“How Can Earth Observation Data Be Implemented To Improve Parameterisation of Carbon Models”

Confirmation Report

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Introduction

Increasing concern over the effects of CO_2 and other greenhouse gasses on the climate is evident from recent political trends: Since the United Nations Framework Convention on climate change over a decade ago, consideration of likely consequences of climate change, and mitigation strategies to deal with these changes, has been an active area of research. In 1997 the Kyoto protocol was agreed upon, to enforce legally binding measures to address the issue of climate change. Since ratification of the treaty on February 16th 2005, signatory governments are required to reduce their CO_2 emissions to pre 1990 levels: Article 2 of the protocol stipulates that such reductions are to be pursued by the "enhancement of energy efficiency in relevant sectors of the national economy", coupled with the preservation and enhancement of natural sinks of greenhouse gases; principally by the promotion of sustainable forestry practices, afforestation and reforestation. The quantification of the strength of carbon uptake by forests is therefore important if we intend to offset emissions by the management of forests for sequestration.

Current technology for measuring mass and energy flow from vegetation to the atmosphere (as manifested by the absorption and efflux of CO_2) is based on eddy flux correlation techniques (Reynolds, 1895; Baumgartner, 1969). These techniques are limited to the measurement of gas exchange over locations of homogenous and level terrain, in order to simplify dynamic processes. Whilst an improved understanding of carbon dynamics has resulted from such studies, problems persist in closing energy budgets (e.g. Anthoni *et al.*, 2000) and describing the flow of mass; especially in complex terrain where lateral flow must be accounted for. Most commonly, forests are situated on marginal land, with slopes or soil conditions unsuitable for agriculture. In order to capture the regional dynamics of real forest situations, it is therefore necessary to extensify such measurements via a modelling process. In addition, the modelling process provides a method to scale between measurements taken over different spatial scales (Turner *et al.*, 2004): Often in the spatial modelling scenario we have to make use of data collected for other purposes (projects) than our own, and thus a variety of data from different programs and sampling schemes must be integrated; modelling provides a tool to perform this integration.

Regionalised modelling of carbon budgets has already been undertaken in this study area (e.g. Law *et al.*, 2004), the primary model of choice has been Biome-BGC; this model ignores the dynamics of the vegetation layer by 'spinning-up' to a near steady set of parameters, including the soil and vegetation carbon pools and soil temperature profiles. As previously mentioned, the area is under constant management, and is highly dynamic. I intend to quantify the problems associated with the spin-up procedure and determine alternative approaches that make better use of Earth observation (EO) products. The approach taken will focus heavily on the quantification and spatial distribution of errors.

Study Site

The study site is located on the eastern slopes of the central Cascade Mountains of Jefferson County, Oregon. The site has a strong east-west elevation gradient, ranging from some 3200 m to less than 500 m above sea level. The resulting precipitation gradient shapes a varied ecology, shifting between three distinct ecotopes, dominated by grand fir (*Abies grandis*) and Douglas-fir (*Pseudotsuga menziesii*); pine (*Pinus ponderosa*); and juniper (*Juniperus occidentalis*) respectively. A four year time series of data is available for the region, which contains three eddy flux towers and thirty two weather stations from a variety of networks. The use of earth observation data is further facilitated by the use of the area as a MODIS calibration site.

Objectives

The aims of this project are threefold:

1. Quantify the problems associated with standard spatial interpolation procedures
2. Develop and apply new geostatistical approaches for generating spatial products
3. Determine errors associated with spatial products so that these errors can be propagated into any modelling products.

Science Questions

The key questions to be addressed in this project can be thought of as four separate papers with a common thread:

1. To what extent can geostatistical techniques reduce the error of meteorological surfaces for modelling applications?
2. Can estimation of vegetation state variables be improved by the application of EO techniques?
3. To what extent can the application of EO techniques reduce the error of soil surface characteristics?
4. Does application of a data driven, EO based model significantly improve estimation of the carbon flux, over simpler 'spin-up' approaches?

Proposed Methodology

In this project, an array of field observations and weather stations, coupled with earth observation data, are to be used to generate spatial estimates local meteorological conditions, and carbon stocks in soils and vegetation at a regional scale.

Paper 1

Hypothesis

Existing methods of generating meteorological parameter surfaces fail to adequately capture regional variation: Interpolation schemes misrepresent the climate of drainage features and hollows.

Objectives

1. To generate meteorological parameter surfaces from temporally dense, spatially sparse point data.
2. To quantify error in these surfaces as a PDF at each pixel.

Rationale

Meteorology at the land surface is one of the principal drivers of the terrestrial biogeochemical system. Although measurements of surface meteorology are made at many locations, there is often insufficient data for simulations on the regional scale, where the number of grid pixels to be estimated often exceeds the number of stations present. In order to resolve these difficulties, three main approaches have been historically pursued: Mesoscale modelling, Regression, and Interpolation.

Mesoscale modelling simulates the detailed processes underlying large scale weather patterns in order to predict surface conditions: Data records are utilised *post hoc* fashion for validation. Unfortunately, the use of mesoscale climate models was found to be ineffective at capturing the known climatological features of the study area (L. Mahrt, *personal comm.*) Regression techniques have met with some success for modelling the regions climatology (Thornton *et al.,* 1997). Essentially, temperature records inform a statistical model of temperature against the local topography to predict surface meteorology. The PRISM and MTCLIM models are examples of this approach (Daily *et al.,* 1997; Thornton and Running, 1999). Whilst these models perform well, the spatial distribution of their errors is unknown; furthermore, the accuracy of the resulting products is often questionable, especially in areas of high topographic variability, as drainage and lateral flow become significant (e.g. Mahrt, in press).

Interpolation uses the data in an *ad hoc* manner by 'gap filling' using a set of rules derived from the data. Interpolation schemes exploit a property of spatial data known as autocorrelation; that is, samples closer together are more likely to have similar values than those with greater separation distances. During the interpolation process, it is necessary to remove external trends form the data, as these may obscure the autocorrelation structure of the data; in the case of meteorological parameters this generally involves the removal of a linear topographic trend (or 'drift'), and in some cases, an east-west gradient (e.g. Wackernagel, 2003). The partitioning of the underlying processes which generate the spatial distribution into linear (or, to be precise, quadratic) drifts, and a spatially autocorrelated noise process is the rationale of non-stationary geostatistics. The strength of this approach is we remove the large scale components of trend form the data (those trends which are understood *a priori*), and incorporate the residual processes (small scale components of trend), which are either too complex or poorly defined to be modelled as spatially structured noise (for further discussion, see Cressie, 1993).

Unfortunately, trend removal adds an element of subjectivity to the process, as the solution is not unique. When de-trending data it is therefore preferable to utilise as few trends as possible, or remove the large scale component by statistical means (Cressie, 1993).

By using a combined approach, where data are de-trended by regression with a microclimatic model of solar interception for the region (e.g. Rich, 1995), and the residuals interpolated, interpolation skill should be improved. The benefit here is that temporal and spatial trends are integrated into a single parameter, which is known to have a direct relationship with temperature. (Barry, 1992; Jones, 1992; Oke, 1987) The magnitude of the model based trend can be compared with statistical methods, such as PCA (Pearson, 1901) or Median polishing (see fig 1; Cressie, 1993; Emerson and Hoaglin, 1983; Tukey, 1977).

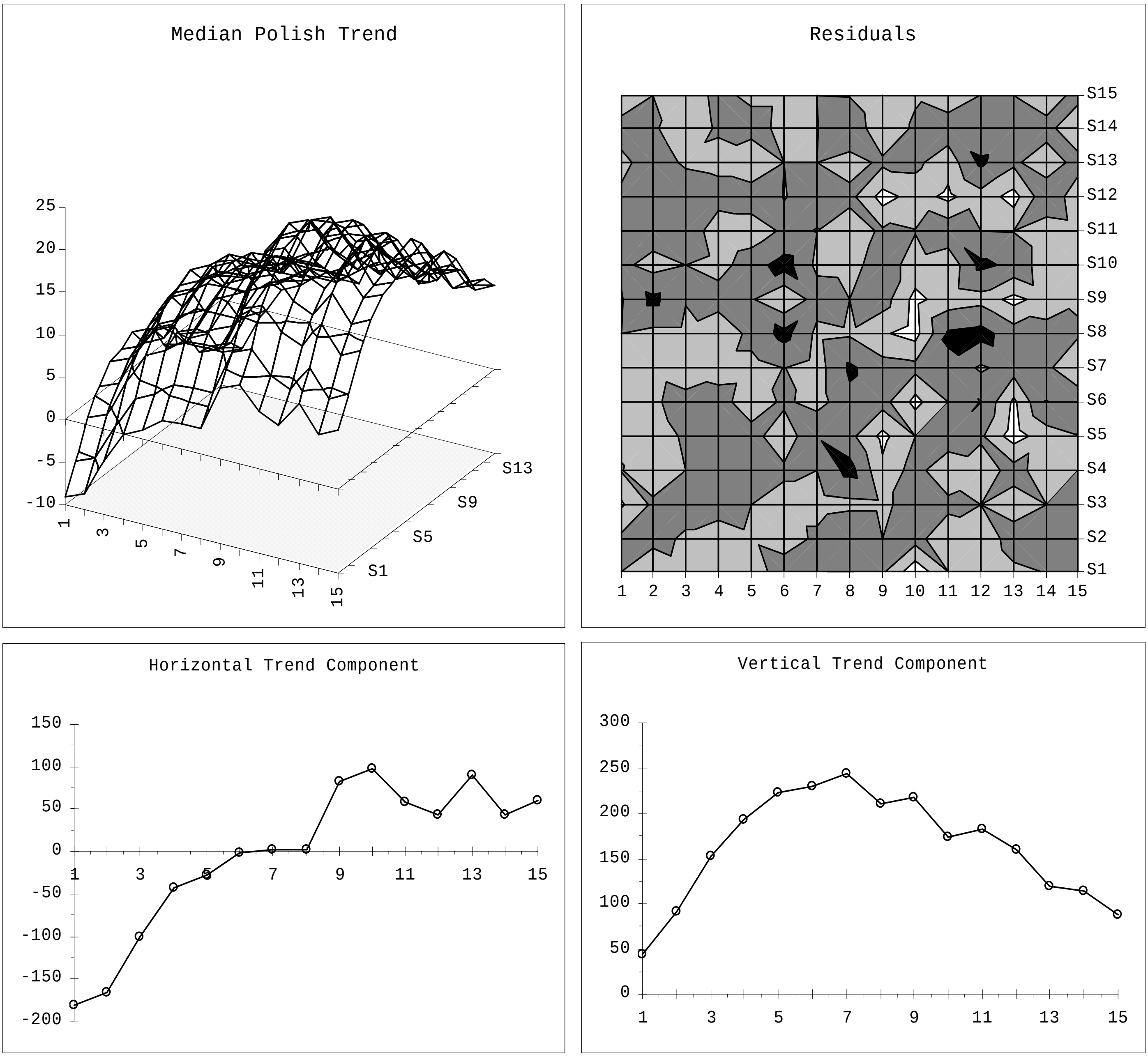

Fig 1: Partitioning the large and small scale components of trend via median polishing (simulated data). Large scale = trend, small scale = residual.

The combination of trend model and residual interpolation is documented in Wackernagel (2003). Interpolation via Kriging (a distance weighted interpolation based on the statistical distance between points) allows variance surfaces to be generated, and thus a PDF of the parameter to be computed for each grid cell. An example of combined regression/interpolation output is given in fig 2. Areas of uncertainty can be identified from the PDF, and predicted output compared with ground truth met stations.

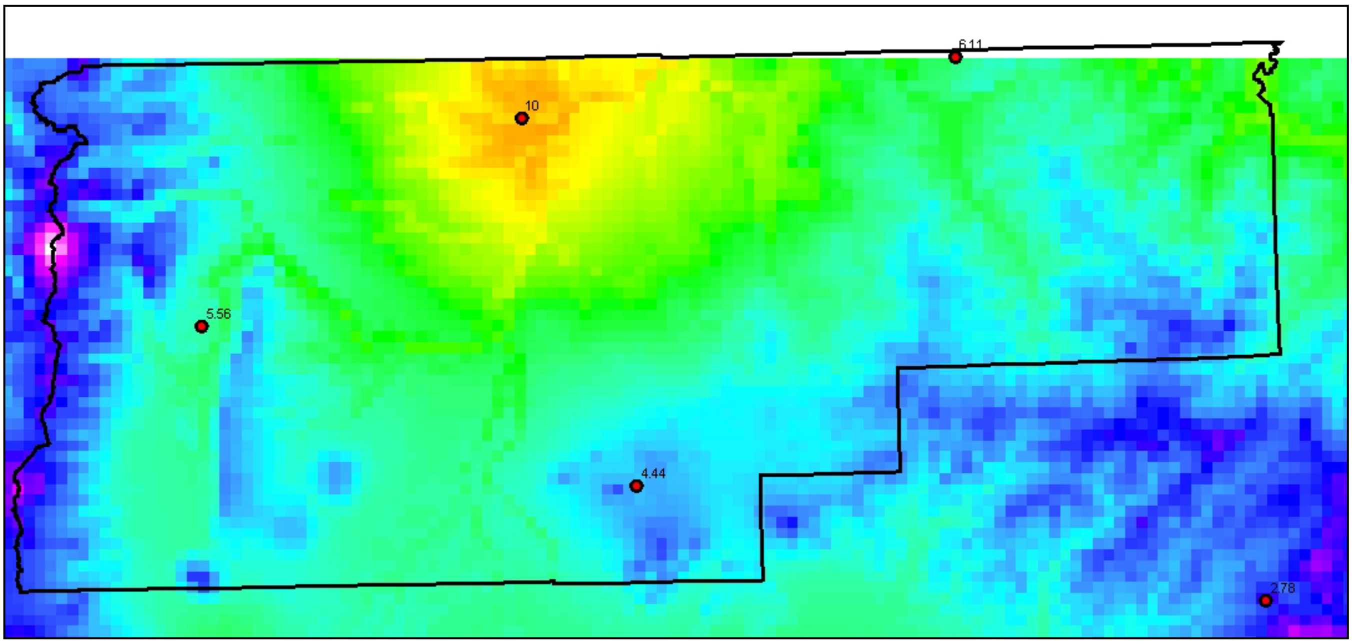

Fig 2: Combined regression/interpolation of max temperature data for the study site. Black outline indicates Jefferson county boundaries, red spots indicate stations.

Inputs

1.	Met station data	>80 points
2.	USDA 30 m resolution Digital Elevation Model (DEM)	All points
3.	AMERIFLUX flux tower data	4 points

Tasks

1. Obtain and QC met data.
2. Generate topographic data from DEM
3. Model potential solar influx for region over the year
4. Regression of temperature against solar influx for station data; remove trend
5. Interpolate residuals
6. Use empirical relations to derive SRAD and VPD
7. Evaluation and comparison with existing methods

Deliverables

1. A high quality database of meteorological data for the study area, comprising daily observations, error flags for inconsistent data, station daily means (with distribution information) and assimilated values.
2. A stack of meteorological parameter surfaces suitable to drive models of ecosystem process which accurately reflect the temporal trends and interrelations of the data, along with the underlying microclimatic effects of the areas complex topography.
3. Paper: "To what extent can geostatistical techniques reduce the error of meteorological surfaces for modelling applications?

Paper 2

Hypothesis

Modelling non-climax ecosystems with a 'spin up' approach fails to capture the regional variation in the carbon balance, as ecological gradients in vegetation carbon pools are inadequately expressed. Estimates of vegetation state variables derived from EO products are likely to better reflect the distribution of biomass and its allocation than the 'spin up' approach.

Objectives

1. To generate detailed surface vegetation state variables from EO derived products and a spatial database of management and fire history.
2. To quantify error in the parameter surface.
3. To evaluate the significance of ecological gradients in estimating the carbon storage pools of the region: Is it worth the extra complexity and time commitment of capturing these dynamic gradients, or can 'spin up' results in a near equilibrium state adequately capture the regional carbon pools.

Rationale

Many regional scale carbon budgets are derived from multi scale measurements, combined with a process based model as a scaling tool (e.g. Turner *et al.,* 2005). Many of these models require a 'spin up' to recreate existing carbon storage pools for the vegetation on the ground. The resulting state variables of the vegetation layer are in a near equilibrium state; that is, the dynamics of the vegetation layer are unrealistic for non-climax communities. Dynamic processes (e.g. regeneration and succession) and ecological gradients are not reflected in such models, and as such, the resulting carbon budgets may contain significant errors. Models which reflect the ecological processes in the vegetation layer are likely to predict a representative carbon budget more successfully, particularly in areas with intensive management or fire activity.

Parameterisation of the vegetation layer via EO derived data will proceed by supervised and unsupervised classification techniques (e.g. Eastman, 2003), based on spectral information from

LANDSAT, and textural information derived from IKONOS imagery. Ground survey data from a number of sources (see below) will be used to validate and assess these classifications. Crucially, error statistics will be calculated for the classification using linear spectral un-mixing (LSU) models (Adams and Smith, 1986; Marsh *et al.*, 1980), 'soft' (Bayesian) classifiers (Eastman, 2003) and ground data. LSU takes the set of generated thematic classes, and assigns pixels to each based on the probability of membership to that class. It is assumed that each pixel is a linear additive combination of the generated classes, and so mixed pixel problems are highlighted. LSU thus provides a method for measuring the uncertainty inherent in classification of heterogeneous ecosystems. 'Soft' classification is another probabilistic technique which allows generation of error statistics. The 'soft' classifier assigns pixels to a class via Bayesian belief statistics; here any pixels which poorly match any of the generated classes are highlighted as a residuals image. Thus 'soft' classification can inform us of areas poorly represented by the known classes.

Phenology and biomass data are to be mapped through calibration of orthogonal transformations of EO radiance data (tasselled cap indices; Crist, 1983; Crist and Cicone, 1984a; 1984b) against intensive ground survey data and existing databases (e.g. Turner *et al.*, 2005). The use of tasselled cap rotations decreases the dimensionality of the problem, resulting in two orthogonal planes of information relating to soils and vegetation. Production of physiologically meaningful indices is massively useful for interpretation, and the resulting component planes are known to be highly correlated with vegetation characteristics (e.g. Turner *et al.,* 2005) such as leaf area index (LAI). Physiological correlates, combined with data from LIDAR (Light detection and ranging) and crown texture derivatives from EO data provide a means to generate spatial estimates of vegetation carbon storage pools from published allometric equations.

Inputs

1. EO imagery from a variety of platforms (1m – 1km)
2. SOLARFLUX spatial insolation model
3. US Forest Services plant associations floristic database
4. Pacific North West Research Station forest inventory database
5. GAP analysis vegetation classification
6. OSU 'OTTER' transect LIDAR data (light detection and ranging)
7. Ground survey data from OSU and field visits

Tasks

1. Process imagery; filter noise and extract TC components and texture information
2. Thematic mapping via 'in process classification' (map eco-regions)
3. Error analysis and statistics on classification
4. Extract EO derivatives at sample locations and extend biophysical data via regression
5. Evaluate accuracy via re-sampling

6. Generate 'spin up' estimates of state variables
7. Comparison with 'spin up' approach and sampled data

Deliverables

1. An improved vegetation classification for the study region, including error estimates at the pixel level, with errors partitioned between misclassification error (confusion between classes due to 'mixed pixels'), and identification error (pixels which poorly match and known class).
2. Biomass mapping and estimated fuel loads for the study region.
3. A comparison of model initialisation techniques between a prescribed, near equilibrium vegetation layer (Biome BGC), and a dynamic gradient based vegetation layer (Dalec/ACM/SPA), parameterised from EO data.
4. Paper: "How can EO data best be employed in the estimation of vegetation state variables for carbon modelling?"

Paper 3

Hypothesis

A data driven approach, combined with EO derivatives more accurately represents the soil surface than a pure simulation approach.

Objectives

1. To generate accurate soil depth, moisture and carbon storage state variables from EO derived products, pit samples and a spatial database of management and fire history.
2. To quantify error in the parameter surface.
3. To evaluate the performance of EO derived and data driven methods of the soil surface state variable calculation against the results of 'spin-up' simulation.

Rationale

Perhaps the main reason ecosystem carbon stocks are simulated via 'spin up' is the difficulty or prohibitive cost of intensively sampling at a large scale. In this project we intend to demonstrate that advances in remote sensing and geostatistical techniques can provide regional scale estimates of carbon stocks which more accurately reflect ecological dynamics and presented data. Whilst some authors have demonstrated that EO data can potentially predict soil carbon stocks (e.g. Stephens *et al.,* 1995), such studies rely upon open ground or sparse canopy cover for success. Other authors (e.g. Heuvelink and Webster, 2001) present the case for statistical interpolation of soil parameters.

The mixed vegetation types found in the proposed study area may provide some opportunity for remote sensing of the soil surface, particularly at the eastern end of the transect, where open canopy juniper ecosystems dominate. Recent advances in EO technology could possibly be exploited to retrieve soils parameters from sparse canopy areas, via canopy scattering models (e.g. Lewis & Disney, 1998). EO derived vegetation surfaces from the previous paper may also be of use here, as known relationships between above ground biomass and soil parameters can be exploited (e.g. Law *et al.*, 2004).

Statistical relationships between topographic and soil TC components (see above) could potentially be exploited to extensify measurements from open canopy areas. This process could be aided and informed from existing soils maps, pit data (supplied by the US Department of Agriculture), and an intensive sampling excursion to be undertaken next year (spring/summer 2006). Existing research (Homann *et al.*, 1998) has compared existing soils organic carbon maps with ground data to supply error statistics for these products. If suitable data density can be achieved, geostatistical techniques outlined above may be of use. Finally, soil temperature profiles can be easily estimated using known empirical relations (e.g. Fu and Rich, 2002).

Inputs

1. EO imagery from a variety of platforms (1m – 1km)
2. Ground survey data from OSU and field visits
3. SSURGO spatial soils database
4. US Forest Services plant associations floristic database (contains soil indicators)
5. 'Spin up' state variables generated above (see paper 2)

Tasks

1. Field excursion to increase data coverage
2. Identify and implement EO techniques
3. Incorporate EO data and ground sampled data via statistical techniques
4. Validation using USDA data
5. Comparison with 'spin up' data

Deliverables

1. SOC, temperature profile and depth mapping for the study region.
2. A comparison of model initialisation techniques between a prescribed, near equilibrium soil surface (Biome BGC), and a dynamic gradient based surface (Dalec/ACM/SPA), parameterised from EO data.
3. Paper: "To what extent can EO data improve the estimation of soil carbon pools for modelling purposes?"

Paper 4

Hypothesis

Initialising and driving carbon exchange models with parameter sets derived from a combination of EO data and ground based observations improves performance over the 'spin up' approach. The representation of ecosystem processes in near equilibrium inadequately captures carbon dynamics on the regional scale.

Rationale

Spatially explicit modelling of the carbon flux has an important role in our understanding of climate change. Whilst it is relatively simple to parameterise a model for a single pixel, such intensive measurements of state variables, parameters and drivers are not possible on even a modest spatial scale. In order to overcome these issues, it is necessary to extend the data we do have by such processes as detailed above. However, such methods are time consuming, and likely to be computationally intensive. An alternate approach is to simulate parameters which are difficult to extensify via a 'spin up' process. Whilst the differences in the model drivers and state variables derived from EO techniques and those generated by 'spin up' may be large, it is unclear whether these differences will be relevant in terms of the predicted carbon flux for the region. It may be possible that the effects of these regional gradients averages out, and has little impact on the overall carbon budget; however, interesting patterns may immerge here. Local differences may correspond to certain topographic features, temporal scales or combinations of surface variables. In order to explore these issues, two runs of the same model (DALEC) will be initialised; one with a parameterisation based around the 'spin up' approach, the other using an ensemble of parameter sets derived from EO estimates, perturbed around their error statistics. Results of these runs will be compared. Since one run is essentially probabilistic, the 'spin up' results can be compared with the PDF of the EO driven run. Local areas with large differences (exceeding the 95% confidence of the PDF) can then be flagged, and correlated against topographic, ecological and temporal factors.

Inputs

1. EO and ground data derived surfaces of drivers and state variables
2. 'Spin up' derived state variables

Tasks

1. Parameterise and run DALEC using the drivers generated in paper 1, and the 'spin up' state variables
2. Generate an ensemble of DALEC runs using the drivers and state variables derived from spatial data sources
3. Statistically summarise the stochastic run for each pixel
4. Flag pixels where the 'spin up' run exceeds the 95% CI of the stochastic run
5. Analyse and summarise performance and error of 'spin up' approach

Deliverables

1. An accurate, probabilistic assessment of the regional carbon budget
2. An assessment of gross differences (exceeding 95% CI) in flux estimation between an EO based parameterisation, and a 'spin up' approach
3. Paper: "An assessment of the effects of a near equilibrium treatment of carbon pools on the estimation of the regional carbon budget"

Progress to Date

Progress towards the project goals has been steady over the last 9 months. Contacts have been made both in the UK and abroad, particularly at Oregon State University and the United States Forest Services. Work so far has focussed on the acquisition, reformatting and collation of datasets. Generation of a meteorological database for the processing of paper 1 has been successful, although recent meeting during field work in Oregon have highlighted areas for concern, particularly in the area of quality control. The assimilative step inserted into the processing path will alleviate these problems. Spatial data products acquired have been organised in an Arc/Info geodatabase for ease of cross tabulation and processing. This required the re-projection of many sets, along with general housekeeping steps, such as cropping datasets to the required size. Progress with meteorological drivers has mainly been made in the temporal dimension; analysis has highlighted interesting trends in the regional weather patterns, particularly the variable large scale lapse rate over the seasonal cycle (see fig 3). So far I have successfully partitioned the large and small scale components of trend in time, with the resulting temporal variance structure (fig 4). Note the rapid increase in variability within a week, whilst intra monthly variation stabilises. This reflects the time scale of frontal systems for the region (Taylor and Hannan, 1999). For time scales beyond those graphed, seasonal effects become relevant (fig 5).

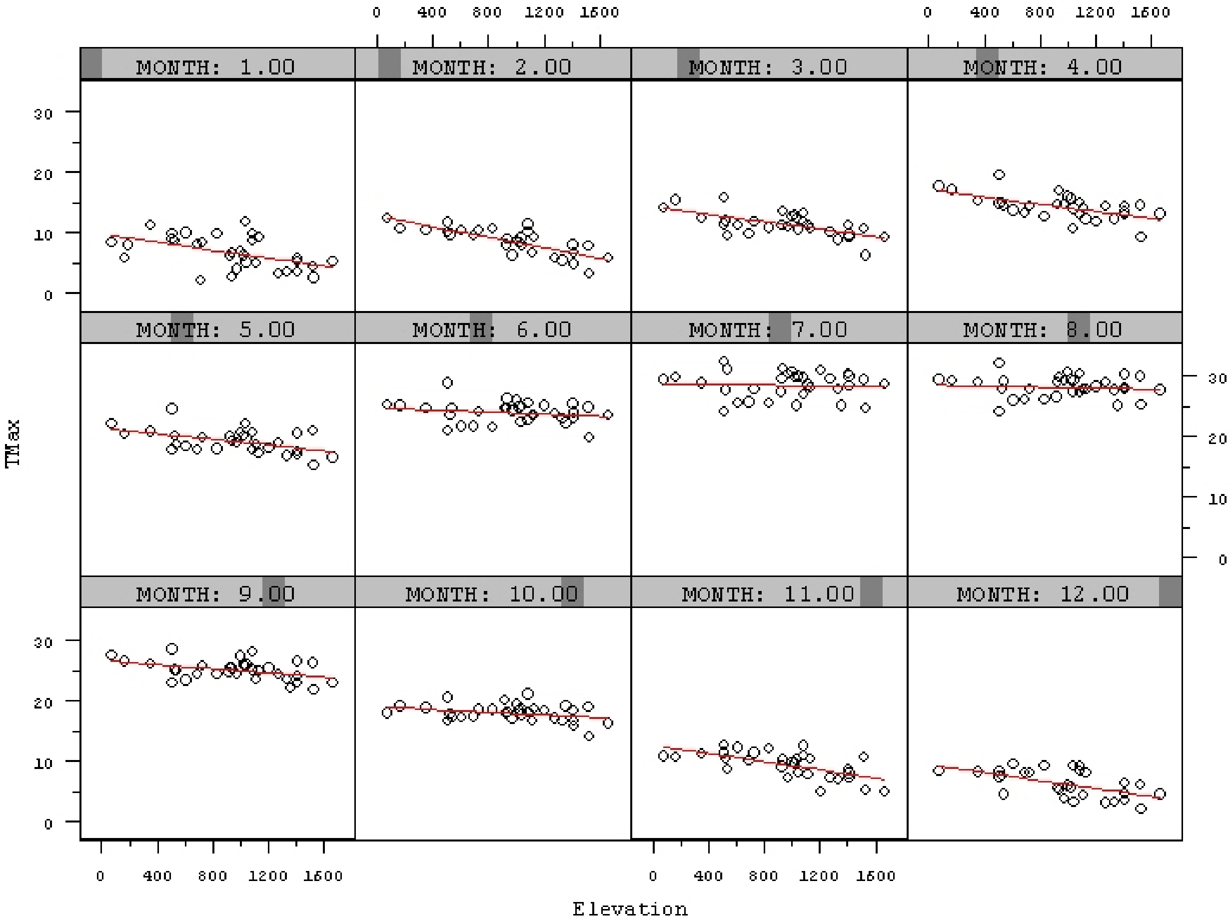

Fig 3: Seasonal cycle of regional lapse rate.

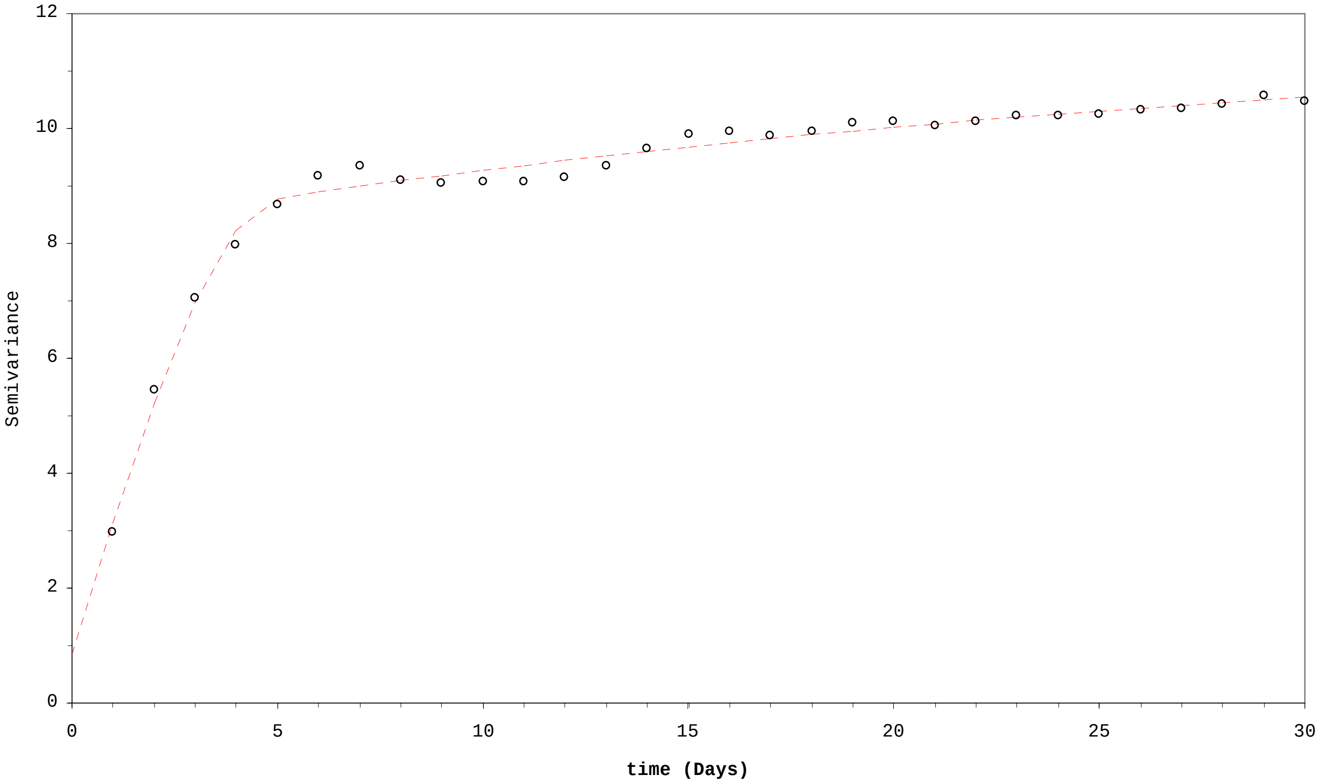

Fig 4: Small scale component of trend; between day variance increases with temporal separation.

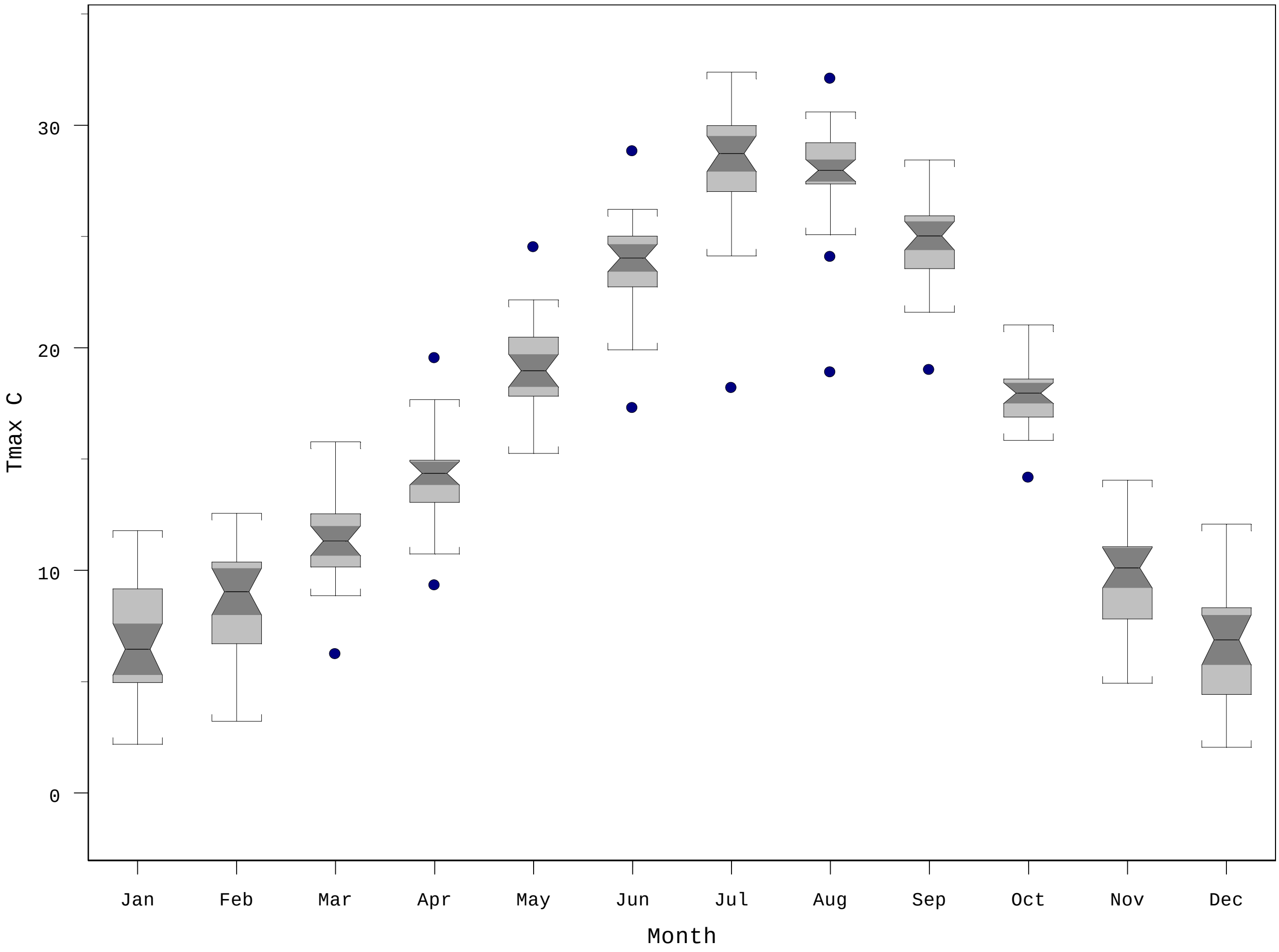

Fig 5: Large scale (seasonal) trend component of max temperature.

Having partitioned the trend components, it is easy to visualise where pure regression techniques (which filter the small scale 'noise' component) may fail. Fig 6 is a slice through the 4D space, indicating areas of high residual variation in elevation and time. Here we see that particularly high errors occur for all elevations in May and high elevations in November if the small scale component of variation is ignored. To a lesser extent, negative errors occur at low to mid elevations in February through March, and at high elevations from June through October.

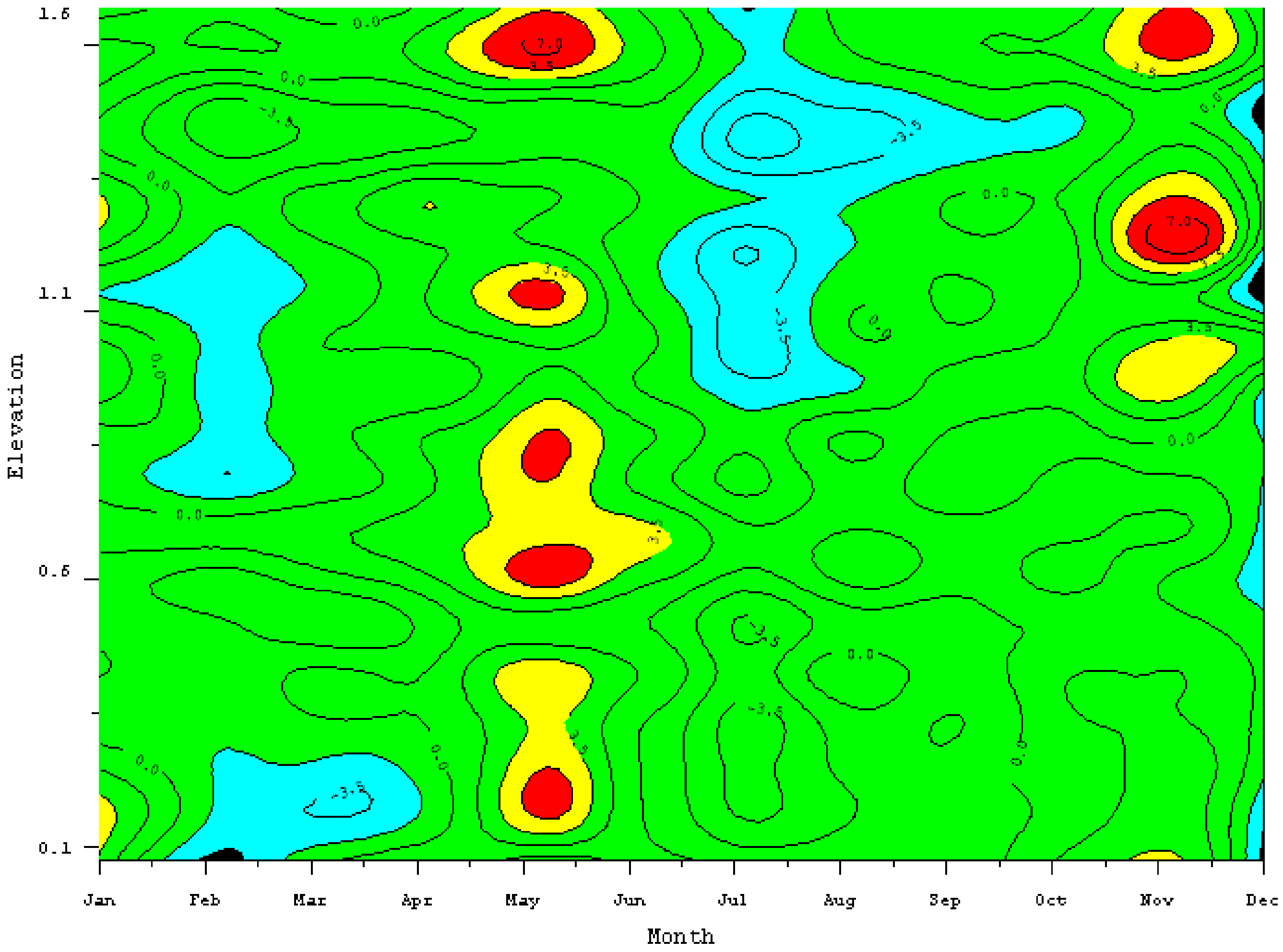

Fig 6: Distribution of errors in space and time for the large scale trend component. Scale runs low to high as follows: blue, green, yellow, red. (Elevation in Km.)

Recent fieldwork in Oregon has increased data coverage for vegetation classification and biomass mapping; particularly in the poorly sampled juniper and fir ecotopes. Field visits also improved my understanding of the regions ecosystem, which will be invaluable when the modelling exercise begins in earnest. Finally, during the course of the last 9 months I have made many contacts from various institutes and organisations. Possible collaborators include Larry Mahrt for paper 1, and Bernard Bormann for paper 3.

Skills Acquired

During the course of the last 9 months I have attended MSc courses on GIS, digital image analysis and fundamentals of remote sensing. This has improved and extended my existing skills in this area. I have also been studying elements of non-stationary and multivariate geostatistical analysis, including space time methods. My supervisor has secured funding for my attendance of an advanced geostatistics course in Michigan, in October 2005. I have also spent time acquiring database construction and management skills, as the datasets for the project are typically very large, and may be required in different spatio-temporal scales for analysis; storing data as a database allows intelligent query and summary functions which are hard to perform with simple spreadsheets. Flexible software tools can also be implemented with ease within the database.

Other areas of interest include computational statistical methods (Monte Carlo sampling etc.), particularly the use of ensemble Kalman filters for non-linear systems. Currently I am learning Fortran 90 programming, Matlab programming, and S-Plus statistical programming: It is intended that development of a suite tools with these languages will provide a generalised environment for the analysis of space time data problems, by dynamically linking software in different environments with the geodatabase.

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