Representing Scale in the Open Modelling Engine

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Abstract When building a model, a modeller ensures that the model formulation is consistent with the scale of the process being modelled and the problem addressed by the model. A generic modelling environment such as the Open Modelling Engine can contain a library of model components that may be connected to form a system model, enabling rapid model building. The library would include models that represent processes at different scales, so the modelling system should be capable of representing the appropriate scale range for each model, identifying the scale and units of various input data and enforcing consistency between data and models and between connected model components. This paper reviews the issues of spatial and temporal scale in modelling and suggests mechanisms by which scale and scaling operations can be included in a generic modelling environment such as the Open Modelling Engine.

1. THE OPEN MODELLING ENGINE CONTEXT

The Open Modelling Engine (OME) (Reed et al., 1997) is a generic modelling system oriented towards environmental modelling applications at the management level. It features a visual model building environment using a library of pre-defined model algorithms, so models can be constructed rapidly from building blocks. Models can also be built from scratch using procedural code, but the emphasis is on re-useable components.

Such a system requires a degree of intelligence to prevent accidental misuse by linking incompatible model components or mixing physical units. A more subtle problem is the possibility of using data or intermediate model results at inappropriate scales. The purpose of this paper is to discuss the need for representing the scale of temporal and spatial data; to suggest some possible mechanisms for representing and enforcing the consistency of units and scale; and to suggest tools for sensibly manipulating the scale of data.

2. DATA AND SCALE

2.1. Scales of Observation

All environmental data are measured or interpreted at a particular scale. The scale of a series of observations can be described in terms of their spacing, support (or integration volume) and extent (Blöschl and Sivapalan, 1995).

- Spacing is the distance or time between the measurements. For environmental data this ranges from seconds to years and from centimetres to many kilometres, depending on the quantity being measured and the purpose of the measurements.

- Support is the time or area or volume over which the measurement integrates the quantity being measured, and is determined by the characteristics of the measurement process. The temporal support of most measurements is a few seconds, but some measurements integrate over time – for example, a simple rain gauge accumulates rainfall between readings. The spatial support of most measurements is also small, amounting to a few square centimetres but again there are exceptions – remotely sensed imagery accumulates information over the area of each of its pixels which can be as large as 1 km for AVHRR for example. Some measurements represent spatially or temporally averaged quantities, such as catchment runoff.

- Extent is the duration or area covered by the set of measurements.

The degree to which a set of observations adequately captures the temporal or spatial variation of the quantity being measured is determined by the relationships between the spacing and support of the measurements and the coherence of the quantity being sampled. The spacing is typically much larger than the support, meaning that most of the area or time remains unsampled and some form of smooth behaviour is assumed between the measurements (although this is not the case for remote sensed data, for example). The measurements are effectively scaled up from the support scale to the spacing scale. If the quantity is coherent within the measurement spacing so that there is relatively little variation between measurements, the measurements will accurately reflect the structure of variation of the quantity. However if there is considerable variation within the measurement spacing (the quantity is incoherent within the measurement spacing), the structure of variation will not be captured by the measurements.

Two contrasting examples are air temperature and soil hydraulic conductivity. Both measurements have small support, integrating the value of the measured property over an area of a few square centimetres, or perhaps as large as one square metre. The spatial extents represented by those two measurements are very different because air temperature has much less spatial variability – it is coherent over larger length scales – than soil hydraulic conductivity. The air temperature measurement might adequately represent the conditions over several kilometres (apart from elevation effects), while the hydraulic conductivity measurement will probably represent the conditions only within a few metres of the measurement point (eg. Loague and Gander, 1990). To adequately capture the complex spatial structure of hydraulic conductivity requires closely spaced samples.

Air temperature and wind speed provide a temporal example of a similar flavour: both measurements have a temporal support of a few seconds, but the air temperature measurement is more likely to be representative of the conditions over a period of one hour. There can be large rapid fluctuations in wind speed so that a single measurement over a few seconds might be very different to the average speed over one hour – wind speed lacks coherence at time scales of one hour.

2.2. Matching Scales

The preceding observations demonstrate that it is important to match the scale of observation of a data set with the use to which it is put. Models that use environmental data as parameters should use data derived or collected at the appropriate temporal and spatial scale. Taking data measured at one scale and applying it at a different scale can cause serious errors in model predictions.

As an example, if a process model requires hourly rainfall rate as a forcing variable, but only monthly rainfall was available, it would be foolish to use the monthly rainfall divided by the length of each month to determine hourly rainfall rates. The reason this is inappropriate is that the processes driven by rainfall are non-linear, so a short period of high intensity rain produces a very different result to a long period of low intensity rain, even though the total rainfall amount is the same. This non-linearity is a major source of scaling problems.

Another source of scaling problems is internal feedbacks within a process, such as in a temporal model whose state at one time step influences the state at the following time step, a very common situation. These linkages correspond to processes operating at a particular temporal scale; if the model was naively used at a different temporal scale (e.g. on a monthly instead of daily basis) the representation of these internal feedbacks would be incorrect. This is because, at short time scales, the state of the system does not change much from one time step to the next, so using the state at the previous time step to control behaviour at the current time step is quite accurate. At longer time steps, the state can change substantially from one time step to the next so the use of information from a previous time step is invalid. In some cases, changing parameter values can be used to compensate for the change in scale, but in other cases the model structure must change to reflect the different processes operating at the different scale. For example, a daily rainfall-runoff model has a different structure to a monthly model.

Corresponding spatial examples are topographic slope and a spatial water balance model. Topographic slope determined from 10 m resolution spatial data and 1 km resolution data are not the same thing, and cannot be interchanged (Lewis, 1995) because they do not influence environmental processes in the same way. In a spatial water balance model, spatial interactions and patterns at 10 m resolution are of a different character to those at 1 km resolution (Quinn et al., 1991).

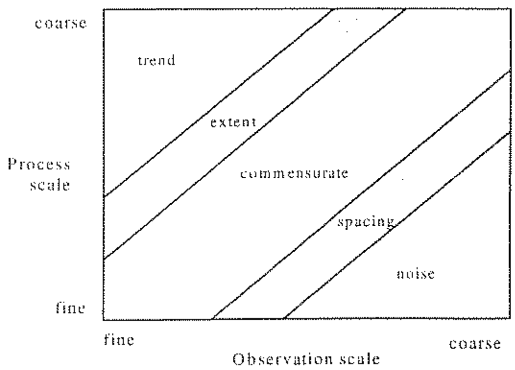

Figure 1 The effect of sampling is dependent on process and observation scales (after Blöschl and Sivapalan, 1995).

Mismatches between spatial scales are common and difficult to avoid. Soil data are a common source of scale problems because modelling of soil-dependent processes is frequently conducted at resolutions of 100 m or finer over broad spatial areas, with only a broad-scale soil map or a few measurements to define soil properties. Compounding this problem is the large variation in soil properties over small distances (a few metres).

Figure 1 depicts the effect of sampling when the process and observation scales differ, with the extent and the spacing of the data set shown. Variation at broader scales than the extent of the data appears as a trend in the data; variation at finer scales than the spacing appears as noise. In both cases the structure of the variation is not resolvable.

3. SCALE IN A MODELLING ENVIRONMENT

3.1. Representing Data Scale

Given these considerations, a tool such as the Open Modelling Engine (OME) should incorporate the idea of scale into its data representation, so that each data item has a scale associated with it. Models should also be constructed with scale attributes, indicating the range of scales over which they are applicable. Consistency between model scale and input data could then be enforced (or at least advised) by the modelling system.

Each data item in the OME has associated metadata that describes the structure of the data. A regular time series for example is represented as a one-dimensional array of values, with metadata describing the start and end dates/times and the time step. Likewise spatial data in raster form can be represented as a two-dimensional array with metadata specifying the location and spatial resolution. Additional metadata items could also be included.

For regularly sampled data, the scale is represented by the sampling interval in either time or space. Other data are not so neatly characterised and would need an explicit scale description in its metadata. A universal measure of scale is required, and the resolution with units of length or time is probably the simplest. For an irregularly sampled data set (such as a polygon coverage), the resolution is the size of the smallest feature reliably resolved by the data. For cartographic data, the resolution of a paper map is typically 1 mm, so the resolution corresponding to a particular mapping scale is approximately the scale of the map divided by 1000. For example, a 1:100 000 scale map has a resolution of about 100 m, while a 1:25 000 scale map has a resolution of about 25 m.

Mismatch in scale does not occur abruptly at particular scales, but becomes progressively more problematic as the difference between scales increases. The comparison between scales to enforce consistency would need to reflect this progression, with information passed back to the user or model builder about the severity of scale mismatch. The scale information associated with a model should also contain information to support this: a model could specify over what scales it is applicable and then a wider range of scales over which it could be applied with caution; the degree of mismatch increases as the scale approaches the limits of this outer scale range. In most cases the specification of these scales requires the judgement of an experienced scientist, and quantitative measures of scale mismatch are yet to be developed.

3.2. Working Across Scales

In many instances the scale of the available data does not match the scale of the available models, or the scale at which modelling is desired. The two simple answers to this problem are to ignore the scale mismatch and hope that the results are not too wrong, or to avoid modelling at all. If users of a modelling system are faced with only these choices, they will tend to ignore the scale mismatches and press on regardless. If the system prevents this, it will either not be used or the scale matching will be circumvented in some way.

More sophisticated approaches are to change the scale of either the model or the data. To change the scale of a model usually requires modification of the model structure and algorithms, and amounts to building a new model. This can be a worthwhile undertaking but requires considerable effort in conceptualising, designing, implementing and testing the model. Ideally, there would be a number of models available for a particular process at different scales, but this is not yet the case. Changing the scale of data can sometimes be a more fruitful approach although, as noted previously, this change of scale is frequently not a simple procedure because of the non-linearities in the processes.

The transfer of information across scales is called *scaling* and the problems associated with it are *scale issues*. Transferring information to a coarser scale is called *upscaling* while transferring to a finer scale is called *downscaling* (Blöschl and Sivapalan, 1995). Using a point rainfall measurement to estimate rainfall over a catchment is an example of upscaling. Inferring the spatial pattern of soil water from catchment runoff is an example of downscaling.

Blöschl and Sivapalan (1995) describe upscaling and downscaling as two-step processes (Figure 2). Upscaling firstly requires distributing information from the fine to coarse scale via a spatial or temporal pattern or a statistical distribution; secondly, the pattern is aggregated to provide a single value at the coarser scale. Downscaling is the reverse process: disaggregation to a spatial or temporal pattern or a statistical distribution, followed by singling out (choosing one value from the pattern or distribution) the desired fine scale value. Singling out is a trivial operation and in most cases aggregation is also trivial, so most of the work is associated with distributing values for upscaling and disaggregating values for downscaling. Note that both these processes are associated with creating patterns or distributions within space or time, either by extrapolating from a fine-scale point value (distributing as part of upscaling) or dividing up a coarse-scale average value (disaggregating as part of downscaling). In most cases the actual patterns or distributions are unknown and must be synthesised from some ancillary information. A modelling system like the OME could provide a suite of upscaling and downscaling tools to complement the suite of models it contains. Implementation of this concept requires that accepted or at least reasonable methods for distributing, aggregating and disaggregating be developed or adopted.

3.2.1. Aggregation

Aggregation converts a set of fine-scale observations to a single coarse scale value. Most of the time aggregation is a trivial problem, such as converting daily to monthly rainfall which simply requires adding up the daily rainfalls for each month.

More complicated aggregation operations are required where the values being aggregated contribute to a non-linear process. So, as noted before, while aggregation of rainfall amount from daily to monthly is simple, determining an effective average rainfall rate to drive a rainfall-runoff or soil erosion model at a monthly time scale is much more difficult. Similarly, aggregating saturated hydraulic conductivity to a single catchment-average value is difficult, and there are no universally accepted methods for doing so. In some situations, a coarse-scale effective parameter does not exist, in the sense that it is not

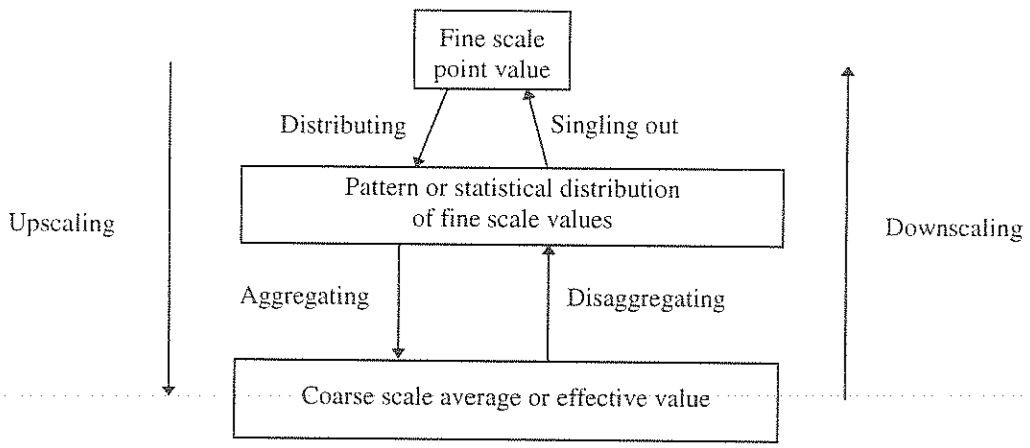

Figure 2. Upscaling and downscaling as a two-step process. Most of the work is in distributing and disaggregating (after Blöschl and Sivapalan, 1995).

possible to represent the system behaviour using a spatially averaged model with constant parameters (Blöschl and Sivapalan, 1995; Sivapalan and Kalma, 1995; Beven, 1996).

3.2.2. Disaggregation

Disaggregation converts a single coarse-scale value to a spatial or temporal pattern or a statistical distribution of fine-scale values. This requires the creation of a pattern or distribution over which the aggregated value will be broken up into fine-scale values.

Temporal disaggregation of rainfall is one example, using weather generators parameterised by the statistical properties of the rainfall distribution. Methods are available to generate hourly rainfall from daily data, and daily rainfall from monthly data. In both cases, statistical techniques are used that require some additional parameters describing the statistical properties of the fine-scale structure of the data.

Spatial disaggregation of soil water content has been performed using the wetness index (Beven and Kirkby, 1979; Wood *et al*, 1990; Blöschl and Sivapalan, 1995).

3.2.3. Distribution

Distribution converts a single fine-scale value to a spatial or temporal pattern or statistical distribution of fine-scale values. It differs from disaggregation by starting with a fine-scale point value representing the conditions at only one point in the domain of interest, rather than a coarse-scale aggregate value representing the conditions over the whole domain.

Techniques for distributing can be identical to those for disaggregating.

4. IMPLEMENTATION IN THE OPEN MODELLING ENGINE

4.1. Sample model structure

Figure 3 shows a very simple spatio-temporal model of soil water balance. Rainfall and potential evapotranspiration from the *Climate data* object are passed to the *Surface water* object, which models the dynamics of soil water content and surface runoff, and the *Evapotranspiration* object which models evaporation as a function of potential evapotranspiration and soil water content. The Δt object implements a delay of one time step, making soil water content from a previous time step available to the current time step's evaporation calculation. The Δt object also serves to break the circular loop of data flow.

The arrows in Figure 3 represent the flow of data between the components, and it is on these links that the OME can enforce constraints on units, dimensions and scale of the data.

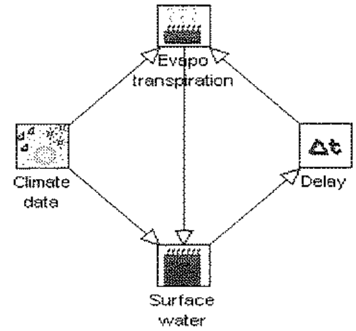

Figure 3. A simple water balance model constructed within the Open Modelling Engine, showing data flow links.

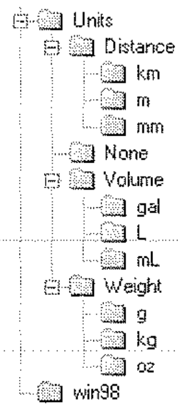

Figure 4. Tree of units

4.1.1. Matching units

All data in the OME has units associated with it, such as *mm*, *ha*, and *kg*. The simplest form of scale enforcement is insisting an output of x units can only supply an input of x units. This is done when the link is defined by checking the source and destination units and only allowing the link if they match.

Matching units when defining a link is fairly restrictive if the two models do not work in exactly the same units. It is not difficult for the OME to automatically rescale compatible units within the link if they do not match. To do this, the OME must have a description of each unit, and how it relates to other units. For example, the *mm* unit can be scaled to the *m* unit by dividing by 1000, but it cannot be converted to the *kg* unit. In Figure 4 a tree defining groups of units and their scaling is shown.

4.1.2. Matching dimensions

More advanced forms of data used in the OME are temporal and spatial.

Temporal data has units describing each element, and units describing the interval between each element. For example, *Rainfall* could be a 365 daily sequence of measurements in *mm* units. Temporal data are implemented as a one-dimensional array with temporal metadata attached to it.

Spatial data are two-dimensional arrays with metadata describing the location in space and the dimensions of the array. For example, a map of a catchment could have its top left cell located at 35°S 147°E and consist of one square kilometre cells.

By checking the metadata for each array and comparing it with the description of the input to a model, the OME can prevent inappropriate use of data.

4.1.3. Matching scales

A better solution to the problem of unmatched data is to develop a set of methods to automatically up- or down-scale data where appropriate.

Consider the problem where one model runs at a daily timestep, producing daily data, which is then fed into a monthly model. A tool to aggregate the daily amounts is easy to implement, but converting monthly to daily values requires a statistical disaggregation model, such as a weather generator. While these tools are not trivial, there are accepted methods for some types of data scaling, and such tools are planned to be implemented within the OME and made available in object libraries.

5. SUMMARY

Scale is an important issue in modelling, and a generic modelling framework must include tools to manage scaling issues. Facilities should be provided for specifying the scale of data and the scales over which a model is applicable, and mechanisms for manipulating the scale of spatial and temporal data should be provided where possible.

6. ACKNOWLEDGEMENTS

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7. REFERENCES

Beven, K.J. 1996. The limits of splitting: Hydrology. Science of the Total Environment, 183:89-97.

Beven, K.J. and Kirkby, M.J. 1979. A physically-based variable contributing area model of basin hydrology. Hydrological Sciences Bulletin, 24:43-69.

Blöschl, G. and Sivapalan, M. 1995 Scale issues in hydrological modelling: A review. Hydrological Processes 9:251-290.

Lewis, A. 1995. Scale in Environmental Spatial Databases. PhD Thesis, Centre for Resource and Environmental Studies, Australian National University.

Loague, K. and Gander, G. 1990. R-5 revisited: 1. Spatial variability of infiltration on a small rangeland catchment. Water Resources Research 26(5):957-971.

Quinn, P., Beven, K., Chevallier, P. and Planchon, O. 1991. The prediction of hillslope flow paths for distributed hydrologic modelling using digital terrain analysis. Hydrological Processes 5:59-79.

Reed, M., Cuddy, S,M., and Rizzoli, A.E. 1997. A Framework for Modelling Multiple Resource Management Issues: an Open Modelling Approach. MODSIM '97 – International Congress on Modelling and Simulation. Hobart 8-11 December, 1997. Vol 2, 681-686 Modelling and Simulation Society of Australia.

Sivapalan, M. and Kalma, J.D. 1995. Scale problems in hydrology: Contributions of the Robertson workshop. Hydrological Processes 9:243-250.

Wood, E.F., Sivapalan, M. and Beven, K.J. 1990. Similarity and scale in catchment storm response. Reviews in Geophysics, 28:1-18.