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Chapter 12

Assimilation of remotely sensed data into hydrologic modeling for ecosystem services assessment

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Abstract

As the importance of ecosystem services is recognized by society, a growing interest in mathematical models as tools which provide necessary information for decision-making processes has arisen. The quantification of the ecosystem services associated to a region relies on the adequate simulation of hydrology, water quality and ecosystem dynamics. In this chapter we explore the evolution of hydrological models into more sophisticated tools which take advantage of the capabilities of remote sensing to characterize spatial trends at large scales. Physically based calculations distributed throughout the territory offer a reliable basis for further modeling, such as the quantification of regulation services related to the mediation of water flows, or to the maintenance of water quality conditions. In this framework, remote sensing constitutes a valuable source of data suitable to improve the results obtained from the models through assimilation. Some examples are given to illustrate the potential of the connection between distributed models and remote sensing to assess environmental issues, and highlight the benefits from this not so new but evolving source of data.

Keywords

Hydrology - Water quality – Modeling – Assimilation - Quantification

12.1 Introduction

The so-called “water cycle” was already observed, studied, and described by the ancient civilizations (Biswas 1970). But it was during the 19th century when hydrology was consolidated as an individual science, when the measuring capacity reached a significant level to acquire relevant volumes of data. It led to a rationalization of hypotheses, conclusions, and modeling during the 20th century, which finished with the development and use of complex hydrological models. It was in the last decades when observation of the Earth’s surface took a leap from the ground to space, shifting the concern about the scale effects arising from the use of point measurement to characterize continuous 3-dimension systems (upscaling), to the downscaling of remotely sensed data and their products. Good examples of application and state of the art of remote sensing for hydrological observation and modeling can be found in Schultz and Engman (2000), Schmugge et al. (2002) or Su et al (2011).

The hydrologic simulation of systems, whatever their scale, is a first and significant basis for analyzing and simulating water quality and, thus, ecosystem dynamics. However, the accuracy of hydrologic simulation is one of the most significant sources of uncertainty in calculations derived for ecological variables in the complete chain of interactions and forcing of processes. Wagner et al. (2009) addressed the need for improving modeling strategies based on these new means of observation and the capture of the macro-scale processes as well as the quantification of associated uncertainties, as the main challenge for hydrologists and scientists in general. In this context, data assimilation methods play a key role in fostering the application of remote sensing in hydrology and other sciences.

12.2 Hydrologic modeling and ecosystem services quantification

As the importance of ecosystem services is recognized by society, a growing interest in mathematical models as tools which provide necessary information for decision-making processes has arisen. The use of these models has increased over the last 30 years mainly due to a greater availability of information and data acquisition techniques (satellite images, aerial photography, remote data transmission, digital elevation models, etc.), and an increase in computer calculation capacity.

A huge number of models have been developed and adapted to different processes and systems. Thus, we can distinguish between biogeochemical models, e.g. CANDY (Franko et al. 1995), ICBM (Andren et al. 2004), terrestrial vegetation models, e.g. TRIFFID model (Cox 2001), YieldSafe (Van der Werf et al. 2007), carbon cycle models, e.g. Hybrid (Friend et al. 1997), CenW (Kirschbaum 1999), ASPECTS (Rasse et al. 2001) or hydrologic models e.g. TOPMODEL (Beven and Kirkby 1979) or SWAT (Arnold et al. 1998; Neitsch et al. 2005). Each of these models gives results linked to the system or subsystem for which they were developed taking into account the spatio-temporal scales of the processes, the initial information available, and the final results desired for decision making. The complexity of all the systems and processes involved in a widespread evaluation limits even nowadays the possibility of a global modeling. Recently, some works have begun to integrate different models, either in a coupled way or embedded in a single model, allowing the quantification of services corresponding to systems that, although interrelated, have traditionally been modeled separately.

The hydrologic cycle is a clear example of the conceptualization of nature as a set of connected systems (atmosphere-earth-sea), in which concatenated physical processes take place (precipitation, snowmelt, runoff, infiltration, subsurface flow, aquifers contributions, etc.). Such processes directly condition morphologic, chemical, biological, economic, and social behavior with evident influence on the services to society. Hence, it is no coincidence that many of the works developed for assessing ecosystem services with a modeling approach are structured, in one way or another, as subroutines based on hydrologic modeling (e.g. Band et al. 1991; Tague and Band 2001; Yates et al. 2005). The processes involved in the hydrologic cycle allow a discrete quantification of their components (e.g. volume of available water, soil loss, snow or groundwater storage) and, therefore, the possibility of measuring both accessible and non-accessible benefits. This potentially powerful quantification of tangible resources (water, snow, sediments, nutrients, etc.) is often far removed from the actual benefit obtained by society in practice. The existence of less tangible resources to be included in the analysis, such as cultural or aesthetic values, adds a complexity to the valuation process. Some authors (Porras et al. 2008; Carpenter et al. 2009) refer to a relative success in the services quantification coming from the results obtained by hydrologic modeling, mainly due to the difficulties in estimating the benefits derived by the water cycle and user's needs. This aspect needs to be improved in future studies aimed at the hydrologic modeling assessment of ecosystem services.

In general, two different approaches can be identified in the use of hydrologic models for ecosystem services quantification (Vigerstol and Aukema 2011; Bellamy et al. 2011): 1) from traditional hydrologic models, which requires a second step or post-processing from the results in order to assess the final quantification, and 2) from integrated ecosystem models recently developed by the combination of different methodologies or models, which gives, as a final result, a service quantification and its spatial distribution.

Hydrologic models have been used for decades to estimate different processes related to the water cycle, such as flooding (see Chapter 17), water resource availability, soil loss valuation, and so on. Strictly speaking, they have been providing decision makers with relevant information for the valuation of processes long before the concept of ecosystem services was consolidated by the scientific community and society. These tools have evolved from lumped/aggregated and event-based models, e.g. HEC-1 (USACE 1982), TR-20 (USSCS 1982), to more sophisticated models with a physical basis, and/or the generation of distributed and continuous simulation, e.g. WMS (Dellman et al. 2002), MIKE-SHE (Abbot et al. 1986) or WiMMed (Polo et al. 2009; Herrero et al. 2010). From the point of view of ecosystem services quantification, lumped-conceptual and event-based models have a limited interest, although they require less information and less computing capacity. In contrast, as mentioned previously, physically-based and distributed models allow for the estimation not only of the water balance, but also of the spatial distribution of the hydrologic variables, and they can quantify both the hydrologic processes and their interactions.

The SWAT (Soil and Water Assessment Tool) model, with a semi-empirical and semi distributed basis, has been widely applied in many studies especially focusing on the quantification of ecosystem services. These works include the assessment of the availability of hydrologic resources (Notter et al. 2012), the pollutant distribution in basins (Prochnow et al. 2008; Schilling and Wolter 2009), the evaluation of different climate scenarios (Stone et al. 2001), the best practices in basin management (Gassman et al. 2007), water storage in snow and snowmelt contributions in mountain areas (Herrero et al. 2005) and soil loss evaluation (Shen et al. 2009), to mention some relevant works. The main limitations found, however, are related to the empirical approach of many of the processes and the spatial discretization performed, since it aggregates the space in uniform hydrologic response units (HRU), which sometimes do not include the spatial distribution of many significant processes.

It is important to highlight the role of physically-based and distributed models for ecosystem services quantification, although different works mention their limitations due to high computing and data requirements, and the need to calibrate a large number of parameters. It is important to point out the contribution of remote sensing and its ability to provide models with distributed information in relatively short periods of time (e.g. land cover types, soil moisture, LAI, etc.), which allows both the initial configuration of the model and the final validation of the obtained results (snow cover evolution, flooded areas, soil loss, and so on). Furthermore, it is possible to develop relationships between remotely sensed data and different hydrologic parameters in order to create new information from those observations (Kite and Pietroniro 1996; Chen et al. 2005;

Liu and Li 2008; Feng et al. 2010; Su et al. 2010; Aguilar et al. 2012). Examples of this are included in the next section.

A second approach is related to models which integrate hydrologic modeling and ecosystem service quantification, related or not to water. These models are in their first developmental stages and, despite not being fully contrasted yet, they constitute highly promising tools. The InVEST (Integrated Valuation of Ecosystem Services and Tradeoffs) model (Tallis et al. 2011) allows the assessment of the quantity and value of different ecosystem services for current or future scenarios. The results are provided in distributed maps for services directly related or not to water (reservoir hydropower production, prevention of reservoir siltation, water purification, biodiversity sustainability, carbon storage, timber production assessment). A large number of application examples are given for biodiversity loss (Goldman et al. 2012; Reyers et al. 2012) and present/future soil management scenarios (Daily et al. 2009; Nelson et al. 2009; Johnson et al. 2012). In this case, some limitations can be found related to the simplification of many of the hydrologic processes involved and the absence of some important contributors, such as groundwater resources (see Chapter 13). Other models following this philosophy are based on Bayesian network approaches to establish relationships between the input data and the different services pursued. Such is the case of the ARIES model (Villa et al. 2009), which has been applied for the valuation of different climate scenarios. Further details of both models can be found in Castro et al. (2013, this book).

Box 12.1 Annual and seasonal variation of surface albedo and cover fraction of the vegetation from Landsat images. Assimilation into a hydrologic model as input variables.

Energy and water budgets on the Earth's surface are coupled processes which share evaporation and transpiration terms. The available water on the surface and upper layer of the soil acts as a source or sink of the deficit or excess of energy in this budget; vegetation directly transports water from the root zone to the atmosphere by means of respiration, and also modifies the soil evaporation regime through stoma control of the transpiration rates under water scarcity conditions. In practice, it is difficult to discriminate transpiration and evaporation rates in vegetated areas, and “evapotranspiration” (ET) is the term used to refer to this transport of water vapor. Moreover, the local and regional energy and water budgets in the atmospheric boundary layer and in the surface soil layer are also deeply related through the presence of vegetation: the root zone determines the effective soil depth to be considered as control volume in the soil budgets; the vegetative cover, its species, density, and structure constitute a rough 3-dimensional layer with a fundamental role in the turbulent transfer of momentum, energy, and water between the atmosphere and the terrain surface; vegetation type, its vigor, and its density also influence the fraction of the incident solar energy that is reflected back to the atmosphere, its albedo; the aerial structure of the vegetation can retain a given fraction of rainfall, which is evaporated back to the atmosphere instead of infiltrating through soil, the interception term in the water budget. On a spatial basis, the surface density of the vegetation is estimated by the "cover fraction", the fraction of the horizontal projection of the terrain surface which is covered by vegetation, ranging from 0 (bare soil) to 1 (completely vegetated soil). The cover fraction is, thus, the index which scales the terms in the energy and water budgets in which the vegetation is involved from the unit vegetation area to the unit surface area (see Figure 12.1).

For medium to large scale hydrologic analyses, quantifying the cover fraction evolution is of great interest. Different products can be used to acquire this information through the calculation of the NDVI index and its relationship to the cover fraction (Curran 1981; Sellers 1989; Bannari et al. 1995), such as MODIS data, although in heterogeneous areas, their spatial resolution poses a constraint for a proper quantification, since significant scale effects arise. Landsat images have been widely used (Ramsey et al. 2004) instead, due to their balanced spatial resolution, to estimate Normalized Difference Vegetation Index (NDVI) values at the watershed and regional scales. To quantify interception losses in the Guadalfeo River watershed (Southern Spain), a heterogeneous mountainous coastal area, Díaz-Gutiérrez (2007) coupled an interception model based on Gash (1979) and Rutter et al. (1971, 1975) approaches to a vegetation cover fraction map series obtained from a seasonal characterization of NDVI, by means of analyzing 4-6 Landsat 5 TM and 7 ETM images per year during the 2002-2005 period; a simple interpolation algorithm with a steady-state and evolving periods proved to be satisfactory for simulating a continuous daily time step in the series production (Polo et al. 2011).

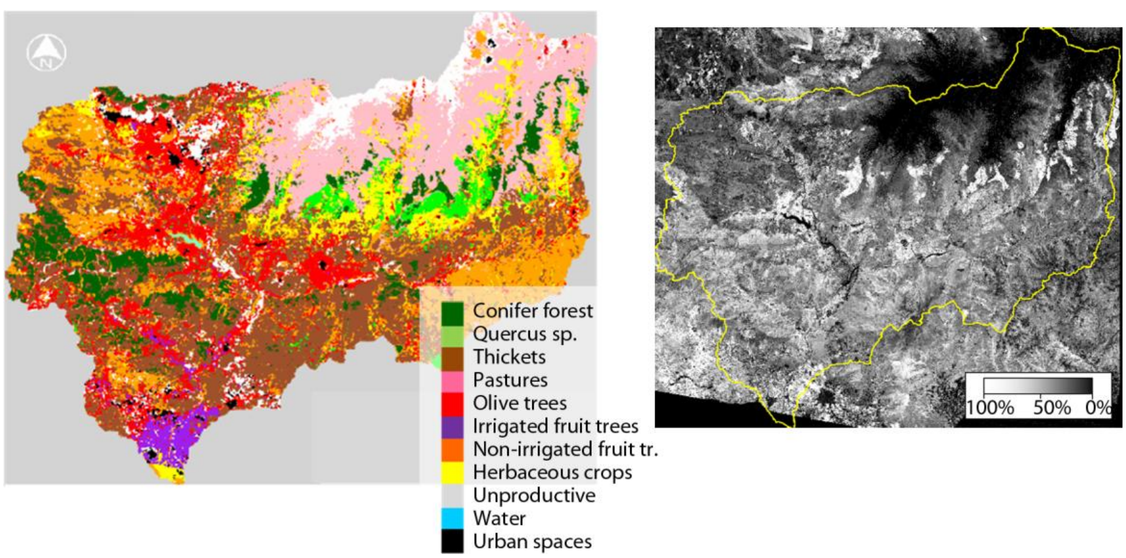

Figure 12.1 Vegetation classification (left) and example of cover fraction distribution (right), March 2005 in the Guadalfeo River watershed.

The assimilation of this time series into the hydrologic model WiMMed resulted in the estimation of rainfall interception (see Figure 12.2) losses along the watershed and provided managers with an efficient tool to evaluate different options of crop selection, wildfire effects, and drought consequences in terms of the intercepted fraction change at watershed scale.

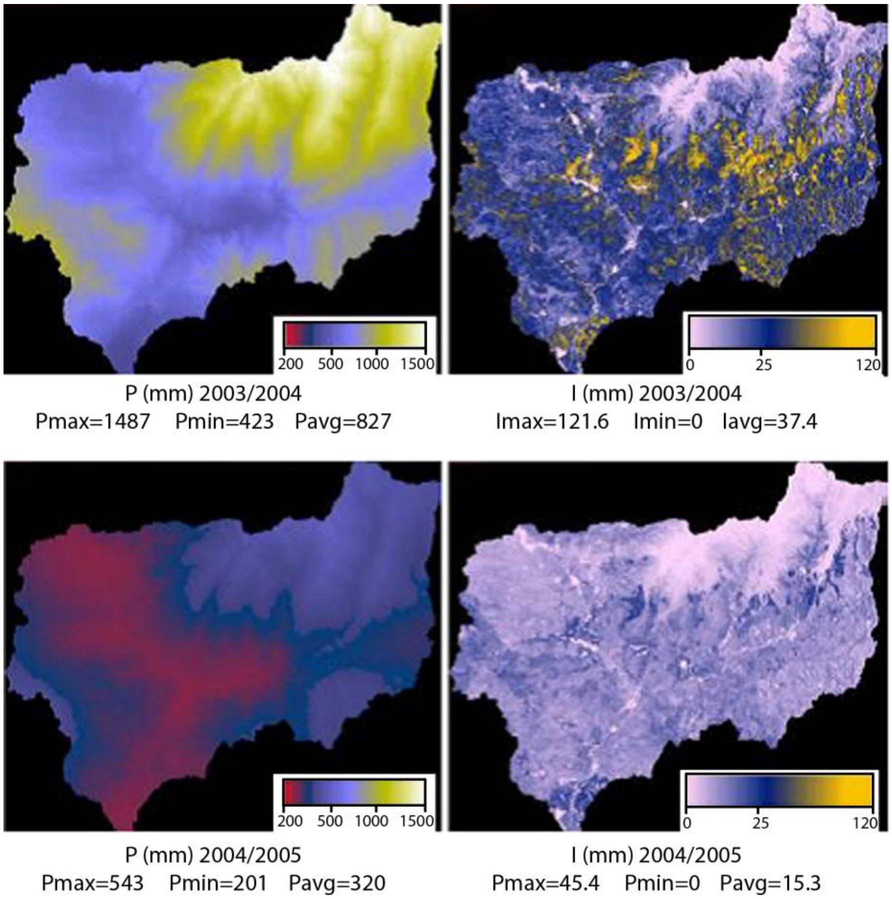

Figure 12.2 Precipitation (P, left) and interception (I, right) in two consecutive hydrological years in the Guadalfeo River watershed.

Box 12.2 Delta coastal areas retail related to sediments supply (the Guadalfeo study case)

Bedload erosion processes significantly affect fluvial dynamics and frequently condition fluvial management due to their high impact on dam siltation, streambed-particle stability, and estuarine dynamics, among others. The social and economic repercussion of sediment loads has different effects, sometimes opposed, which suggests the need for more complex methodologies in order to understand these processes and their associated costs.

The Guadalfeo river basin (southern Spain) exhibits an important amount of alluvial sediments stored throughout its main stream and secondary dry-affluents or “ramblas” to its mouth in the Mediterranean Sea. The building of the Rules Dam in 2004, with 110 hm^3 of capacity, posed a risk for significant environmental changes in the up and downstream surroundings, especially in the delta.

Monitoring works in two control points located at the main channel were complemented by an analysis of remote sensing information to estimate not only the loss of storage capacity in the reservoir due to siltation, but also the impact downstream on the delta dynamics. Orthophotography and satellite images between 1956 and 2008 (Red de Información Ambiental de Andalucía 2010) were used together with field bathymetries during 2003-2011 to estimate siltation rates from 2002, with an estimated volume of

2.000.000 m^3 of sediment infilling.

This strong sediment retention in the reservoir resulted in an enhanced regression of the delta from 2005, since the fluvial inputs practically ceased, causing an unbalanced loss of beach material during intense storms in the coast and tidal and wave dynamics, which is retreating. Under normal conditions, the coastal erosive action performed by the currents and breaking waves maintains the same direction and transports the sediment from the delta to the adjacent coastal areas, mainly beaches and harbors (Ávila 2007). The direct impact can be valued from the additional expenses in beach nourishments in this touristic area, quantified in 1.121.000 m^3 between 2004 and 2009, with an associated cost of 7,286,500 € (Ruiz de Almirón 2011). These dynamics can be found in many deltas and estuaries in regulated Mediterranean watersheds.

12.3 Hydrologic modeling and remote sensing

The coupled water and energy budgets on the Earth determine the primary local regime of the environmental conditions, with most of the physical, chemical, biological, and ecological regimes being highly dependent on them. Moreover, water constitutes one of the major pathways for sediment, nutrients, pollutants, etc. throughout the different scales at the ecosystem. The biogeochemical cycle is a similar conceptualization of the ecosystems dynamics to the water cycle definition, since it defines systems and subsystems, their internal links and exchanges, their external forcing and associated responses, and their interactions. To quantify biogeochemical fluxes, the water and energy fluxes must be estimated first. The biogeochemical cycle relies both physically and mathematically on the hydrological cycle and, thus, receives and propagates the quality level achieved in the performance of the latter, as well as the uncertainty associated with its results. This fact justifies the importance and influence of the hydrologic modeling in the ecosystem service quantification.

A computer model for the simulation of the hydrologic cycle permits, not only being able to predict behaviors in foreseeable future scenarios, but also to deepen the actual knowledge of this behavior in the present time for a particular region. To take advantage of the spatial resolution provided by remote sensing abilities nowadays, distributed models must be used. Moreover, to fully exploit the present hydrologic knowledge to describe the different processes taking place and to estimate with enough accuracy the different water paths and interactions, these models should be physically based. A model with both characteristics is capable of estimating a significant number of components and water fluxes within the hydrologic cycle, which are otherwise impossible to quantify reliably.

There are numerous distributed and physically based hydrologic models widely used, such as TOPMODEL, DHSVM (Wigmosta et al 1994) or SHE, just to give some examples. Despite these similarities, they differ in how they solve some particular hydrologic processes. For example, some of them attach importance to the subsurface flow, or the overland flow, as part of a strategy for the implementation in wetter or drier environments, such approaches being usually related to the area where the model was originally developed. The time step for continuous simulations varies from daily to hourly calculations. WiMMed (Watershed integrated Management for MEDiterranean environments) is a distributed and physically based hydrologic model developed by the Universities of Granada and Córdoba, in Spain (Polo et al. 2009; Herrero et al. 2010). Initially conceived for Mediterranean mountainous environments, it is specially intended for dealing with mountainous basins where snowmelt at low latitudes is present in a context of extreme variability sources: abrupt topography, meteorological gradients, vegetation cover heterogeneity, mountainous aquifers with preferential topographic subsurface flow, torrential precipitation and dry period during the seasons, great production of sediments, and extended hyper-annual droughts. The physical approach to the resolution of the different equations related to such processes is especially important in such a highly heterogeneous and time variable environment. This is particularly relevant for the snow hydrology (see Chapter 15), which can only be correctly simulated by an energy and mass balance approach. As in many other distributed models, remote sensing plays a significant role during the hydrologic simulation with WiMMed.

The use of remote sensing technologies in the modeling process allows the identification of parameters attached to some physical meaning, as well as the description of water presence over a whole region or hydrologic unit simultaneously. These parameters can be incorporated into the model as input data, which can be considered constant or variable in time. Distributed models must be able to simulate water cycles on the same resolution as that from the satellite information, to fully exploit these data. Data assimilation, as well as the comparison between model results in cells and remote measurements of state variables, will be straightforward in such a case. As an example, if Landsat multispectral data are used to obtain information to be incorporated into a distributed model, 30x30 meter is the minimal spatial resolution that the model should reach in order to take advantage of all the available information. The high required computing capacity for that used to be claimed as a major constraint for the use of these models, but is no longer true nowadays.

A distributed hydrologic model can assimilate data from different sources and approaches (Houser et al. 1998, 2012; Reichle et al. 2002; De Lannoy et al 2011; Malik et al. 2012). As an example, WiMMed is fed by two direct results from multispectral data through the calculation of the Normalized Difference Vegetation Index (NDVI): the vegetation cover fraction, fv, and the surface albedo, α (Díaz-Gutiérrez 2007). The first indicates the fraction of each pixel that is covered by vegetation, whereas α is the shortwave reflectivity of the terrain, both of them obtained as effective values for the spatial resolution of the multispectral sources. When Landsat TM data are used, a time frequency of 15 days is available, provided no clouds interfere. The resulting fv or α maps can then be interpolated to obtain daily distributed series, which constitute direct inputs to the model to estimate rainfall interception or the energy budget in the soil or in the snowpack. Among other variables, the reference evapotranspiration (see Chapter 18) and the actual evapotranspiration are derived from these calculations (Aguilar et al 2010). This is an example of direct assimilation of physical parameters obtained from remote sensing data as inputs to the equations in a model.

On the other hand, hydrologic models can also use estimated values of their state variables by means of remotely sensed information to calibrate and validate their performance. The snow cover distribution (see Chapter 15) or the soil moisture are reference examples of this (see Chapter 14). The assimilation procedure can incorporate correction techniques to include the quality and uncertainty of the source data, by means of methods based on the use of Kalman filtering, such as the DART (Data Assimilation Research Testbed) model (Anderson et al 2009). A simpler approach is a Direct Insertion, which consists of replacing the simulated variable with the "measured" values at the given states in which a satisfactory degree of adjustment is not achieved, as WiMMed does with snow data from aerial or remotely sensed sources (Pimentel et al 2012) (Box 12.3). The presence of snow can be detected by visible images or multispectral ones, by means of the near-infrared reflectance analyses through the use of indexes such as the NDSI (Normalized Difference Snow Index) (Hall et al 1995). In a similar way, the water equivalent of the snow can be estimated from LiDAR (Light Detection And Ranging), radar, or terrestrial gamma-ray attenuation data (DeWalle and Rango 2008), and soil moisture from microwave, multispectral analysis or gamma radiation measurements (Carrol 1981; Wang and Qu 2009).

Box 12.3 Calibration and validation of a snowmelt model through snow maps derived from remote sensing.

Herrero et al (2011), when applying a hydrological model in the Guadalfeo River Basin (near the Sierra Nevada Mountain Range, Spain), used the WiMMed model to map at an hourly scale the snow cover extension and its water equivalent. With a 30m spatial resolution, the results from the model were directly compared to the snow cover map obtained from Landsat for specific days with an adequate visibility. This comparison led to the definition of four possible different combinations for every pixel: 1) pixels with simulated and measured snow, 2) pixels free of simulated and measured snow (both 1) and 2) correct cases), 3) pixels with measured but not simulated snow, and 4) pixels free of measured snow but covered with snow in the simulation. The goodness of the calibration-validation process was performed by means of different indexes deduced from the four possible combinations described.

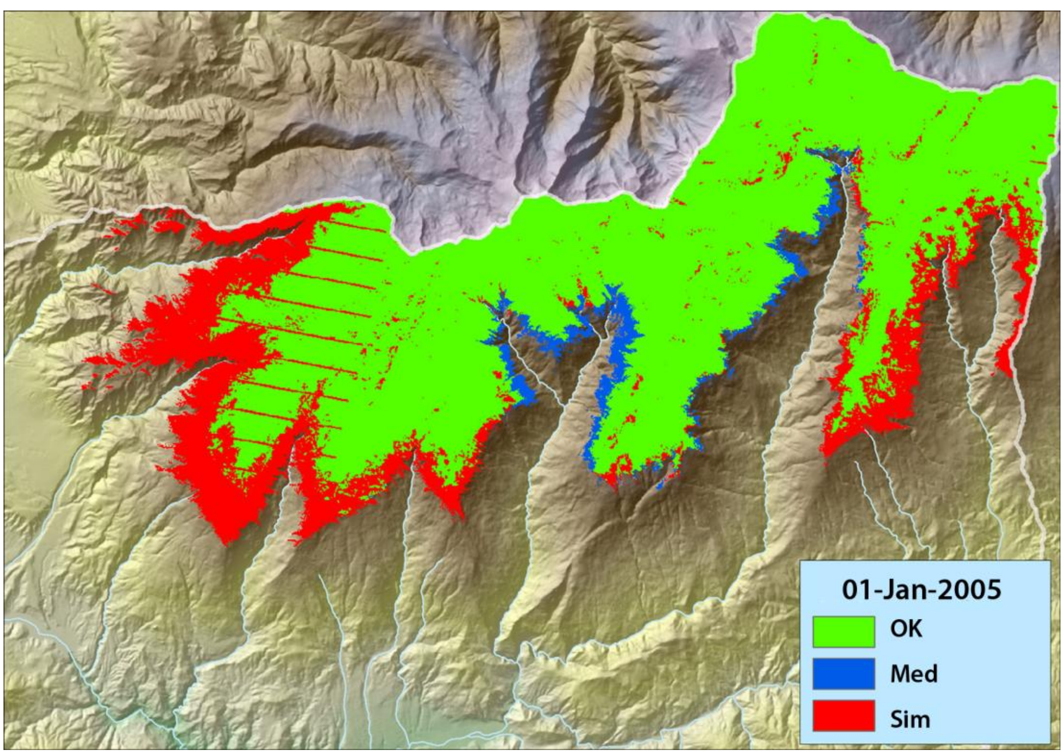

Figure 12.3 Pixel to pixel comparison between the snow cover simulated with WiMMed and measured

from Landsat TM7 for the 1st of January of 2005.

Figure 12.3 shows an example of this pixel to pixel comparison between the simulated and measured snow presence. Measurements were obtained after the processing of a Landsat TM7 image, while simulation was run with the snow module of WiMMed model. Some correct pixels are in green and others in a transparent color, while blue and red pixels stand for underestimation and overestimation of the snow cover by the model. The identified deviations were mainly due to an incorrect assignment of the temperature and the precipitation in every pixel during the simulation, which is usually the main source of uncertainty in hydrologic simulations in mountainous basins, where gradients are very pronounced and the coverage of the meteorological networks is usually insufficient, this being even more important than the inherent limitations of the physical modeling itself.

12.4 Water quality monitoring and remote sensing

Surface water bodies offer very different provisioning, regulating and cultural ecosystem services, such as water supply, fish production, transportation, recreation, etc. They are also vital to the survival of many key species that use them to live, feed and reproduce. As a consequence of the constant and variable interaction between human pressures and natural forces, water bodies are constantly changing. Therefore, surface water systems are at once resilient and fragile (Ji 2008).

As rivers flow throughout watersheds, they collect water, sediment, nutrient, and pollutant discharges. Other surface water systems such as reservoirs and estuaries filter the water and associated pollutants, sediments, nutrients, toxics, etc., from the upstream contributing areas. Abrupt changes in land uses, which may increase the discharges of pollutants or cause the overexploitation of water bodies, often lead to common environmental problems downstream such as eutrophication, loss of habitat, algal bloom development, decline in fish and wildlife, seawater intrusion, siltation of hydraulic infrastructures, etc. Therefore, the management and planning of water resources require the correct assessment of not only the amount, but also the quality of the water.

The first concerns about poor water quality focused on health and sanitation issues. Control measures were mainly implemented in sewage treatment plants and industrial discharges through pipes or open channels (Engman and Gurney 1991). But, more recently, non-point source pollution has been the subject of both general concern and scientific investigation. Non-point source pollution is considered as part of storm runoff and so the identification, measurement, and control of this type of pollution may be very complex. Once again, integrated models at watershed scale constitute an important tool for water resource management, by combining both quantity and quality criteria. These models aim to characterize precisely the hydrologic and erosion processes that influence water and sediment fluxes throughout the watershed, coupled with the physical, chemical, and biological processes that affect water quality. In non-monitored areas, physically-based models allow to estimate the watershed response, although some level of calibration from field measurements is always required.

There are numerous hydrological models that reproduce non-point source pollution processes at watershed scale with different details such as ANSWERS, SWMM, AGNPS, HSPF, GLEAMS, SWRRBWQ, CREAMS, SWAT, etc. However, most of them can be very complex to implement and calibrate due to the large amount of parameters involved. Besides, the quantification of non-point source discharges is difficult due to the lack of available measurements or to the historical data record not being long enough to determine its dynamics and evolution at the required temporal scale. In this way, remote sensing is a very valuable source in water quality evaluation, especially when the spatially distributed nature of non-point source pollution and the broad spatial scale required for these kinds of studies is considered (Engman and Gurney 1991). At the regional scale, the availability of high frequency monitoring is only economically viable through remote sensing. Also, the global coverage of satellites nowadays allows for the estimation of water quality in remote and inaccessible areas, and provides modelers with data for historical water quality studies during periods lacking ground measurements (Hellweger et al. 2004).

Once again, remote sensing constitutes a very valuable data source at three levels in the application of non-point source pollution models: as input data, state variables, and measured data for the calibration and validation of the model estimates. As for input data and state variables, remote sensing data are often used for the generation of facts related to coverage and land uses, topography, and soil types, information that greatly affects the potential water quality of runoff. Regarding the model outputs or water quality indicators, remote sensing permits the derivation of surface estimations of turbidity, suspended sediments and chlorophyll concentrations, colored dissolved organic matter, and temperature in water bodies. These water quality characteristics can be used as indicators of more specific pollution problems (e.g. eutrophication levels) and be related to non-point source model outputs (Engman and Gurney 1991).

Turbidity is an optical effect related to the total concentration of suspended sediments and other organic matter. Chlorophyll-a is a key indicator for the monitoring of aquatic populations, mainly phytoplankton, and the state of aquatic ecosystems can be obtained by sensors able to quantify the photosynthetic process. Colored dissolved organic matter (CDOM) is a product of plant and animal decomposition processes. All these water quality variables can be measured in situ using conventional techniques that involve direct sampling of water (Salama et al. 2012). However, they greatly vary in both space and time affected by the loadings received in the water body and the hydrodynamics of the system. Thus, the monitoring from point samples is often inadequate as it is time consuming and only representative for a limited spatial and temporal domain. In this way, remote sensing sources provide very valuable spatial and temporal data due to its capability to monitor vast areas nearly instantaneously (Hadjimitsis et al. 2006; Budhiman et al. 2012).

Reflectance in the visible and near infrared regions of the spectrum is used for the evaluation of water quality indicators in the surface or near surface of water. Thermal infrared is also used for estimating water quality indicators from the direct measure of emitted energy (Engman and Gurney 1991). In general, sediments present a high reflectivity in all the bands in the visible regions even though the correlations between the Secchi depth, an indirect measure of turbidity, and reflectances in the blue and green bands (450-600 nm) are much lower than those in the red ones (600-690 nm). However, the spectral response is strongly influenced by the nature of the water system. In water bodies affected by the discharge of freshwater, there is a high correlation between turbidity and the reflectance in the red band. In coastal waters with low discharges of freshwater and, therefore, non-significant sediment loadings, reflectance is more affected by the concentration of phytoplankton, estimated from chlorophyll-a (Hellweger et al. 2004; Lane et al. 2007).

Water quality variables can remotely be quantified following empirical approaches based on regression analysis between measurements and observations. Another option is the use of semi-analytical methods that apply a hydro-optical model that describes the relationships between the observed spectrum and the concentrations of the water constituents (Salama et al. 2012).

Regarding sensors and platforms, the choice is determined by the resolution of the data required according to the variable to be estimated and the spatial extent of the study area. This is why the relatively small dimensions of rivers, lakes and estuarine waters has often restricted the derivation of water quality variables from satellite data to the open ocean and some coastal areas (Salama and Su 2010, 2011; Shen et al. 2010; Budhiman et al. 2012). In rivers, the focus is mostly on LiDAR, altimeter and airborne hyperspectral data as the number of satellite sensors that provide the needed spectral and spatial resolutions is limited even for large rivers (Salama et al. 2012). For instance the spatial resolution of EnviSAT (300 m) is too coarse for capturing even the largest rivers whilst in Landsat data the limited number of visible bands and the coarse spectral resolution of these bands is the main constraint (Dekker and Peters 1993). Nevertheless, Landsat has been the dominant source of satellite images for lake water quality monitoring due to the fine spatial resolution (30 m). In the literature there are numerous studies in inland lakes that have developed expressions to estimate suspended solids, turbidity, chlorophyll-a, salinity and temperature from Landsat data (Lathrop 1992; Baban 1993; Mayo et al. 1995; Hadjimitsis et al. 2006; Wang et al.2006). On the other hand, the higher spatial extent of coastal systems such as estuaries, deltas and lagoons, allows the use of data from satellite sensor with medium spatial resolutions such as MODIS (Hellweger et al. 2004; Chen et al. 2007) and MERIS (Mathews et al. 2010). However, there are also a lot of studies that apply finer spatial resolutions satellite data for the estimation of water quality parameters such as Landsat (Lavery et al. 1993; Hellweger et al. 2004; Kabbara et al. 2008; Wang and Xu 2008; Bustamante et al. 2009) or EO-1 ALI (Chen et al. 2009). The main limitation of these studies is that, unlike the studies that apply hydro-optical models (Salama et al. 2012), most of them are site specific; however, they allow to establish an assessment of the status of water bodies at a large scale that in many cases cannot be obtained by other means (Engman and Gurney 1991). In the future, more effort is expected to fully understand the variability of the optical properties of these water bodies (Budhiman et al.

2012).

12.5 Conclusions

Remote sensing undoubtedly constitutes a powerful data source for hydrologic modeling at the watershed, regional, and global scales, a necessary basis for ecosystem services assessment, mapping and quantification. In fact, the increasing availability and quality of these data provide modelers with schemes to include certain assimilation techniques in the modeling environment itself. Both approaches, that is, the direct estimation of the spatial distribution of the properties of the terrain which are relevant in the hydrologic processes, and the calculation of different state variables at the frequency of the satellite, provide scientists and technicians with discrete spatial information on a given location, which can be considered to be continuous at the scale given by the spatial resolution of the sensor. Scale issues, thus, constitute a significant matter to be considered. Current and future development of satellite sources, together with the already on-going effort to combine data from multiple satellites by taking advantage of their individually higher spatial or time resolution, constitute a reliable horizon for technicians and scientists' work. On the other hand, the possibility of acquiring such detailed distributed information has greatly increased and broadened human capacity not only for the observation of the Earth, but also for the simulation of processes, during the last decades, and will still do so in the future.

As for water quality modeling, remote sensing provides useful information regarding the spatial distribution of the terrain and soil properties. These data can be used as input data to hydrological models that reproduce non-point source pollution processes at watershed scale. Nevertheless, the main field of application of remote sensing data in water quality modeling is the estimation of water quality parameters in receiving water bodies. This information could be used in the calibration and validation of water quality models. However once again, scale issues and the complexity of the optical properties of water bodies constitute the main lines of future research.

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