parabola) is a matter of choice between a 2nd or 3rd order parabola as an idealized cross-section geometry.

### 3.2.2 Parameterizing the Synthetic Rating Function

In the previous section, the synthetic rating was derived from theoretical considerations. The only unknown parameter of equation 3.11 was \(k\), which related the depth/width ratio at the mean discharge to the riverbed slope. Estimates of \(k\) can be derived by fitting equation 3.11 to observed rating curves.

**Observed Rating Curves**

Operational discharge estimates are typically based on calibrated stage-height measurements. The stage (or flow height) calibration is a time-consuming and costly procedure, since it involves surveying the whole riverbed cross-section and measuring the velocity dis-
tribution within the cross-section at different stage-heights (Rantz, 1982). These measurements allow rating curves to be established, which relate stage-height to actual discharge. Typically the discharge survey records, which were used to establish rating curves are not widely available, but hydrometeorological services often publish stage-height and discharge records together. Therefore rating curves can be reconstructed from these records. These records are not truly "observed" rating curves, but we will refer to them as such for the sake of simplicity in the remainder of the chapter.

The United States Geological Survey publishes stage-height and discharge records in real-time for over 5000 gauging stations via the World Wide Web (http://water.usgs.gov/). The observation frequency varies by station between five minutes to three hourly and the time series are sometimes interrupted (mostly during the winter, probably due to ice conditions). Most of the stations have both stage-height and discharge data but some stations report stage-height only. These stage-height and discharge data are presented as provisional and USGS keeps them on-line for only a week. These are published one year later as finalized discharge data time series in USGS archives. The Water Systems Analysis Group of the University of New Hampshire has developed an automated retrieval system, which downloads and archives the USGS real-time data continuously. This system has collected discharge and corresponding stage height records from November 1999. This archive provides an excellent opportunity to parameterize the synthetic rating curves developed in section 3.2.1.

The original USGS real-time stage-height and discharge records required preprocessing before they could be used to parameterize the synthetic rating function. Those stations which did not have discharge records were eliminated. Stations with negative discharge (probably due to tidal influence) were also removed. This resulted in 4506 out of a total of 5388 gauging stations being retained for further analysis.

The next step involved filtering the real-time data series. This filtering was necessary to remove multiple instances of the same stage-height discharge entries, and to eliminate
some of the most severe anomalies. The stage-height/discharge records were sorted by stage-height and those entries where the discharge did not increase with stage-height were removed. Next, outliers were removed. Extreme values where identified by calculating the distribution of stage-heights and discharges by dividing their respective value ranges into ten equal sized groups (deciles). The first and the last deciles were examined and the lowest and the highest entries (for discharge and stage-height) entries were removed if the frequency of the lowest or highest category was less then 2.5 % of the total number of entries (i.e. 1/4th of the expected number in the decile). This procedure was repeated until the all the extreme values were eliminated. Finally, those stations, where the number of entries in the filtered stage height/discharge were less than fifty were removed from the station list. Figure 3-7 shows the typical anomalies eliminated by the filtering procedure. After filtering the 2686 station was kept out of the 4506, which had discharge and stage-height records.

**Parameterizing the Synthetic Rating Function Using Observed Rating Curves**

The general form of equation 3.11 can be written as:

$$Q = p y^q$$  \hspace{1cm} (3.12)

where p and q are:

$$p = \frac{c}{k} \left( \frac{b}{b+1} \right)^{1+d} \frac{1-\frac{1}{b}}{\bar{y}_{\text{mean}}}$$ \hspace{1cm} and \hspace{1cm} $$q = 1 + d + \frac{1}{b}$$  \hspace{1cm} (3.13)

The only parameter to be determined in this equation is p. Knowing parameter p then the k parameter of the original equation 3.11 can be calculated from equation 3.13.

Considering "observed" rating curves given as a series of measured stage-heights ($H_1, H_2, \ldots, H_N$) and the corresponding discharges ($Q_1, Q_2, \ldots, Q_N$), parameter can be determined by fitting equation 3.12 to the observed data series. Unfortunately, stage-heights are almost
Figure 3-7: Observed rating curves before and after filtering for anomalous outliers. Panels a) and b) show "Charlie Creek Near Gardner", AL and panel c) and d) show "Colorado River Near Kremmling", CO.
never identical to the flow depth since normally river flow heights are measured relative to an arbitrary but fixed datum instead of the river bottom, which is difficult to identify and may change over time. The stage-height is offset by an \( H_0 \) (the elevation of the river bottom from the stage’s datum) relative to the flow depth, so the relationship between flow depth \( y \) and \( H \) is \( y = H - H_0 \), therefore equation 3.12 becomes:

\[
Q = p (H - H_0)^q
\]

(3.14)

Since the elevation of the river bottom \( H_0 \) is unknown it has to be included in the list of parameters to fit the “observed” rating curves. Using least square method, parameter \( p \) and river bottom elevation \( H_0 \) of equation 3.14 was approximated for the 2686 stations, which were selected after the filtering described in section 3.2.2. A second order parabola \( (b = 1/2) \) was chosen as the idealized cross-section and the exponent of the hydraulic radius was set according to Manning \( (d = 2/3) \). Therefore exponent \( q \) in equation 3.12 was set to 2.1667. Normalized error expressed can be expressed as:

\[
\bar{\varepsilon} = \frac{\sqrt{\sum_{i=1}^{n} [Q_i - p (H_i - H_0)^q]^2}}{n (Q_{max} - Q_{min})} \times 100 \% \tag{3.15}
\]

was calculated for each stations. The distribution of the errors is shown on figure 3-8. The majority of the stations (\( N = 2394 \) out of the 2686 stations) has less than 5% error, which is remarkably good and strongly supports the formulation of the synthetic rating function. Figure 3-9 shows several observed and synthetic rating curves with different levels of normalized error.

By fitting equation 3.11 to observed rating curves, parameter \( k \) was optimized for 2686 stations. Figure 3-10 shows the logarithmic distribution of \( k \) considering the 2394 stations where the fitting resulted less the 5% error. According to figure 3-10, the value of \( k \) ranges between 0.01 and 100, but most of the \( k \) values are in the 0.1 and 10.0 range. The
logarithmic average ($\bar{k} = 10^{\log_{10}\bar{k}}$) of $k$ is 0.97.

Considering the wide spread of $k$, the predictability of particular cross-sectional geometries and corresponding rating curves is very limited. The local riverbed geometry is probably influenced by local slope, riverbed material, bedrock/geology, vegetation, etc. and it can change rapidly along a river in a rather unpredictable manner.

At the same time, it can be demonstrated that the rating curves do behave with some statistical regularity. Figure 3-11 shows the scatter plot (panel a) and the box diagram of $k$ with respect to the mean discharge (panel b). The average of $k$ is around 1.0 regardless of the mean discharge. The box diagram shows the 5, 25, 50, 75 and 95 percentiles of 15 mean discharge groups. Log-linear regression of the $k$ in the 15 discharge group shows strong correlation ($R^2 = 0.84$). The regression function can be written as:

$$k = 1.67Q^{-0.17}_{\text{mean}}$$  \hspace{1cm} (3.16)
Figure 3-9: Observed and synthetic rating curves. The figure shows four sites (panel a) "Okanogan River Near Tonasket", WA, 12445000, b) "Little Fishing Creek Near White Oak", NC, 02082950, c) "Eleanor C Nr Hetch Hetchy", CA, 11278000, d) "Reedy River Near Ware Shoals", SC 02165000) that has different error characteristics after fitting synthetic rating curves. These errors range from 0.48 % to 10.23 %.
Figure 3-10: Distribution of parameter $k$ from equation 3.11.

The negative exponent of the mean discharge ($Q_{\text{mean}}$) in equation 3.16 show a slight decrease in $k$ as the mean discharge increases. Despite the stochastic nature of the local riverbed geometry, the strong correlation of the discharge group-averaged $k$ values to discharge, and the similar distribution of $k$ across all discharge categories suggest that larger river reaches are behaving much more regularly, and the characteristic riverbed geometry of longer river reaches are predictable.

This suggests that large rivers do not fully utilize their potential in deepening their river bed, therefore these rivers are relatively shallower (i.e. their depth/width ratio is lower than the smaller rivers).

3.2.3 Comparison of Synthetic and Empirical Rating Functions

The general formulation of flow depth ($y$), flow width ($w$) and velocity ($u$) rating curves was given by Leopold (1994,1964) as:
Figure 3-11: Relationship between parameter $k$ from equation 3.11 and the mean discharge ($Q_{\text{mean}}$). Panel a) shows the scatter plot of mean discharge versus parameter $k$. Pane b) shows the box-plot of the parameter $k$ distribution by discharge groups. The box-plot shows the 5, 25, 50, 75 and 95 percentiles of $k$ value and the regression line of the group averages weighted by the number of entries by group.

\begin{align*}
Q &= p y^q \quad (3.17) \\
Q &= r w^s \quad (3.18) \\
Q &= t u^z \quad (3.19)
\end{align*}

He showed that the product of coefficients ($p \times r \times t$) and the sum of exponents ($q + s + z$) has to be equal to 1.0 in order to satisfy flow continuity. We note that equation 3.17 is identical to equation 3.12 introduced in section 3.2.2. Numerous empirical formula relating slope and cross-sectional area or flow width and depth to a particular stage of discharge (mean or bankful) have been proposed in the literature. Equation 3.20, 3.21 and 3.22 are examples of these different empirical formulations. The Chezy (3.23) and Manning (3.24) equations are also shown for comparison to the empirical relationships.
\[ Q_{\text{max}} = 4.0 A_{\text{max}}^{1.21} \left( \frac{dZ}{dl} \right)^{0.28} \]  
\text{Williams (1978)} \quad (3.20)

\[ \overline{Q} = 4.62 A^{1.17} R^{0.4} \left( \frac{dZ}{dl} \right)^{0.34} \]  
\text{Dingman and Sharma (1997)} \quad (3.21)

\[ Q_{\text{max}} = 17 A_{\text{max}} R_{\text{max}}^{0.5} \left( \frac{dz}{dl} \right)^{0.33} \]  
\text{Henderson (1966)} \quad (3.22)

\[ Q = c A R^{0.5} \left( \frac{dz}{dl} \right)^{0.5} \]  
\text{Chezy} \quad (3.23)

\[ Q = \frac{1}{n} A R^{0.667} \left( \frac{dz}{dl} \right)^{0.5} \]  
\text{Manning} \quad (3.24)

where

- \( Q_{\text{max}} \) - bankfull discharge \([L^3/T]\);
- \( A_{\text{max}} \) - cross-section area at bankfull discharge \([L^2]\);
- \( R_{\text{max}} \) - hydraulic radius at bankfull discharge \([L]\);
- \( \overline{Q} \) - mean discharge \([L^3/T]\);
- \( \overline{A} \) - cross-section area at mean discharge \([L^2]\);
- \( \overline{R} \) - hydraulic radius at mean discharge \([L]\);
- \( \frac{dz}{dl} \) - riverbed slope \([L/L]\);

All of these equations have the form of:

\[ Q_* = b A_*^{-\frac{d}{2}} R_*^d \left( \frac{dZ}{dl} \right)^e \]  
\text{(3.25)}

Approximating riverbed cross-section with 2nd order parabola \((y = a w^2, R = \bar{y} = 2/3y)\),
equation 3.25 becomes:

\[ Q_* = b \left( a^{\frac{1}{2}} y_*^{1+\frac{1}{2}} \right)^c \left( \frac{2}{3} y_*^d \right)^e \left( \frac{dz}{dl} \right)^e \]  
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Coefficient $p$ and exponent $q$ from equation 3.17 can be expressed from equation 3.26 as:

$$p = \left(\frac{2}{3}\right)^d b a^e \left(\frac{dz}{dl}\right)^e \quad \text{and} \quad q = c + \frac{c}{2} + d$$

(3.27)

Unfortunately the coefficient $p$ is a function of the shape coefficient of the parabola and the riverbed slope, therefore the different empirical functions cannot be compared without the information, but exponent $q$ depends only on the parameters of the different empirical equations. The values of $q$ are 1.815 (Williams, 1978), 2.155 (Dingman and Sharma, 1997), 2.000 (Henderson, 1966). These values are remarkably similar to 2.1667 used in the synthetic rating function derived in section 3.2.2. It is important to note that using the 3rd order parabola as the idealized cross-section and considering Chezy’s hydraulic radius exponent in equation 3.13 would have yielded $q = 1.833$.

### 3.3 Estimating Global River Surface Area and Volume

The runoff fields described in Chapter 2 and the river networks discussed in Section 3.1, along with the river bed geometric relations described in the previous section provide the basis for a complete global mapping of channel depth, width and mean velocity. It also permits a global flow routing to be established. The formulation of such a complex, time-varying routing scheme is beyond the scope of the present dissertation. The current section does, however, demonstrate the first step in this process. We will capability by apply a simple flow accumulation scheme to calculate mean annual discharge, and then apply the synthetic rating function to estimate mean river depth, width and cross-sectional area for the entire discharging portion of the continental land mass.

Mean annual runoff was accumulated along simulated networks. Since, the storage over the long-term is zero, the accumulated runoff is equal to the mean annual discharge. This discharge can be used to calculate mean depth, width, cross-section area and mean velocity.
for every grid cell of the river network by applying equation 3.11 developed in section 3.2.1. Applying equation 3.11 to the mean flow \((Q_{\text{mean}}, y_{\text{mean}})\) yields:

\[
y_{\text{mean}} = \left[ \frac{Q_{\text{mean}}}{\frac{c}{k} \left( \frac{b}{1+5} \right)^{1+\delta}} \right]^{\frac{1}{1+\delta}}
\]  

(3.28)

Once the mean flow depth \((y_{\text{mean}})\) associated with the mean discharge \((Q_{\text{mean}})\) is calculated, the corresponding width \((w_{\text{mean}})\) can be calculated from equation 3.9 as:

\[
w_{\text{mean}} = \frac{y_{\text{mean}}}{k (dZ/dl)^{1/\delta}}
\]  

(3.29)

These equations were then applied to the different resolution networks representing Europe. The resulting river volumes and surfaces were compared to assess the impact of river network resolution on the river surface area and volume calculations.

3.3.1 Impact of Network Resolution on River Surface Area and Volume Estimates

The influence of river network resolution on the estimation of river surface areas and volumes was assessed by accumulating the mean annual composite runoff along four resolutions (5', 10', 15', and 30') of simulated topological networks. The mean annual UNH-GRDC composite runoff (described in section 2) was interpolated to the appropriate resolution using the "4-6-9" distance-weighted interpolation algorithm (see appendix C) and was accumulated along each simulated network.

Equation 3.29 requires river bed slope, which was derived from HYDRO1k elevation data set (USGS EROS Data Center, 1998b). The original 1 km resolution elevation data were aggregated to each target network resolution. Since aggregation of elevation and the NSA network rescaling introduces inconsistencies between the elevation and simulated networks.
(i.e. local depressions resulting uphill slopes along downhill river courses), a special pit removal filter was applied to the elevation data set. Starting from the headwater grid-cells, the filter performed a downstream search and lowered the elevation to sustain a minimum 0.01 m/km slope along the 6' network.

Once the mean depth ($y_{\text{mean}}$) and width ($w_{\text{mean}}$) were computed, the percent river surface area was calculated for each river basins. The percent river surface areas were grouped by basin area and averaged for the basin area groups Figure 3-12a-d shows the relationship between the basin area and the percent river water surface at the different resolutions tested.

The percent river surface area is a log-linear function of basin size regardless of resolution. There is an apparent decrease in the percent water surface as the resolution decreases. However the slope ($b_1$) of the log-linear regression line is fairly similar, the offset ($b_0$) decreases with resolution figure 3-12a-d). This is partly due to the reduced river length at coarser resolution discussed in section 3.1.1. Applying the length correction equation 3.2 slightly improves the water surface estimates at coarser resolutions (figure 3-12e-h) but still the difference between the water surface area calculated at fine resolution can be up to 20 % higher than at coarser resolution.

Similar analysis considering the river volumes is presented on figure 3-13. The square root of river volume / basin area ratio appears to be log-linear function of the basin area. Furthermore, this ratio has less sensitivity to the network resolution. While the smaller rivers (which are not represented in coarser resolution networks) can have significant surface area relative to the large rivers, volume-wise large rivers dominate the the river water distributions.
Figure 3-12: Relation between basin area and percentage of river water surface at different resolutions. Panel a through d shows the comparison without river length correction. Panel e through h shows the percentage of river water surface as a function of basin area after applying river length correction (equation 3.2). Linear egression parameters ($b_0$ - intercept, $b_1$ - slope and $R^2$ correlation coefficient) are shown in figure title.
3.3.2 Global Distribution of Surface Area and Volume of Rivers

This section presents an estimate of three key attributes of the global system of rivers, namely, surface area, volume, and residence time of runoff. These calculations are based on the UNH/GRDC Composite runoff field, which was accumulated along a 30' resolution simulated global river network (STN30p). The resulting discharge was applied in equations 3.28 and 3.29 to estimate mean flow depth and width. Figure 3-14 shows the estimated mainstem depth and width profiles of four large river systems (Amazon, Nile, Mississippi, Yenisei). The depth profiles are relatively smooth curves relative to the width profiles, due to their independence from riverbed slope. The sudden drops in the width profiles are due to drastic change in the riverbed slope according to HYDRO1k digital elevation model, which served as the basis for the calculation of riverbed slopes. These sudden drops can be reduced by applying average filtering to the digital elevation model.
Figure 3-14: Depth and width profiles of the Amazon, Nile, Mississippi and the Yenisei rivers. The sudden drops in the width profiles are due to the local changes in the riverbed slopes derived from HYDRO1k digital elevation model.
The estimated width and depth provides the basis of the assessment of the surface area and the volume of the global river networks. Table 3.2 summarizes the volume of the STN30p rivers by continents and receiving water bodies. The total river volume according to this estimate is 1396 km$^3$. This agrees very well to 1250 km$^3$ given by van der Leeden et al.

Table 3.3 gives the river volume/catchment area ratio ($r_v$) by continents and receiving water bodies. This term can be used to compute the mean residency time of continental runoff. Considering the mean annual runoff ($\overline{R} = 299$ mm/yr) (Table 2.2) an aggregate estimate of global residency time can be calculated as $r_v/\overline{R} = 10.50 \text{ [mm]} / 299 \text{ [mm/yr]} = 0.035 \text{ [yr]} \sim 13 \text{ [days]}$, which agrees with the estimates in the literature.

Table 3.4 summarizes the river surface area / catchment area ratio by continents and receiving water bodies. This information is rarely available, but is essential for estimating evaporation from rivers. The relationship between river discharge and flow surface has potential importance in the development of remote sensing techniques to measure discharge.
Table 3.2: River volume [km$^3$] by continents and receiving water bodies.

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<tr>
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<th>Africa</th>
<th>Asia</th>
<th>Australasia</th>
<th>Europe</th>
<th>North America</th>
<th>South America</th>
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<td></td>
<td>14.3</td>
<td>33.3</td>
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Table 3.3: River volume/catchment area ratio [mm] by continents and receiving water bodies.

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Table 3.4: River surface/catchment area ratio [%] by continents and receiving water bodies.

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</table>
SUMMARY

The present dissertation work aimed to improve our current understanding of the spatial and temporal distribution of runoff and its delays during its travel to the river basin's outlet. A variety of GIS and modeling tools along with state-of-the art global data sets were used to derive better estimates of the contemporary runoff and its spatial distribution. The dissertation demonstrated the use of water balance calculations and its limitations.

Extensive sensitivity analysis was performed to assess the uncertainties in water balance calculations. The sensitivity analysis showed that the two most important elements of the water balance calculation are the accurate precipitation and the formulation of the evapotranspiration calculations. It is not surprising that the precipitation plays an important role in the runoff generation, since it is the only meteorological variable which directly affects the water balance calculations. Less trivial is the significant uncertainty in the evapotranspiration calculations.

The evapotranspiration functions tested result in wide differences in the runoff estimates. However, there is a clear divide between the simpler reference crop type functions and the more sophisticated land cover dependent potential evapotranspiration functions, but these differences cannot be attributed to the land cover sensitivity. The reference crop type functions are cover independent by definition, but even Shuttleworth-Wallace's method, which is the most sophisticated land cover dependent potential evaporation function, is not very sensitive to land cover differences. The sensitivity of the water balance calculations to rooting depth is even less than the sensitivity to the land use. These results suggest that despite the importance of a better understanding of the evapotranspiration processes, substantial improvement of the water balance calculations can not be expected from more sophisticated
land surface parameterization. The key to more accurate water balance estimates is better precipitation data.

The dissertation also demonstrated the value of river discharge data for the validation of the water balance calculations. River discharge is one of the most accurately measured components of the hydrological cycle. It is a spatially and temporally integrated signal of the runoff. River discharge information can be used not only as validation data, but to tune water balance estimates. The dissertation presented a simple method to combine measured discharge and water balance simulated runoff, which simultaneously preserves the high accuracy of the observed discharge and the spatial distribution of the water balance model runoff. An application of this method was the development of the UNH/GRDC composite runoff fields, which is a joint product of the University of New Hampshire and the Global Runoff Data Center. The resulting data set represents our best estimate of the continental runoff.

In addition to analyzing the runoff processes, the present dissertation also discussed some elements of the horizontal water transport with a focus on riverine water transport. Rivers play a dominant role in the horizontal water transport processes due to their high efficiency in delivering water. The dissertation discussed the grid representation of rivers, and demonstrated the limitation of such simulated river networks. The relationship between network performance (in terms of representing the geomorphometric characteristics of the actual river networks) were identified providing important guidance to the design of gridded networks for various analysis.

The potential for simulating not only the horizontal distribution of river reaches, but their flow properties such as depth, width, cross-sectional area and mean velocity were also studied. The theory of an idealized rating function relating these properties to discharge was derived from traditional flow theories by introducing and parameterizing idealized cross-sections. Stage height and the corresponding discharge of over 4000 discharge gauging stations were used to verify the idealized rating function and its underlying as-
sumptions. Important relationships for the parameterization of the idealized cross-section and the corresponding synthetic rating function were found.

As an application of the river bed parameterization, estimates of the total volume of water stored in rivers was calculated by continent and receiving oceans, which agreed well with literature data. The capability to represent flow characteristics such as width, depth, surface area, volume, etc. is an important step for the design of flow routing schemes with full river channel dynamics including adjustment of the riverbed. The relationships developed in the dissertation could be important in the development of future remote sensing techniques to measured discharge.

The present dissertation contributed several important pieces to the understanding of the hydrological processes and ultimately to the answering of the ambitious questions posed in the introduction, but numerous pieces remain missing. The dissertation neglected many elements of the hydrological processes. Probably the most important one is ground-water, which may not play significant role in the horizontal water transport, but certainly is one of the most important storage pools. The ground-water is actually an important inter­mediator between the river and the land surface. Another important missing element is the interaction between the different hydrological components. Water balance calculations, river routings and groundwater simulations are often performed separately, using outputs from one component as an input to the other. However, this approach is reasonable in many cases, but the interaction among these components are rarely unidirectional, and interaction among them is important. One of the goals of the future research is to develop a fully coupled system, which incorporates the water balance calculations into a ground­water transport scheme, which in turn is coupled with a river routing scheme. Such a system should be capable of representing such complex hydrological situations as the Niger or the Nile, where the river originated from the wet tropics and traveled through dry regions feeding the surrounding vegetation via groundwater and regular flooding.

The Nile as an example brings the important aspect of representing the human impact
in hydrological processes. Human activities have already caused significant alteration of the hydrology of many regions. The Nile and the complete water uptake from the Colorado river are well known examples, but less documented are the substantial changes in water regimes due to land use change (e.g. Tisza river, in Hungary, where the recent extreme floods were attributed to the significant changes in the headwater regions in Romania and Ukraine). Besides altering the rivers by water uptake or changing the surrounding tributaries, humans are also actively altering rivers by river regulation and damming. Future work needs to address the impact of these human activities on the hydrological processes.
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Appendix A

Global Data Sets for Water Balance Studies

A.1 Land surface Characterization Datasets

In the present dissertation most of the water balance analyses were carried out at 30' resolution therefore relatively old but well tested land surface characterization data sets were used. The contemporary land cover classification was assembled by combining Terrestrial Ecosystem Model (TEM) (Melillo et al., 1993) "potential" vegetation overlayed with cultivated areas from Olson's land-use classification (Olson, 1991). The TEM/Olson composite vegetation was remapped to eight cover types (conifer forest, broad-leaf forest, savannah / shrub-land, grassland, tundra / non-forested wetland, cultivation, desert, open water) which were found to have characteristic evapotranspiration properties (Federer et al., 1996). Dominant soil type and texture were from the FAO/UNESCO soil data bank (FAO/UNESCO, 1986). Land cover classification and dominant soil types were combined to estimate rooting depth and water holding capacity as given by Vörösmarty et. al. (1996). Topographic data was aggregated from GTOPO30 (Gesch et al., 1999; USGS EROS Data Center, 1996).
A.2 Climate Data sets

The primary climate data sets were from Willmott-Matsuura (Willmott, 1999) providing mean monthly air temperature and precipitation and the Climate Research Unit (University of East Anglia), which provided mean monthly time series for not only air temperature and precipitation but cloud coverage and vapor pressure for the 1901-95 period. This data set also provided wind speed but as long-term monthly mean only. Besides the Willmott-Matsuura and CRU data sets, Global Precipitation Climate Center (GPCC) and Global Precipitation Climatology Project (GPCP) precipitation data sets were also tested in several experiments.

A.2.1 Willmott-Matsuura Precipitation and Air temperature

Willmott-Matsuura global air temperature precipitation data sets (Willmott, 1999) at $0.5^\circ \times 0.5^\circ$ resolution (longitude $\times$ latitude in geographical coordinates) were developed at the Department of Geography, University of Delaware. These data sets originated from Legates and Willmott climatological data sets (Legates and Willmott, 1990a). The Legates and Willmott climatologies were among the first global data sets which break the tradition of using stations only with long observation records. They argued that the spatial variation of climate fields are more significant than the inter-annual variation and therefore the inclusion of all the available stations to resolve the spatial heterogeneity is more important than to maintain rigorous time series consistency (Willmott et al., 1996; Willmott and Rowe, 1985).

The recently released Willmott-Matsuura data set is based on the same set of meteorological stations as the original Legates and Willmott data set but uses an improved version of the Shepard interpolation algorithm (Shepard, 1968) and more robust neighbor finding method. The maximum number of nearby stations considered in the interpolation were increased from 7 to 20 resulting in smaller cross-validation error and "visually more realistic" precipitation fields (Willmott, 1999).
The Willmott-Matsuura precipitation data set comes in two versions. The standard one is based on the original observational records, while the gauge corrected version applies correction to compensate for the known problems of gauge under-catch in certain condition geographical regions (Willmott et al., 1994; Legates and DeLiberty, 1993; Legates and Willmott, 1990a).

### A.2.2 Climate Research Unit Data Sets

The Climate Research Unit (CRU) of University of East Anglia developed both mean monthly climatologies and time series (1901-95) of air temperature, precipitation, cloud coverage, number of wet days, vapor pressure, and wind speed (New et al., 1998a; New et al., 1998b). They collected station data from various (formal and informal) sources and applied thin-spline interpolation (Hutchinson, 1995; Wahba, 1979). They adopted the Legates and Willmott approach by developing a climatology first from relaxed time series consistency and superimposed inter-annual anomalies based on stations with long record (New et al., 1998a).

The CRU data set was developed at several resolutions. The climatologies (at 0.5° × 0.5° resolution) and the time series data at coarser resolutions (5° × 5° and 2° × 3.75°) are freely available through CRU's web site, however the 0.5° × 0.5° resolution time series data are only available on CD-ROM at a nominal price.

### A.2.3 GPCC Precipitation Data Sets

Global Precipitation Climate Center (GPCC) hosted at the German Weather Service (Deutscher Wetterdienst, Offenbach, Germany) as the official precipitation data center of the World Meteorological Organization (WMO). GPCC collects and archives global precipitation data and develops derived data products (Rudolf et al., 1994). GPCC has data for ~48,000 stations and near real-time access to 6000 to 7000 SYNOP and CLIMAT reports via the
WMO's Global Telecommunication System (GTS).

GPCC has two major monthly precipitation data products. The first one is called "Monitoring product" based on the SYNOP and CLIMAT data. This data product is available near real-time (i.e. with two month time lag) from 1986 to present at 2.5° x 2.5° and 1° x 1° resolution. Along with the precipitation data product, GPCC also provides separate gauge correction data using the Legates and Willmott (1990) method to account for known problems of gauge under-catch. This data set provides the ground observation basis for the Global Precipitation Climatology Project. GPCC's second product is the "Verification Product" which is based on 30,000-40,000 archive stations. This data product is not available yet for the scientific community, therefore we used the "Monitoring product" in our present study.

A.2.4 GPCP Precipitation Data Sets

Global Precipitation Climatology Project (GPCP) as part of the Global Energy and Water Cycle Experiment (GEWEX) of the World Climate Research Program was established to develop monthly precipitation data product based on remote sensed data from geostationary and polar orbiting satellites and ground observations. The currently available GPCP products (Version 1c and 2.x) combine precipitation estimates from microwave (Special Sensor Microwave/Imager, SSM/I) and infrared sensors at 2.5° x 2.5° resolution and GPCC ground-based precipitation estimates with gauge correction. The Version 1.c and the Version 2.x products are very similar except the Version 2.x products incorporates TIROS Operational Vertical Sounder (TOVS) and OLR Precipitation Index (OPI) for time periods when SSM/I was not available (Susskind et al., 1997). The Version 1.c product covers the time period of 1987 through present while the Version 2.x product is available for 1979 to present.
Appendix B

Comparison of Precipitation Data Products

The present chapter attempts to assess the uncertainties in precipitation by comparing six precipitation data products and identifying the regions where the different data products show the best agreement and the greatest disparities. The tested data sets originally had different spatial resolutions and represent different observation periods. Section B.1 analyzes the impact of these differences so the known disparities can be identified. Section B.2 compares the mean annual precipitation derived from the different data sets. This analysis gives an insight to the spatial distribution of the total annual precipitation estimates and the range of uncertainties by regions. Section B.3 compares the differences in the seasonality by the various precipitation data products.

B.1 Assessing the Impact of Differences in Resolution and Temporal Coverage

The six precipitation data sets compared in the present dissertation have known inconsistencies in both the spatial resolution and the temporal coverage. Some of the data sets were only available at coarser resolution (GPCC at 1°, GPCP and NCEP at ~ 2.5°). These data sets were interpolated to 30' resolution using inverse distance weighted 4-6-9 point
Comparison of regridded data sets

![Graph showing comparison of regridded data sets.]

Figure B-1: Assessment of the impact of regridding. Willmott-Matsuura mean annual precipitation at $0.5^\circ \times 0.5^\circ$ resolution was aggregated to $1.0^\circ \times 1.0^\circ$ and $2.5^\circ \times 2.5^\circ$ resolutions. The aggregated coarse resolution grids where resampled to the original fine resolution. Latitudinal profiles of the regridded fields show that the regridding had little impact on the large scale characteristics. The regridding introduced negligible bias (0.70 and 0.59 mm/yr respectively), however, cell by cell comparison between the original and the regridded $1.0$ and $2.5^\circ$ resolution fields shows 46.3 and 97.7 mean absolute difference.

Interpolation (described briefly in the appendix C).

The impact of differences in resolution were tested by downgrading Willmott-Matsuura $30^\prime$ annual precipitation to $1^\circ$ and $2.5^\circ$ and then the coarser resolution precipitation gridded fields were re-interpolated to $30^\prime$ resolution. Figure B-1 shows the latitudinal distribution of the original $30^\prime$ Willmott-Matsuura annual precipitation and the degraded and later re-sampled annual precipitation. However, the degradation and re-interpolation introduced substantial local differences, but sufficiently preserved the large scale patterns of the original precipitation field and introduced negligible bias.

Besides the resolution differences, the different data sets cover different time periods. The CRU data set represents 1901-95, GPCC and GPCP is available for 1986 to present, NCEP dataset used in present study covers 1957-97, while Willmott-Matsuura is only available as climatology from varying but not necessary overlapping, periods of station records.
In order to assess the impact of different time periods represented in the monthly climatologies, the CRU data set was subset to four time periods (1901-95, 1901-60, 1961-95 and 1986-95) and monthly climatologies were calculated for each of these periods.

The latitudinal profiles of the different climatologies are remarkably similar regardless of the time frame of the climatology (Figure B-2). This strongly supports the Legates and Willmott's (1990) argument that the spatial variation of the precipitation is much more important than the inter-annual variation. The lack of significant differences in the precipitation in different time period and the water balance calculations insensitivity to the slight changes in air temperature suggest that the runoff regimes of the continents did not change in the last hundred years. Therefore discharge records are very unlikely to show climate change signal.
B.2 Comparison of Mean Annual Precipitation

Once the impact of known differences between the studied data sets were clarified, mean annual precipitation was calculated and compared. Table B.1 summarizes the mean annual precipitation differences between the tested data sets. The mean annual continental precipitation varies between 731.2 mm/yr (GPCC) and 858.3 mm/yr Willmott-Matsuura gauge corrected. Willmott-Matsuura gauge corrected (WMcor) is slightly higher than the NCEP reanalysis product (846.9 mm/yr). CRU and Willmott-Matsuura standard are very close (786.1 and 790.0 respectively). This is not surprising since CRU and Willmott-Matsuura data sets were developed using the same philosophy - considering as many rain gauges as many was possible regardless of the temporal overlap between the observational records. Neither CRU nor WMstd applies any gauge correction.

Figure B-3 shows the latitudinal profile of the six precipitation climatologies. However all of them depict the same precipitation patterns, but the differences among them far exceed the differences that can be attributed to inconsistencies in spatial resolution and temporal coverage. The latitudinal profiles reveal more details about the differences between the different data sets. The NCEP data sets seems to be fairly consistent with Willmott-Matsuura and the CRU data sets. GPCC and GPCP tend to be lower particularly in the tropics, however GPCP picks up more in the high Northern latitudes.

The comparison in pairs gives more insight to the differences between the tested data sets. First the precipitation gauging station derived data products (i.e. CRU, GPCC, WMcor, WMstd) were compared. Figure B-4 shows the spatial distribution of the absolute and relative difference between the GPCC, WMcor, WMstd and the CRU data set. According to Figure B-4 CRU and GPCC largely agree in the higher latitude, but CRU is higher in the wet tropics. WMcor is higher than CRU almost everywhere while WMstd is higher in the wet tropics and lower in the higher altitudes. The relative differences show similar trends, but in relative terms the differences appear to be more significant in the dry regions (especially in the Sahara).
Table B.1: Comparison of mean annual precipitation fields. First row contains the mean annual precipitation over the continental land mass depicted by the six precipitation data sets. The cross-matrix gives mean spatial anomaly differences (MSAD) calculated as $\sum_{i=1}^{n} (X_i - \bar{X}) - (Y_i - \bar{Y})$ where $X_i$ and $Y_i$ are mean annual precipitation at grid-cell $i$, $\bar{X}$ and $\bar{Y}$ are the mean annual precipitation over land.

<table>
<thead>
<tr>
<th>Mean Annual Precipitation</th>
<th>CRU [mm/yr]</th>
<th>GPCC [mm/yr]</th>
<th>GPCP [mm/yr]</th>
<th>WM Std [mm/yr]</th>
<th>WM Cor [mm/yr]</th>
<th>NCEP [mm/yr]</th>
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<td>CRU</td>
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<td>790.0</td>
<td>858.3</td>
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<td>163.9</td>
<td>104.1</td>
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<td>-3.9</td>
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<td>MSAD Bias</td>
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<td>92.7</td>
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<td>163.9</td>
<td>43.3</td>
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<td>-11.4</td>
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</tr>
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</table>
Comparison of Precipitation Climatologies

Figure B-3: Latitudinal profiles of the CRU, GPCC, GPCP, NCEP and Willmott-Matsuura mean annual precipitation.

Figure B-5 shows the absolute and relative difference distributions of the cell by cell difference shown on figure B-4. The absolute difference is around 100 mm/yr for all the station based precipitation data, and the largest difference can exceed 1000 mm/yr. The average relative error is around 10%.

Figure B-6 shows the absolute and relative differences between CRU, GPCC, WMcor and GPCP data sets, where the first three are station based and GPCP is a composite of station based and satellite estimate. According to Figure B-6, GPCP in most regions is higher than CRU or GPCC. CRU annual precipitation is higher only in the wet tropics. WMcor is generally higher in the tropics and the mid latitudes but lower in the higher altitudes.

The distribution of the absolute and relative differences is shown on figure B-7. The mean absolute differences between CRU and GPCP and WMcor and GPCP are slightly higher than between GPCC and GPCP. This can be explained since GPCC and GPCP are strongly related. The difference is largely due to the rain gauge correction applied in GPCP. It is interesting to note however, that the cell by cell comparison shows less
Figure B-4: Comparison of mean annual precipitation derived from gauge stations. Panels a,c,e show the differences between GPCC, WMcor, WMstd and CRU mean annual precipitation. Panels b,d,f show the relative difference computed as $\frac{X_i - Y_i}{X_i + Y_i} \times 100$ for each $i$ grid cell.
Figure B-5: Distribution of the absolute (panels a-c) and relative (panels d-f) differences between GPCC, WMcor, WMstd and the CRU mean annual precipitation. Mean absolute difference is given in brackets. Note that this is different than the mean spatial anomaly difference (MSAD) given in table B.1.
Figure B-6: Comparison of precipitation gauge station derived data sets to GPCP station based and satellite composite. Panels a,c,e show the difference between CRU, GPCC, WMcor and the GPCP mean annual precipitation. Panels b,d,f show the relative difference computed as it was shown on figure B-4.
difference between GPCP and CRU or WMcor despite the large bias found in the comparison of the mean annual continental precipitation (table B.1). Apparently the bias is due to the precipitation differences in the northern latitudes, while the mean absolute differences are heavily influenced by the degree of agreement between the different data sets in the wet tropics.

Figure B-8 shows the comparison of CRU, WMcor, GPCP and NCEP precipitation. The cell by cell absolute and relative difference between NCEP and the CRU, WMcor and GPCP data sets have much larger differences than any of the previous comparisons. The
NCEP data has a systematic error pattern, which results in extremely large differences in some regions. Despite the relatively good performance of NCEP in terms of depicting similar latitudinal profiles as the other five data sets, the regional anomalies are substantial.

The absolute and relative difference distributions (figure B-9) demonstrates the large discrepancies between NCEP and the other data sets. The mean absolute difference and mean relative differences are twice as high (200 mm/yr and 20% respectively) as seen for the other data sets and the absolute difference can exceed 2000 mm/yr.

The six precipitation data sets represent our current "state-of-the-art" understanding of the global precipitation distribution. The differences among them can be viewed as an estimate of the uncertainties in the spatial and temporal distribution of the global rainfall. Figure B-10 shows the absolute $\max - \min$ and relative $\frac{\max - \min}{\max + \min \times 100}$ ranges of difference between CRU, GPCC, GPCP and Willmott-Matsuura data sets where $\max$ and $\min$ are the highest and lowest grid cell value amongst the five data set. The NCEP product was excluded from this analysis because of its extreme anomalies compared to the other five data products.

The range in differences appears to be high in the wet tropics and less in dry regions, but the relative ranges are actually the opposite and show greater relative differences in the dry regions and more consistency in the wet regions. This finding is not surprising, but emphasizes the need to improve accuracy of the precipitation measurement in dry regions, where the relative differences between the different datasets could be as high as 100%.

The uncertainties in the mean annual precipitation are certainly lower than the year-to-year variation of the annual precipitation according to CRU’s 95 times series but close. The accuracy of our precipitation monitoring capability is not much higher than the year-to-year variation the precipitation itself. Figure B-11 shows the absolute and relative ranges of the annual precipitation for 1901-95 according to CRU precipitation time series and figure B-12 shows the distribution of the absolute and relative range of inter-annual variation versus the differences among the different mean annual precipitation.
Figure B-8: Comparison of NCEP precipitation to CRU, GPCC and WMcor data sets. Panels a,c,e shows the difference between CRU, GPCC, WMcor and the NCEP mean annual precipitation. Panels b,d,f show the relative differences computed as it was shown on figure B-4.
Figure B-9: Distribution of the absolute (panels a-c) and relative (d-e) differences between NCEP and the CRU, GPCC, WMcor and GPCP mean annual precipitation data sets. Mean absolute difference is given in brackets. Note that similarly to figure B-5 this is different than the mean absolute spatial anomaly difference (MSAD) given in table B.1.

Figure B-10: Absolute and relative differences between CRU, GPCC, GPCC, WMcor and WMstd precipitation climatologies. The NCEP product was excluded from this analysis because of systematic regional anomalies.
Figure B-11: Absolute and relative range of the inter-annual variability of the mean annual precipitation according to the CRU 1901-95 time series.

Figure B-12: Distribution of the absolute and relative ranges of mean annual precipitation from the CRU, GPCC, WMcor, WMstd and GPCP data sets (a and b) and the CRU 1901-95 annual precipitation (c and d).
Considering the ranges of the annual precipitation for 1901-95 according to CRU, one should notice the big blue spot in the middle of the Congo basin in Africa (figure B-11). This region apparently has no inter-annual precipitation variation, which is an artifact in the CRU data set. CRU inserted dummy stations with no anomalies whenever the inter-station correlation of the neighboring station (from which the grid cell value would have been interpolated) was too low. Without questioning the justification of CRU's approach, figure B-11 should be a warning sign in terms of how well the CRU data sets represent the inter-annual variability.

B.3 Comparison of Seasonality

After analyzing the differences in the mean annual total precipitation, normalized mean monthly precipitation was calculated by dividing the mean monthly precipitation by the mean annual total precipitation for each cell. The normalized mean monthly precipitation can be viewed as how much of the annual total precipitation proportionally falls in each month. The differences in the normalized precipitation between pairs of mean monthly data sets were calculated. The normalized mean monthly precipitation data set were then paired with the other data sets and the total of the positive differences between the normalized monthly values were calculated. By definition this should be equal to the sum of the negative differences since the data sets were normalized such that the sum of each data set equals one and therefore their monthly mean must be 1/12. The sum of the positive (or the negative differences) can be viewed as the portion of the annual precipitation distributed differently through the season by the different data sets. Comparing the normalized monthly values eliminated the differences between the different data sets in terms of total precipitation volume, and offered a simple metric to measure the difference in the seasonality according to the various datasets (figure B-13).

The average sum of the positive normalized differences between the data sets typically were around 0.20 (i.e. 20% annual precipitation is partitioned differently throughout the year).
Figure B-13: Seasonality difference between the CRU and the GPCC, GPCP, NCEP, WMcor and WMstd data sets.
The lowest difference 0.13 was found between GPCC and GPCP, which is not surprising since the two data sets are closely related. The largest differences (0.30) were between NCEP and all the other data sets. The differences are higher in those regions where the mean annual total differences are the highest. Apparently, the uncertainties in total precipitation go hand-in-hand with the uncertainties in the proper seasonality of precipitation.
Appendix C

469 inverse distance weighted interpolation

The water balance calculations were performed on a \(0.5^\circ \times 0.5^\circ\) resolution geographical (longitude × latitude) grid as the highest resolution among the input data sets. All of the coarser resolution data sets were regridded to this resolution using inverse distance weighted 4-6-9 point (IDW469p) interpolation. This interpolation was developed at UNH for grid-to-grid interpolation. The IDW469p method uses four, six or nine neighboring grid point depending on the location of the point to calculate the interpolated value (Figure C-1).

The purpose of the IDW469p interpolation reduces the memory effect of the distance weighted interpolation which occurs as the target point moves from one neighborhood configuration to another. The advantage of the inverse distance weighted interpolation is its simplicity in geographic coordinate space, since bilinear and spline interpolations are non-trivial in non-Cartesian coordinate space.

We tested the IDW469p interpolation by aggregating Willmott-Matsuura \(0.5^\circ \times 0.5^\circ\) resolution mean annual precipitation field to \(1.0^\circ \times 1.0^\circ\) and \(2.5^\circ \times 2.5^\circ\) resolution and resampling the aggregated fields to the original \(0.5^\circ \times 0.5^\circ\) resolution figure B-1. However the cell-by-cell comparison shows that the aggregation and regridding significantly altered the individual cell values (especially when the fine resolution grid was aggregated to the coarser resolution, but the regridded fields preserved well the large scale precipitation patterns.
Figure C-1: Inverse distance weighted 4-6-9 point (IDW469p) interpolation. This inverse distance weighted interpolation method considers four, six or nine points depending on the location of the point at which the interpolation is performed. In the white zones only the four nearest grid points \((P_{i-1,j+1}, P_{i,j+1}, P_{i-1,j}, P_{i,j})\) are used for the interpolation. In the medium gray zones two more point are included in the interpolation (e.g. zone B uses \(P_{i-1,j+1}, P_{i,j+1}, P_{i-1,j}, P_{i,j}, P_{i-1,j-1}, P_{i,j-1})\) are considered. In the black zones (e.g. C) all the neighboring nine points are used.

This exercise convinced us that the comparison of the different precipitation fields, which originally had different spatial resolution, won't be significantly biased due to the regridding and the differences we find are indeed representative characteristics of the compared data sets.
Appendix D

Network Scaling Algorithm

The advent of high-resolution gridded river networks having global coverage offers new opportunities for the study of regional, continental, and global-scale hydrological processes. Gridded river networks typically are derived from Digital Elevation Models (DEM) using maximum downhill (decreasing) elevation gradient search procedures (Jenson and Domingue, 1988). Unfortunately, gridded networks derived from currently available DEMs are often inaccurate, since most DEMs were not designed with the intent of representing river flow patterns.

Automated methods and algorithms have been proposed to correct DEMs or derived gridded networks (Band, 1993; Hutchinson, 1989; Jenson and Domingue, 1988). Gridded networks derived from resampled DEMs typically are fragmented due to spurious local depressions (Hutchinson, 1989). Automated methods to derive gridded networks are most sensitive over flat terrain where the maximum downhill elevation gradient search algorithm is more sensitive to DEM errors due to the lack of pronounced gradients. At global scales and coarser spatial resolutions, average gradients between grid cells are lower and, as a result, river networks derived at the coarser resolutions are subject to substantial error. An automated procedure with manual correction and careful validation against several independent sources has recently been applied to the global network of rivers (Vörösmarty et al., 2000b).

Numerous gridded networks at various spatial resolutions, yielding continental and global coverage, have been released recently (USGS EROS Data Center, 1998b; Renssen
and Knoop, 2000; Vörösmarty et al., 2000b; Graham et al., 1998; Oki and Sud, 1998). The most ambitious project is HYDRO1k, which seeks to deliver a 1 km resolution gridded network with global coverage. At present, its global scale implementation at the full 1 km resolution would be far too computer intensive for most global applications. Clearly, a derived river network at suitably coarser spatial resolutions would be better suited to continental and global-scale applications. Effective procedures for rescaling the otherwise useful high-resolution river networks, however, have not been developed.

Typical grid resolutions for global hydrologic modeling are on the order of ten minutes (~10 km) to 2 or 3 degrees (few hundred km) (Coe, 1998; Hagemann and Dümenil, 1998; Fekete et al., 1999). It has been argued that the 30 degree resolution is suitable for a broad variety of global hydrological modeling and emerging constituent flux research (Vörösmarty et al., 2000b; Vörösmarty et al., 2000a). Finer-resolution networks would be needed for the representation of individual or small local basins and tributaries. Since the development of high-quality gridded networks is generally a time consuming process, a procedure for streamlining the re-aggregation of finer-resolution networks would be valuable to a broad suite of land surface hydrology, climate dynamics, and water resources studies. The availability of finer-resolution gridded networks potentially offers new opportunities for the development of coarser-resolution networks, provided the problems associated with automated rescaling of the fine-resolution grids can be solved. One network grid aggregation algorithm developed thus far (O’Donnell et al., 1999) is not generic enough to use in applications where the original fine resolution grid needs to be projected before deriving flow routing at a coarser resolution.

We demonstrate here a method for converting fine resolution river networks to coarser resolutions while preserving the topology and key geomorphometric properties of the original data set. The proposed method has been successfully applied to all continents covered by HYDRO1k (Africa, Asia, Australia, Europe, North America and South America) to derive 0.1 degree (6 minute) resolution networks. In the current paper, however, we present results for Europe only. The remainder of the paper presents NSA methodology, where model
accuracy is assessed by quantifying sources of error in the aggregation procedure. Changes in geomorphometric attributes across grid resolutions from 1 km (30 seconds) to more than 30 minutes (50 km) are also presented.

D.1 Basic Algorithm

Our overall strategy for reconfiguring fine-resolution river networks into coarse-scale flow paths relies on drainage area calculated for all grid cells at the source resolution. This attribute, which is easily computed, is an integrated, conservative measure and a key property of drainage systems. At any scale, drainage area can be used as an input to automated procedures for rebuilding the aggregated river network. Figure D-1 shows the aggregation of a fine-resolution grid using a 3x3 kernel. In order to preserve the high drainage-area values along mainstems, the finer-resolution grid needs to be aggregated using a maximum-value search within the aggregation kernel. When the rescaling involves both grid aggregation and projection, the high drainage-area values can be preserved by projecting the drainage-area grid with sufficient oversampling before the projection aggregation of the oversampled drainage-area grid.

Grid projection is normally performed as sampling, where the procedure steps through the cells of the projected grid and calculates the coordinates of each grid cell center on the original projection. The procedure then samples the original surface at the projected locations. The sampling either a) assigns the value of the nearest grid cell (nearest neighbor method) to the projected grid cell or b) searches for several nearby cells within a specific radius and interpolates from these neighboring grid cells using a distance-weighted, bilinear, spline, or similar technique. Since the drainage-area grid is a highly non-smooth surface (i.e., the high drainage-area values along mainstems are surrounded with low values), any interpolation would distort these high values through smoothing. The nearest neighbor technique does not alter the sampled grid values, thereby preserving the high drainage-area values.
Figure D-1: Network Scaling Algorithm (NSA) using a maximum value operator to aggregate 3x3 grid cells. Small numbers represent drainage area (# of cells) of the fine scale network (small grids) and the larger numbers are the drainage areas for the coarse-scale grid. One coarse-scale grid cell = 9 fine-scale grid cells. The coarse-scale cell drainage areas are set to the maximum drainage area of the 9 fine-scale cells. The coarse-scale river network is then recreated using a maximum “uphill” (or increasing) drainage-area gradient search algorithm.

The oversampling results in a projected upstream area grid with a finer resolution than the original upstream area grid (i.e., values from the original grid will be present repeatedly in the projected grid). This redundancy ensures that the high drainage-area values are not missed during the grid resampling. The oversampling allows the separation of the projection and the aggregation (i.e., the grid projection is done first, resulting in a projected high resolution grid that consistently preserves all features of the original grid). The projected high-resolution grid is aggregated later. In our case, the aggregation should apply a maximum-value search—since the high contributing area values are carrying the information needed for the network reconstruction.

Drainage-area grids can be used to derive flow directions similar to the manner in which DEMs are used but, in contrast to the use of DEMs which use a maximum downhill (de-
creasing) elevation gradient search procedure, the drainage-area grid instead defines flow directions based on maximum “up-hill” (increasing) drainage-area gradients (pathways with increasing upstream catchment area). We refer to this procedure as the Network Scaling Algorithm (NSA). This procedure can be performed with standard Geographic Information System (GIS) raster functions, which are commonly available in many GIS software packages.

Following construction of a re aggregated network, several network-related geomorphometric attributes such as drainage area, distance to outlet, and stream order can be derived for individual stream links, tributary subbasins, and entire drainage systems. Comparisons to the original fine scale data set can then be made for each attribute. We treat the flow directionality grid and the derived network attributes as one coherent data set, the Simulated Topological Network (STN) (Vörösmarty et al., 2000b).

D.1.1 Input Data

The NSA was tested on HYDRO1k, which is derived from GTOPO30 30 second (~1 km) global elevation data set (Gesch et al., 1999). HYDRO1k is a hydro graphically-corrected DEM, wherein local depressions are removed and basin boundaries are consistent with topographic maps. Unlike other DEMs, HYDRO1k includes numerous hydrology-related data layers such as aspect, flow direction, drainage area (flow accumulation), elevation gradient, compound topographic index (wetness or topographical similarity index (Moore et al., 1991; Beven and Kirkby, 1979)), basin and subbasin boundaries with Pfafstetter encoding (Pfafstetter, 1989; Verdin, 1991; Verdin and Verdin, 1999), and DEM-derived stream lines. In order to maintain uniform grid cell area, the HYDRO1k data set was developed on a Lambert Azimuthal Equal Area projection (Steinwand and Hutchinson, 1995) and therefore is truly a 1 km resolution DEM.
D.1.2 Test Areas

We first applied NSA to the Danube basin to create a 5 minute resolution network from HYDRO1k. The Danube basin and the 5 minute resolution were chosen as a first test area because of the availability of a similar, carefully validated network (STN-05) we had developed (Figure D-2). This network, developed before GTOPO30 and HYDRO1k became available, was derived from ETOPO5 (Edwards, 1989). The initial 5 minute routing was intensively edited (manually) using RiverGIS, a specialized GIS tool developed at the University of New Hampshire as part of our Global Hydrological Archive and Analysis System. RiverGIS facilitates the viewing and editing of simulated gridded networks using vector river networks (e.g., the 1:3M ARC/World (ESRI, 1992a), 1:1M Digital Chart of the World (ESRI, 1992b)) displayed in the background for guidance. RiverGIS also has the capability to quickly derive network attributes such as drainage area, mainstem length, and next station downstream at discharge gauging stations. Actual drainage area, supplied as part of the meta data from discharge gauging data sets, provides another means to identify potential errors in the simulated network. For the 5 minute gridded network of the Danube basin, we used reported drainage area from 113 monitoring stations contained in the VI-TUKI (Water Resource Research Centre, Budapest, Hungary) archive to improve routing accuracy while developing STN-05.

A second step in testing the regridding algorithm examines the sensitivity of drainage-area representation to network resolution. By applying this test to the European continent west of the Aural Mountains (Figure D-3), assessments of the rescaled networks over a broad spatial domain and for rivers encompassing several orders of magnitude in drainage area (≈100 to 3.2×10^6 km^2) can be made.
Figure D-2: Manually edited Danube Simulated Topological Networks (STN-05) at 5 minute resolution and discharge gauging stations from the VITUKI (Water Resource Research Center, Budapest, Hungary) archive. The gauging stations were used to help validate and correct the network based on reported drainage area.

D.1.3 Reference Subbasins

Reference subbasins were derived from the fine-resolution networks by partitioning them into approximately equally sized subbasins. The subbasins were identified by the coordinate of their basin outlets and the corresponding subbasin grid. Network-derived attributes were calculated for each reference subbasin at its basin outlet. Both the basin outlets and the subbasin grids were projected to coarser resolutions. The outlet points of the reference subbasins were used to identify the corresponding subbasins on the coarser-resolution gridded network, in order to compare the network-derived attributes calculated at the different spatial resolutions.
Figure D-3: Simulated river network for Europe at 10, 15, and 30 minute resolution derived from HYDRO1k using the Network Scaling Algorithm.
D.2 Analysis of NSA Errors

To understand potential limitations in the NSA procedures, we compared the network-derived attributes at the original 1 km resolution and the 5 minute regridded resolution for the Danube basin. The following sections identify error sources and outline potential improvements to the NSA procedures to limit these errors.

D.2.1 Verification of the NSA procedures

The first verification of NSA was done through visual inspection of the regridded networks at the different resolutions tested (Figure D-3). Qualitatively, the regridded networks retain the main river patterns and network continuity.

For quantitative evaluation of the NSA procedures, the Danube basin was partitioned into 1364 reference tributaries of approximately 500 km² each at the original HYDRO1k resolution. The outlets of the reference tributaries defined overlapping subbasins ranging from 500 to 780,000 km² in size. Figure D-4a shows good correspondence between the drainage areas derived from the original HYDRO1k and the rescaled 5 minute network. As expected, smaller basins show larger numerical dispersion while larger basins have less error. As a measure of this correspondence, we introduce symmetric relative error (SRE) ($\varepsilon_{sym}$) (Fekete et al., 1999) as:

$$\varepsilon_{sym} = \frac{X_{sim} - X_{obs}}{\max(X_{sim}, X_{obs})} \times 100\%$$

(D.1)

where $X_{obs}$ is the observed (or 1 km) value and $X_{sim}$ is the simulated (5 minute) value. This error term is symmetric regardless of over or underestimation of the observed value, and it ranges between -100% and 100%. Using equation D.1, the error distribution by drainage area can be calculated (Figure D-4b). The mean SRE (for all basin sizes) is -4.09%, with a standard deviation of 17.06% and mean absolute SRE of 16.56% (Figure D-4b).
D.2.2 Comparing NSA-generated and Manually Edited 5 Minute Networks

Comparison between the manually edited and the HYDRO1k-derived 5 minute networks to Digital Chart of the World 1:1M scale river networks shows good correspondence. The manually edited network, however, has much higher accuracy in the rendering of actual river courses than the uncorrected HYDRO1k-derived network (Figure D-5). The large bend on the Tisza River in Hungary before its confluence with the Danube—according to the HYDRO1k derived (uncorrected) network—is an error in HYDRO1k that was inherited from the original 1 km routing. This is one example of many, which underlies the need for careful hand editing of digital river networks derived from automated methods. The development of new methods, which use not only elevation but also additional information such as digitized river networks and drainage-area benchmark points may further improve regridding methods.

Comparison of reported and simulated network derived drainage area at discharge gauges

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Danube Simulated Topological Networks

5-minute spatial resolution

ARC/World Rivers    Manually Edited Network    HYDRO1k Derived Network

Figure D-5: Danube-Tisza Confluence. Comparison of manually edited and HYDRO1k-derived 5 minute networks to ARC/World rivers.

contained in the VITUKI archive shows that the drainage-area error is significantly less when manual editing is applied (Figure D-6). The drainage-area error, compared to a manually edited network, is within ±10 % for 90 % of the stations (Figure D-6a), while only 68 % of the stations are within ±10 % when compared against the HYDRO1k-derived network (Figure D-6b). It should be noted that the manually edited network was heavily optimized to represent accurately these discharge gauging stations. Considering other stations not included in the manual editing may result in a smaller difference between the manually edited and the HYDRO1k-derived networks' performance. We would argue, however, that strong benchmarking of manually edited networks to a fairly dense set of discharge gauging stations along with careful editing to actual river networks should result in better performance between the gauging stations.
Figure D-6: Comparison of reported drainage area (at 113 gauging stations from VITUKI archives) and estimated drainage area derived from manually edited STN-05 network and HYDRO1k-derived simulated networks. Panels a) and c) show one-to-one comparisons of the reported and derived drainage area of the manually edited and HYDRO1k-derived networks, respectively. Panels b) and d) show the symmetric error distributions of the manually edited and HYDRO1k-derived networks by drainage area. The differences between the HYDRO1k-derived and the manually edited networks reflects the inaccuracies in HYDRO1k rather than the errors introduced by the NSA regridding and emphasizes the need to incorporate more information (e.g., existing river networks and reported drainage areas) in the delineation of gridded networks.
D.2.3 Analyzing the Sources of the NSA Errors

The NSA yields two sources of errors. The first error is due to generic grid resampling which does not involve the river network. The minimum grid resampling error can be assessed by considering a rounding error analogy. We express the maximum rounding error of the subbasins' grid representation as $\varepsilon = \Delta A/2$, where $\Delta A$ is the cell area. Since the rounding error of any basin at the 5 minute resolution ($\Delta A \approx 60 \text{ km}^2$) should be less than $\approx 30 \text{ km}^2$, the average of the absolute rounding errors should be approximately half of that. This can be tested by projecting the HYDRO1k-derived reference subbasin grid using simple grid resampling and then comparing the projected areas of the reference subbasins with the original subbasins at the HYDRO1k resolution. Figure D-7 shows the comparison of HYDRO1k catchment area and the regridded accumulated subbasin area at the 1364 subbasins outlets for the Danube. The mean absolute error was 92.3 km$^2$, which shows that the generic resampling method introduces errors in addition to the rounding error of the 5 minute grid representation.

The mean SRE of the basin regridding is $-0.28 \%$, with a standard deviation of 4.96 % and mean absolute SRE of 4.41 %. This is substantially less than the NSA overall error (Figure D-4) and represents an upper bound on the achievable accuracy of the NSA algorithm.

The second source of error arises from the use of a drainage-area grid as the surface to derive a river network. Although this method is simple and robust enough to preserve the major flow patterns, it has limitations. Networks derived from a particular drainage-area surface do not result in exactly the same flow pattern as the original network. Typically, the differences between the original network (which is used to define the drainage-area surface) and the derived networks are small (Figure D-8). The error can be more severe, however, when two major flow lines fall close to each other.
D.2.4 Network Scaling Algorithm with Basin Enhancement

The most important limitation of the NSA rescaling algorithm is that the simulated network—derived from drainage area—may not precisely match the original network used to generate the initial drainage-area surface. Improvements can be realized by limiting the largest of the potential differences to ensure that the regridding algorithm maintains the subbasin configuration as accurately as possible.

An approach toward improving NSA is to incorporate subbasins in the regridding procedure. The subbasins derived from the original HYDRO1k—projected and resampled to the target network resolution—can be used in a modified maximum “uphill” (increasing) drainage-area gradient search procedure. On a first pass, the modified procedure (while searching for the maximum drainage-area gradient) considers only those neighboring cells which fall into the same subbasin region as the cell for which the flow direction is to be determined. Should the procedure fail to find any flow direction (i.e., the cell is the outlet of a subbasin) on the first pass, a second pass then extends the search into neighboring...
Figure D-8: Regridding error due to reconstructing flow routing from drainage area. The figure shows a) the original network and b) the reconstructed network from drainage area. The reconstructed network is not exactly the same as the original network. Therefore the drainage-area surface derived from the reconstructed network differs from the original drainage-area surface. The small numbers in both figures represent the drainage area in grid cells and the crossed numbers in 8b show where the reconstructed network and the drainage area derived from the reconstructed network differs from the original network. This error is a deficiency of the NSA and occurs without any aggregation projection.
The Network Scaling Algorithm with Basin Enhancement (NSA-BE) was applied to the Danube basin, with the 1364 subbasins used to guide the algorithm in deriving a 5 minute network. The use of subbasins helped to improve NSA performance (Figure D-9); the mean SRE dropped from -4.09 % (NSA) to -0.55 %, and approaches the -0.28 % basin regridding error. The standard deviation of the SRE also decreased substantially from 17.06 % to 7.74 %, approaching the 4.96 % standard deviation of the regridding SRE. Similarly, the mean absolute SRE decreased from 16.56 % to 9.12 %, which is about twice as high as the 4.41 % mean absolute SRE from regridding.

This procedure described above can be extended to consider any number of hierarchically nested subbasin partitions, starting with the finest set of subbasins (which partitions the network to the smallest sub-catchments) and continuing the search to larger subbasins. HYDRO1k—with different Pfafstetter encoding levels (Pfafstetter, 1989; Verdin and Verdin,
provides an excellent set of hierarchical subbasins for NSA-BE rescaling. This more general NSA-BE with HYDRO1k hierarchical subbasins was used to rescale the river networks of Europe to different resolutions.
Appendix E

Discretization Errors

The grid representation of any quantity introduces discretization error similar to rounding error, where the quantity \( X \) is approximated by a finite number \( n \) of discrete elements \( (\Delta X) \), \( X^* = n\Delta X \), and \( X^* \) is the approximation of \( X \). The maximum rounding error can be expressed as \( \epsilon = \Delta X/2 \) and the relative error then becomes \( \epsilon = \epsilon/X \) or \( \epsilon = \Delta X/2X \). The required resolution as a function of a desired accuracy \( (\epsilon) \) can be expressed as

\[
\Delta X = 2\epsilon X \quad (E.1)
\]

In the gridded river network context, the two most important quantities are the catchment area and distance to the basin outlet. Applying equation E.1 to grid cell area, we find that to achieve a desired area accuracy \( (\epsilon_A) \), the grid cell area has to be smaller than

\[
\Delta A = 2\epsilon_A A \quad (E.2)
\]

where \( A \) is the area of the smallest basin or subbasin we expect the gridded network to represent with \( \epsilon_A \) accuracy. Therefore, the minimum number of grid cells within the smallest subbasin equals

\[
n = \frac{1}{2\epsilon_A} \quad (E.3)
\]
Since the distances to the basin outlet vary within the basin, it is harder to apply the same criteria to river lengths. We seek to represent the mean river length ($\bar{L}$)—the average distance from any point within the basin to the basin outlet—at some accuracy $\epsilon_L$. Applying equation E.1 to mean river length ($\bar{L}$) the necessary resolution $\Delta L$ becomes

$$\Delta L = 2\epsilon_L \bar{L} \quad (E.4)$$

The catchment area of the smallest basin of interest is more often known than the mean length. We therefore relate $\Delta L$ resolution to catchment area by using a modified version of the basin shape (equation 3.1), which relates mainstem length to catchment area. Introducing mean length shape ($S_m$) as

$$S_m = \frac{\bar{L}}{\sqrt{A}} \quad (E.5)$$

where $A$ is the basin/subbasin area [km] and $\bar{L}$ is mean river length.

Using equation E.5, we can define $\bar{L} = S_m \sqrt{A}$. Substituting $\bar{L}$ in equation E.4 yields

$$\Delta L = 2\epsilon_L S_m \sqrt{A} \quad (E.6)$$

In equation E.6, the resolution was expressed as the distance ($\Delta L$) between the adjacent grid cells. We approximate grid cell area as $\Delta A = \Delta L^2$. Therefore, the resolution expressed as grid cell area $\Delta A$ becomes

$$\Delta A = 4\epsilon_L^2 S_m^2 A \quad (E.7)$$

The minimum number of grid cells ($n = A/\Delta A$) becomes
Equations E.3 and E.8 represent two criteria for the minimum number of grid cells needed to maintain $\epsilon_L$ length and $\epsilon_A$ area accuracy. Assuming that the desired length and area accuracies are equal ($\epsilon_L = \epsilon_A = \epsilon$), we find for rounded (low shape value) basins, the length criteria is typically more strict than the area criteria. We also note that the length criteria is also more strict when higher accuracy is required. For practical purposes (less than 10 to 20 % error), the satisfaction of the length criteria requires more grid cells.