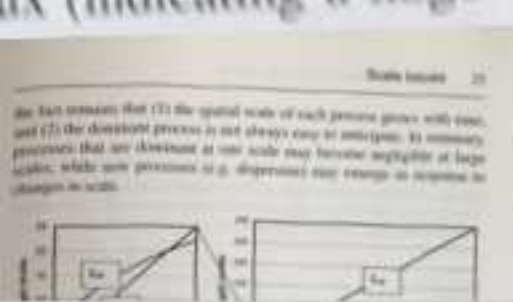
singly clear that questions relating to the uptake
use gasses by terrestrial vegetation cannot be seen
irect interaction of vegetation with the atmosphere,
r exchange, with possibly global and regional effects
This calls for scientific studies addressing not only
for long-term carbon sequestration but also possible
sult of changing land use, and with explicit accounting
in hydrological cycle.

bon balance is the sum of the amount of carbon
on and released through heterotrophic respiration. In
al emissions, fluxes to/from terrestrial vegetation are
gical and hydrological cycle. Carbon stored in plants
the atmosphere on the time scale of decades (plants)
wo-thirds of the terrestrial carbon is found in the soil.
gement, for example, may be aimed at strengthening
carbon into below-ground, rather than above-ground

et al. (2000a,b) present the results of a numerical
a carbon-climate model indicating that carbon-cycle
ficantly accelerate climate change. In several studies,
orests in the global carbon cycle have been estimated.
es, based on a review of *static conversion* (without
dbacks) of national forest inventory data of European
strength for the European forest of 101 Tg C y^{-1} for
uurs et al. 1997). This large sink would compensate
n fossil fuel emissions. However, Martin et al. (1998)
sed on the EUROFLUX data of 120 to 280 Tg C y^{-1}.
rly due to the fact that the latter estimate represents
ux (indicating a large sink in the soils) and therefore



tory. Studies using the NOAA
n of the uptake of the terrestrial

to Phillips et al. (1998) up to 5.9 t ha^{-1} y^{-1} according to Mahli et al. (2002). Changes in the global signal of seasonal CO_2 concentrations (Keeling et al. 1996) show the sensitivity of climate variability and the consequences for source/sink relations of the biosphere.

Possible causes of these differences in carbon uptakes, and whether they are transient in nature, are heavily discussed at present and are clearly linked to the level of our understanding of the feedbacks involved. Possibilities include climatic variations (ENSO), reforestation, and carbon dioxide fertilisation. Schimel et al. (2000) recently questioned the latter possibility for a larger uptake of CO_2 by the biosphere under higher CO_2 concentrations and a warmer climate, because that would also mean at least a doubling of nitrogen fluxes into ecosystems. Current nitrogen deposition trends do not indicate such increases, suggesting that the future C-cycle will probably be limited by nitrogen. Therefore it is of utmost importance to integrate biogeochemical and water cycles.

1.2 Scale Issues

Axel Bronstert, Jesus Carrera, George Leavesley, Nicole Mölders

1.2.0 Introduction

In the development and application of coupled process models, the effects of space and time scales on process interactions and interpretations are major. It is important to have in mind, therefore, that the concept of different scales can be applied on various levels, in particular see Blöschl (1996) for example:

- *Process scale*: spatial and/or temporal extent for which a certain process occurring in nature can be called representative;
- *Measurement scale*: spatial and/or temporal extent which is determined by the measurement device or sampling principles;

The main point in this figure is that the input is displaced and diffused. Therefore, one can define an advection scale as the distance travelled by the centre of mass and a diffusion scale as the distance over which this mass has diffused. As shown in Fig. 1.2-1, the expressions for these two scales are:

$$L_A = vt \tag{1.2-2}$$

$$L_D = \sqrt{2Dt} \tag{1.2-3}$$

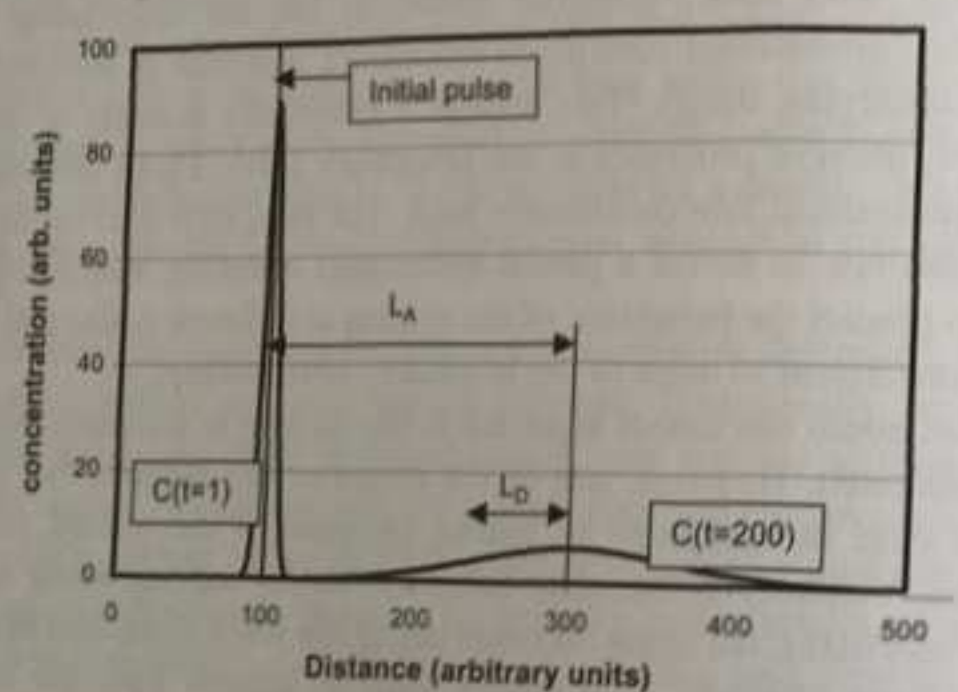


Fig. 1.2-1 Concentrations after 1 and 200d in response to a pulse injection of 1000g mass at x = 100 m in a fluid moving to the right at 1 m d^{-1} (actually, units are arbitrary). The diffusion coefficient is 10 m^2 d^{-1}. Notice that advection is negligible after 1 day, while diffusion displays a sizable effect (that is, the centre of gravity does not appear to change, but concentrations define a Gaussian bell, quite different from the initial point pulse). After 200 d, the pulse has moved 200 m to the right. Diffusion, still relevant, is overcome by advection, so that concentration is negligible at the injection point

These two scales are represented versus time in Fig. 1.2-2. Simple inspection of the figure makes it apparent that, for very short time intervals one might as well ignore advection because L_D is much larger than L_A. On the other hand, for long time intervals diffusion becomes negligible. Actually, things can be a bit more complex, because D itself may grow with scale, leading to dispersion in response to the increase of velocity fluctuations around its mean (e.g. the size of eddies in the atmosphere or heterogeneities in an aquifer that a contaminant may encounter grow as it disperses). Still,

the fact remains that (1) the spatial scale of each process grows with time, and (2) the dominant process is not always easy to anticipate. In summary, processes that are dominant at one scale may become negligible at large scales, while new processes (e.g. dispersion) may emerge in response to changes in scale.

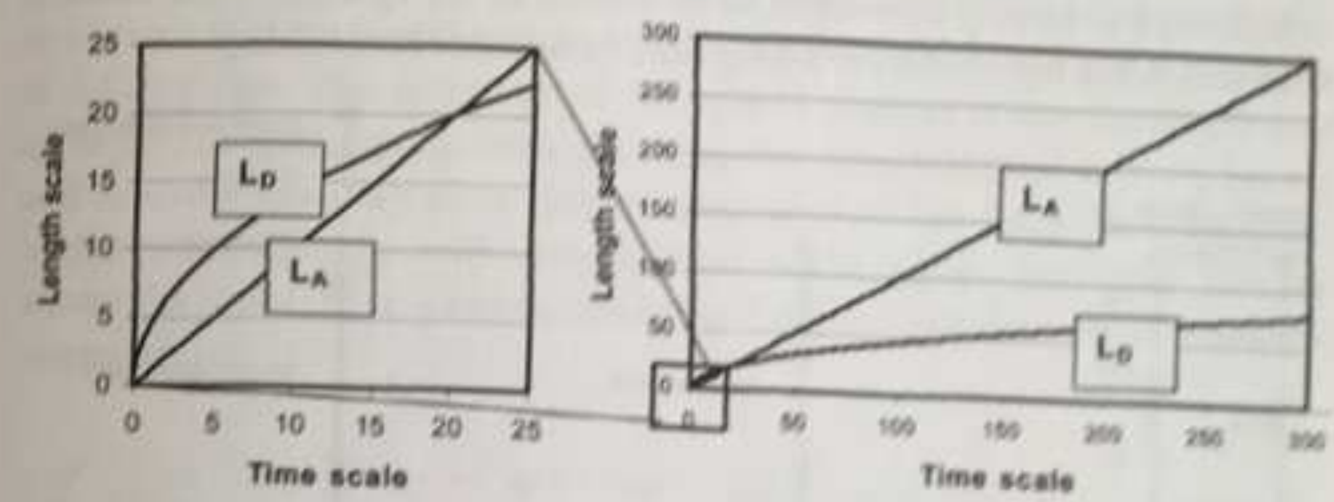


Fig. 1.2-2 Advection and diffusion length scales (L_A and L_D, respectively) versus time in the example of Fig. 1.2-1 (v=1 m d^{-1}, D=10 m^2 d^{-1}). Notice that, before 20 days, diffusion dominates advection, which is negligible before 1d

This example is restricted to a single subsystem (transport of solutes in a river or vapour in the atmosphere). The problem becomes eerie when coupling several subsystems. Each of them will have its own time and spatial scales and their corresponding dominant processes, which may not be easy to anticipate. Worse, the relative importance of each subsystem is problem-dependent. For example, regional groundwater flow may not be important when dealing with floods but may control river base flow. This is why it is important to understand the process, measurement and modelling scales that are relevant for each subsystem. Thus, it is important to define the basic hydrological scales, which is the topic of the following section.

1.2.2 Terminology of Scales in Hydrology and Atmospheric Sciences

The terminology concerning temporal and spatial scales used in different science disciplines is far from uniform. Thus, many disciplines derived their own notion for typical scales for that particular scientific area. Even within one scientific area, there may be several terms for a specific spatial or temporal extent. In the case of coupling processes, concepts or models of two or more scientific disciplines, it is of particular importance to understand the meaning of the terminology at the scales of the corresponding discipline.

In Fig. 1.2-3 the time scale terminology applied in hydrology and atmospheric sciences is presented and related to actual times or durations. One can see that the terminology of the hydrological time scales are derived from the distinction of rainfall/non-rainfall periods ("event scale"), or the diurnal and the seasonal periodicities, respectively. In atmospheric sciences, terminology is mainly derived from or related to the synoptic time scale, a term which has been used for a long time in weather forecasting.

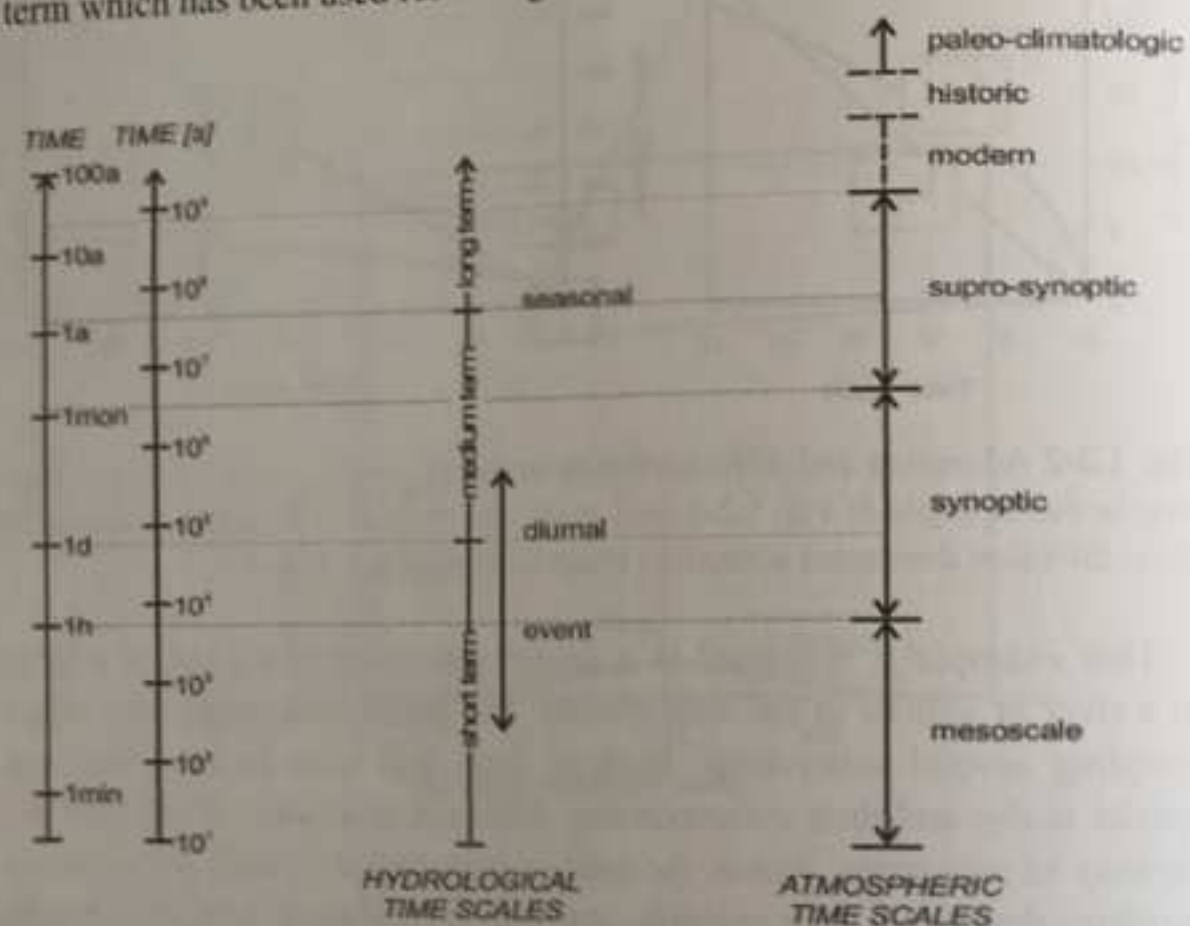


Fig. 1.2-3 Time scales in hydrology and climatology

In Fig. 1.2-4 the terminology on spatial scales applied in hydrology and atmospheric sciences is presented and related to actual spatial lengths or areas. In hydrology, two concepts are mainly applied: first, the distinction of the typical size of different landscape fractions (such as local/point scale, hillslope, catchment, region, continent). Second, the terms micro-, meso- and macroscales are applied to distinguish between the dimensionality of the processes considered: the hydrological microscale is often (but not always!) treated as one-dimensional in the vertical direction and relates to small spatial extensions of usually not more than a few metres (e.g. a soil column in the laboratory, a lysimeter, an experimental field plot). The hydrological mesoscale is mostly attributed to more or less uniform landscapes or catchments where, on the one hand, many different hydrological processes

are occurring, but – on the other hand – might be described by so-called "lumped" concepts, aggregating the hydrological cycle of the whole area in a straightforward systems approach. Finally, the hydrological macroscale covers large areas with very different landscape features (e.g. mountains and lowlands) and hydrological systems (e.g., river systems and lakes), which cannot be aggregated by a lumped approach. Having this in mind, it is obvious that the interface between the hydrological meso- and macroscale is a fuzzy one. The definition of the spatial scale in atmospheric sciences is more straightforward, distinguishing the climatological micro-, meso-, and macroscales with clear defined interfaces (2 km length and 2000 km length respectively), with subdivisions noted alpha, beta and gamma, where the alpha, beta, gamma stands for the large, medium, small subscale, respectively.

Fig. 1.2-4 Spatial scales in hydrology and climatology

There is a typical relationship between space and time scales. For example, the smaller the spatial extent investigated, the shorter the appropriate time (Hugget 1991).

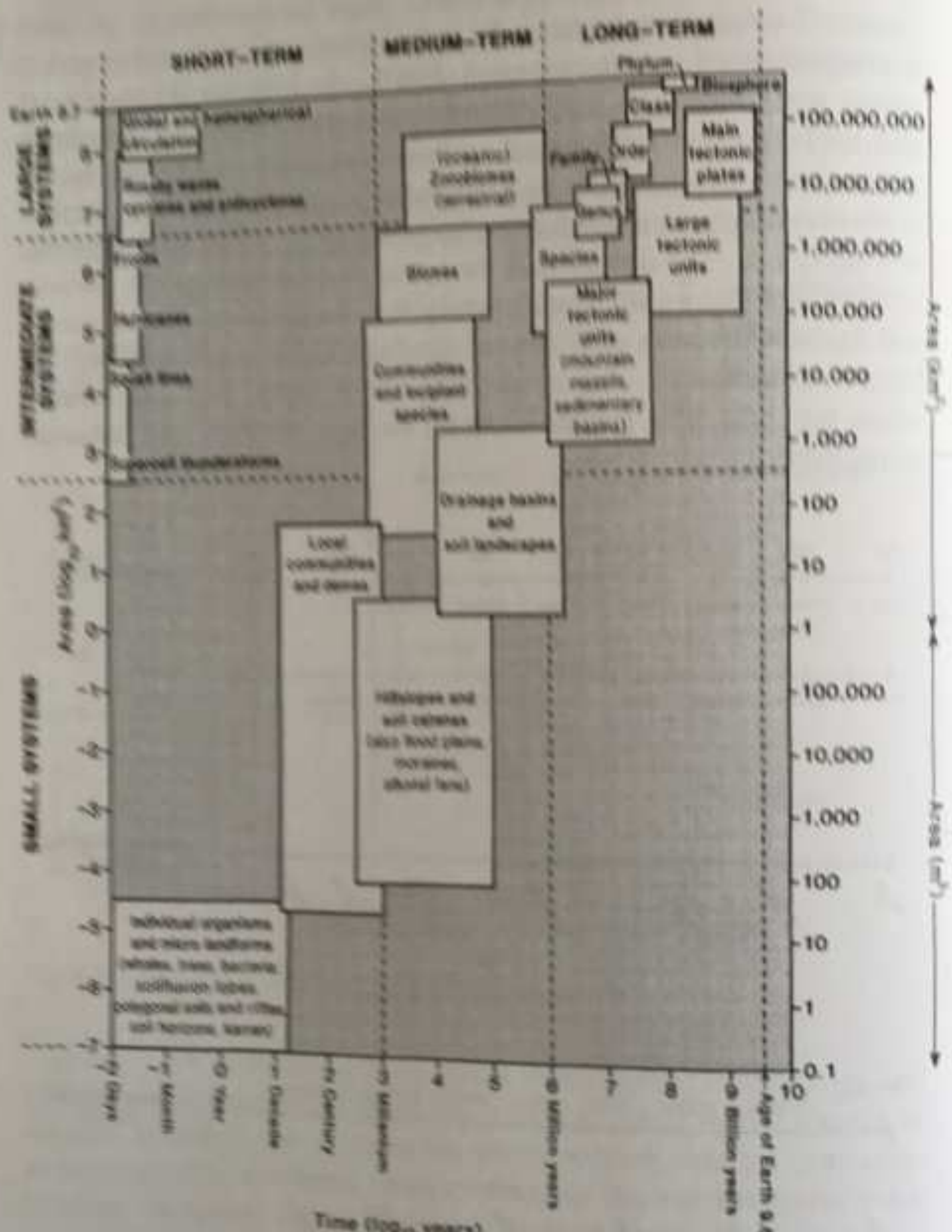


Fig. 1.2-5 Schematic relationship between spatial and temporal process scales for a variety of Earth system processes (Hugget 1991)

Fig. 1.2-5 gives a very comprehensive example of this relationship putting all kinds of Earth system processes in a framework of space and time scales, ranging between durations of about an hour to a billion years and areas of a few dm^2 to the complete surface of the globe.

This concept has been adopted by Blöschl (1996) to relate the space and time scales of rather different hydrological and atmospheric processes (Fig. 1.2-6). Precipitation processes are shown to range from spatial scales of tens of metres to more than 1000 km and over time scales from minutes to days. Hydrological processes are shown to have a wide range of scale effects depending on the process of interest. Infiltration and surface runoff processes occur at scales from metres to 100s of metres at time scales of minutes. Subsurface and groundwater processes, however, range from 10s of metres to a 1000 km at time scales from hours to much more than a 100 years. Coupling this range of process variability with spatial variations in topography, soils and vegetation presents a complex problem in resolving the linkages and interactions among these processes across the wide range of space/time scales of interest to hydrologist and atmospheric scientists.

One can see from Fig. 1.2-6 that the relationship between characteristic space and time scales (i.e. the gradient of the regions of particular processes, which is the ratio of characteristic space and time scales for a given process over a range of scales) is pretty constant for the specific processes but varies significantly between those processes. This relationship has been noted as characteristic velocity by Haltiner and Williams (1980) and Blöschl (1996). Additionally, one can see, if a time/space scale is fixed and the space/time scale is varying, the processes of relevance are changing. This varying relevance of processes depending on scales has been illustrated before by the convection-dispersion equation (Eq. 1.2-1). The different time scales of importance for a number of parameters in biosphere-atmosphere interactions are summarised in Box 1.2-1.

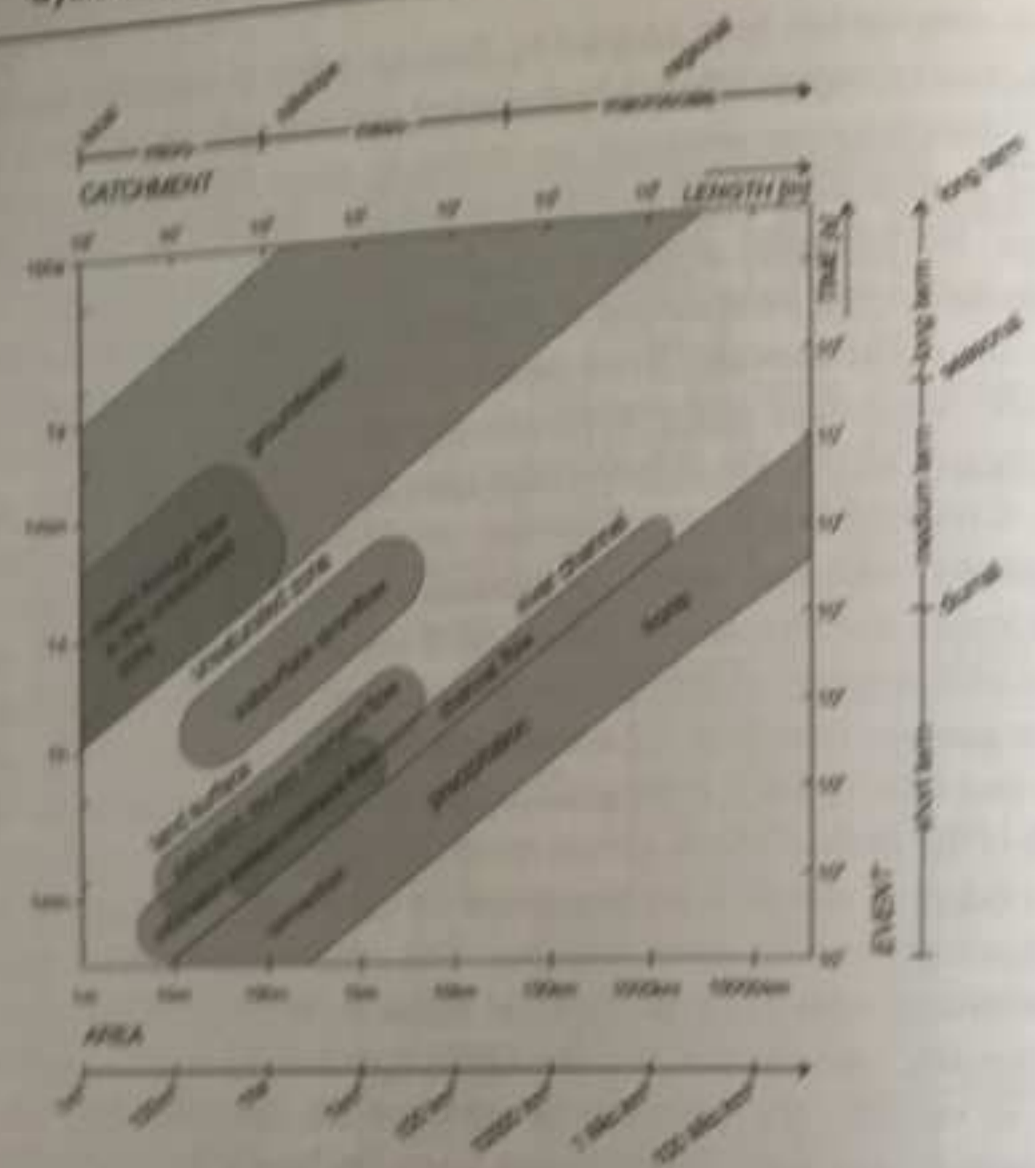


Fig. 1.2-6 Schematic relationship between spatial and temporal process scales for a variety of hydrological and atmospheric processes, from Niehoff (2002), extended from Blöschl (1996)

1.2.3 Scaling of Hydrological Processes to be used in Atmospheric Models and vice versa

Coupling the range of process variability presented, e.g. in Fig. 1.2-6, with spatial variations in topography, soils and vegetation, presents a complex problem in resolving the linkages and interactions among these processes across the wide range of space/time scales of interest to hydrologists and atmospheric scientists.

This is of particular importance if hydrological and atmospheric models are to be coupled in order to provide information about the hydrological or atmospheric processes, including their feedbacks, to the corresponding model. Atmospheric model scales are spatially too coarse to provide reliable assessments for smaller scale basins where most of the concerns of

hydrologists and resource managers occur. At the same time, the hydrological process models typically used in basin studies operate at scales that are too small for their direct incorporation into atmospheric models. As discussed by Hostetler (1994), there is a problem of discordant scales between atmospheric and hydrological models which is being addressed by scaling up or aggregating hydrological models and downscaling or disaggregating atmospheric models. Below, we summarise the current methods applied to aggregate (upscaling) or disaggregate (downscaling) information between hydrological and atmospheric models and vice versa.

Aggregation (Upscaling)

Aggregation of subscale hydrological or land-surface processes for the purpose of describing land-atmosphere interactions is accomplished using a variety of methods. Several different strategies have been developed to parameterise subgrid-scale heterogeneity of land-surface processes. For instance, an "effective" parameter approach attempts to describe the heterogeneities or distribution of a given process using a single aggregate or weighted value by averaging surface properties (e.g. Lhomme 1992; Dolman 1992) or by a statistical-dynamic weighting approach (e.g. Wetzel and Chang 1988; Entekhabi and Eagleson 1989). Computationally more expensive procedures to consider patchy surface properties are the mosaic approach (Avissar and Pielke 1989), the explicit subgrid strategy (Seth et al. 1994), or the mixture strategy, wherein, for the different surface types, tightly coupled energy balances are determined (e.g. Sellers et al. 1986; Dickinson et al. 1986). Several authors comparing the results provided by simulations with and without consideration of subgrid-scale surface heterogeneity found that for very patchy surfaces large differences in the predicted atmospheric fluxes can occur (e.g. Avissar and Pielke 1989; Seth et al. 1994; Mölders and Raabe 1996). A review of methods to treat heterogeneity is given by Giorgi and Avissar (1997).

Another approach uses a probability distribution function to describe heterogeneities of land-surface processes. The *variable infiltration capacity* model (Wood et al. 1992) couples a distributed function of soil moisture storage values in a catchment to account for subgrid variability of soil moisture. This also allows for the simulation of the effects of changing probability density functions of soil moisture on runoff generation and other hydrological processes. The topographic index of Beven and Kirkby (1979) has also been used to describe soil moisture distribution and to aggregate subgrid variability of a soil-vegetation-atmosphere transfer processes (Famiglietti and Wood 1994).

Delineation by elevation zones has also been used to account for subgrid variability in mountainous regions. Leung et al. (1996) developed a subgrid orographic precipitation model that was then included in the Pacific Northwest Laboratory (PNL) regional atmospheric model. The scheme partitions a grid cell into elevation classes and radiative transfer, turbulent mixing, convection and land-surface physics are computed for each elevation class. A full set of hydrological variables, including precipitation, snow water equivalent, soil moisture and surface runoff, are simulated for each elevation class as well.

The process of aggregating small-scale hydrological process model formulations to macroscale formulations suitable for incorporation in a General Circulation Model (GCM) has been a focus of a number of climate research programs such as FIFE, BOREAS and GCIP. Research is also being conducted independently of these large projects and the extent of this research is demonstrated in the large number of land-surface models participating within PILPS. References to these models are available in Henderson-Sellers et al. (1995).

Subscale variability is not only of importance for coupling hydrological and atmospheric processes, i.e. land-atmosphere interactions. Many authors (e.g. Dooge 1995) have stressed the importance of small-scale variability on soil moisture dynamics and on infiltration conditions. Looking on runoff generation processes, Bronstert and Bárdossy (1999) presented an example on how strongly the spatial subscale variability of soil moisture can influence the runoff generation process. In Bronstert and Bárdossy (2003) the problem has been elaborated for the temporal subscale variations of precipitation, i.e. short-term fluctuations of rainfall intensity, which proved to have an enormous impact on the generation of surface runoff, in particular if the runoff is only a small fraction of the precipitation, i.e. the soil has a large storage potential.

Disaggregation (Downscaling)

While downscaling attempts to address the heterogeneities within a model grid, the simulation of regional climate variations at the scales required for environmental impact assessments is unreliable at individual grid and subgrid box scales (Intergovernmental Panel on Climate Change 1996). This mismatch, between what the climate impacts community requires and what the GCMs are able to supply, has been a confounding issue affecting the confidence placed in impact scenarios at the hydrological mesoscale (Hostetler 1994; Xu 1999). Two techniques have been developed that attempt to counter this deficiency: semi-empirical (statistical) downscaling (SDS) of GCM outputs, and regional climate models (RCMs) nested within a GCM (Giorgi and Mearns 1991; Wilby and Wigley 1997).

Statistical downscaling (SDS) bridges the two different scales by establishing empirical (statistical) relationships between large-scale features (such as geopotential height fields) and regional or local climate variables (such as temperature and precipitation at a certain location). It is analogous to the "model output statistics" and "perfect prog" approaches used for short-range numerical weather prediction (Klein and Glahn 1974) which both use correlations with atmospheric variables at the synoptic scale (such as geopotential height fields) to simulate weather at the local scale (such as single site precipitation). Common SDS procedures involve weather-type classification, linear and non-linear regression, or modifications to stochastic weather generators (see Wilby and Wigley 1997). A key strength of SDS is the low computational demand which facilitates the generation of ensembles of climate realisations. However, realistic SDS scenarios are contingent on strong/stationary empirical relationships, and on the choice of predictor variable(s) and transfer function(s) used for the downscaling (see Winkler et al. 1997).

Although many studies have discussed the theory and practice of statistical downscaling (e.g. Bárdossy and Plate 1992; Hay et al. 1992; Karl et al. 1990; Kim et al. 1984; von Storch et al. 1993; Wigley et al. 1990; Bürger 1996), relatively few have considered explicitly the limitations of such techniques (Giorgi and Mearns 1991; Wilby and Wigley 1997). However, sensitivity analyses have demonstrated the susceptibility of downscaled scenarios to season definitions, the choice of data standardisation technique, length of calibration period, function form and predictor variable(s) (e.g. Winkler et al. 1997). It has also been shown that different circulation schemes (Buishand and Brandsma 1997) and downscaling methodologies (Wilby et al. 1998b) yield markedly different regional climate change scenarios, even when common sets of GCM predictors are used. Finally, there is scepticism regarding the assumed stationarity of predictor-predictand relations (Wilby 1997), and the reproduction of low-frequency surface climate variability in downscaling schemes continues to be problematic (Katz and Parlange 1996).

Dynamic downscaling is performed by applying regional atmospheric models. They simulate subscale climate features (relative to global models) dynamically at resolutions of 20-50 km, given time-varying atmospheric conditions supplied by the GCM bounding a specified domain (see reviews by McGregor 1997; Giorgi and Mearns 1999). The main advantage of regional atmospheric models (RCMs) is their ability to respond through

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There are other issues with RCMs. The use of a mesoscale model forced by a GCM which still remembers its initial conditions can add value through its lateral boundary conditions (i.e. dynamical downscaling) in all cases. This is the numerical weather prediction mode of dynamical downscaling. A GCM forced by observed SSTs also should insert skill into a RCM through the lateral boundary conditions. In the RCM area, detailed knowledge of surface forcing will add value when using the data from a larger scale model or reanalysis grid (with the resolution of those grids).

However, atmospheric structure in the RCM cannot be improved from a GCM which is not constrained by observed data and that is dependent on the lateral boundary conditions from the GCM. This conclusion has been reached in Castro and Pielke (2004), and is supported by the work of von Storch et al (2000; see their Table 1). Surface forcing can add value, however, its skill is dependent on the extent its effect is dependent on the lateral boundary condition information. If it is weakly dependent, than driving the RCM with the coarse resolution GCM results and the detailed surface forcing, for example, will add significant value.

Spectral nudging (von Storch et al. 2000; Miguez-Macho et al. 2004) appears the optimal way to include some "initialisation" yet still leave some freedom for the RCM to create smaller scale structure in response to that nudging, and from the surface forcing. Any spectral skill in the smaller scale features is a result of surface forcing and the spectral nudging, not the lateral boundary conditions. Of course, with spectral nudging, the RCM is then constrained in its larger scale features to what the larger model provides, and the ability for the RCM to alter this large-scale structure is lost.

A simplified method to downscale hydrologically-relevant information from atmospheric models is the explicit subgrid-scheme: Here, a higher resolution grid is defined at the land-atmosphere interface consisting of several subgrid cells per cell of the atmospheric model (see also Sect. 3.3). According to the mixture approach, these subgrid cells may be covered by at least one vegetation- and/or soil-type. Thus, coupled energy (for soil and vegetation) and hydrological budgets are maintained for each subgrid cell using the subgrid cell surface characteristics and the micro-climate at the representative location. Soil water content, soil temperature, near-surface

air-temperature and humidity are simulated dynamically for each subgrid cell. The coupling of the subgrid cells to the atmospheric grid cell – which is actually an aggregation procedure – is realised by one of the upscaling strategies mentioned before, e.g. in a simple manner by the arithmetic average of individual subgrid cell fluxes (e.g. Avissar and Pielke 1989, or Mölders et al. 1996).

The explicit subgrid scheme belongs to the class of mosaic approaches. The main advantages of the subgrid scheme, as compared to a simple (non-explicit) mosaic approach, are that by explicitly breaking down the grid cells of the atmospheric model (1) the spatial location of each subgrid flux is known, (2) precipitation can be disaggregated explicitly, and (3) the coupling can be realised at the resolution and the surface parameters of the subgrid cells. The disadvantage of the explicit subgrid scheme is that it is much more computationally expensive, especially when the surface conditions are relatively homogeneous (see Mölders et al. 1996).

A particular challenge is the downscaling of precipitation as when applying the above-mentioned explicit subgrid scheme, the precipitation provided by a cloud module within the atmospheric model has to be downscaled (e.g. von Storch et al. 1993; Leung and Ghan 1995) to the subgrid resolution. In most regions, long-duration precipitation increases with elevation, due to the orographic uplift and cooling of moist air leading to precipitation. Assuming that precipitation increases with elevation and taking into account the direction of wind, stratiform precipitation can be disaggregated (e.g. Leung and Ghan 1995; Leung et al. 1996). For convective cases, the disaggregation of rainfall cannot easily be related to surface characteristics because of the more random character of the appearance of convective cells.

Box 1.2-1 Important Time Scales for Biosphere-Atmosphere Interactions

Pavel Kabat, Roland W.A. Hutjes

The following tables give an indication of the most relevant time scales of importance / variance for a number of parameters in biosphere-atmosphere interactions.

Atmospheric Processes / Energy Exchange

Seconds	Hours	Days	Week/ synoptic	Season	Year
u	H/LE	P	Θ_v	P	Θ_v
R_g	CO_2	R_g	P	T_{air}	P
	T_{air}	T_{air}		T_{soil}	
	R_g			R_g	

(u: wind velocity; R_g: global radiation; H/LE: heat fluxes; CO_2: flux of carbon dioxide; T_{air}: air temperature; P: precipitation; Θ_v: potential virtual air temperature; T_{soil}: soil temperature)

CO_2 Exchange

Seconds	Hours	Days	Week/ synoptic	Season	Year
P_s	g_s	R_{soil}	LAI	P_s capacity	disturbance
	P_s		Vegetation height	g_s max	decomposition
				Leaf nitrogen	stand structure
				LAI	species
				Phenology	P_s capacity
					Soil carbon and nitrogen

(P_s: photosynthesis; g_s: stomatal conductance; R_{soil}: soil respiration; LAI: leaf area index)

Water Vapour Exchange

Seconds	Hours	Days	Week/ synoptic	Season	Year
Transpiration from canopy	z_{PBL}	ET	surface wetness	z_{PBL}	ET
	G	R_n	G_c	R_n	
	G_c			ET	
	E_{soil}			G	
	H			G_c	
	T			T	

(z_{PBL}: height of the planetary boundary layer; G: soil heat flux; G_c: heat flux in the canopy; E_{soil}: soil evaporation; H: sensible heat flux; T: surface temperature; ET: evapotranspiration; R_n: net radiation)

Box 1.2-2 ***Comparison of Dynamically and Statistically Downscaled Global Atmospheric Model Output***

George Leavesley

The ability to simulate adequately the spatial and temporal distribution of meteorological variables such as precipitation, temperature and radiation within an atmospheric model grid cell is of major importance to the adequate simulation of the subgrid heterogeneity of hydrological and ecosystem processes. Differences in daily precipitation and temperature for the Animas River basin, southwest Colorado, were examined using raw NCEP (National Centers for Environmental Prediction) data, statistical downscaling (SDS) and regional atmospheric model (RCM) simulations for current climate conditions (Wilby et al. 2000). The simulated surface climate variables were used to drive a distributed hydrological model. Since the hydrological response of the basin is an integration of the regional climate (in time and space), the results provide insights into the overall "value" added (or lost) to hydrological model skill due to the choice of downscaling technique.

Area-average daily precipitation (P) and maximum and minimum temperatures (T_{max}, T_{min}) were computed for the water years (WYs) 1980 to 1995 using two Snow Telemetry and one National Weather Service station. Area-average data for WYs 1987-95 were used to calibrate the SDS method and WYs 1980-86 to evaluate all models. Both the SDS and RCM were driven by gridded (approx. 200 km grid spacing) variables obtained from the NCEP/NCAR re-analysis (Kalnay et al. 1996). The SDS method (see Wilby et al. 1999) uses step-wise multiple linear regression to identify parsimonious sets of NCEP atmospheric variables – at the grid-point nearest the Animas basin – to predict local P, T_{max} and T_{min}. Separate regression equations were produced for each climatological season (i.e. DJF, MAM, JJA, SON) and surface variable (i.e. P, T_{max} and T_{min}).

RCM output was produced by RegCM2 (Giorgi et al. 1996), employing the continental U.S. domain of the Project to Intercompare Regional Climate Simulations (Takle et al. 1999). Initial and boundary conditions from the NCEP/NCAR re-analysis were supplemented by observations of water-surface temperature in the Gulf of California and the Great Lakes which are under-resolved in the re-analysis. Model grid spacing equates to 52 km on a Lambert conformal projection of the mid-latitudes.

The mean elevation of the RegCM2 and NCEP grid cells were adjusted on a monthly basis by solving for elevation using observed monthly z-climate relations. The fictitious elevations were then used to distribute P, T_{max} and T_{min} as in the case of observed and SDS data (for more details see Hay et al. 2000). This correction is necessary because of the coarseness of the RegCM2 and NCEP grids, which cause the model terrain heights to depart from the actual elevation of the basin.

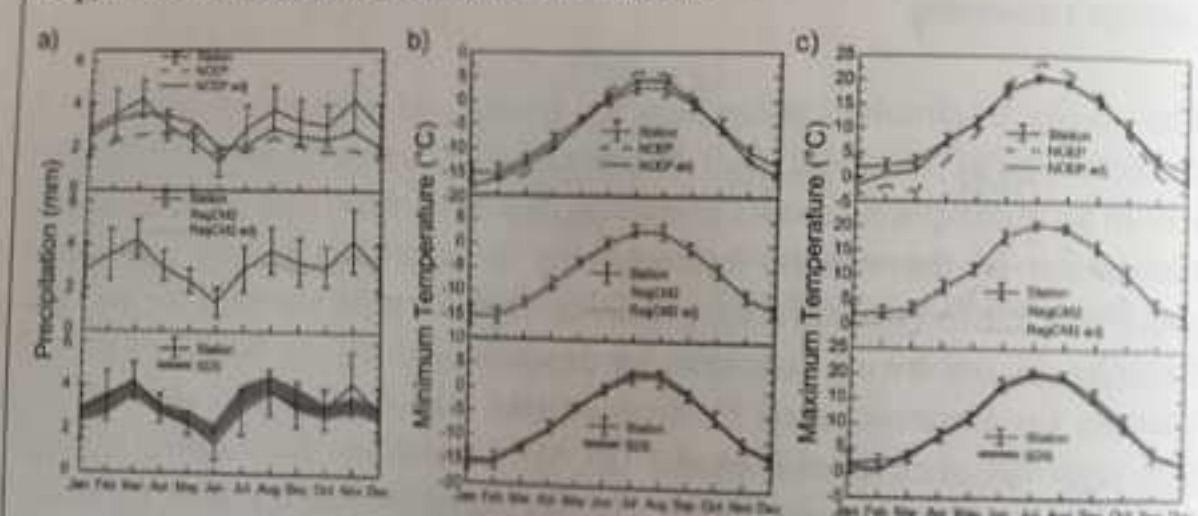

Fig. 1.2-7 Downscaled monthly mean daily (a) P, (b) T_{min} and (c) T_{max} for WYs 1980-86, compared with area-averaged station data for the Animas River basin. The error bars for station data correspond to 2 SE. The dashed lines for NCEP and RegCM2 represent the uncorrected model output. The grey shading for the SDS results shows the range of values produced by an ensemble of twenty members

Fig. 1.2-7a shows that the NCEP output captures the timing of the June imum and March maximum wet-day amounts but underestimates infall by 47% in the uncorrected case and by 36% in $NCEP_{adj}$. In comparison, RegCM2 output for both the corrected and uncorrected cases is closer to the observed seasonal cycle, with mean-bias values of –6 and –5% respectively. The SDS ensemble spans the observed rainfall regime in all months except for June (too high) and November (too low), but underestimates the rainfall total by 6%. It is noteworthy that relative to temperature and runoff (see below), the explained variance for daily P is low for all models, ranging between 14% (NCEP) and 26% ($RegCM2_{adj}$).

In contrast, T_{min} (Fig. 1.2-7b) is well represented by all methods. NCEP output shows a warm bias in summer and cold bias in winter that is reduced by elevation correction in $NCEP_{adj}$. The comparable monthly biases are smaller in RegCM2 and the corrected output of $RegCM2_{adj}$ has a mean bias of –0.1° C. However, NCEP and RegCM2 show large biases in T_{max} (Fig. 1.2-7c) with values of –2.0 and –4.6° C respectively. NCEP has a significant cold bias in winter and spring that is partially offset by correction, whereas RegCM2 has a cold bias throughout the year that is removed by $RegCM2_{adj}$ except in November to March. In comparison, SDS has a mean bias of –0.5° C for T_{max}.

The Precipitation-Runoff Modelling System (PRMS) (Leavesley and Stannard 1995) was used to simulate daily runoff (Q) given time series of surface climate variables (P, T_{max} and T_{min}). Fig. 1.2-8 compares the relative skill of the downscaling methods at simulating daily runoff using annual values of the coefficient of efficiency (CE) (Nash and Sutcliffe 1970). The station data provided the best simulation results with the majority of the years having CE scores of 0.8 or higher. The magnitude of these values indicates that, even though parameters were not optimised, the performance of the hydrological model is still quite good.

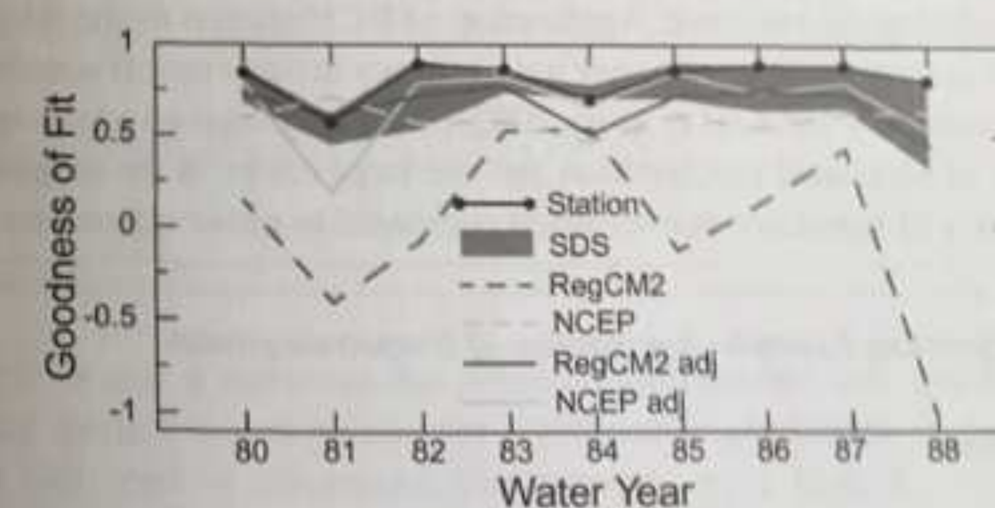

Fig. 1.2-8 Nash-Sutcliffe scores of simulated versus observed daily Q computed on a water year basis for different downscaling methods. The goodness of fit scores for the station output provide a measure of errors due to the hydrological model and/or choice of stations since observed P, T_{max} and T_{min} were used in this case

Overall, the CE scores for station data fall within the ensemble range of the SDS method. The CE scores for RegCM2$_{adj}$ and NCEP$_{adj}$ also lie within the bounds of the SDS ensemble for all years except WY1984 and WY1981 respectively, when the dynamic models had lower skill. In comparison, the skill of NCEP was lower than that of SDS in all years apart from WY1981 when the modelled runoff from NCEP was closest to observed. The least skilful model output was obtained from RegCM2: the negative CE scores in WYs 1981, 1985 and 1988 indicate that the observed mean of Q is a better predictor of daily Q than the model (Wilcox et al. 1990).

From the single-basin study it was concluded that the SDS and RCM methods have greater skill (in terms of modelling hydrology) than the coarse resolution data used to drive the downscaling. The SDS has the advantage of requiring very few parameters – an attribute that makes this procedure attractive for many hydrological applications. The RCM output, once elevation-corrected, provides better estimates of the water balance than the raw and corrected NCEP output. However, since the methods provide varying results, care must be taken in interpreting scenarios of basin-scale hydrology under both present and future climate forcing.

The reasonable simulations of daily runoff obtained using SDS and RCM output in the Animas River basin is in part related to the fact that this is a snowmelt-dominated basin. Daily variations in winter precipitation are less important than the volume of precipitation over the accumulation season. As noted by Wilby and Dettinger (2000) in a similar study in the Sierra Nevada mountains, hydrological "skill" arises from the fact that the snowpack acts as an integrator of the hydrological processes. Alternatively, daily variations in a rainfall-dominated basin are much more important in the simulation of basin hydrological response. Application of RCM output to the Alapaha River basin in Georgia showed a very low accuracy in daily runoff simulation for the period 1979-1988 (Hay et al. 2002). This is related to errors in the seasonality of simulated precipitation and the large errors in the magnitude and frequency of simulated storms when compared to observed storms.

Box 1.2-3 *Upscaling Example: Aggregation of Evapotranspiration*

Nicole Mölders

In meteorological modelling, computational capacity, parameterisation limitations, or reasonable simulation times[1] require coarser grid resolutions than are desirable to describe realistically the exchange of momentum, heat and matter at the earth-atmosphere interface. The task to be solved is to aggregate information of the exchange from smaller to larger scale so as to consider various vegetation and soil types.

Let us assume that the land-use and soil-type data are given in a resolution of 1 x 1 km^2 and that they represent the land-use or soil type dominating in this one square kilometre area. The meteorological model is intended to be run at a coarser resolution but the fine resolution of the land-use and soil data is to be taken into account by a mosaic approach (see Avissar and Pielke 1989; Mölders et al. 1996). A fundamental assumption of this approach is that the local-scale near-surface meteorological forcing at the patch, which is experienced by the surface of the patch, is important in determining the net exchange of heat, moisture and momentum at the earth-atmosphere interface. For each patch of equal land-use/soil type, unique energy and hydrological budgets are maintained using the grid cell forcing of wind, temperature, moisture, pressure and radiation predicted by the meteorological model. For each patch, its own soil temperatures, soil wetness, and near-surface meteorological forcing in the immediate vicinity of the Earth's surface is used to determine the fluxes of the respective patch. These individual quantities result as a consequence of the consideration of the individual land-use and soil type at the patch level. The fluxes of net radiation, Q, sensible, H, and latent heat, L_vE, as well as the soil heat flux, G, for the ith patch of the jth grid cell are written as (e.g. Mölders et al. 1996)

$$Q^i_j = R^i_{S\downarrow,j}(1-\alpha^i_j) - \varepsilon^i_j R^i_{L\downarrow,j} + \varepsilon^i_j \sigma T^{i\ 4}_{g,j} \tag{1.2-4}$$

$$H^i_j = \rho^i_j c_p C^i_{h,j} u_{R,j} (\Theta^i_{g,j} - \Theta_{R,j}) \tag{1.2-5}$$

$$L_v E^i_j = \rho^i_j L_v C^i_{q,j} u_{R,j} [q^i_{g,j}(T^i_{g,j}) - q_{R,j}] w^i_{e,j} \tag{1.2-6}$$

$$G^i_j = -\lambda^i_j \frac{\partial T^i_{s,j}}{\partial z} \tag{1.2-7}$$

where Θ and q represent the potential temperature and specific humidity at the surface (index g) and the reference height (index R) located at the first half level of the model. Furthermore, α, ε, λ, σ, $R_{S\downarrow}$ and $R_{L\downarrow}$ stand for the albedo, the emissivity of the surface, the soil thermal conductivity, the Stephan-Boltzmann constant, the short-wave and long-wave radiation, respectively. T_g and T_s denote the surface and soil temperature, and u_R is the wind speed at the reference height. The density of air is denoted as ρ,

[1] In the case of introducing a finer resolution, all meteorological processes have to be calculated on that fine resolution for which not only the amount of grid points increases, but also the time step has to be reduced to fulfill the Courant-criteria.

c_p and L_v are the specific heat at constant pressure and the latent heat of condensation, C_h and C_q are the transfer coefficients for heat and water vapour. For bare soil, the wetness factor, w_e, equals the soil surface wetness while for vegetated surfaces it considers the canopy conductivity, g_c, which depends on the maximal evaporative conductivity, the insolation, the water vapour deficit, the air temperature and the soil wetness (e.g. Deardorff 1978).

In the simplest approach, the n individual fluxes $F_j^{i,k}$, ocurring at the (local) patch scale within the j^{th} grid cell are upscaled to the flux, F_j^k, of this j^{th} grid cell by the area weighted mean (e.g., Avissar and Pielke 1989; Mölders et al. 1996)

$$F_j^k = \sum_{i=1}^{n} a_j^i F_j^{i,k} \quad . \qquad (1.2\text{-}8)$$

Here, the index k refers to net radiation and soil heat flux as well as the fluxes of sensible and latent heat. The letter n is the number of patches occurring within the j^{th} grid cell, and a_j^i is the relative area covered by these subgrid-scale patches of equal land-use/soil type i where

$$\sum_{i=1}^{n} a_j^i = 1 \quad . \qquad (1.2\text{-}9)$$

Note that the variables of state (e.g. soil temperature, soil moisture, etc.) are upscaled in the same manner. To investigate the effect of upscaling, the following simulations have been performed: (1) a simulation with a resolution of 4 x 4 km² using distributions of land-use and soil types that were derived from the fine resolution data by assuming the dominant soil/land-use type of the grid cell to be representative (HOM4; Fig.1.2-9), (2) same as HOM4, but for a grid resolution of 8 x 8 km² (HOM8), (3) a simulation with a resolution of 4 x 4 km² applying the upscaling procedure (HET4), and (4) same as HET4, but for a grid resolution of 8 x 8 km² (HET8). Note that in this example land use is linked to a typical soil type. A change in dominant landuse might lead to a drier surface if urban area increases, and also by an increase in dunes, or coniferous forest growing on sandy soil. Moreover, the different land use yields to other aerodynamic roughness for which wind speed changes. The altered surface fluxes lead to different moisture and temperatures states of the near-surface atmosphere that again affects the fluxes. Thus, differences may increase with time. Other authors reported similar results (e.g., Shao et al. 2001).

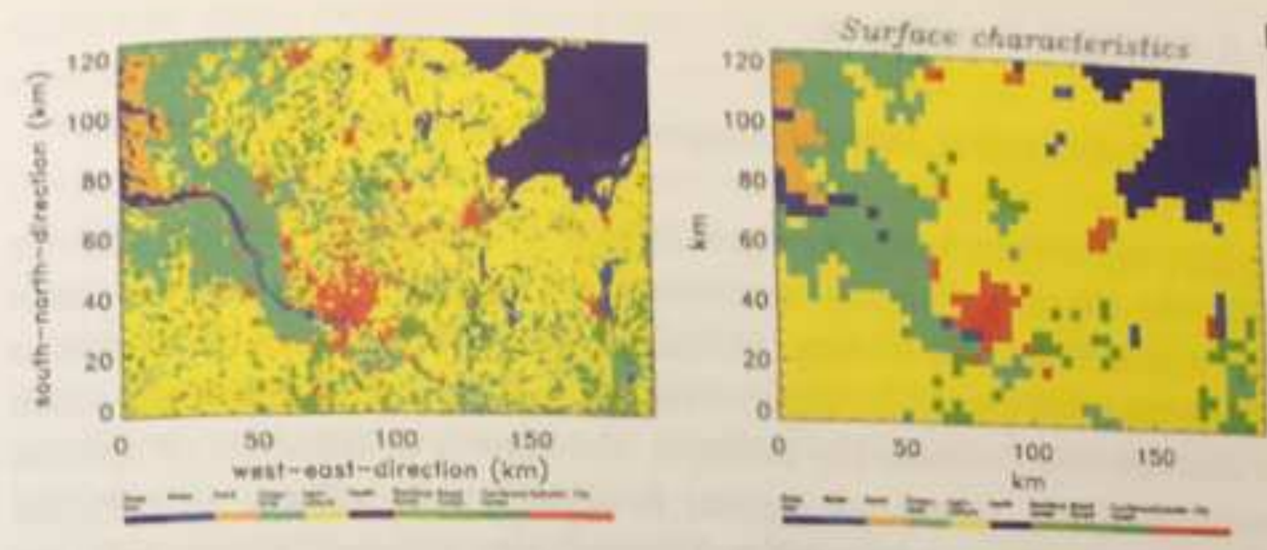

Fig. 1.2-9 Distribution of land use on the fine resolution of 1 x 1 km² used in the upscaling (HET4, HET8) and the coarse resolution of 4 x 4 km² used under the assumption of dominant land-use type in HOM4. Note that the information loss is even worse for a resolution of 8 x 8 km² (HOM8) (after Mölders and Raabe 1996)

Here, upscaling of evapotranspiration is discussed exemplarily. The model results showed that upscaling influences predicted evapotranspiration, which could be derived by comparing HOM4 and HOM8. The detailed consideration of land use (by direct simulation of the 1 x 1 km² resolution, or by the mosaic approach with an enlarged resolution, e.g. HET4 and HET8) allows consideration of the often subgrid-scale cities, dunes and coniferous forests that have a low evapotranspiration as compared to the surrounding agricultural land, grassland or deciduous forests. Thus, upscaling without accounting for such subscale features by considering only the dominant land use (HOM4 and HOM8), yields to an over-prediction of evapotranspiration. Note that in semi-arid areas, upscaling without accounting for subscale features may lead to an under-prediction of evapotranspiration because subscale wet spots, such as irrigated fields and plots, river riparian zones, or oases, which provide more water to the atmosphere than their environments, are disregarded with respect to the resolution of the meteorological model. However, the mosaic approach (coarse resolution but accounting for subgrid variations) can account for such effects. It also allows for consideration of lake surface temperatures different from the terrestrial environment (e.g. colder in spring and warmer in autumn), where evaporation can be rather different from that of the surrounding fields. Mölders and Raabe (1996) have shown that upscaling by applying the mosaic approach (HET4, HET8) provides nearly the same domain-averaged evapotranspiration, independent of the grid resolution.