

Quantifying uncertainty from large-scale model predictions of forest carbon dynamics

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Abstract

Linking environmental computer simulation models and geographic information systems (GIS) is now a common practice to scale up simulations of complex ecosystem processes for decision support. Unfortunately, several important issues of upscaling using GIS are rarely considered; in particular scale dependency of models, availability of input data, support of input and validation data, and uncertainty in prediction including error propagation from the GIS. We linked the biogeochemical Forest-DNDC model to a GIS database to predict growth of *Eucalyptus globulus* plantations at two different scales (~ 0.045 ha plot $^{-1}$ scale and ~ 100 ha grid $^{-1}$ scale) across Victoria, in south-eastern Australia. Results showed that Forest-DNDC was not scale dependent across the range of scales investigated. Reduced availability of input data at the larger scale may introduce severe prediction errors, but did not require adjustment of the model in this study. Differences in the support of input and validation data led to an underestimation of predictive precision but an overestimation of prediction accuracy. Increasing data support, produced a high level of prediction accuracy ($\bar{\epsilon}\% = -3.54\%$), but a medium level of predictive precision ($r^2 = 0.474$, ME = 0.318) after statistical validation. GIS error contribution could be detected but was not readily or reliably quantified. In a regional case study for 2653 ha of *E. globulus* plantations, the linked model GIS system estimated a total standing biomass of 95 260 t C for mid-2003 and a net CO₂ balance of $-45\,671$ t CO₂-Cyr $^{-1}$ for the entire year of 2002. This study showed that regional predictions of forest growth and carbon sequestration can be produced with greater confidence after a comprehensive assessment of upscaling issues.

Keywords: carbon sequestration, DNDC, environmental modelling, Eucalyptus, forestry, GIS, prediction error, uncertainty analysis, upscaling, validation

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Introduction

Once a computer model for the simulation of ecosystem processes has been calibrated and validated, a primary challenge is to scale up simulations from the field or plot level to a regional or even global scale (Heuvelink, 1998b; Tickle *et al.*, 2001; Pielke & Conant, 2003). Regional predictions hold great appeal to decision makers in politics and private industry who struggle with the implications of complex and controversial environmen-

tal issues. Unfortunately, model predictions are often scaled up with little understanding of their applicability and without systematic evaluation of their reliability or uncertainty. This can lead to researchers, and their research, losing credibility in the eyes of the public, politicians and industry (Pielke & Conant, 2003).

Applying models developed and validated at a small scale, to larger scales carries implicit considerations. Heuvelink (1998b) listed three major issues of concern: (i) scale dependency, (ii) availability of input data and (iii) support of model input and validation data. When applying a model to a large scale requires association with geographic information systems (GIS), a fourth

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issue of concern should be added (iv) error contribution from spatially aggregated GIS input data to model predictions (Heuvelink, 1998a; Mummery & Battaglia, 2002).

(i) *Scale dependency*: The majority of models have been developed and tested at a specific spatial scale. At the scale of model development, certain processes are often identified as important for (or drivers of) system behaviour. At other scales, different processes might be important. Therefore, the majority of environmental models are scale dependent. When a model is applied at a scale different from that for which it was developed, the appropriateness of the existing model structure must be examined. If the model is not appropriate, it has to be adjusted before being applied at the new scale or a new model has to be chosen (Heuvelink, 1998b; Jansen, 1998).

(ii) *Availability of input data*: The second issue of concern when applying a model at a scale larger than that for which it was developed, is that less input data are generally available at larger scales. At the scale of model development, data are often derived from direct field or laboratory measurements. At larger scales, measurements of similar detail are often not available across the study area, and input data have to be taken from general information sources – for example GIS databases, general soil maps, statistics or expert judgement (Heuvelink & Pebesma, 1999). The decrease in availability and the quality of input data has led many model developers to simplify their models when moving to larger scales. It makes little sense to model subprocesses if they require information that is either not available or dubious. A primary requirement in environmental modelling studies is that all input parameters should be available at the scale of model application (Heuvelink, 1998b).

(iii) *Support of model input data and validation data*: The concept of support is closely related to 'level of aggregation' (Heuvelink, 1998b). At the small scale, model input data are usually derived from point measurements. At larger scales, model input data often become an average of point values within larger spatial units (e.g. grids or blocks), i.e. the data are aggregated and therefore the support changes. A change of support may require a model adjustment because the relationships between model variables might be different at a different support (Heuvelink & Pebesma, 1999). Often, model output is required at a support much larger than that at which the model was developed. Heuvelink & Pebesma (1999) analyse in detail how a change of support should be carried out. Our paper will focus on the role of support in the assessment of prediction error. When validation is used to analyse error in prediction, model input and output data are usually

not at the same support as validation measurements. For example, many large scale, forest modelling studies use data from GIS to simulate growth over hundreds of grid cells that are often as large as ~ 5000 ha (Jenkins *et al.*, 2001). To determine the uncertainty of the modelled growth predictions, independently measured validation data are required (Scurlock *et al.*, 1999). Regularly, measurements from individual field plots, often as small as 0.1 ha, are used for this purpose (Jenkins *et al.*, 2001). It is doubtful that growth measured at the small scale (e.g. <0.1 ha field plots) can reliably represent the growth for the larger scale (e.g. 5000 ha grid cells), unless a sufficient number of plot scale measurements can be aggregated, such that input and validation data have similar support. Our paper analyses the importance of data aggregation for the validation of large-scale model predictions of forest growth.

(iv) *Contribution of GIS error to the uncertainty in prediction*: The application of environmental models to large spatial scales frequently requires association with GIS for input data. Just as a model is a simplification of reality, GIS data are also a simplification of reality, and contain errors (Heuvelink, 1998a, b; Crosetto *et al.*, 2000). Both, the model error and the GIS error contribute to the overall prediction error, generally referred to as the uncertainty in prediction. The uncertainty in prediction has to be investigated when a prediction is intended to support decision making and it is useful to know the contribution of the GIS error (Pielke & Conant, 2003). Unfortunately, many GIS do not specify the expected range of errors within their data, and the interaction between model error and GIS error may not be linear (Heuvelink, 1998a). The contribution of the GIS error to the overall predictive error may be investigated when model simulations can be performed with both comprehensive, field-measured input data and GIS data. The uncertainty in predictions from these two simulations can then be analysed and compared against comprehensive, field-observed validation data.

Although these issues of concern are evident and relevant, they have rarely been addressed in studies that scale up predictions to regional levels (Jansen, 1998). The relative importance of each issue of concern to model accuracy and precision is unknown for most model predictions, because we lack the data required to enable such an analysis.

The aim of this study was to evaluate the relative importance of the four major issues of upscaling for the analysis of uncertainty in prediction and the actual uncertainty in prediction of a forest growth model. A data set consisting of biomass growth data and soils information of 302 permanent sample plots (PSPs) in 93 *Eucalyptus globulus* plantations across Victoria,

in south-eastern Australia, provided the basis for such an analysis. We used the process-based model Forest-DNDC to predict biomass growth of *E. globulus* on a subset of these PSPs. Inputs were soil data either collected from the field or derived from existing GIS. PSP data (~0.045 ha) and GIS data (~100 ha) were at different levels of aggregation, i.e. they had a different support. Accuracy and precision of model predictions were calculated by performing an uncertainty analysis through statistical validation of model predictions against measured observations of growth of *E. globulus*. The field-measured observations of growth were aggregated to the same levels of the field soil data, so that the issue of support could be accounted for. Single-tree measurements of growth were aggregated to the scale of the PSPs (~0.045 ha) and the growth data of three to four PSPs were aggregated to the scale of the GIS grid cells (~100). Thereby, large-scale and small-scale model predictions could be validated against data of similar support and of different support to test for the importance of *support* between input and validation data and for model *scale dependency*. The comprehensive growth and soil data set also allowed a detailed analysis of the effect of *data availability* on model predictions and to estimate the contribution of *GIS data error* to the overall uncertainty in prediction. Finally, a case study of predicted plantation growth in north-eastern Victoria was performed to investigate the carbon offset potential of establishing plantations using an annual budget approach.

Material and methods

The Forest-DNDC model

The Forest-DNDC model is a process based model for predicting forest growth and production, soil carbon and nitrogen dynamics, carbon sequestration and soil-borne trace gas emissions in upland and wetland forested ecosystems. It integrates two existing models; Wetland-DNDC, a hydrology-driven model (Zhang *et al.*, 2002; Cui *et al.*, 2005), and PnET-N-DNDC, an upland forest biogeochemical model (Li *et al.*, 2000; Stange *et al.*, 2000). The PnET-N-DNDC model (from photosynthesis and evapotranspiration-nitrification-denitrification and decomposition) consists of two components. The first component is driven by environmental variables, in particular climate, soil properties, vegetation type and anthropogenic activities. These variables drive submodules for soil climate, forest growth and decomposition to predict biomass accumulation in roots, aboveground woody tissue and foliage as well as soil temperature, moisture, pH, redox potential and substrate concentration profiles. The second

component utilizes the modelled soil environmental factors as inputs to nitrification, denitrification and fermentation submodules and predicts NO, N₂O, CH₄ and NH₃ fluxes.

Minimum input parameters required by the model are daily maximum and minimum air temperature, rainfall, ambient CO₂ concentration, N concentration in rainfall, humus layer type, litter layer depth, litter layer pH, bypass flow (surface efflux), mineral soil texture, mineral soil pH, stone content, organic carbon content, depth to groundwater level, latitude and management operations (e.g. planting date, fertilization scenario, harvest date, etc.). Further details on model development (Li *et al.*, 1992, 2000, 2004a; Zhang *et al.*, 2002), validation (Miehle *et al.*, 2006) (Stange *et al.*, 2000; Butterbach-Bahl *et al.*, 2001; Kiese *et al.*, 2004) and regional and local scale applications (Butterbach-Bahl *et al.*, 2001, 2004; Li *et al.*, 2004a), are available.

The GIS database

Soil data. GIS layers of soil data were taken from the Australian Soil Resources Information System (ASRIS) of the Australian Natural Resources Data Library provided by the Australian and New Zealand Land Information Council. Soil properties included in the database are soil organic carbon content, mineral soil pH and clay content. Estimated soil properties are presented as interpolated grids with a cell size of approximately 1 km² (0.01°) and cover the whole state of Victoria (McKenzie *et al.*, 2000).

The available data set on groundwater depth was not integrated into the GIS database as its classification was too coarse for growth simulations. Therefore, we generally assumed there were no plant-accessible groundwater bodies. There were insufficient data on stone content in soils and this parameter was set at a default of zero. The influence of these assumptions was also tested explicitly.

At the time of tree planting, it was assumed that a litter layer was not present. Tree plantations were generally established on land previously used for agriculture and site preparation usually included ripping and mounding. During simulation, the accumulating litter was assumed to have a neutral pH of 7 that gradually developed into a Rohhumus layer.

Climate data. All daily rainfall and air temperature data were taken from the interpolated climate surfaces of SILO Data Drill, supplied by the Queensland Government, Department of Natural Resources and Mines. The climate surfaces were created by interpolating daily historic climate observations (1 January 1957 until 20 June 2003) to a resolution of 0.05°

(approximately 5 km² (500 ha) cell size) over all of mainland Australia and Tasmania (Jeffrey *et al.*, 2001). Daily rainfall, temperature, radiation, evaporation, relative humidity and vapour pressure data are available for each grid cell. To interpolate daily climate variables a thin plate smoothing spline was used. Ordinary kriging was used to interpolate daily and monthly rainfall. The temporal and spatial error of the interpolated data was analysed using independent cross validation.

For the simulations of aboveground biomass growth, ambient CO₂ concentration was assumed to be 350 ppm. As the concentration of nitrogen in Australian rainfall is generally very low this was set to 0.05 ppm L⁻¹ (Holland *et al.*, 1997). All predictions presented in this study were simulated using the closest climate data, restricted to a scale of 5 km² or 500 ha.

Management data. Information on plantation management was taken from a farm forestry database (the PSP database) for south-eastern Australia (Feikema *et al.*, 2003a, b). *E. globulus* plantations were planted to produce pulpwood and sawn timber products on a 10–25-year rotation cycle. Silvicultural practices were similar whether the plantations were managed by farmers or timber companies. A generalized management scenario for the regional simulations consisted of:

- Trees were planted on 1 July of the year of establishment.
- Nitrogen fertilizer was applied 2 months after planting, at a rate of 40 kg N ha⁻¹, and 14 months after planting at a rate of 100 kg N ha⁻¹.
- No pruning or thinning was simulated.

Field-based measurements

Growth data of *E. globulus* plantations (and information on soils and relevant management operations such as fertilizer application) were collected to develop a climate and soil database for farm forestry research (Feikema *et al.*, 2003a, b). The study involved a network of 302 PSPs in 93 plantations across south-eastern Australia, predominantly in Victoria. The PSPs are located in plantations of *E. globulus* or *Eucalyptus nitens* that were established between 1997 and 2001 on land previously used for grazing or agricultural production.

Adjacent to each PSP, a soil pit was dug to a maximum depth of 4 m, or to the depth of an impeding layer, bedrock or the groundwater level. Profile descriptions were prepared for the range of observed soil types. Soil chemical and physical analysis was under-

taken on samples from each layer for a subset of the PSPs (e.g. soil pH, soil texture, EC, exchangeable cations (Ca, Mg, K, Na), exchangeable Al and Ac, total N and organic C). Also, 16 soil cores were taken in each plot. The soil cores were taken systematically from the undisturbed interrows and then bulked and mixed thoroughly before a 500 g subsample was taken for analysis (Feikema *et al.*, 2003b).

Growth information for each PSP consisted of standard inventory measurements (i.e. tree density, survival rate, mean dominant tree height, basal area and volume). Measurements of the PSPs were taken at 2-year intervals at ages of 2, 4 and 6 years after planting. Growth measurements at age 2, 4 and 6 years of *E. globulus* were available for 33 PSPs established in 1997. Measurements at age 2 and 4 years were available for 132 PSPs established 1998 and 1999. For the remaining 137 PSPs, growth measurements were available at age 2 years. This database is referred to as the PSP database, in contrast to the GIS database which contains input data for regional model simulations in this paper.

Analysis of the uncertainty in model predictions through statistical validation

The preferred approach to analyse uncertainty in model predictions is a statistical validation of model predictions against independent field observations (Heuvelink, 1998b; Scurlock *et al.*, 1999). The Forest-DNDC model simulates growth of a forest as accumulated carbon in tonnes of carbon per hectare (tC ha⁻¹). Simulated growth of total aboveground biomass was validated against measured field data based on total aboveground biomass estimates (stems, branches and foliage) in tC ha⁻¹. Available growth data were in the form of basal area and basal area increments. Although relationships between basal area and biomass are not consistent across soils and climates, we used a fixed relationship between the two variables in order to limit sources of variability. Aboveground biomass was thus calculated from the inventory data using a linear relationship with basal area as suggested by the Australian Greenhouse Office for carbon accounting in eucalypt plantations (Snowdon *et al.*, 2000):

$$y = ba \times 6.6t \text{ dry weight m}^{-2}, \quad (1)$$

where y is total aboveground biomass [t dry weight m⁻²] and ba is the basal area over bark [m² ha⁻¹]. Biomass was converted to tonnes of carbon per hectare [tC ha⁻¹] assuming an average tissue carbon concentration of 0.5 in *E. globulus* trees (Gifford, 2000; Resh *et al.*, 2003).

The computation of the validation data from the measurements introduces errors. Estimates of above-

ground biomass of forests from inventory measurements are particularly prone to error because of site-specific differences in allometric relationships (Snowdon *et al.*, 2000). Therefore, all modelling studies that focus on forest growth suffer from a lack of accurate and reliable data for parameterization and validation. Snowdon *et al.* (2000) report that Eqn (1) explains about 74% of the variation found in total aboveground biomass of eucalyptus plantations. Gifford (2000) indicates that a suitable value for mean carbon content is $50 \pm 2\%$. Miehle *et al.* (2006) have used these equations for the parameterization and validation of Forest-DNDC for *E. globulus*. A part in the obtained values for model error is consequently caused by errors in the validation data. All validation scenarios presented in this paper are affected by the described uncertainties. The assessment of the importance of upscaling issues has therefore been based on comparisons of different validation scenarios and not on the analysis of single validation scenarios (see 'Assessment of upscaling issues through comparison of validation scenarios').

Statistical analysis of the simulation results consisted of calculating the mean error of prediction (\bar{e} , Eqn (2)), the relative mean error of prediction ($\bar{e}\%$, Eqn (3)), the mean and relative mean absolute error (MAE and MAE%, Eqns (4) and (6)), the root mean and the relative root mean square error of prediction (RMSE and RMSE%, Eqns (5) and (7)), the coefficient of determination (r^2 , Eqn (8)) and the Nash–Sutcliffe index of model efficiency (ME, Eqn (9)) (Janssen & Heuberger, 1995; Legates & McCabe, 1999; Huang *et al.*, 2003).

\bar{e} and $\bar{e}\%$ examine predictions and observations on an average level and investigate the bias and the accuracy of model predictions:

$$\bar{e} = \frac{\sum_{i=1}^n (O_i - P_i)}{n} = \bar{O} - \bar{P}, \quad (2)$$

$$\bar{e}\% = 100 \frac{\bar{e}}{\bar{O}}, \quad (3)$$

where O_i and P_i are the observed and predicted values, \bar{O} and \bar{P} are their averages and n is the number of cases.

MAE assesses the size of prediction errors on an individual level. It does not allow for compensation of positive and negative prediction errors (such as in \bar{e}).

$$\text{MAE} = \frac{\sum_{i=1}^n |P_i - O_i|}{n}. \quad (4)$$

Similar to MAE, RMSE measures absolute prediction errors, but in a quadratic sense, and is therefore more sensitive to outliers:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^n (P_i - O_i)^2}{n}}. \quad (5)$$

In the quadratic function of RMSE large errors have a greater effect compared with large errors in the linear function of MAE. Therefore, the greater the difference between MAE% and RMSE% is, the greater is the likelihood of significant prediction errors. For this comparison, it is preferable to express MAE and RMSE not as absolute numbers, but as MAE% and RMSE%; proportions relative to \bar{O} .

$$\text{MAE}\% = 100 \frac{\text{MAE}}{\bar{O}}, \quad (6)$$

$$\text{RMSE}\% = 100 \frac{\text{RMSE}}{\bar{O}}, \quad (7)$$

The coefficient of determination (r^2) is reported as a measure of statistical correlation between model predictions and field observations:

$$r^2 = \left(\frac{\sum (O_i - \bar{O})(P_i - \bar{P})}{\sqrt{\sum (O_i - \bar{O})^2 \sum (P_i - \bar{P})^2}} \right)^2. \quad (8)$$

The Nash–Sutcliffe index of model efficiency (ME, Eqn (9)) examines the agreement of individual predictions and observations as a quantitative measure of improvement in prediction in relation to the benchmark situation \bar{O} . Any positive value for ME indicates that the model prediction is better than \bar{O} ; the closer to +1 the better (Nash & Sutcliffe, 1970; Janssen & Heuberger, 1995; Legates & McCabe, 1999; Huang *et al.*, 2003):

$$\text{ME} = 1 - \frac{\sum_{i=1}^n (P_i - \bar{O})^2}{\sum_{i=1}^n (O_i - \bar{O})^2}. \quad (9)$$

The statistical assessments described above investigate different aspects, and provide a good overview, of model performance. \bar{e} and $\bar{e}\%$ indicate the accuracy and investigate the bias of predictions. Additionally, MAE% is a measure of prediction accuracy, whereas; ME and r^2 indicate the level of precision (Huang *et al.*, 2003). The difference between RMSE% and MAE% is, as described, a measure of the likelihood of significant prediction errors. Although ME reflects the goodness-of-fit based on a 1:1 line between predictions and observations, r^2 provides a more common regression coefficient indicating the ability of the model to explain variations in the observed values (Janssen & Heuberger, 1995; Legates & McCabe, 1999).

Model simulations runs

In total, four sets of simulation runs were performed. The first three, the PSP set, the ground water (GW set) and the soil stone content (SSC set), used field data for soils from the PSP database. The fourth, the grid set, used soil data from the existing GIS.

Simulations for 28 PSPs at plot scale (PSP set). Growth of *E. globulus* was simulated for 28 PSPs that were established in 1997 (Fig. 1). Soil data for each PSP for these simulations were taken from the PSP database of field data. These input data were already aggregated to plot scale (~0.045 ha) (see 'Field-based measurements'). Growth was predicted for a plantation aged 6 years. The same 28 PSPs have been used by Miehle *et al.* (2006) for estimating model error and for model validation. The predictions of these simulation runs are subsequently referred to as the 'PSP Set'.

Simulations for 28 PSPs at plot scale without groundwater data (GW set). To test the effect of unavailability of groundwater data, growth of *E. globulus* was simulated again for the 28 PSPs of the PSP set (Fig. 1), but this time ground water data were excluded. The trees on two of the 28 PSPs had access to groundwater. The predictions of these simulation runs are subsequently referred to as the 'GW set'.

Simulations for 28 PSPs at plot scale without soil stone content data (SSC set). To test the effect of unavailability of stone content data, growth of *E. globulus* was simulated again for the 28 PSPs of PSP set (Fig. 1). This time, data on soil stone contents were excluded. The soils on 10 of the 28 PSPs had stone contents between 20% and 65%. The predictions of these simulation runs are subsequently referred to as the 'SSC set'.

Simulations with GIS soil data for 23 grid cells (grid set). Simulations with GIS soil input data were performed for 23 GIS grid cells (Fig. 2) that contained three to four PSPs. Thereby, sufficient field measured growth data were available for the aggregation of validation data in the uncertainty analysis to account for the issue of support. Growth for 16 grid cells was predicted for a plantation aged 4 years and for seven grid cells for a plantation aged 6 years. The predictions of these simulation runs are subsequently referred to as the 'grid set'.

Assessment of upscaling issues through comparison of validation scenarios

The validation scenarios. To analyse the uncertainty in prediction of the four simulation runs (i.e. PSP set, GW

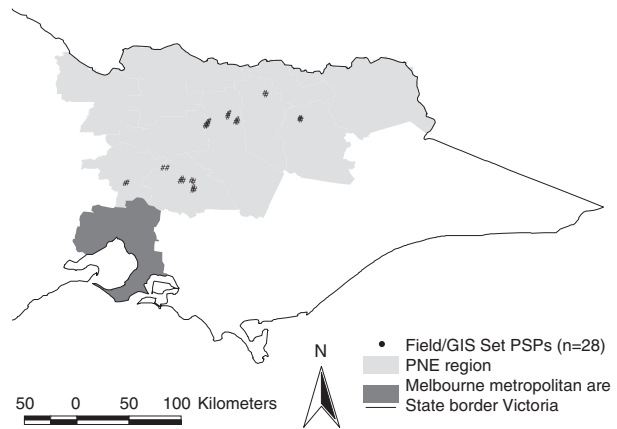


Fig. 1 Location of the 28 permanent sample plots (PSPs) (PSP set, GW set and SSC set) in the state of Victoria, south-eastern Australia. The map also shows the PNE region and the Melbourne Metropolitan Area.

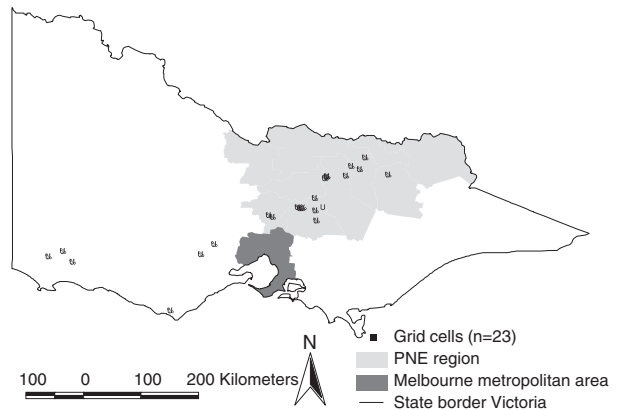


Fig. 2 Location of the 23 validation grids (grid set) in the state of Victoria, south-eastern Australia. The map also shows the PNE region and the Melbourne Metropolitan Area.

set, SSC set and grid set), we prepared five statistical validations (Table 1) of growth predictions from Forest-DNDC using field data for growth of *E. globulus*. In all validations, validation data and input data were of similar support (level of aggregation), apart from validation No. 4 where grid scale growth predictions (grid set, ~100 ha) were validated against plot scale growth measurements (~0.045 ha).

Scale dependency. To test for scale dependency of the model, we compared the mean relative error of prediction ($\bar{e}\%$) of validations No. 1 (PSP set) at plot scale and No. 5 (grid set) at grid scale (Table 1). $\bar{e}\%$ measures the accuracy of model predictions and is an indicator of bias (Huang *et al.*, 2003). If $\bar{e}\%$ is similar,

Table 1 Five validation scenarios and four sets of model predictions of *Eucalyptus globulus* biomass growth using soil input data and growth validation data at two different scales or levels of aggregation (\emptyset) for comparison and uncertainty analysis (statistical validation)

Validation no.	Simulations	Soil input data			Growth validation data	
		Number	Scale (ha)		Number	Scale (ha)
1	PSP set	PSP 28	0.045	No groundwater data No soil stone content data	PSP 28	0.045
2	GW set	PSP 28	0.045		PSP 28	0.045
3	SSC set	PSP 28	0.045		PSP 71	0.045
4	Grid set	Grid 23	100		\emptyset PSP 23	100
5	Grid set	Grid 23	100			

PSP, permanent sample plot; GW, ground water; SSC, soil stone content.

then the model is not scale dependent between the sales investigated (Heuvelink, 1998b; Mummery & Battaglia, 2002).

Availability of input data. The importance of input data availability was investigated by comparing the results from validation No. 1 (PSP set), No. 2 (GW set) and No. 3 (SSC set). The predictions in the PSP set, the GW set and the SSC set used the same soil input data (i.e. field sampled from 28 PSPs). In the GW set, groundwater information was excluded and in the SSC set soil stone content information was excluded. All three validations used growth measurements from the same 28 PSPs as validation data.

Support of input and validation data. To investigate the importance of support in input and validation data, the results from validation Nos. 4 and 5 (both grid set) were compared. Both, validation Nos. 4 and 5 analysed the uncertainty in prediction at the grid scale (Table 1) using field measured growth data from the 71 PSPs. In validation No. 4, model predictions were compared directly with the growth data from the 71 PSPs. Input data were aggregated (GIS) and validation data were disaggregated (PSP) and there was a consequent difference in data support. In validation No. 5 a design-based approach was used to aggregate growth measurements within a grid cell (Heuvelink & Pebesma, 1999). The grid average is the unweighted sample mean of the available PSP values ($n = 3-4$) within a grid cell. This approach, unlike block kriging, does not make assumptions about the spatial variability of the aggregated variable.

GIS error contribution. To investigate the contribution of GIS error to the uncertainty in large-scale predictions, we compared the results of validations Nos. 1 and 5 (Table 1). Validation No. 1 is a measure of model error (Miehle *et al.*, 2006) with field sampled soil input data,

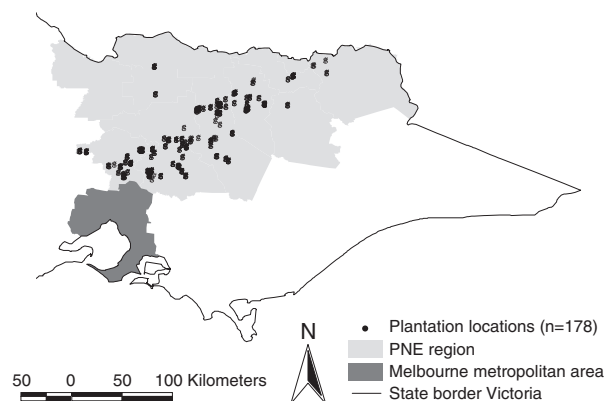


Fig. 3 Location of the 178 *E. globulus* plantations in the PNE region in north-east Victoria. The map also shows the Melbourne Metropolitan Area.

whereas validation No. 4 is a measure of model error plus GIS error (Heuvelink, 1998a, b). The differences between the results of validations Nos. 1 and 5 indicate the contribution of GIS error to overall prediction error.

Case study: growth and carbon storage of E. globulus plantations in the PNE region

A spatially explicit, plantation inventory was integrated into the GIS database and soil properties and climate data were retrieved for all plantation locations. The digital plantation inventory (Fig. 3) was provided by the Plantation Inventory Project of the Department of Sustainability and Environment, Victoria. The data set contained information about plantation locations and boundaries, tree species, planting year, productivity status, previous land-use and owner type.

By the end of 2002, there were 178 *E. globulus* plantations in the PNE region. These plantations were established between 1996 and 2001 and covered about

2653 ha, ranging in size between 0.2 and 187.6 ha with an average size of 14.8 ha (Table 3). Intersecting the plantation layer with the soil layer resulted in 336 unique polygons that were used for the regional simulation.

From the various outputs of the Forest-DNDC model, we analysed the amount of standing aboveground biomass for 21 June 2003 (stems, branches and foliage). Additionally, we analysed the simulated net CO₂ flux for the entire year 2002. Net CO₂ flux (Eqn (10)) was calculated by subtracting the carbon lost above and belowground via plant respiration (R_{Plant}), microbial respiration in the mineral soil (R_{Soil}) and the litter layer (DC_{Litter}) from the amount of carbon gained through gross photosynthesis (GrossPSN). The Net CO₂ flux therefore describes the overall amount of carbon that has been taken out of the atmosphere and sequestered in the soil-plant system (or vice versa the net loss of carbon to the atmosphere). A negative number for the net CO₂ flux indicates that the soil-plant system under investigation acts as a carbon sink:

$$\text{NetCO}_2 = -\text{GrossPSN} + R_{\text{Plant}} + R_{\text{Soil}} + DC_{\text{Litter}}. \quad (10)$$

Results

The validation scenarios

Uncertainty in the PSP set predictions. There was small bias in predictions ($\bar{e} = -1.62 \text{ tC ha}^{-1}$, $\bar{e}\% = -3.19\%$; Table 2). MAE% was 14.6% (7.41 tC ha^{-1}) and RMSE% was 17.9% (9.07 tC ha^{-1}). The difference between MAE% and RMSE% amounted to 3.3% (1.66 tC ha^{-1}), indicating that there were no severe prediction errors. The model predictions had a good level of precision – ME was 0.645 and the correlation between predicted and observed values had an r^2 of 0.730 (Fig. 4a). Plotting measured aboveground biomass growth against predicted growth provides a qualitative, visual evaluation of model performance.

Uncertainty in the GW set predictions. The bias in predictions was small ($\bar{e} = 1.76 \text{ tC ha}^{-1}$, $\bar{e}\% = 3.47\%$; Table 2). Here, however, the difference between MAE% and RMSE% (5.23 tC ha^{-1} or 10.3%) suggested the occurrence of significant prediction errors. Model predictions had a very low level of precision – ME was 0.052 and the correlation between predicted and observed values had an r^2 of 0.153 (Fig. 4b).

Uncertainty in the SSC set predictions. The bias in predictions was small ($\bar{e} = 1.61 \text{ tC ha}^{-1}$, $\bar{e}\% = -3.18\%$; Table 2). MAE% was 14.6% (7.40 tC ha^{-1}) and RMSE% was 17.9% (9.10 tC ha^{-1}). The difference between MAE% and RMSE% (1.70 tC ha^{-1} or 3.4%) indicated that there were no severe prediction errors. Model predictions were precise with an ME of 0.642 and the correlation between predicted and observed values had an r^2 of 0.728 (Fig. 4c).

Uncertainty in the grid set predictions with unaggregated validation data. There was a small bias in the grid set predictions validated against unaggregated field measurements of *E. globulus* growth ($\bar{e} = -1.16 \text{ tC ha}^{-1}$, $\bar{e}\% = -2.91\%$; Table 2). The difference between MAE and RMSE was 4.68% (1.86 tC ha^{-1}). There were no severe prediction errors. ME was 0.274 and the correlation between predicted and observed growth values had an r^2 of 0.412 (Fig. 5a).

Uncertainty in the grid set predictions with aggregated validation data. There was a small bias in the grid set predictions when validated against aggregated measurements of *E. globulus* growth ($\bar{e} = -1.41 \text{ tC ha}^{-1}$, $\bar{e}\% = -3.54\%$; Table 2). The difference between MAE and RMSE was only 5.1% (2.01 tC ha^{-1}), indicating an absence of severe prediction errors. This was reflected by the model efficiency (ME = 0.318) and the correlation between predicted and observed growth values ($r^2 = 0.474$; Fig. 5b).

Table 2 Results of the uncertainty analyses (statistical validations) for predictions of *Eucalyptus globulus* growth using soil input data and growth validation data at two different scales with different support (levels of aggregation \emptyset)

Validation no.	Simulation	\bar{e} (tC ha ⁻¹)	$\bar{e}\%$	MAE (tC ha ⁻¹) (and MAE%)	RMSE (tC ha ⁻¹) (and RMSE%)	ME	r^2
1	PSP set	-1.618	-3.19	7.407 (14.60%)	9.071 (17.88%)	0.645	0.730
2	GW set	1.758	3.47	10.384 (20.47%)	15.614 (30.78%)	0.052	0.156
3	SSC set	-1.613	-3.18	7.403 (14.60%)	9.101 (17.94%)	0.642	0.728
4	Grid set	-1.159	-2.91	7.555 (18.96%)	9.419 (23.64%)	0.274	0.412
5	Grid set \emptyset	-1.407	-3.54	6.675 (16.80%)	8.683 (21.86%)	0.318	0.474

PSP, permanent sample plot; GW, ground water; SSC, soil stone content; ME, model efficiency; MAE, mean absolute error; RMSE, root mean square error.

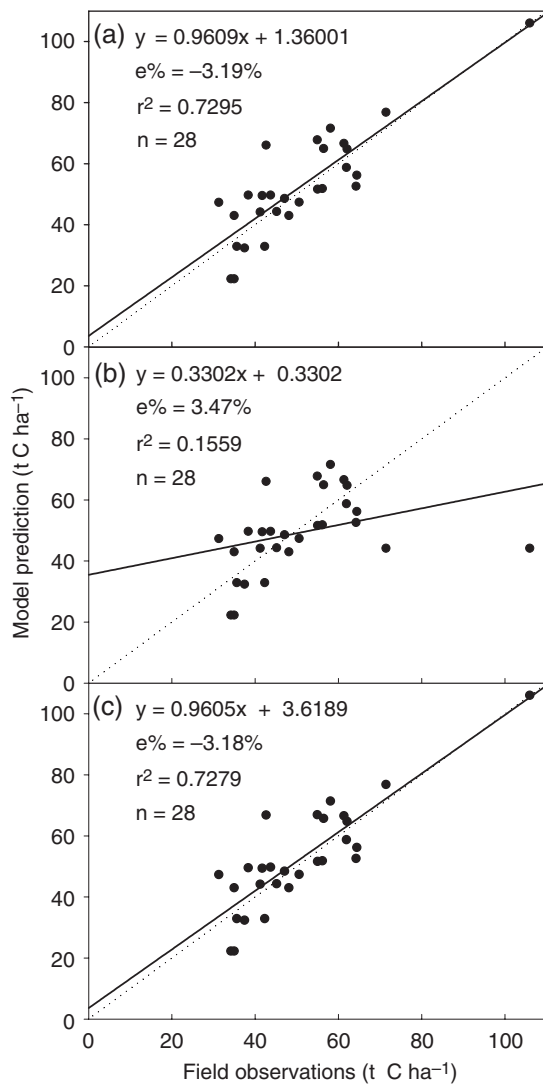


Fig. 4 Plot scale field measurements (~ 0.045 ha) of above-ground growth of *Eucalyptus globulus* plantations plotted against model predictions using field sampled soil data (a) fulfilling all input data requirements of Forest-DNDC (PSP set, validation No. 1), (b) lacking groundwater data (GW set, validation No. 2) and (c) lacking soil stone content data (SSC set, validation No. 3) (dashed line represents the 1:1 line, solid line represents the regression line).

Importance of the issues of upscaling

Scale dependency. The relative mean error of prediction ($\bar{e}\%$) in validations No. 1 (PSP set) and No. 5 (grid set) differed only by less than 0.4% (Table 2). Hence, Forest-DNDC showed little scale dependency across the investigated scales (~ 0.045 and ~ 100 ha).

Input data availability. When groundwater data were excluded, $\bar{e}\%$ increased by 6.7% (Table 2). When

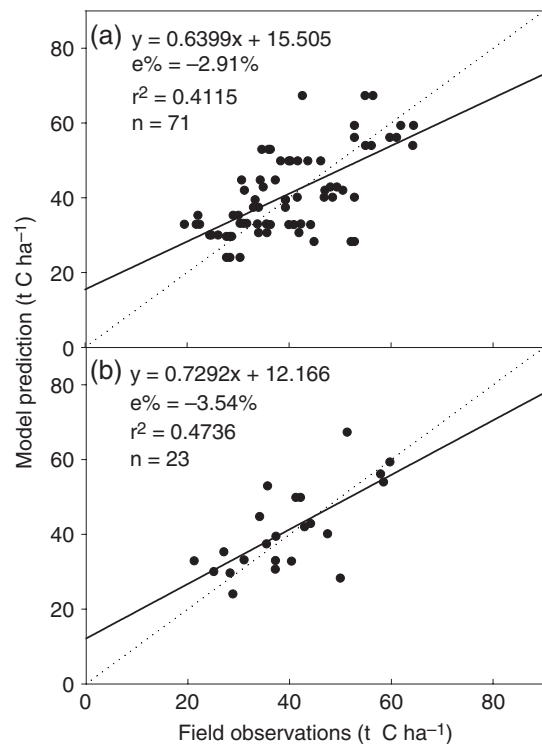


Fig. 5 Grid scale model predictions (grid set, ~ 100 ha) plotted against (a) field measurements at plot scale (~ 0.045 ha, validation No. 4) and (b) against aggregated measurements at grid scale (~ 100 ha, validation No. 5) of aboveground growth of *Eucalyptus globulus* (dashed line represents the 1:1 line, solid line represents the regression line).

groundwater data (PSP set) were included, the model slightly overestimated growth. Conversely, excluding groundwater (GW set) resulted in slightly underestimated growth. MAE% increased by 5.9% indicating an increase in absolute prediction errors without groundwater data. The simultaneous increase of the more sensitive RMSE% by 12.9% suggested that the increase in MAE% was caused by a few severe prediction errors as indicated in Fig. 4b. The lack of groundwater data consequently led to considerable loss of precision in *E. globulus* growth predictions (Table 2, Fig. 4b).

Excluding data on soil stone content had little effect on the certainty of prediction (Fig. 4a and c).

Support of input and validation data. The difference of 0.6% in $\bar{e}\%$ between validations Nos. 4 and 5 (grid set; Table 2 and Fig. 5) indicated a slightly higher level of accuracy when input and validation data had a different level of support. In contrast, both, r^2 and ME indicated a lower predictive precision. RMSE% and MAE%, as a measure of the size of prediction errors,

Table 3 Years of establishment, acreage and number of *Eucalyptus globulus* plantations in the PNE region with productivity, total aboveground biomass (both for 21 June 2003) and annual net CO₂ flux (2002) from predictions of the Forest-DNDC model

Plantations			Model predictions		
Year of establishment	N	Area (ha)	Productivity 21 June 2003 (tC ha ⁻¹) Average (min/max)	Aboveground biomass 21 June 2003 (tC)	Annual Net CO ₂ flux 2002 (tC yr ⁻¹)
1996	13	119.8	48.14 (16.45/111.06)	5960	-1904
1997	69	441.9	50.71 (29.82/96.84)	23 043	-8459
1998	66	396.5	44.27 (10.47/86.28)	16 536	-7148
1999	6	506.1	33.67 (20.59/62.96)	18 027	-9062
2000	17	931.4	28.75 (8.90/48.23)	26 542	-15 669
2001	7	257.7	21.59 (18.40/24.28)	5152	-3430
Sum	178	2653.27	-	95 260	-45 671

were approximately 2% greater when data used in the statistical validation had a different level of support.

GIS error contribution. Replacing field data for soils (validation No. 1) with GIS data (validation No. 5) led to a slightly larger mean error in prediction, $\bar{e}\%$ increased by 0.4%. The output in validation No. 5 varies less than in validation No. 1 because the variation within the grid cells is balanced out (Figs 4 and 5) through spatial aggregation. Although there is less variation in model output, MAE% increased by 2.2% and the more sensitive RMSE% increased by 4%. This indicated that the use of GIS data introduced substantial error and was reflected by r^2 decreasing from 0.73 to 0.47 and ME decreasing from 0.645 to 0.318.

Case study: growth and carbon storage of E. globulus plantations in the PNE region

For 2653 ha of *E. globulus* plantations planted between 1996 and 2001 in the PNE region the linked model-GIS system estimated a total standing aboveground biomass of 95 260 tC on 21 June 2003 (Table 3). For the year 2002, the linked system predicted an annual net CO₂ flux (or carbon sequestration) of -45 671 tCO₂-C over the entire *E. globulus* estate of the PNE region. The predicted average net CO₂ flux varied between the different age classes from 13.2 to 19.0 tC ha⁻¹ yr⁻¹ (Table 3).

Discussion

Scale dependency of forest productivity models

The uncertainty analyses of forest growth predictions showed that the Forest-DNDC model was not scale dependent across the two investigated scales. The relative mean error of prediction ($\bar{e}\%$), that serves as an indicator of bias (Janssen & Heuberger, 1995; Legates &

McCabe, 1999; Huang *et al.*, 2003), changed little when the scale of model application changed. This finding confirms results from Mummery & Battaglia (2002) who also found that predictions of forest productivity models can be unbiased across a similar range of scales. When scaling up, growth predictions of forest productivity models can be independent of scale because the important processes driving forest growth (e.g. photosynthesis, respiration, etc.) are the same at the plot and larger scales. In contrast, when scaling down to single leaves, other processes become dominant (Sands, 1995; Aber *et al.*, 1996; Heuvelink, 1998b). Problems might occur when factors constraining growth are not well correlated to broad environmental processes, such as insect pests or disease. Hence, the issue of scale dependency of models can be of minor importance for large-scale applications of general forest productivity models.

Availability of input data

At the regional scale of this study, we had access to input data for all required parameters of the Forest-DNDC model, with the exception of data on groundwater and soil stone contents. The importance of availability for these input data was investigated by simulating growth of *E. globulus* for 28 PSPs, 2 PSPs had access to ground water and 10 PSPs had soil stone contents between 20% and 65%.

Excluding data on ground water levels considerably increased the uncertainty in prediction (Fig. 4b). Although the size of the mean error in prediction, $\bar{e}\%$ (a measure of the accuracy of growth prediction), varied little, the precision of growth predictions was severely reduced. Access to groundwater disassociates the dependency of tree growth on rainfall. When field data included the height of the groundwater table (Fig. 4a), Forest-DNDC predicted well the growth of trees in the two PSPs with groundwater access. The decrease in

predictive precision was caused by missing input data. However, only the trees in three of the 302 PSPs were known to have access to groundwater. As such, we decided that the model did not need adjustment for this study area.

Excluding data on soil stone content produced little change in the certainty of prediction (Fig. 4a and c). We again concluded that the lack of data on stone content of soils did not limit the applicability of Forest-DNDC to the study area. The fertility of each plantation was evaluated before plantation establishment. Sites where stone content would considerably limit tree growth are generally not selected for the establishment of commercial *E. globulus* plantations.

In a study of the productivity of *E. globulus* in Tasmania, Mummery *et al.* (1999) circumvented the lack of state-wide estimates of soil nutrient status, soil water-holding capacity and water logging by applying an environmental sensitivity analysis and a terrain analysis. In other studies, simple forest productivity models have also been successfully applied at a large scale without being adjusted. The limited data requirements of these simpler models meant that sufficient input data were available (Sands *et al.*, 2000; Mummery & Battaglia, 2001; Mickler *et al.*, 2002).

Support

The uncertainty analyses of the forest growth predictions showed that the level of support of validation data affected the results of a statistical uncertainty analysis (Table 2, Fig. 5). Predictive precision was estimated to be lower when validation data had a different level of support to the input data (and predictions). In other words, when the issue of support is not accounted for, a statistical uncertainty analysis may underestimate the precision of model predictions. In contrast, the relative mean error of prediction, $\bar{e}\%$, indicated greater prediction accuracy when the issue of support was not accounted for. This may be due to the larger number of cases in the validation data ($n = 72$), which facilitates a balancing of positive and negative prediction errors and leads to an overestimation of prediction accuracy. The conclusion that prediction accuracy was overestimated because of a balance of errors in $\bar{e}\%$ is supported by the MAE, which, in contrast to $\bar{e}\%$, indicated an increase in prediction error. When the issue of support is not accounted for, the results of an uncertainty analysis may be biased.

A similar result, decreased predictive precision but maintained prediction accuracy, i.e. an overestimation of prediction accuracy, was obtained by Mummery & Battaglia (2002) when they investigated the effects of an increase in scale of GIS input data on plot scale predic-

tions of the forest productivity model PROMOD. When highly aggregated GIS data were used as inputs, the confounding effect of support greatly decreased precision of growth predictions at the plot scale, especially in the upper and lower quartiles of the measured range. This decrease in precision may not be as evident when the issue of support is accounted for. In our study, the change in scale was similar, but with suitable aggregation of validation data to adjust the support between validation and input data the detected decrease in predictive precision was much smaller.

GIS error contribution

Replacing field with GIS data for soils, led to a slightly reduced accuracy in prediction, but a considerably reduced precision in growth predictions of *E. globulus*. The small increase of MAE and RMSE indicated that the loss in predictive precision may be overly emphasized by the values of r^2 and ME. Both r^2 and ME are sensitive to the size range of values used in statistical correlation, i.e. they are very sensitive to data at the upper and lower ends of the value range. As MAE and RMSE contradicted detected changes in r^2 and ME, and as the range of plantation productivity was not the same in both data sets, we conclude that this study has limited ability to quantify the contribution of GIS error to overall prediction error. Nonetheless, use of GIS data in place of field data increased the uncertainty in prediction and introduced substantial prediction errors.

In the absence of sufficient field observations, Monte Carlo analysis, the Delta method and model sensitivity analyses, are all methods of assessing the uncertainty of large-scale predictions and investigating the contribution of GIS error (Heuvelink, 1998a, b; Crosetto *et al.*, 2000; Crosetto & Tarantola, 2001). However, these methods are not applied routinely by researchers (Jansen, 1998) and have limitations (see also 'Uncertainty analysis in large scale ecosystem predictions'). Quantifying the errors in prediction introduced by GIS data remains a difficult task and the interaction of model error and GIS error is still not fully understood (Heuvelink, 1998a).

Case study – biomass growth and carbon sequestration potentials in the PNE region

The results from the PNE case study have some relevance to the current interest in carbon accounting at regional and national scales. The Forest-DNDC model has previously been successfully calibrated and validated (Miehle *et al.*, 2006), and this study has dealt with key issues associated with scaling up, particularly data availability and support. As a consequence, large-scale

predictions of growth and carbon accumulation in biomass can now be produced using the Forest-DNDC model and provided to policy makers and industry members with some confidence.

The linked model-GIS system estimated a total yearly CO₂ uptake of $-45\,671\text{ t C yr}^{-1}$ for the PNE region for 2002. According to the Australian Greenhouse Office, an average Australian household produces around 4 t of CO₂-C per year (Pearse, 2003). Therefore, the *E. globulus* plantations in the PNE region could offset the CO₂ emissions of approximately 11 418 households in 2002. Each hectare planted with *E. globulus* potentially takes up the CO₂ emissions of about 4.4 households per year. This assumes that the trees do not reach maturity and are not harvested. Long-term CO₂ gains will depend more on the amount of coarse woody debris produced by such stands and its rates of decomposition (Mackensen & Bauhus, 1999) than aboveground biomass used for pulp and paper production.

Uncertainty analysis in large-scale ecosystem predictions

In this study we compared model predictions with field observations to assess the uncertainty in predictions of growth of *E. globulus* over large scales. At larger spatial scales, sufficient field observations for a statistical validation are rarely available (Heuvelink, 1998b; Jenkins *et al.*, 2001; Tickle *et al.*, 2001). This is the main reason why many published estimates of tree growth, of NPP or of carbon sequestration at the regional scale (Falloon *et al.*, 1998, 2002; Heuvelink, 1998b; Jansen, 1998; Ollinger *et al.*, 1998; Mummery *et al.*, 1999; Sands *et al.*, 2000; Jenkins *et al.*, 2001; Mummery & Battaglia, 2001, 2002; Tickle *et al.*, 2001; Zierl, 2001; Chen *et al.*, 2003) have either been validated against sparse field observations at a scale different from model input data, or against other model predictions or have not been validated at all. Even when field-based data seem to be insufficient for an empirical (statistical) uncertainty analysis, other methods of uncertainty or sensitivity analysis are rarely used in model performance studies. Jansen (1998) assumed this was because many authors are unfamiliar with the available methods of uncertainty and sensitivity analysis or because of the recognized limitations of these methods:

- Uncertainty distributions of model inputs are often not known or difficult to determine. Consequently, the results of an uncertainty analysis are only approximate and it is difficult to determine if the approximation is acceptable (Heuvelink, 1998b).
- Uncertainty analysis has a tendency to underestimate prediction errors (Jansen, 1998).
- Monte Carlo analysis can require enormous computational resources (Heuvelink, 1998b; Jansen, 1998).

- Most sensitive factor method (Li *et al.*, 2004b), only applies when the sensitivity of a few factors is dominant.

An uncertainty analysis is imperative for a systemic evaluation of uncertainty in large-scale predictions. Large-scale ecological modelling studies can only gain credibility when suitable methods of uncertainty analysis are applied and their limitations reported. Statistical validation of model predictions against suitable aggregated field observations remains the preferred methods for uncertainty analysis (Heuvelink, 1998b; Jansen, 1998).

Conclusion

An extensive collection of growth measurements of *E. globulus* in south-eastern Australia provided a rare opportunity for rigorous assessment of the uncertainty in large-scale predictions made using the Forest-DNDC model linked to a GIS database. The main conclusions from the statistical analysis of uncertainty in prediction are that:

- Upscaling did not affect growth predictions from the Forest-DNDC model. However, the aggregation of data that is associated with upscaling reduced the variability in growth predictions.
- Simple forest productivity models with low input requirements, such as Forest-DNDC, are less likely to confront issues of data availability at regional scales.
- When the issue of support of input and validation data is not accounted for, then prediction accuracy may be overestimated.
- The errors in GIS input data led to a lower accuracy and precision in predictions. The contribution of GIS error to this increased uncertainty in prediction remains difficult to quantify.
- The predictions of the linked model-GIS system could explain about 50% of the observed variation in plantation growth with an average error of -3.5% .
- Following a comprehensive assessment of upscaling issues, regional predictions of plantation growth using the linked model-GIS system can be produced with greater confidence, and can hence be used in policy development and decision support with an understanding of the uncertainty in these predictions.

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