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Chapter 3

A data acquisition framework for prediction of runoff in ungauged basins

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3.1 Why do we need data?

Most river basins around the world are ungauged; indeed, only a few are gauged. Therefore, when runoff is required at any ungauged river or catchment, it is estimated through some kind of extrapolation from a gauged site to that ungauged site, and this is not straightforward. This is the whole *raison d'etre* of the PUB initiative. One way or the other, this extrapolation requires data, of many kinds.

Extrapolation from gauged to the ungauged catchments requires a model of some kind, be it statistical, process based or a combination thereof. Implementation of models need data – all types of models will need data to implement at the ungauged location, indeed all models gain legitimacy from data as part of a validation process. Normally, and certainly throughout this book, we consider data of three different kinds: runoff data (in gauged locations), climate (input) data, and catchment characteristics data.

Statistical models attempt to build statistical (e.g., regression) relationships between runoff at gauged locations and associated climate and catchment data, which can then be extrapolated for predictions in ungauged basins with the use of local climate and catchment data. Process based models do the same, except that they benefit from the use of universal balance laws (mass balance, momentum balance etc.), but they too need all three kinds of data (runoff, climate and catchment) at gauged locations for calibration/validation/conditioning, and climate and catchment data at the ungauged locations where predictions are needed.

However, one should not be fooled into thinking that the data are just inputs to a model, in the sense of "grist to a mill". Data has hydrologic context, and contains hydrologic content. The data relating to runoff, climate and catchment one collects from any place, interpreted by a trained hydrologist, and informed by prior knowledge from outside the place, can reveal a lot of the hydrology of the place, it can inform what models we should choose, and it can help us interpret, condition and reject the predictions made by a model.

Hence data are more than just input to a model. The value of data becomes paramount when one begins to accept the notion that catchments are complex systems, reflecting the co-evolution of climate, soils, topography and vegetation, and the patterns one sees in the landscape structure and the runoff response (e.g. signatures) are emergent patterns, and reflect more than the mere balance equations that are embedded in many of today's process based models. Therefore, there is value and much to be learned from the combination of runoff,

climate and catchment data, a learning process that we have called "*reading the landscape*". Data will be ultimate source of the understanding that is embedded in all the models, because when understood properly, they reflect the co-evolution that is common to all catchments.

We can thus summarize the need for data in three categories: (i) data needed to read and understand the landscape in a hydrologic context, (ii) data needed to develop regression relationships that will be used in statistical models, and (iii) data needed for process based models, as climatic forcing and parameter values, data to assist with model development (inference from rainfall-runoff data), and to calibrate or validate models developed elsewhere.

The starting point for any PUB study therefore has to include an assessment of available data and the information that can be derived from this data. This activity includes the need for catchment interpretation based on the available database and the time frame of the study. Depending on the application and the resources available, runoff prediction in ungauged basins is generally based on different data acquisition strategies, ranging from global data sets of typically low resolution to local and regional data sources of varying availability and accuracy followed by field observations/assessment of local system characteristics. If the resources are available, the most accurate runoff predictions can be obtained by utilizing very local data describing the specific characteristics and behaviour of the system. Input data requirement will be dependent on the nature of runoff prediction desired. While global or regional data will be useful for annual runoff prediction, more intensive local data will be needed for hydrograph prediction.

The objectives of this chapter are to provide an assessment of the data available for PUB, and to provide some initial guidance on how this data might be acquired. These data products can often be estimated from global or national data sets but their availability at higher resolution or as a directly measured or observed product from regional to local scales can enhance data quality and therefore PUB. Some data sources and observations can be direct (e.g. model input parameters or forcing) or indirect (e.g., likely runoff dynamics interpreted from regionalization, similar catchments, or experience). Indirect data or observation can provide qualitative information and aid in model selection and evaluation. Auxiliary data types and higher resolution information become increasingly important at short time scales and smaller spatial extents. The following sections provide an overview of hydrologic landscape interpretation based on hierarchical data from the global to regional to local scales that provide a general and practical pathway to PUB. The introduction of this acquisition framework is followed by a discussion of the main data sources (separated by hydrologic variables) from global to local scale. In addition, three case studies illustrate the hierarchical data acquisition strategy discussed here.

3.2 A hierarchy of data acquisition

Most river basins around the world are ungauged. Interestingly, this lack of data often increases with decreasing catchment sizes. Figure 3.1 shows an example of the data bias towards larger scales with respect to the US stream gauge network (see discussion in Wagener and Montanari, 2011). At what spatial scale this lack of data becomes a problem for decision-making varies from country to country. A general consequence, however, is that data scarcity is a major issue even for highly developed (and therefore often highly monitored countries). At the global scale, data sources are primarily limited to remote sensing and global climate models, notwithstanding aggregated products such as global soils maps. In the last few decade new satellite sensors have also made available useful measurements across large areas. These global products, together with regional and local observations and landscape interpretation, can provide data corroboration and validation and a hierarchy of inputs for

hydrologic modelling and runoff estimates. Paradoxically, data requirements to achieve accurate simulations increase with decreasing temporal and spatial scale of prediction. This is because at small spatial scales runoff tends to be more tightly linked to details of landscape structure and climate forcing and exhibit greater space-time variability thereby hampering parameter regionalization and scaling (Wood et al., 1988). At greater spatial scales, much system heterogeneity is subsumed and averaged often leading to simpler catchment response to climate forcing (Sivapalan, 2003). Therefore, data needs and the value or information content of data products from global data sets to local observations for runoff prediction are scale dependent. Indeed, the issue of data adequacy and availability, in the context of natural variability present across regions of the world will be a recurring theme throughout this book, including in the assessment of the performance of prediction methods.

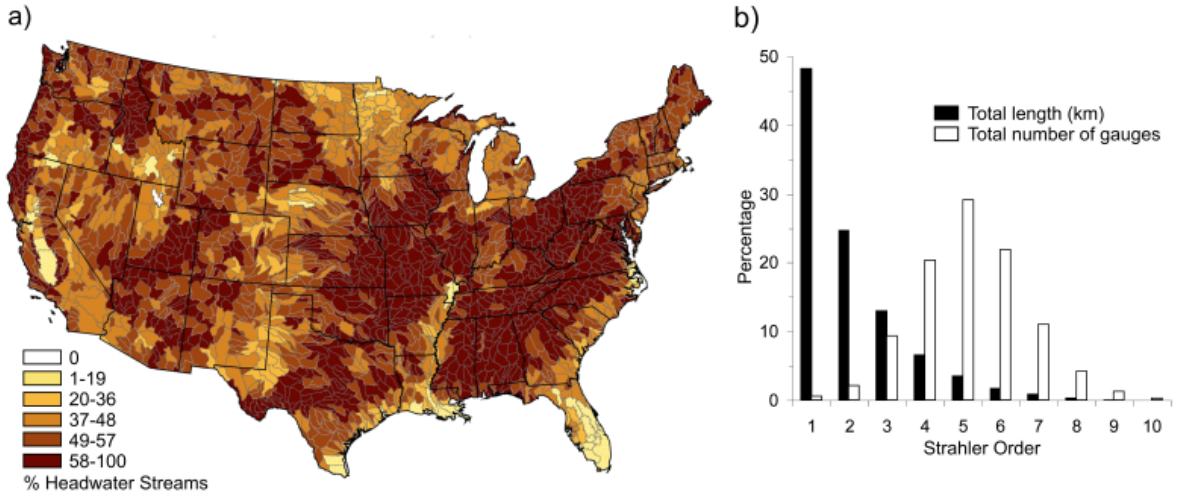

Figure 3.1 (a) Spatial distribution of headwater stream length as a percentage of total stream length in the USA. From Nadeau and Rains (2007). (b) Distributions of stream length and stream gauges against stream order in the USA. From Poff et al. (2006).

A hydrologist has a number of options to approach the problem if runoff is to be predicted in a particular ungauged catchment. Typically, the choice of data acquisition depends on time and other resources available (Fig. 3.2). Data sets at the global scale provide the context and bounds on hydrologic behaviour and runoff potential via basic climatology. Numerous global data sets that are of relevance to predicting runoff in ungauged basins exist that can be downloaded at no or little cost to the user. In many instances, this broad scale information will not suffice to predict runoff with the required accuracy or the required spatial and temporal resolution, so the hydrologist will acquire hydrologic data from any hydrological network that is operated by the national or state authorities. This usually involves more effort of data quality checking and predictive methods than when only using the global data sets. If more time and resources are available the hydrologist will make a field visit to assess the hydrological landscape based on his/her expert knowledge. Local characteristics of climate forcing and internal catchment characteristics provide insight into likely catchment water storage, surface partitioning and internal redistribution, and release of water to runoff and evaporation. Finally, if time and financial resources were even larger, one would clearly collect some short-term measurements or even install a stream gauge and other hydrologic equipment to get a better understanding of the catchment response. This means that acquiring information for estimating runoff from ungauged catchments can follow a hierarchical approach, depending on resource availability.

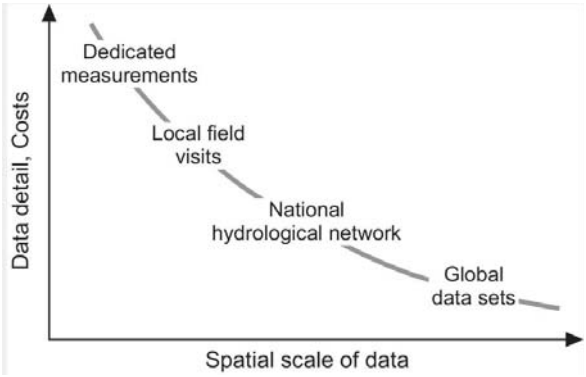

Figure 3.2 Hierarchy of data acquisition: Dedicated measurements provide detailed information at high costs over small spatial scales. Global data sets provide more generalised information at lower costs to the individual user.

The prediction methods presented in Chapters 5-10 that follow make use of the data acquired at a range of scales, from proxy data at the local scale to global scale data sets. The remotely and locally observed catchment characteristics can be combined for catchment regionalization and/or qualitative description for *a priori* model selection in the context of PUB. What data is acquired specifically depends on the system under study, e.g., whether it is located in an arid or in a humid region, and on the purpose of the predictions. For example, if we are interested in predicting low flow characteristics then taking a few selected runoff measurements during low flow conditions might be most helpful, while we might be interested in indicators of historical flood levels such as flood marks for inundation mapping. The following four-point discussion (a-d) provides an example of hierarchical data acquisition, moving from globally available to locally specific data.

Assessment based on global data sets

A catchment located anywhere in the world will have an annual and seasonal climatology characterized by a given precipitation regime and a basic energy balance. This broad scale context is often discussed in terms of the annual water balance and a climatic index. The well-known Budyko (Budyko, 1974) diagram represents this as the ratio of mean annual evaporation to mean annual precipitation versus the ratio of mean annual potential evaporation to mean annual precipitation, thereby relating a metric of the mean annual water balance to a climatic aridity or dryness index (Fig. 3.3). The location of a given catchment on this general relationship or curve represents the relative degree of water versus energy limitation and can inform the coarse interpretation of the controls on catchment runoff. While valuable, this type of broad scale assessment does not include internal catchment characteristics that can influence runoff dynamics nor shorter-term climate and weather forcing that lead to dynamic hydrology and storm runoff, but rather provides a starting point for more localized assessment.

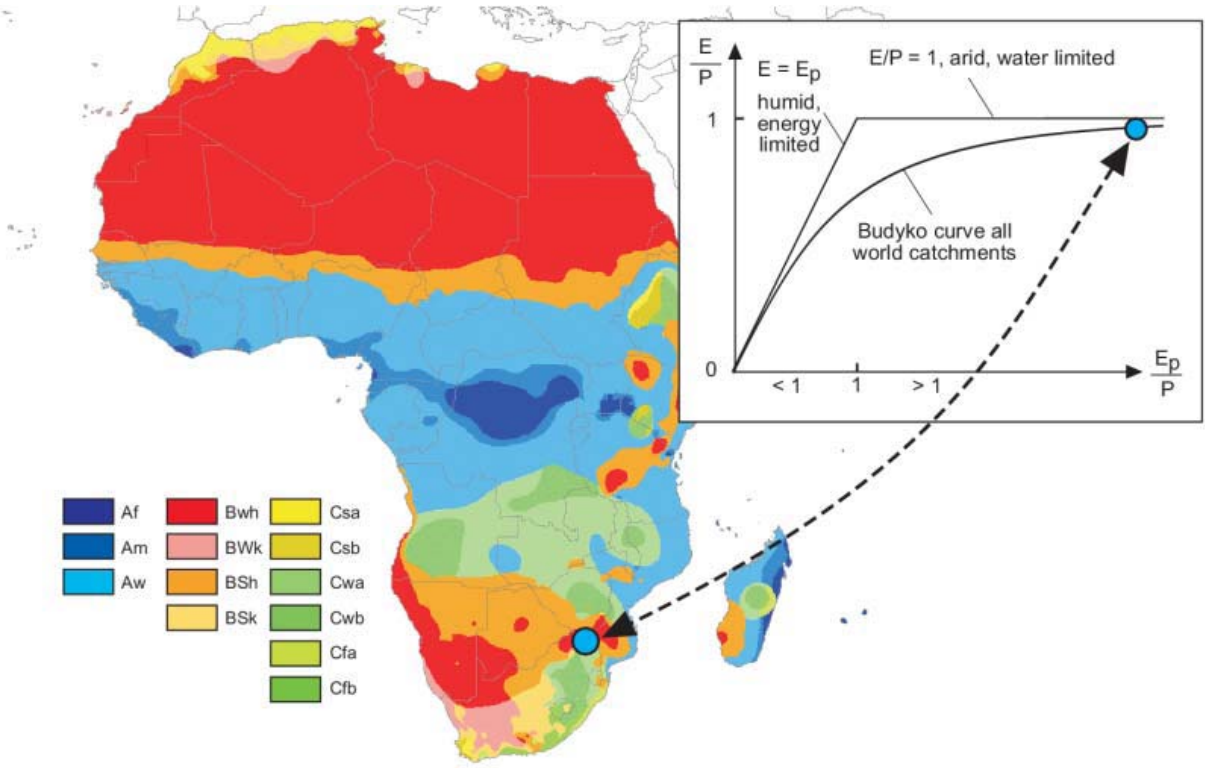

Figure 3.3 Placing a catchment in its climatic regime enables a first order assessment of its energy and water balance at coarse time scales. Left: Revised Koeppen classification with location of Olifants basin in Southern Africa marked as a dot on map from Peel et al. (2007). Right: Budyko curve showing the relationship between evaporation index (E/P) and aridity index (E_P/P).

Assessment based on national hydrological network and national surveys

Every country will have some type of national hydrological network, even though the spatial coverage of such gauging networks might vary widely (Fig. 3.4). The density of the stream gauge network in the regional vicinity around the basin of interest at least partially defines what approach to PUB can be utilized. The denser the network, the more likely it is that a statistical approach to transferring hydrologic information will be successful. The need for a more process based modelling strategy increases with the distance between measurement points. One would generally seek any runoff and meteorological data available locally or regionally. The available database is then analysed with respect to annual water balance, seasonality, storm behaviour, variability etc., which will be the main activity for many large-scale studies (especially at national scale).

Typically, there will also be information on the physical characteristics of the catchment that can be used for system characterization. Topographic maps can be used to ascertain catchment size, shape, morphology, and drainage density. Soils information including depth and texture, as well as surface characteristics can be gained from maps and translated into hydrologically relevant information, e.g., through using pedo-transfer functions. Many countries will also possess maps on eco-regions (or land use or vegetation cover) and on geology, which can be used for a first order assessment of catchment characteristics. It is important to remember that these maps will not be able to fully describe extent of natural variability that is likely in specific locations. Local observations will be necessary to utilize vegetation patterns as indicator of moisture stability and landscape heterogeneity (including erosional patterns) that can inform the nature of water redistribution processes.

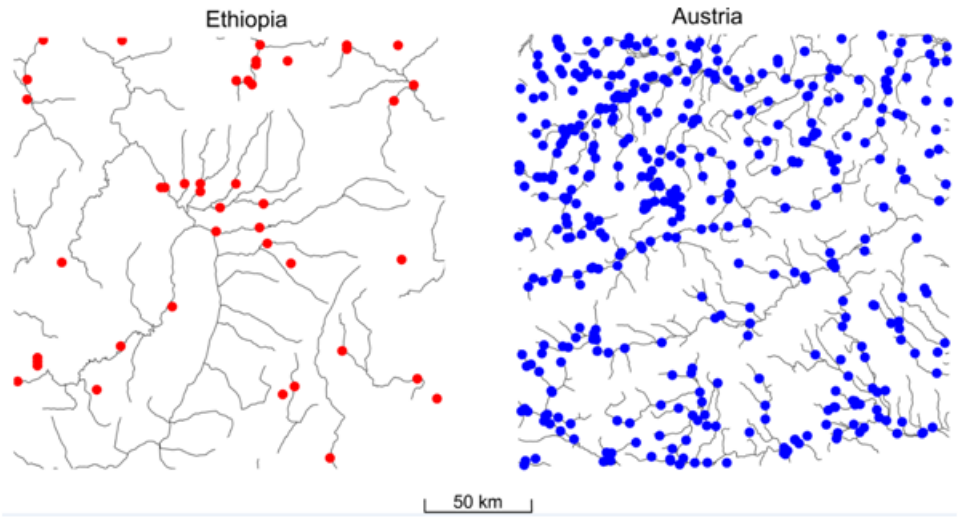

Figure 3.4 National stream gauge networks in Ethiopia (left) and Austria (right).

Assessment based on local field visits including reading the landscape

Despite the high value of remotely sensed observations and analyses, the relative strength of different hydrological processes and dominant runoff generation mechanisms are not easily inferred from topography and surface characteristics alone. Where possible, field reconnaissance and expert judgement can be invaluable for hydrologic assessment, and when coupled with remote analyses, allow for more skilled interpretation and reading of the hydrologic landscape (Fig. 3.5). Field visits allow for comparison of the PUB catchment to similar gauged catchments or heavily researched and more completely understood catchments, thereby allowing transfer of the "hydrologic knowledge library" individuals or teams possess from previous experience. This remotely sensed and field visit derived similarity analysis relies on experience-derived intuition and expert judgement. Interviews with those possessing local knowledge and experienced interpretation of the landscape can help determine or select appropriate models and representation of dominant hydrological processes operating in a catchment to improve PUB.

Bedrock geologic characteristics (e.g. weathering depth, porosity, faults, dip direction, etc) and soil depths provide information about the likelihood and magnitude of subsurface storage and geologic and soil zone contributions to runoff. Additionally, catchment slope and flow path lengths, in connection with forcing information, can be used to infer likely runoff responsiveness (flashiness of the hydrologic system). Vegetation characteristics both reflect and modify long-term hydrological dynamics. For example, dry upland vegetation and wet alluvial vegetation imply deeper groundwater and flow paths that could sustain runoff during low precipitation time periods. They also suggest transient soil moisture availability in the upland environment. A landscape with wet vegetation types across most landscape positions indicates widely available water and a more stable soil moisture regime. Vegetation type, while a function of many complex ecological and environmental variable interactions, can be used as indicators of soil moisture stability/instability and rooting depth water availability. For example, Mediterranean vegetation indicates seasonally available water while sagebrush can indicate low or non-growing seasonal water availability.

Stream channel characteristics can also help infer catchment runoff dynamics. Catchment drainage density can be an indicator of climate and geology. The connection between cross-section form and river runoff can result in a high degree of temporal and spatial regularity as

expressed in the at-a-site and downstream hydraulic geometry relationships (Mejia and Reed, 2011). Scoured channels and floodplains indicate high flows and runoff magnitude while streambed sediment characteristics and morphology can inform estimation of stream power and runoff magnitude when coupled with stream slope measures (Trevisani et al., 2010). Bankfull runoff estimation can be used as indicator of the size of peak runoff, whereas in-channel and near channel vegetation persistence/species can inform interpretation of likely flow stability and riparian corridor water table dynamics.

Runoff mechanisms can also be inferred by combining previously described remote and local observations. Erosional features across landscape positions can indicate the magnitude, frequency, and spatial extent of overland flow. Locations of overland flow indicators can also suggest infiltration excess or saturated overland flow processes. Deep soils and weathered or fractured bedrocks coupled with lower catchment slope can indicate deeper less flashy subsurface flow generated runoff while less permeable bedrock, shallow soils, and steep slopes can promote transient subsurface flow.

The spatial organization and distribution of vegetation offer further indication concerning patterns of water availability. Spatial structures in vegetation are known to naturally arise in response to water availability (Caylor et al., 2004; Rietkerk et al., 2004; Scanlon et al., 2007) at least in arid or semi-arid environments. Because of the two-way coupling between water availability and the presence of vegetation (as a driver of local partitioning), vegetation spatial organization is hypothesized to be both a control and a signature of hydrological processes, although the strength of this relationship may vary depending on the significance of other drivers of spatial variation in water balance (for instance soil hydraulic properties) and vegetation distribution (for instance, energy or nutrient availability, or disturbance regimes) within a particular catchment (Boisvenue and Running, 2006). Therefore, caution must be employed before interpreting vegetation patterns in purely hydrological terms because vegetation responds to other environmental gradients (e.g. in disturbance, nutrient availability or elevation) and co-variation across these gradients often exists (Valencia et al., 2004).

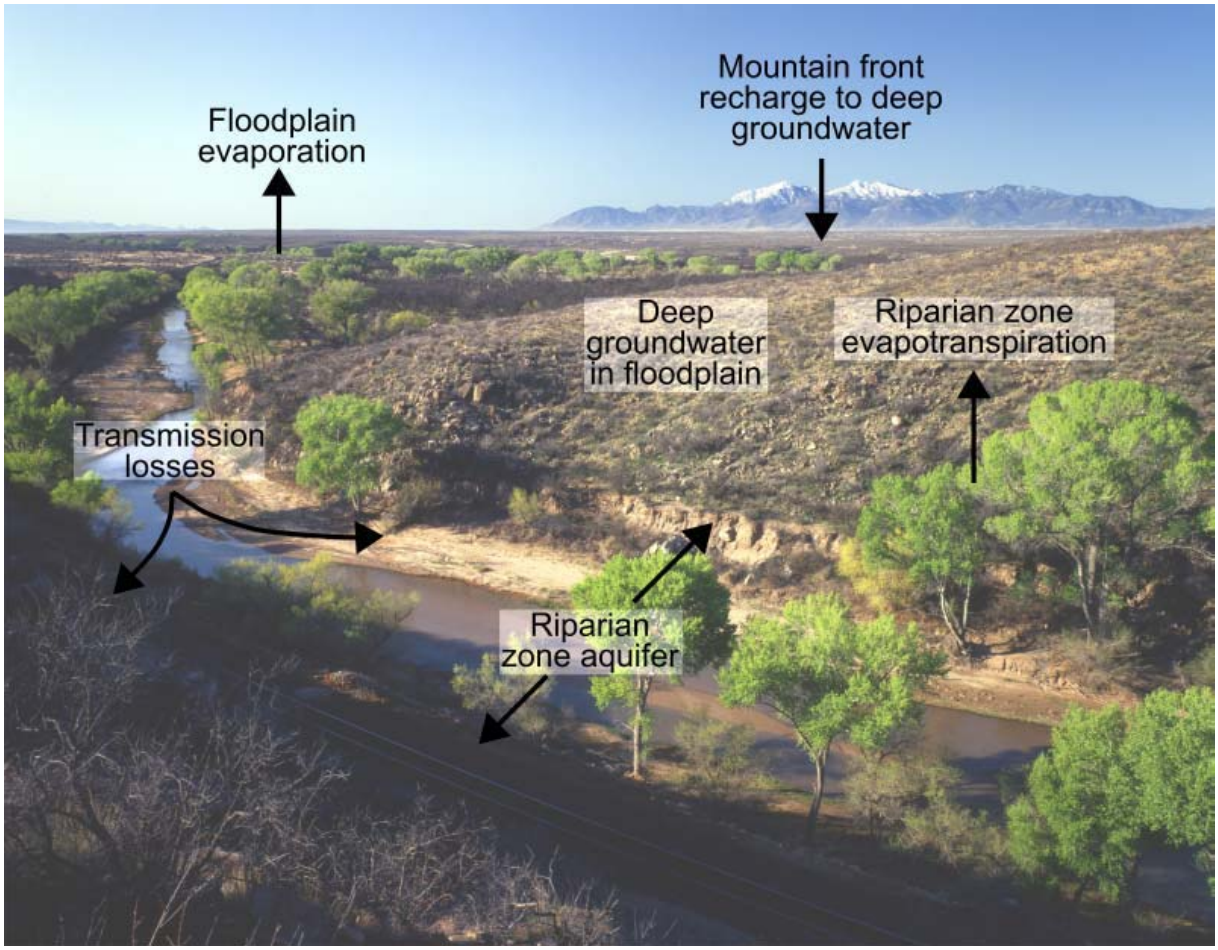

Figure 3.5 Hydrologic interpretation of landscape features. Photo: copyright sahra @ University of Arizona.

Assessment based on dedicated measurements

The measurement of runoff is of course the most direct way of gaining insight into the hydrologic behaviour of catchments for the purpose of PUB. Spot measurement can be very helpful if time and resources – as well as access – permit such an activity (Fig. 3.6). Multiple studies have shown that even limited runoff observations can result in a significant reduction in predictive uncertainty in rainfall-runoff modelling (McIntyre and Wheater, 2004; Rojas-Serna et al., 2006; Perrin et al., 2007; Seibert and Beven, 2009; Juston et al., 2009). Such measurements could be used to further refine the model parameters that have been either locally estimated or have been transferred. Care needs to be taken to account for the particular conditions under which the measurements are taken (e.g. low flow period during summer) to not unduly bias the parameter estimates. Krasovskaia (1988) proposes a procedure in which catchment characteristics are used for identifying representative locations for runoff spot gauging. She also gives an indication of the errors involved in using spot gauged data as compared to other methods of measuring and estimating runoff. The value of such a short-term measurement campaign for the direct estimation of signatures will depend on the signature under study.

Figure 3.6 Spot measurement of runoff in Alaska. Photo: M. Gooseff.

The data mentioned above can be interpreted creatively depending on available information to guide PUB model selection and constrained to maximize PUB. No two PUB exercises will be the same in terms of the data available and the particular characteristics of the system under study. Hydrologic intuition built through years of experience can be invaluable for PUB. Unfortunately there is no single or simple recipe that can be passed on. PUB skill will be largely situation and practitioner specific but can be enhanced with creative interrogation and synthesis of available observations (Jackisch et al., 2011). How data at these different levels can be used for the prediction of specific signatures is discussed in the following chapters and only illustrative examples are given here. The approach to interrogating the landscape depends on the type of runoff signature one is interested in. For example, if one is interested in the flood runoff of a recently occurred flood, the IPEC (Intensive Post Event Campaign) concepts give guidelines on how to interpret high water marks and river morphology (Borga et al., 2008, also see Chapter 9). Multiple authors have reported on the value of post-event field surveys for understanding flood water levels (Brauer et al., 2011). If one is interested in low flows, one typically takes spot measurements of runoff during a low flow period and relates them to the runoff in neighbouring catchments. If one is interested in continuous runoff predictions using a rainfall-runoff model, then multiple runoff measurements during well-chosen time periods might be most helpful.

3.3 Runoff data

What runoff data are needed for PUB?

Observed runoff is an integrative indicator of the predominant hydrologic processes in a catchment. Therefore runoff data is the most valuable source of information, which cannot be adequately replaced by other data sources. All PUB methods, and it does not matter how appropriate or innovative, are only the second best option after the use of observed runoff data. However, if the best option is not available we have to think about alternative strategies to gain insight into catchment runoff characteristics. To use stream gauge time series data

from neighbouring gauges is a good strategy, because the data structure and sensitivity is similar. Depending on the aim of the PUB study, information about catchment runoff at different temporal scales is useful for predictions in the fields of various hydrologic aspects, such as low flow, flood forecasting and design value estimation. The data needed can best be discussed separately for statistical and process based methods.

Statistical methods for predicting runoff signatures usually require runoff data in neighbouring catchments. This is for identifying pooling groups as well as for the statistical predictive methods. For example regression equations between catchment characteristics and runoff in neighbouring catchments are used to estimate runoff at the target location based on the catchment characteristics in that catchment.

Process based methods for predicting runoff often need runoff data in neighbouring catchments for estimating model parameters through calibration that are then transferred in space, or to transfer runoff characteristics to act as constraints. Most importantly, runoff data may be available at upstream or downstream locations. If these are close, the more elaborate methods in Chapters 5 to 10 may not be needed and simply scaling of the observed runoff to the target area by the ratio of the catchment areas may be more straightforward and more reliable. Also, opportunistic gauging or short-term measurements at the basin of interest can provide very valuable insight and aid as predictive constraint. Generally, stream gauge rich environments or regions might lend themselves best to statistical approaches to PUB since interpolation distances are mostly short. On the other hand, stream gauge poor environments might require more process based approaches to PUB. Ideally, both tracks can be taken to constrain likely predictions.

What runoff data are there?

Although not fully globally available, an extensive database is available (GRDB, Global Runoff Data Base) at the Global Runoff Data Center (GRDC) containing runoff records from about 7,300 gauging stations from 156 countries, with an average record length of 38 years. GRDC operates under the auspices of the World Meteorological Organization (WMO) and also offers other data products, such as freshwater fluxes into oceans along coastlines, and river basin outlines. A second database, also available through the GRDC, is the European Water Archive (EWA), of EUROFRIEND, the European group of the FRIEND (Flow Regimes from International Experimental and Network Data) initiative. EWA also contains information about smaller, relatively undisturbed catchments. Data is stored from about 3700 gauging stations in 29 countries. However, most of the gauging stations are concentrated in Western Europe. A more regional database than EWA, also hosted by GRDC, is the ARDB (Arctic Runoff Data Base), which is actually a subset of GRDB. The database currently holds river runoff time series data from a total of 2405 gauging stations in the arctic region with earliest records from 1877 and an average time series length of 33 years, with a range from 1 to 123 years. 1024 stations feature daily data, while 2193 stations only contain monthly data. At the GRDC-website, there are various other datasets and subsets that might be suitable for specific purposes and data availability will vary widely depending upon the country and region of interest.

An emerging technology to gauge water levels remotely, is laser altimetry by satellites, for which spatial and temporal densities are rapidly increasing through the launch of more and more satellites (such as TOPEX/Poseidon, Jason-1, ICESat, etc.) (Lettenmaier and Famiglietti, 2006; Alsdorf et al., 2007). Not only can laser altimetry potentially be used to record lake and river levels (Höfle et al., 2009), it can also be used to measure cross-sections (by measuring the width at different levels) or to derive rating curves (on the basis of slopes

and cross-sectional information). In the future it can also be used for real time flood forecasting or flood inundation modelling.

The availability of continuous and long term data sets on runoff varies dramatically throughout the world (Kundzewicz, 2007). Its lack and the decline of gauging stations is of course the reason for PUB in the first place (Stockstad, 1999), despite the fact that the value of runoff data is often much larger than the cost of monitoring (Cordery and Cloke, 1992). The decline of networks also suggests that in many cases there will be inactive gauges that nonetheless will provide some indication of the dynamics of the system during previous time periods and conditions (e.g. Winsemius et al., 2009). Also, availability of data may sometimes be an issue due to administrative barriers (Viglione et al. 2010)

Regardless of how the runoff observations are obtained, measurement uncertainty will always be present and can be considerable. Assessment of data quality and estimation of data uncertainty are therefore important steps in any modelling exercise. Stream gauges typically take continuous measurements of river stage, which are translated into runoff values using a rating curve. The stage-discharge relationship in the rating curve has been derived from spot measurements at a location with a (reasonably) fixed cross-sectional geometry at different flow conditions or has been pre-calibrated for a particular flow control structure. Many studies have estimated the magnitude and impact of rating curve uncertainty on runoff data and hydrologic modelling (Clarke et al., 2000; Peterson-Overleir, 2004; Yanli et al., 2009; Di Baldassarre and Montanari, 2009; McMillan et al., 2010). Major sources of uncertainty include data scarcity at high or low flow conditions, flow outside the control structure during high flow conditions or changes to the channel geomorphology. In some cases the rating curve and the data points it was calibrated to might be available and uncertainty can reasonably be estimated. Uncertainty will likely be larger when ephemeral streams are considered, due to the difficulty of measuring runoff in such streams (Blasch et al., 2002; Adams et al., 2006). The consideration of uncertainty in the runoff estimates (historical or spot gauging) can be useful to account appropriately for the value of data available and avoid over conditioning.

How valuable are runoff data for PUB?

Transferring of hydrologic information (e.g., model parameters, hydrologic indices, runoff values) from neighbouring gauged to ungauged catchments has been widely investigated in the last decades as a way for runoff prediction in ungauged basins (Merz and Blöschl, 2004; Oudin et al., 2008). These works showed that use of data from the nearby donors generally, even though not always, improves the quality of the runoff predictions. As runoff propagation through branching network provides a fundamental constraint to the distance metric, upstream and downstream catchments would have to be treated differently from neighbouring catchments that do not share a subcatchment. Also, climate plays a role in the predictive power of data transfer. Patil and Stieglitz (2011) showed that high runoff similarity among nearby catchments (and therefore, good predictability at ungauged catchments) is more likely in humid runoff-dominated regions than in dry evaporation-dominated regions.

3.4 Meteorological data and water balance components

What meteorological data and water balance components are needed for PUB?

Appropriate meteorological inputs (precipitation, air temperature, evaporation, snow cover) are needed to estimate the required runoff response in ungauged basins either based on rainfall-runoff models or to transfer information from gauged catchments. Depending on the

objectives of the PUB study, meteorological data at different temporal and spatial scales are useful for predictions of various runoff signatures (low flow, flood forecasting, design value).

Statistical methods for runoff predictions often require catchment precipitation data. Analogously to the use of runoff data, this is for identifying pooling groups as well as for statistical predictive methods. For example, catchment precipitation estimates (for instance, the mean annual precipitation) are sometimes used as an auxiliary variable in regionalisation methods (Chapters 8,9).

Process based methods for predicting runoff are always driven by meteorological data as model forcing. Actual soil moisture conditions directly affect runoff generation processes and therefore are also important for flood and low flow prediction. Soil moisture is usually simulated as an internal model state in hydrologic models, while the main emphasis lies on runoff simulation. Soil moisture data provide useful information to simulate the temporal and spatial soil moisture dynamics in a more realistic way.

Precipitation

Information about precipitation at different temporal and spatial scales is essential for many PUB applications. It is used as an auxiliary variable in statistical analysis (runoff regression) or as input for hydrologic rainfall-runoff-models. Precipitation data is available at the global scale as a modelled and remotely sensed product down to the point scale at rain gauges. The temporal scale varies from minutes (at rain gauges) to monthly mean values for the global products.

Global precipitation data - Many precipitation databases are available globally. Global precipitation data usually is a combined product from rain gauges, weather radar, numerical weather prediction models and estimates from remote sensing (Cheema et al., 2012). Examples are the Climate Research Unit database, CMAP, and WORLDCLIM (Hijmans et al., 2005). The latter one has a very high spatial resolution (1km or 30 arc-seconds), but contains only monthly climatologies. Reanalysis data are the output of numerical weather prediction models, which are conditioned on available actual observations using data assimilation routines. The NCEP/NCAR reanalysis data is available from 1948 at a spatial resolution of approximately 210 km (Kistler et al., 2001; Kanamitsu et al., 2002) and at a 32 km resolution for North America from 1979 (Mesinger et al., 2006). ECMWF offers three major reanalysis products: ERA15 (1978 –1994, ca. 120 km spatial resolution), ERA40 (1957-2001, 100 km), ERA-Interim (1989 – present, 80 km) (Simmons et al., 2007). Since 1997, the Tropical Rainfall Measuring Mission (TRMM), observes tropical rainfall intensities. The final precipitation product that is available from the TRMM website, is composed from various sensors (TRMM and other satellites) and has a spatial resolution of up to 0.25 degrees, but is limited to 50°S to 50°N. There are products with different temporal resolutions ranging from 3 hours to monthly values (Cheema, 2012). Figure 3.7 shows the weekly global rainfall accumulation for April 2012 derived from TRMM. The Global Precipitation Climatology Project (GPCP), which will be the successor to the TRMM, is a composite database from various sources including rain gauge data. Daily values are available at 1 x 1 degree resolution from 1996 to present (Huffman et al., 2001). The launch of the Global Precipitation Mission (GPM) mission (Uijlenhoet, 2008) is planned for 2013. GPM will make similar observations as TRMM, but will cover a larger domain (80% of the globe) with a higher temporal resolution of 3 hours.

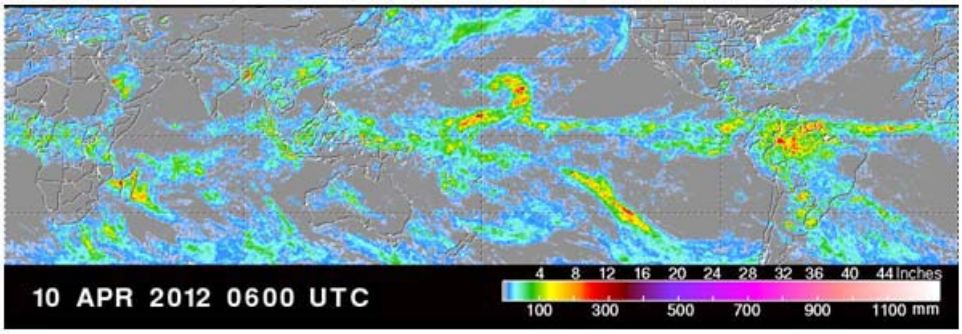

Figure 3.7 Weekly global rainfall accumulation compiled from Tropical Rainfall Measuring Mission (TRMM) data. From http://trmm.gsfc.nasa.gov

Regional precipitation data - Weather radar networks play a central role for precipitation monitoring at the meso-scale, i.e. at regional scale, due to their ability to obtain spatio-temporal information about precipitation structure at a much higher resolution than conventional rain gauge networks (Fig. 3.8). A weather radar measures reflectivity, which is directly proportional to the amount of electromagnetic energy scattered back to the radar by cloud and precipitation particles (e.g., raindrops, snowflakes, hail). Quantitative precipitation estimates (QPE) from radars are typically based on power-law relationships between rain rate and radar reflectivity. Precipitation estimates obtained by weather radars may be affected by multiple sources of error (see below); hence, merging with precipitation data from rain gauge networks is often seen as a way to combine the large scale observation capability of the radar with the point scale accuracy of the gauges (Velasco-Forero et al., 2009).

An example of a weather radar monitoring network is provided by the Next Generation Weather Radar system (NEXRAD) in the US, which comprises 159 Weather Surveillance Radar-1988 Doppler (WSR-88D) sites throughout the United States and selected overseas locations. In Europe, the OPERA project aims to provide a European platform wherein expertise on operationally-oriented weather radar issues is exchanged and data management procedures (including data exchange) are optimized.

Few studies have been devoted to the statistics of extreme areal rainfall depths obtained from weather radar (Morin et al., 2005). The increased quality of quantitative precipitation estimates from radar and the long time series that have become available has led to a renewed interest for this kind of research in recent years (Overeem et al., 2010).

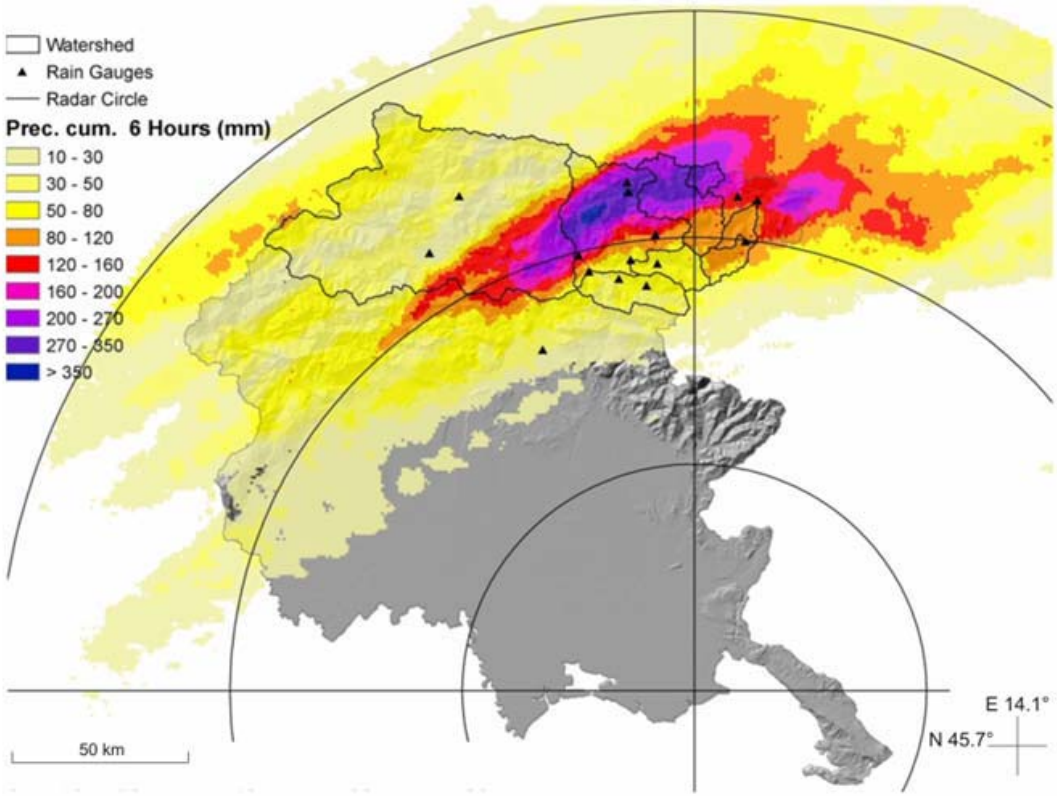

Figure 3.8 Radar-derived rainfall accumulations for a flash flood in north-eastern Italy in 2003.

Local precipitation data - At local scale, rain gauge data provide essential data for hydrological analyses, climatological and statistical investigations, and for providing reference values to adjust radar-based and satellite-based products. Precipitation is observed at a large number of raingauges (about 200,000 world-wide) in national meteorological or hydrological networks. Most of the data are used mainly in a national framework. Data from a subset of the stations (nominally from 8,000 SYNOP stations) is exchanged globally among the national meteorological services using the World Weather Watch Global Telecommunication System (GTS). Monthly-accumulated observations are also globally exchanged as CLIMAT via GTS from nominally 2,200 stations. The CLIMAT and SYNOP collections are partly overlapping. Users can obtain the global, regional or national synoptic or climate data from the national meteorological services on request.

The Global Precipitation Climatology Centre (GPCC) provides monthly precipitation dataset and products from 1951-present, calculated from global station data (Rudolf, 2003). The GPCC is operated by Deutscher Wetterdienst (DWD, National Meteorological Service of Germany) as a German contribution to the World Climate Research Programme (WCRP).

Precipitation data from rain gauges provides essential reference to adjust satellite and radar based products. Validation of remote-sensed precipitation products using *in situ* rain gauge data requires separation of the effects of natural variability from the measurement/estimation uncertainty (Ciach and Krajewski, 1999). This, in turn, implies the need for estimation and characterization of the variability in space and time across spatial and temporal scales, which for rainfall requires specialized networks (e.g., Moore et al., 2000; Ciach and Krajewski, 2006).

How good are precipitation data? The effective use of satellite precipitation estimates in hydrology (e.g. Sorooshian et al., 2009; Hossain and Anagnostou, 2004) is very much dependent upon the type of application and the accuracy, spatial resolution, temporal resolution and latency of the estimates: different applications have different data requirements. For small temporal and spatial scales, satellite-based estimates are subject to quite large errors. For applications which imply larger spatial/temporal scale, satellite derived precipitation products can be of great benefit (Yilmaz et al., 2005). For instance, hydrological model simulations based on TRMM precipitation input over the La Plata basins (with areas ranging up to 1,100,000 km^2) showed a good ability to capture daily flood events and to represent low flows, although peak flows tend to be biased upward (Su et al., 2008). This kind of analyses demonstrates the potential of TRMM products for hydrologic forecasting in data-sparse regions at appropriate spatial scales.

The use of ground based radar-rainfall estimation for rainfall estimation and for hydrological applications such as runoff modeling, gained momentum in the two last decades with the development of correction procedures, which are capable of considering the highly non-linear physics of radar detection of precipitation. Three broad areas of errors may be identified: (1) the electronic stability of the radar system, (2) the determination of the detection space and (3) the fluctuation of the atmospheric conditions. See Villarini and Krajewski (2010) for a more general discussion of error sources. When heavy precipitation in complex terrain is considered, two major sources of atmospheric variability include vertical variability of the echo interacting with the visibility of the radar beam (shielding by mountains and earth curvature) and signal attenuation by rain (an important error source for X- and C- band weather radar). The vertical profile of reflectivity induces large differences in radar measurements taken at different altitudes. In both cases, valuable results can be obtained by applying inverse procedures (Germann et al., 2006).

Even though measured precipitation amounts from rain gauges are generally more accurate compared to remotely sensed precipitation data, rain gauges have their own error sources (Lanza et al., 2009). In the case of tipping bucket rain gauge data, Ciach (2003) conducted experimental studies to develop mathematical models of rain gauge rainfall accumulation random errors. The standard errors decrease with increasing rain amount and time integration scale. Another conclusion from these studies is that tipping bucket rain gauges, when well maintained and deployed as a pair (Steiner et al., 1999) provide accurate observation of rainfall accumulations at temporal scales from 10 min and larger. Systematic errors in rain gauge measurements can be attributed to wind effects that have been extensively studied experimentally (e.g., Sevruk and Hamon, 1984; Yang et al., 1998), and numerically (Constantinescu et al., 2007).

Snow cover data

In the past several decades, the growing importance of the climatic change issue has prompted new needs for PUB-studies requiring snow-cover information over a wide range of spatial and temporal scales. At very large scales, global climate models have generated new needs for information on the global distribution of snow cover and water equivalent at monthly and climatologically averaged time-scales for validating snow-cover simulations as an input to runoff models. At regional scales, hydrological models require information on the spatial distribution of snow-cover properties to validate approaches to account for sub-grid scale variations in snow with terrain and vegetation cover. At local scales, validation of multi-layer physical snowpack models requires detailed information on snowpack structure, surface albedo, temperature profiles, snowmelt and surface energy fluxes.

Space-borne passive microwave radiometer, such as SMMR (Scanning Multichannel Microwave Radiometer), SSM/I (Special Sensor Microwave/Imager), and AMSR-E (Advanced Microwave Scanning Radiometer-Earth Observing System), can penetrate clouds to detect microwave energy emitted by snow and ice and provide information on SWE or snow depth. Space-borne passive microwave data are well suited for snow cover monitoring because of characteristics such as all-weather imaging, a wide swath width with frequent overpass times, and a long available time series. But the coarse spatial resolution (25 km of AMSR-E is the best available now) hinders their application in operational hydrological modelling and snow-caused disasters monitoring.

Optical sensors such as AVHRR (Advanced Very High Resolution Radiometer), MODIS (Moderate Resolution Imaging Spectraradiometer), SPOT and Landsat have been well developed to produce snow cover maps with high spatial resolution. Among these products, MODIS is among the most attractive to assist in estimating runoff in ungauged basins because of its spatial resolution of 500m and daily availability from the year 2000 in various product variants (Parajka and Blöschl, 2012). The accuracy has been found to be excellent for hydrological purposes (Parajka and Blöschl, 2006). The main limitation is cloud cover but a number of cloud removal methods have been developed (Parajka and Blöschl, 2008, Parajka et al., 2010).

Ground-based measurements of snow properties are still needed both to improve understanding of surface-atmosphere exchange processes and to ground truth new remote sensing algorithms. A review of methods for snow-pack water equivalent, depth, density is provided by Pomeroy (2004).

Potential evaporation

Many runoff prediction methods have the need to estimate evaporation as well, and many of them estimate evaporation on the basis of a *potential evaporation*, E_p, which is defined as the evaporation that would occur if there were no moisture constraint or if the system would evaporate at full capacity. It is therefore an important source of data, crucial for PUB.

However, potential evaporation is never measured directly. It is either inferred from other meteorological data (i.e., pan evaporation data), or estimated on the basis of a suite of other basic meteorological measurements. Pan evaporation, despite its acknowledged flaws, remains one of the most widely distributed meteorological measurements required for runoff predictions. Their advantage is that that they offer ready measurement of the integrated effects of radiation, wind, temperature and humidity on the loss of water from a saturated water surface. Pan evaporation is generally not a proxy for potential evaporation or actual evaporation due to the differences in the energy balance of pans compared to the natural environment. These can include differences in the pan albedo, the potential for significant heat storage within the pan, different turbulent, temperature and humidity conditions above the pan compared to other sites of interest and the potential for lateral heat transfer through the pan walls. Therefore, they are applied with a correction, called the pan coefficient.

Alternatively to evaporation pans, a suite of empirical and energy-balance based approaches are available for estimating E_p on the basis of other meteorological data, with the complexity (and often performance) of these methods increasing as the breadth of data at weather stations is increased. For example, the Hargreaves equation computes E_p purely on the basis of data on radiation and temperature. Although simple in formulation, its use of the daily temperature range accounts for effects of cloudiness and is generally correlated with vapor pressure deficits and wind speed. It is widely used in data-short situations and has been evaluated against measured data in multiple studies.

The Penman equation estimates E_p on the basis of data on net radiation, air temperature, atmospheric humidity and wind speed. Priestley and Taylor is a simplified form of Penman's equation: it also needs data on net radiation and air temperature but not wind speed. The Penman-Monteith equation is an adaptation of the Penman equation that accounts for the effects of evaporation taking place from vegetated surfaces, resulting in a correction to the E_p estimates based on the resistance of the plant canopy (stomatal resistance) to diffusion of water fluxes. In this way, the Penman-Monteith equation can be used as a model for evaporation directly, or alternatively if the stomatal resistance is taken at its minimum value, then it can be used to estimate E_p as well.

Note that, throughout the book, the term evaporation (E) is used to describe evaporation from free water surfaces, soils and plant surfaces as well as transpiration from vegetation.

Remotely sensed data for calculating actual evaporation

At the global scale remote sensing data is an important tool to derive estimates of evaporation patterns, E. There are three broad approaches to remote sensing of E: direct empirical methods (Glenn et al, 2007), residual methods (Kalma et al., 2008) and methods based on vegetation indices (Glenn et al., 2010).

Direct methods are based on semi-empirical relationships between E and surface features that can be observed with remote sensing approaches. A widely used example is the relationship between E and the temperature difference between vegetated and non-vegetated areas. These temperature differences are observable using thermal infra-red imaging.

Residual methods are based upon computing the energy budget for the land surface using a combination of empirical relationships and modeled assumptions. Widely used operational models such as SEBAL, S-SEBI and ALEXI are examples of this approach. The Surface Energy Balance Algorithm for Land (SEBAL) of Bastiaanssen et al. (1998) requires spatially distributed, visible, near-infrared and thermal infrared data, which can be taken from Landsat Thematic Mapper. Although approaches differ methodologically, several of these methods have been validated by comparison with moisture flux tower stations in a variety of landscapes and are considered operational (e.g., Bastiaanssen and Chandrapala, 2003; Kustas and Anderson 2009). Residual methods generally have an error or uncertainty factor of 10–30%, which is within the range of error or uncertainty of the ground evaporation measurement methods by which they are validated (Courault et al. 2005).

Vegetation index methods combine vegetation indices (VI) from satellites with ground measurements of actual evaporation (E) and meteorological data to project evaporation over a wide range of biome types and scales of measurement, from local to global estimates. The majority of these indices use time-series imagery from the Moderate Resolution Imaging Spectrometer on the Terra satellite to project E over seasons and years. Vegetation indices depend on an estimate of the density of green vegetation over the landscape, as measured by VIs or related products that use combinations of visible and near infrared bands. However, VI methods cannot estimate bare soil evaporation or differences in stomatal conductance among species and as affected by environmental factors, and these must be approximated from ground data or additional remote sensing data. Coefficients of determination between modeled E and measured E are in the range of 0.45–0.95, and root mean square errors are in the range of 10–30% of mean E values across biomes, similar to methods that use thermal infrared bands to estimate E and within the range of accuracy of the ground measurements by which they are calibrated or validated (Glenn et al., 2010).

Remote sensing of soil moisture and basin storage

In general two types of soil moisture data are available (Grayson et al., 2002). At the point scale in-situ measurements based on sensors in different soil depths are available. The representative area of the sensors is very small (in the range of centimetres or meters). At the global and regional scales remotely sensed patterns of soil moisture are available. Global estimates of soil moisture are currently made from space by several sensors on-board satellites. Soil moisture retrieval has been the subject of many studies and measurement campaigns. Various sensors are currently operational that can provide estimates of soil moisture. Most of these sensors operate in the microwave domain, and can be active (radar) or passive (radiometers). Advantages of the microwave domain are its independence of solar illumination (day and night capability), and its lack of cloud cover sensitivity. Lower frequencies (longer wavelengths) have the additional advantages of a relatively high sensitivity to soil water content, a deeper soil penetration, and less disturbance by vegetation and atmosphere (Hurkmans et al., 2004). However, in spite of these advantages there are still many challenges in reliably obtaining soil moisture estimates, especially in densely vegetated or inhabited areas (radio frequency interference). In addition, only the soil moisture content of the top few centimetres of the soil profile is typically estimated by this technology (this has to be converted to root zone moisture) and, especially in case of passive sensors, the spatial resolution is very low (of the order of 50 km).

One widely used sensor for soil moisture is the Advanced Microwave Scanning Radiometer (AMSR-E) on NASA's Earth Observing System (EOS; hence the E in AMSR-E). One of the most recently introduced passive sensors is the Soil Moisture and Ocean Salinity (SMOS) satellite launched in November 2009 (Kerr et al. 2001, 2010). Another mission planned to start in 2014/15 is the Soil Moisture Active Passive (SMAP) mission initiated by NASA (Wagner et al., 2007). One of the first active soil moisture data sets was derived from the ERS scatterometer data for period 1992-2000 (Wagner et al. 2003). Its successor is the Advanced Scatterometer (ASCAT), which uses a very similar measurement concept while improving significantly on the spatial (25 km) and temporal (1-2 days) resolution. ASCAT has thus very comparable sampling characteristics to SMOS and the SMAP radiometer (Wagner et al., 2007). Soil moisture estimates at a higher spatial resolution are derived by the Synthetic Aperture Radar (SAR) instruments on-board ESA's ENVISAT, or ESA's European Remote Sensing (ERS) satellites. While the spatial resolution of these instruments is typically higher, applications of SAR soil moisture retrievals are typically limited to small areas or specific catchments (e.g., Pauwels et al., 2001; van Oevelen, 2000).

3.5 Catchment Characterization

Basin and catchment characterization is typically focused on assessment and quantification of those aspects of physical and ecological structure that influence the storage, movement, and release of water to evaporation and runoff. As such, topography, soil characteristics, geology, stream network geometry land cover and land use are of primary interest for PUB. These variables are both reflections of long-term hydrologic and geomorphic processes and act to mediate contemporary hydrologic processes such as runoff generation and evaporation, and catchment storage. Catchment characterization can be accomplished via remotely sensed data (e.g. topography and land cover classification) and field assessment. As indicated in the case studies at the end of this chapter, catchment characteristics can inform relative and absolute, as well as qualitative and quantitative assessment of likely catchment response to climate forcing. For example, geologic information can provide insight into deeper groundwater contributions to runoff, while distributions of vegetation cover can inform runoff production mechanisms. Surface flow path lengths, structure, and accumulation can provide additional

insights into the patterns of water redistribution and hydrologic connectivity of uplands to streams (Jencso et al., 2010; Jencso and McGlynn, 2011).

3.5.1 Topography

Some topographic data is available for most regions of the world. The U.S. Geological Survey built a 30 arc-second digital elevation model (DEM) of the world called GTOPO30. Hydrologically relevant derivatives, such as catchment boundaries, river networks, slope, flow direction, aspect, topographic wetness index and flow accumulation have been extracted from GTOPO30 and are available in the USGS HYDRO-1K geographic database at a resolution of 1 km. Recently, the Shuttle Radar Topography Mission (SRTM) updated the global 30-arc second DEM (Farr et al., 2007). SRTM topographic data is available, although the accuracy is much lower in mountainous terrain than in flat terrain (Ludwig and Schneider, 2006). At the national scale, many countries have elevation information at a very fine spatial resolution that is in the range of a few meters, however, it is not always freely available. An example of a freely available DEM is the National Elevation Dataset (NED) at 10 m resolution for the conterminous United States, Alaska, Hawaii, and territorial islands.

Increasingly, airborne LIDAR data is becoming available. Most data will currently be obtained through dedicated research projects for regions with small spatial extent, but large-scale observation missions are becoming feasible. A number of countries around the world are currently creating a state-wide DEM based on airborne LIDAR data with a resolution in the order of 1m. This form of high-resolution topography and vegetation height and density data will become increasingly available in the future. It will prove to be very valuable for inundation modelling and thus offers new opportunities for connecting processes and form at an ever-increasing range of scales, e.g., explicit extraction of channel heads (Tarolli and Dalla Fontana, 2009). The full value of this very high resolution topographic information still has to be exploited (Mallet and Bretar, 2009).

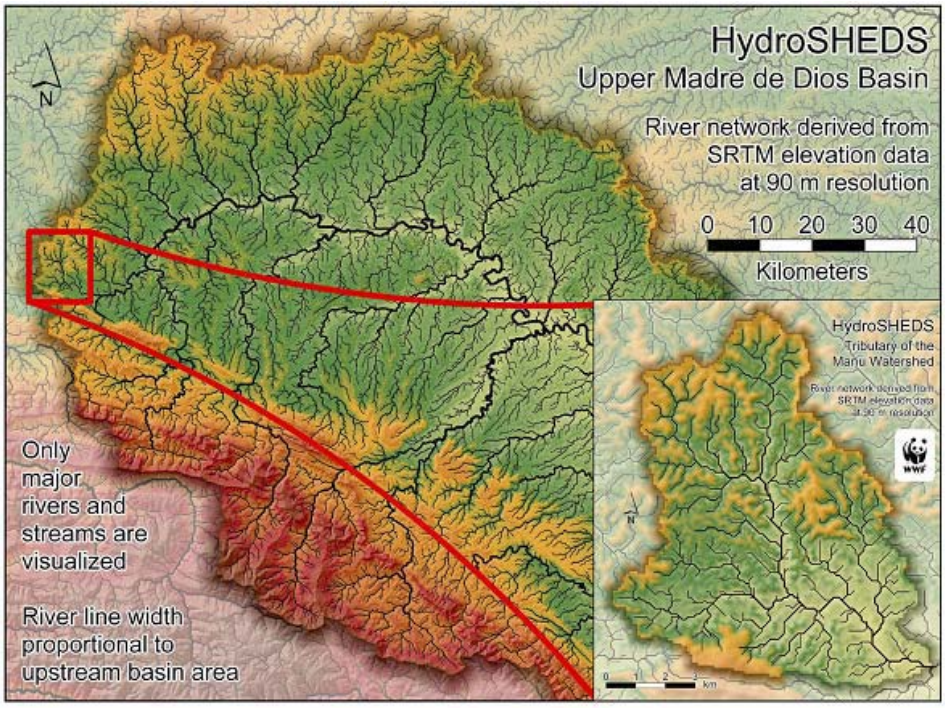

Figure 3.9 Example of a global data set that will be needed for a hyperresolution hydrologic model. The data set consists of elevation, stream networks, catchment boundaries, drainage directions, and ancillary data layers such as flow accumulations, distances, and river topology

at various resolutions from approximately 90 m to 10 km and is based on data from NASA's Shuttle Radar Topography Mission (from Wood et al., 2011).

3.5.2 Land cover and land use

Several global land cover datasets have been compiled from remote sensing imagery. One of the older ones, often applied in large-scale modelling studies (e.g., Troy et al., 2008; Nijssen et al., 2001) is a global land cover classification system that was compiled by the University of Maryland's Department of Geography. Fourteen land cover classes are distinguished, based on AVHRR (Advanced Very High Resolution Radiometer) imagery from the period 1989-1994. Data is available at three resolutions (1 km, 8 km, and 1 degree). For modelling purposes, hydrologically relevant parameters (evaporation resistances, leaf area index etc.) need to be associated with the assigned land use classes. The Global Land Cover Characterization (GLCC) has been more recently developed through a joint effort of the U.S. Geological Survey (USGS), the University of Nebraska-Lincoln (UNL), and the European Joint Research Center (JRC). This dataset was also compiled from AVHRR data at a resolution of 1 km (or 30 arc-seconds), but more land cover classes have been identified (Fig. 3.10). Another very recent global land cover dataset, released in September 2008, is the GlobCover project of the ESA. This dataset, compiled from ENVISAT MERIS (MEdium Resolution Imaging Spectrometer) images between January 2005 and June 2006, has a spatial resolution of 300 meters. Assessing the accuracy of satellite derived land cover data is a challenge as a range of different assessment methods are used in the scientific community (Foody, 2002) and the data sets are not always consistent (Giri et al., 2005; Mayaux et al., 2006).

Besides global datasets, continental scale land cover maps have been developed, especially for the United States and Europe. Two examples of maps for Europe are the CORINE (Coordination of Information on the Environment) and PELCOM (Pan-European Land Cover Monitoring and Mapping project; Mücher et al., 2000) databases. Regional, basin-wide, and local land cover and land use maps have also been developed but their availability varies widely across countries and the globe.

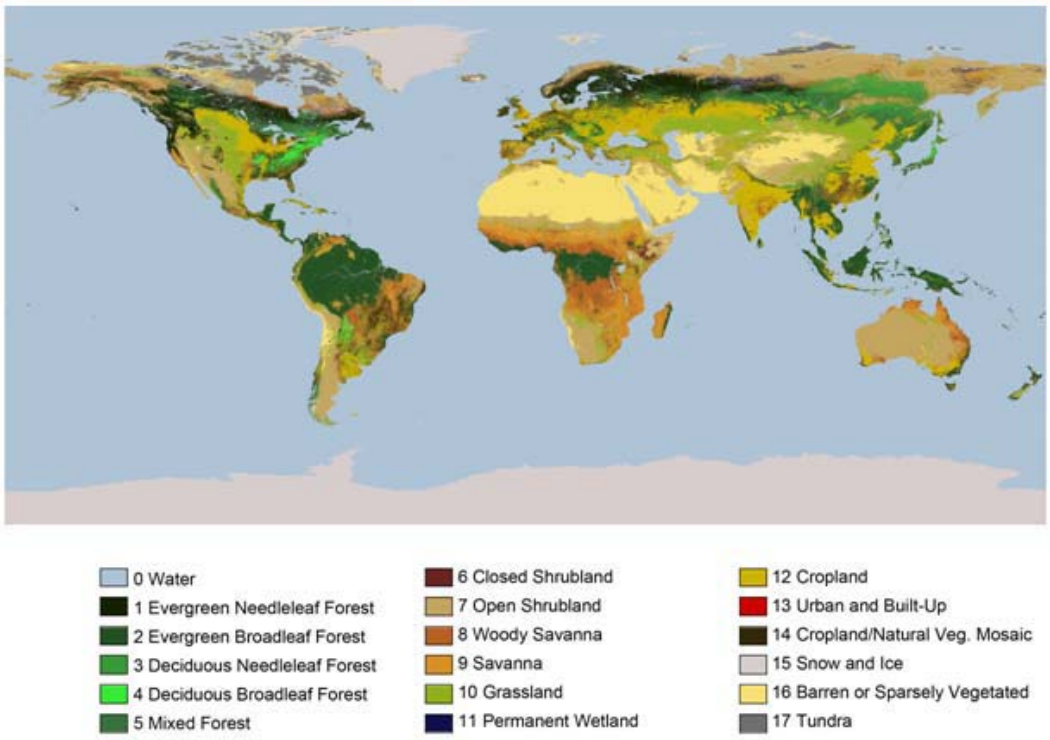

Figure 3.10 Land cover information from satellite data (http://www.nasa.gov/images/content/121557main_landCover.jpg)

3.5.3 Soils and geology

Whereas land cover data can be estimated relatively easily from remote sensing, this is much more difficult for soil properties. The FAO-UNESCO digital soil map of the world, compiled between 1971 and 1981, has been used in many global analyses (e.g., Nijssen et al., 2001; Hurkmans et al., 2008). It has a spatial resolution of 5 arc-minutes, and is compiled from over 600 national soil maps and over 11,000 other maps that were provided by national soil organizations (Reynolds et al., 2000). This map has been extended to the FAO Soil Database system (SDB), where for each mapping unit in the soil map, parameters have been assigned to the topsoil (0-30 cm) and the subsoil (30-100 cm). Parameters include soil texture classes (percentages of sand, clay and silt), porosity, bulk density and organic carbon fragments (Reynolds et al., 2000). A very recent expansion of the FAO soil map of the world, is the Harmonized World Soil Database (HWSD; Nachtergaele et al., 2009). This dataset is a joint effort of FAO, IIASA (International Institute for Applied Systems Analysis), ISRIC World Soil Information, Institute of Soil Sciences, Chinese Academy of Sciences, and the Joint Research Center. It is basically a high-resolution (30 arc-second) soil map of the world, with each pixel containing data including organic carbon, pH, soil depth, water storage capacity, sand, silt and clay contents, USDA texture, exchangeable nutrients, sodicity, salinity, lime and gypsum fractions, and other properties. This data is available for two layers: 0-30 cm and 30-100 cm. Additional information about HWSD is provided by Nachtergaele et al. (2009). For many cases not only information on the topsoil (say the upper metre) may be relevant, as is provided by FAO and HWSD, but also data of deeper aquifers and groundwater systems. The Worldwide Hydrogeological Mapping and Assessment Project (WHYMAP), provides such maps by combining various national, regional and global sources.

In very few cases, extra effort has been made to create a hydrologically focused soil classification. UK soils have been delineated according to their hydrological properties to

produce the 29-class Hydrology Of Soil Types (HOST) classification (Fig. 3.11). The HOST classification is based on a number of conceptual models that describe dominant pathways of water movement through the soil and, where appropriate, substrate. The HOST dataset is available at a 1 km grid which records, for each grid square, the percentage of the 1km x 1km area given to each HOST class present (Boorman et al., 1995). Efforts have been made to expand such hydrologically relevant catchment characteristics across Europe (Schneider et al., 2007).

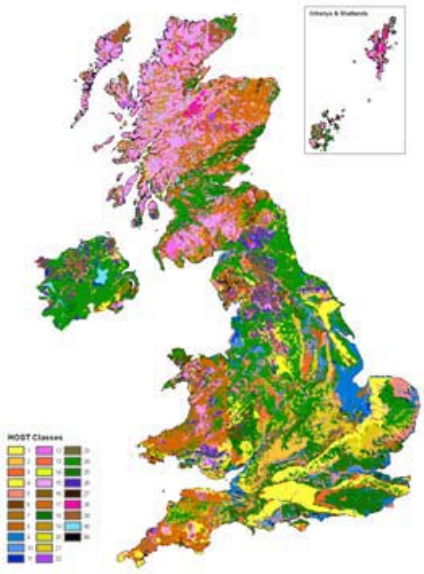

Figure 3.11 Hydrology of Soil Types (HOST) classification system for the UK at 1km resolution (© NERC - CEH, © Cranfield University and © The James Hutton Institute).

3.6 Data on Anthropogenic Effects

Human activities have a significant impact on the terrestrial water cycle (Braden et al., 2009), but quantifying their impact is often difficult (Wagener et al., 2010). Major activities include land cover changes such as urbanization and deforestation, abstractions for irrigation and energy production, and consumptive water use. Related to these activities are increasing emissions of greenhouse gases that alter our climate, as well as water resources infrastructure that changes flow paths and storage behavior of river basins. For example, during the last century, irrigable land increased from 40 million hectares (Mha) to 215 Mha (Freydank and Siebert, 2008). About 40% of the current irrigable land is supplied with surface water that is impounded by large artificial reservoirs and dams built on rivers (Lempérière, 2006). Figure 3.12 provides illustrative examples of anthropogenic effects on runoff due to hydropower generation and irrigation abstractions. At larger spatial scales, land use changes can be observed using remotely sensed information as discussed above. However, the historical extent of this information is rather short, and other, much more time consuming approaches, are needed to create a historical timeline.

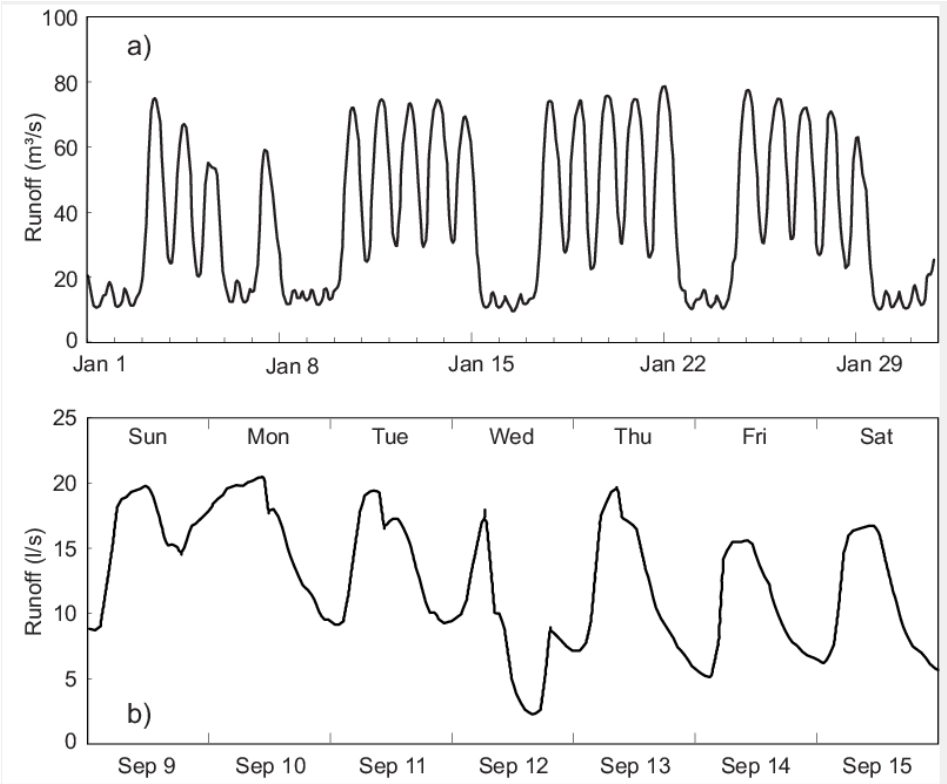

Figure 3.12 Examples of anthropogenic effects on runoff. (a) Runoff of the Inn at Kajetansbrücke, Austria, illustrating hydropower regulation effects on runoff. Note the pattern of the weekdays/weekend and Jan 6 as a holiday (epiphany); (b) Daily runoff pattern at Vudee weir, Tanzania, dominated by farmers managing water diversions. During the day farmers divert water according to agreements with downstream users. On Sunday they release water for downstream use. On Wednesday a nearby group of farmers is allowed to irrigate (Mul et al., 2011).

Dams are constructed for different purposes: diversion, irrigation, flood protection, hydropower, water supply, recreation, navigation, etc. The world has approximately 845,000 dams (Jacquot, 2009), although an exact number is not known. About 50,000 of these are classified as "large" (i.e., over 15 m high) by the International Commission on Large Dams (ICOLD). The water impounded in these large dams amount to about 10% of the annual river runoff and covers one third of the Earth's natural lake in terms of area (Jacquot, 2009). Despite established recognition of the many critical environmental and social tradeoffs associated with dams and reservoirs, global data sets describing dam characteristics and geographical distribution have been largely incomplete. Figure 3.13 shows the distribution of large dams reported in the Global Reservoir and Dam (GRanD) database around the world along with their main purpose (Lehner et al., 2011; Lehner and Döll, 2004). According to the GranD database, about 34% of these large dams are engaged in irrigation. GRanD data includes (in most cases) the dam and reservoir names, spatial co-ordinates, construction year, surface area, storage capacity, dam height main purpose and elevation.

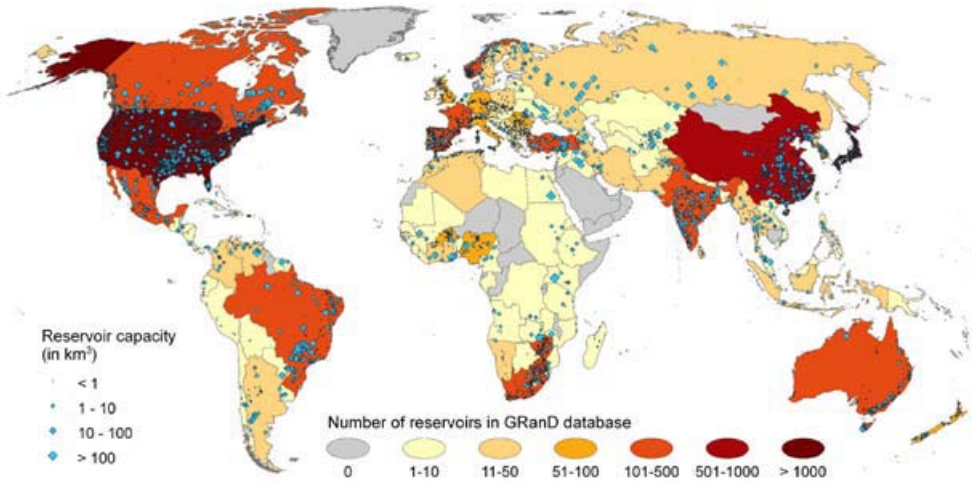

Figure 3.13 Global distribution (by country) of large reservoirs. From Lehner et al. (2011).

3.7 Illustrative examples of hierarchical data acquisition

We end this chapter with the presentation of three different examples involving PUB, each offering unique challenges to predictions, and requiring different strategies for hierarchical data acquisition. The first one, Tenderfoot Creek study, involves a well-established and self-organised catchment which requires standard hierarchical measurements that exploit the natural organisation of the catchment. The second, Chicken Creek artificial catchment in Germany offers unique challenges due to the fact it is an artificial catchment rehabilitated after decades of mining activities, and will take some time to fully understand the dominant processes in a fast changing landscape, and therefore offers unique challenges to the modeller. The third, in the Selška Sora catchment in Slovenia, is a forensic study aimed at understanding the mechanisms that led to flooding, and highlights the challenges in deciphering the mechanisms that led to recorded floods on the basis of the markers left behind. Each example represents the diversity of problems faced under PUB, and the creativity that can be brought to bear on addressing the learning and prediction challenges of PUB.

3.7.1 Understanding process controls on runoff (Tenderfoot Creek, Montana – USA)

The case study describes a sequence of steps and inferences that could be drawn about the Tenderfoot Creek Experimental Forest (TCEF) headwater catchment located in the Little Belt Mountains of Central Montana, USA utilizing hierarchical data acquisition in the PUB context. Each level of the hierarchy narrows the likely catchment runoff behaviour to enhance PUB. The first step includes inferences drawn from general hydrologic understanding of runoff behaviour in the context of the climate, biogeography, and physiography of the area. Second, inferences about likely runoff behaviour can be drawn from nationally or globally available data. Third, field visits further constrain possible behaviour with inference from simple field observations.

Catchments in the Little Belt Mountains and similar environments are characterized by shallow throughflow runoff processes and variable source area hydrology and would therefore likely dominate TCEF hydrology because of its physiographic setting, climate, and likely weather patterns. Shallow, permeable soils overlying less permeable or nearly impermeable bedrock would lead to perched, transient water tables in the soil and weathered bedrock zone.

If deeper groundwater rise into the weathered bedrock/soil zone were a significant mechanism, shallow throughflow could still be a dominant runoff process because of the dramatic increase in hydraulic conductivity above the bedrock zone. Steep slopes and complex topography would further promote rapid throughflow above the soil bedrock interface. Convergence and divergence in the topography would result in more diffuse or more focused flow accumulation and would influence landscape scale runoff patterns, drainage rates, and resulting soil moisture distributions.

Snowmelt dominated water inputs and warm, sunny, dry summers in the region lead to strong seasonality of hydrologic behaviour starting with a long winter period of frozen ground and snow accumulation that could last from November until June. During this period, runoff would be minimal and the catchment would be storing water in the snowpack for more intense melt delivery with spring snowmelt. The duration and intensity of annual snowmelt is climate dependent and its peak varies up to a month or more. This forms the dominant runoff event of the year. The timing and intensity of snowmelt delivery to the catchment soil strongly impact the magnitude of dynamics of the runoff hydrograph. Additionally, the temporal intersection with available energy and vegetation productivity lead to differential evaporation from year to year in this water limited environment. Following snowmelt, the seasonal recession declines rapidly due to the shallow soils and steep slopes that promote rapid soil water drainage. Additionally, strong evaporation further reduces catchment storage and thus water available for runoff. Summer rainstorms produce only modest increases in runoff due to unrequited catchment storage. Decreased potential evaporation and vegetation productivity in the autumn lead to small increases in runoff into the winter snow accumulation period.

Seasonal low flow occurs in late August and early September with peak snowmelt runoff occurring in April through June. Annual runoff ratios (ratio of runoff to precipitation) fall between 0.2 and 0.4 in these high elevation snowmelt dominated semi-arid environments.

Nationally available topography data indicates that TCEF's catchment area is 22 km^2, elevation ranges from 1900–2400m, and it contains 1st through 3rd order streams that form distant headwaters of the Mississippi River system that drains to the Gulf of Mexico. National vegetation products indicate that the forested catchment is predominantly lodgepole pine (*Pinus contorta*). The location of the catchment at high elevation in the northern Rocky Mountains, USA corroborate that it is a snowmelt dominated hydrologic system with 40-90% of annual precipitation in the form of snow and a short snow-free growing season of 3–5 months.

Precipitation inputs can vary by up to 50% from year to year in this region and the timing of snowmelt can vary by months. Annual and seasonal evaporation vary significantly as a function of snowmelt timing and summer rains since it is a strongly water limited as opposed to energy limited system.

Trees in TCEF are predominantly lodgepole pine, a highly adaptable tree that can grow in a wide range of environments, from water-logged bogs to dry sandy soils. The presence of sagebrush in the area, however, suggests a semi-arid environment. Analysis of widely available topographic and surficial geology data indicate that TCEF ranges from north facing to south facing; the main drainage runs east to west with north and south facing sub-catchments; the slopes are moderate for mountainous terrain; the hillslopes are relatively planar; the riparian valley bottoms are limited to 2-4% of the landscape. The catchments show little evidence of glaciation and therefore soils were likely formed on local shale, sandstone, and granite from low to high elevation suggesting differential permeability and bedrock weathering that could exhibit a broad range conditions from intact to highly weathered and fractured bedrock. The landscape form suggests some disequilibrium with current climate conditions.

TCEF is a tributary of the Smith River, which has a downstream real-time stream gauge maintained and served on the internet by US Geological Survey. Historical and real-time runoff conditions that include contributions from TCEF and other nearby mountain catchments corroborate inferences drawn from hard and soft information described above.

Figure 3.14 Tenderfoot Creek Experimental Forest catchment. Note the gentle mountain topography and forested landscape that includes areas of disturbance (forest harvest). Photo: F. Nippgen.

The value of field visits to TCEF is largely a function of the time of year (hydrologic season) and the spatial extent of the observations. Regardless of season, initial observations corroborate that the landscape is of moderate relief and complexity with relatively gentle convex slopes and moderately planar uplands. Open lodgepole pine forest and wet riparian meadows are readily apparent and simple depth to bedrock probing confirms that the soils are shallow (~1m). Little evidence of overland flow is present suggesting subsurface flow dominated hydrology. Stream morphology and streambed material size indicate moderate peak runoff magnitudes. Taken together, these observations suggest that the hydrologic dynamics are moderate and likely lack a flashy response to snowmelt and precipitation. Evidence of recent forest disturbance from logging suggest that the response of some tributaries will be more rapid during spring snowmelt and sustain higher levels of summer base flow due to altered snow energy balances and decreased evaporation. Summer dry season observations indicate low runoff and therefore a steep recession from spring snowmelt. Dry uplands and wet riparian soils imply riparian and perhaps deeper groundwater sources of runoff with little active upland hydrology except for zero order basins and areas of greater upslope accumulated area as evidenced by exfiltration and the hillslope–riparian topographic transition. Field reconnaissance during more hydrologically active times (e.g. spring snowmelt or rainstorms) reveals subsurface stormflow (throughflow) dominated hydrology with variable source area saturated overland flow. Variable landscape contributions to runoff generation are evident in saturation extending from riparian zones into convergent hillslopes of greater area accumulation. Little to no infiltration excess overland flow is observable save in areas of exposed bedrock and forest roads.

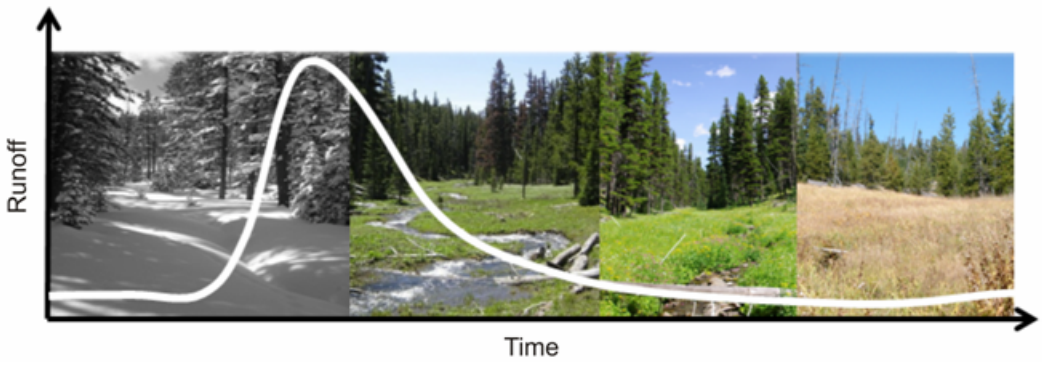

Figure 3.15 Early winter snow cover and frozen streams lead to low base flow and increasing amounts of water stored in the snowpack for spring melt. High flow conditions driven by enhanced landscape hydrologic connectivity and variable source are dynamics. Decreasing base flow through summer growing season and transition to autumn. Photos: F. Nippgen and C. Kelleher.

Despite this the strength of inference that can be drawn from the data hierarchy, quantification of the specific magnitude and timing of catchment runoff dynamics and the relative magnitudes and spatial distributions of runoff process will remain uncertain without additional data collection and interpretation. Attributing specific runoff dynamics to catchment form and runoff processes can require multiple years of intensive field observations but can yield insight into those aspects of catchments that can be used to constrain PUB elsewhere.

3.7.2 Runoff predictions using rainfall-runoff models (Chicken Creek, Germany)

A Predictions in Ungauged Basins (PUB) comparison study using twelve hydrological models was performed at the artificial Chicken Creek catchment in Germany in the context of the Transregio-SFB 38 research project (Holländer et al., 2009; Bormann et al., 2011a; 2011b). The modellers were tasked with modelling the catchment with varying degrees of information available to them. The catchment has a size of 6 ha (450m x 130m) and was created in 2005 (Gerwin et al., 2009; including Figures 3.16-17). It is bounded at the bottom through a 2m clay layer, which is covered by 2-3m of (mainly) sand. A lake has formed in a depression that was implemented close to the catchment outlet. Regional annual average temperature is 9.3˚C (1971-2000) and annual precipitation varied between 335 mm/yr and 865 mm/yr. No vegetation was artificially added to the catchment.

Figure 3.16 Photo of the artificial Chicken Creek catchment near Cottbus, Germany. Photo: BTU Cottbus FZLB, 2007.

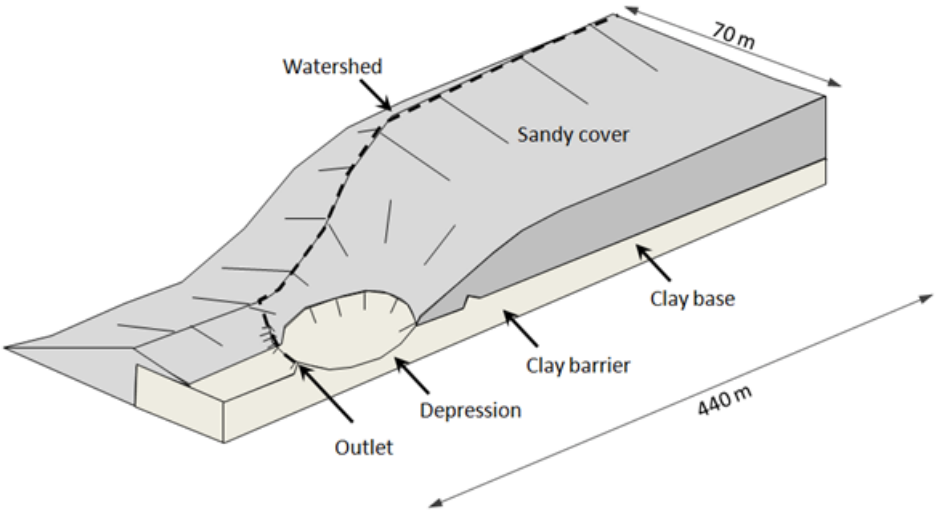

Figure 3.17 Cross-section of the Chicken Creek catchment. From Bormann et al. (2011b).

"*Artificial catchments are per se the opposite of ungauged catchments because they are supposed to provide a well-documented case (e.g. a clear definition of catchment geometry and boundary conditions)*" (Holländer et al., 2009). However, in this study it was assumed to be ungauged in a way that most of the available information on catchment characteristics was withheld by the organizers of the model inter-comparison study. Time series of hydrologic fluxes (e.g. runoff) and state variables (e.g. soil moisture, groundwater tables) were withheld as well in the first modelling steps. Therefore model predictions were *a priori* although the catchment is intensely monitored with respect to water and matter dynamics as well as system characteristics (Gerwin et al., 2009).

The comparison study is broken up into four different modelling stages, reflecting the hierarchy of data acquisition discussed in the rest of this chapter: [1] *A priori* modelling based

only on data about soil texture, soil thickness, clay layer, topography, vegetation cover, hourly climate data, air photography and initial groundwater levels. Modellers were not allowed to visit the catchment. [2] Walk through the catchment, after the modellers discussed and compared their *a priori* model simulations as a group. [3] Additional observations including soil hydraulic, soil physical data, soil water content and infiltration capacity. [4] Runoff observations (for calibration) from a sub-catchment (1.8 ha). Three of these modelling steps have so far been executed and are summarized briefly below. The models applied encompass different modelling philosophies, ranging from 1-D to 3-D models regarding their spatial representation. Most of the models describe the hydrological processes in a physical way, whereas only a few models are based on a lumped, conceptual concept. Eight of the twelve models describe the unsaturated soil water flow by the Richards' equation, and ten models use the Penman-Monteith approach to calculate potential evaporation.

The results of the study showed a very large spread of model results (runoff at the outlet) across the models after stage one (Fig. 3.18). Models simulated from 10 to 330% of observed mean annual runoff. According to Holländer et al. (2009), those differences could mainly be attributed to differences in model parameterization and conceptualization. Unknown initial conditions in terms of soil moisture content were another important issue to be tackled by the modellers. "*Runoff was mainly predicted as subsurface flow with little direct runoff. In reality, surface runoff was a major flow component despite the fairly coarse soil texture. The actual evaporation (AE) and the ratio between actual and potential E was systematically overestimated by nine of the ten models. None of the model simulations came even close to the observed water balance for the entire 3-year study period"* (Holländer et al., 2009).

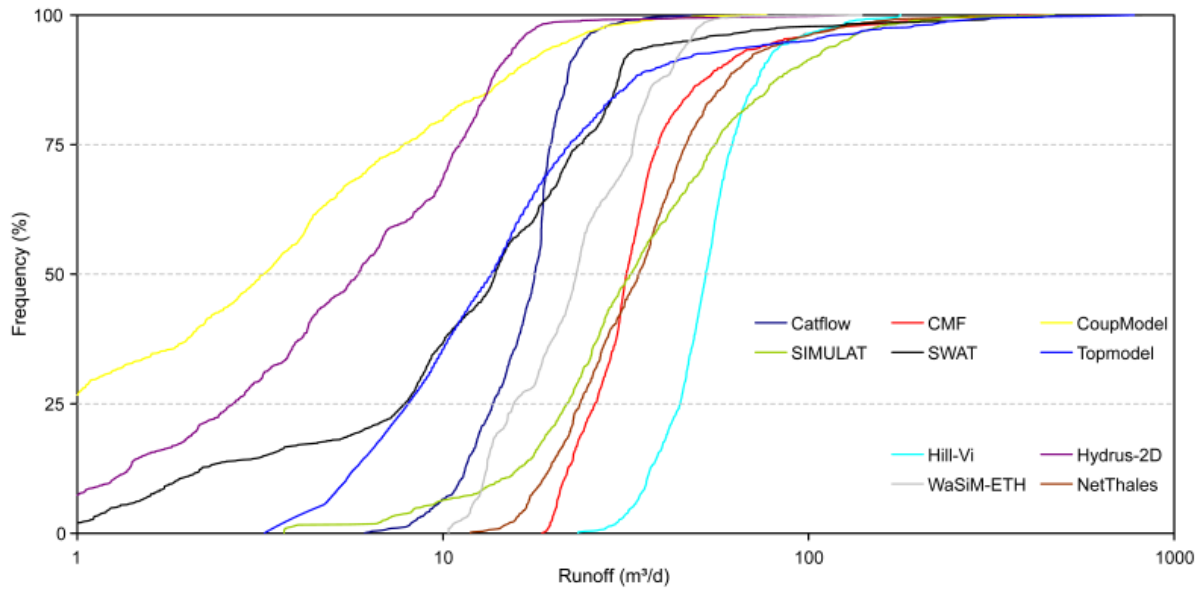

Figure 3.18 Differences in frequency distributions of the different models during a priori simulation, the first prediction for the Chicken Creek. From Holländer et al., (2009).

The spread of the model simulations narrowed during stage two, after modellers had discussed their results and had visited the catchment. As a consequence of the discussions and the field visit, modellers tended to change the model set-up in the same direction (resulting from a common process understanding). All modellers tended to reduce the total runoff generation while increasing surface runoff generation since a biological soil crust had been identified (Fischer et al., 2010). Some modellers also adapted the representation of subsurface storage behaviour and changed initial conditions because it had emerged from discussions that

the catchment was dry after construction.

In the third modelling stage, modellers were asked to select the required data out of an available data pool considering hypothetical costs they would be willing to pay for the data. Most modellers asked for soil hydraulic and soil physical data as well as for soil moisture and infiltration rates, while only a few modellers used the extended vegetation data set, the new digital elevation model and the new aerial photo. Most of the modellers used the data for reassessing model parameters and adjusting initial conditions. However, the spread of the models after these adjustments remained similar to that of the second modelling step. The additional observations available during the third step led to smaller changes in the model simulations than due to initial data, joint discussion and actual visit to the catchment (e.g., water balance terms; Fig. 3.19).

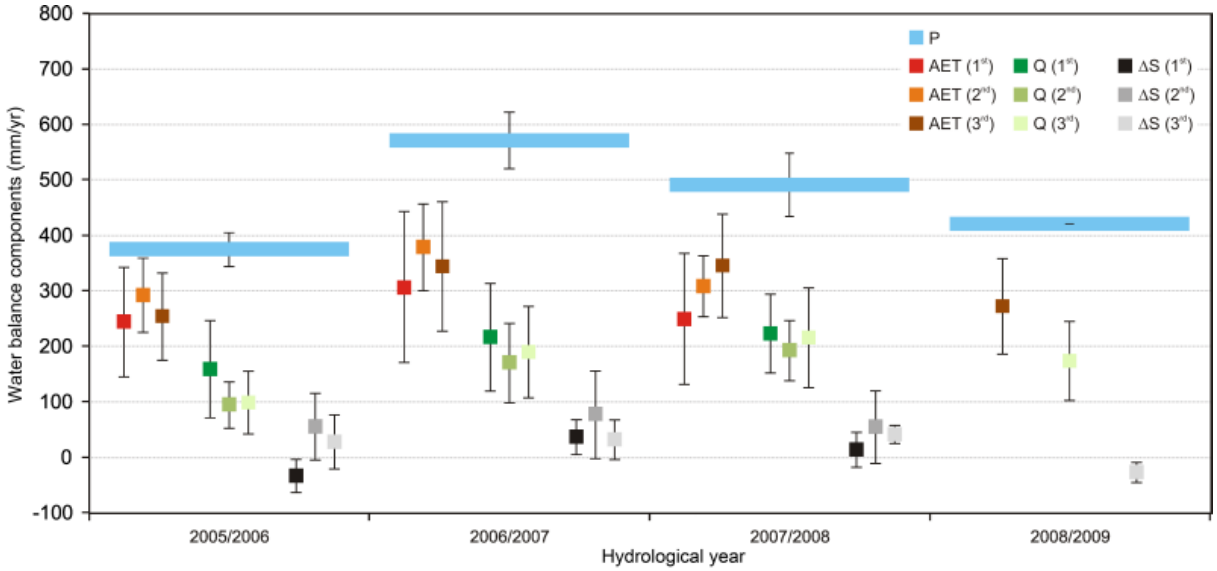

Figure 3.19 Change in annual water balance components (mean and standard deviation) during the three modelling stages for the Chicken Creek. The variability in precipitation is caused by precipitation correction by a few models. From Bormann et al., (2011b).

Overall, the study participants concluded: "*the comparison indicates that, in addition to model philosophy, the personal judgment of the modellers was a major source of the differences in the model results. The model parameterization and choice of initial conditions depended on the modeller's judgment and were therefore a result of the modellers' experience in terms of model types and case studies*" (Bormann et al., 2011b). The study therefore confirms the findings of previous studies (e.g., Diekkrüger et al., 1995) on the importance of the modeller subjective decisions particularly in the case of a priori prediction. "*The most important parameters to be presumed were the soil parameters and the initial soil water content while plant parameterization had, in this particular case of sparse vegetation, only a minor influence on the results*" (Holländer et al., 2009).

The study further showed that the use of soft as well as hard data is valuable (not only) in the case of sparsely gauged catchments. Soft data, e.g., obtained from field visits or even aerial photos, can inform the modeller about dominant or at least important hydrological processes in a catchment that will help improve hydrological process understanding. The modeller can then decide how to use such information in the modelling process. In this study, additional data predominantly only confirmed the modellers' assumptions that were based on field visits

and discussion. They, however, assisted in improving on the adequate choice of initial and boundary conditions. After having carried out the fourth modelling stage, consisting of model calibration against observed event runoff from a sub-catchment, further analysis of the predictive uncertainty of the *a priori* modelling steps will be feasible.

7.3.3 Forensic analysis of magnitude and causes of a flood (Selška Sora, Slovenia)

Observations of traces left by water and sediments during flood events provide an opportunity for developing spatially detailed estimates of peak runoffs along the stream network (Fig. 3.20). This information is helpful for better understanding the role of rainfall accumulation rates and of soil and land use properties in runoff generation in the context of PUB and for flood events characterised by sharp gradients in runoff response properties (such as flash floods). Indirect methods for flood peak estimation include the slope-area, contracted opening, flow-over-dam, or flow-through-culvert approaches. However, any survey not only has to capture the maxima of peak runoffs: less intense responses within the flood-impacted region are important as well. These lesser events can be contrasted with the corresponding generating rainfall intensities and depths obtained by weather radar reanalysis, thus permitting identification of the catchment properties controlling the rate-limiting processes (Zanon et al., 2010). Clearly, not all sections of a river may be suitable for indirect peak runoff estimation. However, Borga et al. (2008) have shown that, provided that a careful logistical planning and properly staffed infrastructure is ensured, post-event surveys may deliver a spatially consistent analysis of the historical flood response. Surveying the geomorphic response, through mapping of landslide/debris flow initiation and deposition areas, is important as well. This may help to properly identify the flow processes that occurred in the basin and hence to avoid questionable peak runoff estimates due to incorrect identification and documentation of debris flows.

Figure 3.20 (a) Example of a flood mark. The vegetation removed from the rocky bank and the moss drenched with silt on the downstream side of the tree show the highest level reached by floodwater (red line). (b) The arrow shows the tree with the flood mark and a phase of the topographic survey of the river section. (c) Surveying the stream bed. Photos: M. Borga.

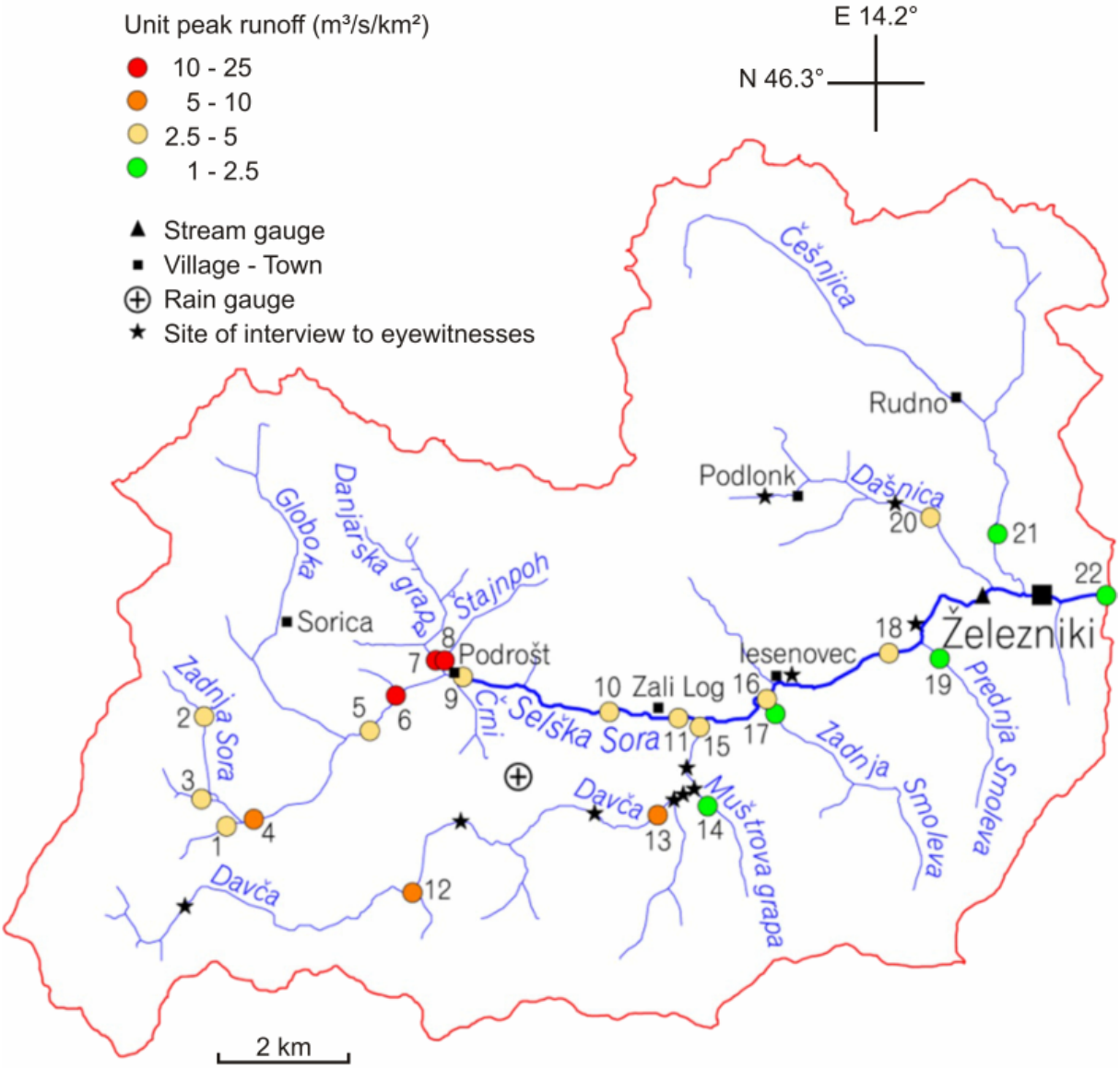

Figure 3.21. Map of the Selška Sora catchment in Slovenia with location of runoff estimates, interviews with eyewitnesses and central values of unit peak runoff. From: Zanon et al. (2010)

An example of a map of unit peak runoff values obtained during a post-flood survey is shown in Figure 3.21 for an extreme flash flood occurred in September 2007 in Slovenia (Zanon et al., 2010). Examination of the flood response shows that the extent and the position of the karst terrain provide major geologic controls on the runoff response in the region during storms. Differences in geology, combined with the orographic and climatic influences, led to pronounced contrasts in flood response between nearby basins, with the major flooding occurring in an area outside the region that received the largest rainfall intensities and accumulations.

Eyewitness accounts and observations represent an integral part of the flash flood response survey. It should be noted that these 'observations' might be collected as digital imagery from movies and pictures. Such observations represent an extremely important information source to refine the assessment of flow type/depth, the estimates of flow velocity and runoff, and for the evaluation of flooding extent. Interviews with eyewitnesses provide information and anecdotal evidence on the time sequence and dynamics of the flood, and as such they add a

time dimension to the spatial patterns of a flash flood response. It should be recognised that accuracy of the witnesses' accounts is limited (up to ±15 min, according to Borga et al., 2008). Consequently, when these observations are used to estimate the timing of the flood peaks, their information content should be related to the catchment response time, and therefore to the catchment scale.

The utility of the individual observations gathered by means of the flash flood survey may be extended using hydrological models driven by the space-time estimates of rainfall obtained from radar re-analysis (when available). Ruiz-Villanueva et al. (2011) integrated the surveying and modelling phases through a three-step procedure (applied to a medium size catchment in South-west Germany), which reflects the hierarchy of data use considered in this chapter: [1] *A priori* modelling of peak runoff at multiple locations based only on land use/land cover data, soil properties, soil thickness, and radar rainfall data. [2] Calibration of the model using runoff data from a (distant) downstream stream gauge, which includes the whole area impacted by the flood. [3] Comparison with the runoff observations collected from the post-flood survey and identification of the critical areas/processes responsible for outlying responses. The methodology based on post-flood survey affords examination of key hypotheses concerning the hydrology and hydraulics of catchment response under flash-flood conditions. Examples include (1) role of antecedent soil moisture conditions on flood magnitude; (2) role of land use and catchment properties on runoff generation; and (3) dependence of flood properties on basin scale by means of space–time scaling properties of precipitation.

Surveys of flash-flood response may provide valuable insights; however, generalizing the findings beyond the areas of interest can prove to be difficult. Each storm episode seems to have particularities that cannot be specified in full detail. Advancing the understanding in the context of flash-flood studies, which are by necessity opportunistic and event-based, requires the development of a parsimonious avenue to synthesis. This may be based on classification and similarity concepts, which can be profitably used when the processes are not fully understood (Blöschl, 2006). Contrasting different case studies and learning from the similarities and dissimilarities should play a central role in PUB studies.

3.9 Summary of key points

- Predictions in ungauged basins (PUB), in one way or another involves extrapolation from gauged to ungauged catchments, which needs data, of all kinds. Three kinds of data will be discussed in this book: runoff data, climate data and catchment data.
- The need for data can be summarised under three categories: (i) data needed to read and understand the landscape in a hydrologic context, (ii) data needed to develop regression relationships that will be used in statistical models, and (iii) data needed for process based models, as climatic forcing and parameter values, data to assist with model development (to make inferences from rainfall-runoff data), and to calibrate or validate models developed elsewhere.
- However, data are more than just inputs to a model. Data have hydrologic context, and contain hydrologic content. Data will be ultimate source of the understanding that is embedded in all models, because when understood properly, they reflect the co-evolution that is common to all catchments. Therefore, there is value and much to be learned from the combination of runoff, climate and catchment data, a learning process that we have called "*reading the landscape*".

- The information content of data products required for accurate PUB, from global data sets to local observations, is highly scale dependent and increases with decreasing temporal and spatial scale of prediction. This is because system heterogeneity is increasingly subsumed at larger spatial and temporal scales, leading to simpler catchment response to climate forcing. On the other hand, at small time and space scales, the heterogeneities and process complexities are much stronger, and are not attenuated, and thus need considerably more data to resolve them.
- The scale dependency of data requirements therefore requires a hierarchical strategy of data acquisition. Given the constraints provided by available resources and time, different data acquisition strategies may be adopted at various levels. Global and low resolution data sets, generally based on remote sensing, provide generalised information at low cost. Regional data sources of varying availability and accuracy provide detailed information at higher cost over smaller scales. Finally, with increasing time and financial resources, organisation and collection of short-term measurements may provide a better understanding of the catchment response at local scale.
- Large or regional data sets even of low resolution are an important basis for performing comparative hydrology, to generate a priori expectations of dominant processes, while very detailed data on the local scale help to confirm and improve process understanding. Extrapolation from gauged to ungauged basins requires that one finds connections between what happens locally and elsewhere: this requires a framework to connect.
- In general two kinds of data can be distinguished: Hard data measured in the field and soft/proxy data that provide additional information on hydrological systems. For PUB the combination of available soft and hard data relating to runoff, climate and catchment, through the reading of the landscape, plays an important role in order to exploit the available information and describe runoff processes in the best possible way.
- Field reconnaissance and expert judgement play a critical role in the assessment of local system characteristics and play an important role in the data acquisition strategy. The relative strength of different hydrological processes and dominant runoff generation mechanism are not easily inferred from topography, remote sensing and conventional hydro-meteorological data alone. Field visits allow for comparison of similar gauged catchments or heavily researched and more completely understood catchments, thereby allowing transfer of the relevant information.
- As modelling and methodological power has increased there has been a reduction in ‘‘data power’’, particularly in hydrological data collection. While the hydrological community has access to large datasets of unprecedented quality over large scales, e.g., remotely sensed data from satellites, the collection of more conventional data at small scales has suffered. There is a need to increase the awareness of the value of such data, especially the gauging of dynamic hydrologic variables in strategic locations and in a transferable manner, and demonstrate the value for targeted gauging of currently inadequate or nonexistent data sources by quantifying the links between increased ‘data power’ and improved model predictions.

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