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# Application of a simple multiplicative spatio-temporal stream water quality model to the river Conwy, North Wales

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## Abstract

We use a simple multiplicative spatio-temporal model to describe variability in a sequence of water quality monitoring data from headwater streams in the Conwy catchment, North Wales. The spatial component of the model treats concentrations as due to simple mixing of a small number of distinct source types, each associated with particular upstream catchment characteristics. The temporal component allows concentration variability due to seasonal or hydrological change. We apply the model using three candidate catchment characteristic classifications to generate mixing concentrations, and a seasonal component to describe temporal variability, and test a range of sub-models. We identify a cross-classification of soil and land cover as providing the best spatial indicator of water quality of the classifications considered. The spatial model based on a selected grouped cross-classification was shown to account for between 35% and 90% of the spatial variability and the seasonal model accounted for between 45% and 100% of the temporal variability in the data.

Analysis of residuals showed an inverse relationship between DOC and sulphate and between hydrogen ion concentration and calcium and magnesium. We also found residual correlations between sites which are strongly related to landscape class. These are attributed to landscape class by time interactions which are not accounted for in the simple multiplicative model.

*Key words*: stream water quality; landscape; classification; multiplicative;

# 1 Introduction

Stream water quality is measured to determine whether acceptable ecological standards are being met, and to support investigations into the source and fate of material in solution and suspension. Water quality management through contaminant source control is based on the interpretation of the data generated by monitoring programmes. Data collected commonly include repeated measurement of water quality variables at fixed sampling locations, generating spatio-temporal datasets. These give useful but limited information on the contaminant budget of a catchment, and a fuller spatio-temporal description of water quality variability can be provided by models representing sources and their fates at a range of scales, supported by water quality measurements and other features of the catchment.

Stream water quality models may rely on the known distribution of sources and source characteristics to track material in solution or suspension through a stream network. The application of these models does not require stream water quality measurements, though they may be useful for calibration. Alternatively, models may use river water quality measurements to infer source magnitudes given the upstream distribution of source locations, and extrapolate locally based on known source locations upstream of unmonitored stream sites. This approach tailors loss estimation to local conditions, but if used without other knowledge may neglect useful information. For local use, a hybrid approach is to start with a model which includes initial numerical estimates of magnitudes of known source types, and calibrate the model from stream water quality measurements.

There are a number of models which use accumulated knowledge of source magnitudes to estimate water quality at new sites. These have been developed largely to account for agricultural diffuse source pollution by the nutrients nitrogen and phosphorus. Losses of these nutrients have been modelled by nutrient budgeting based on farm management including details of livestock, crop management and drainage characteristics. Losses are estimated by a simple accounting procedure, and are often expressed on an annual basis. Johnes[1] presents a simple annual loss accounting model, and this approach has been widely adopted[2,3] . Other models estimate losses at a finer timescale and include a component allowing losses to vary according to hydrological conditions. Catchment scale models of this type generally include a delivery component describing transfers to the larger river network, and a routing component describing transfer through the river network, possibly allowing for point sources. These models include AGNPS[4] , SWAT[5] , HSPF[6] , MAGPIE[7] , and are reviewed by Borah and Bera[8,9].

Models which use stream water quality to infer source magnitudes are generally of regression structure, and may be partially constrained to give some natural mixing interpretation. The simplest such model uses unstructured regression of concentrations on a range of catchment characteristics[10,11]. Unconstrained models of this form may include negative coefficients which have no natural interpretation and which may generate negative concentrations. If logged concentration data are used as response variables, then additive terms imply a multiplicative model of the raw data, which is not compatible with additive contributions from a number of sources. These considerations suggest that the spatial component of a model should be interpretable as a sum of (positive) contributing sources. These simple nutrient accounting models commonly rely on a landscape classification, with characteristic nutrient or other loss from each class[12-17]. Apart from individual studies, a modelling framework, SPARROW, has been developed for estimation of contributing pollutant sources from stream water quality monitoring data using a constrained regression approach[18,19]. Where there is temporal variability in water quality this may be seasonal or driven by hydrological variability which may be due to a dilution effect of relatively uncontaminated precipitation. A simple dilution effect is multiplicative, affecting all concentrations derived from fixed sources equally. In practice, a hydrological response may mobilise new sources, and precipitation does contain some contaminants. Nevertheless, the dilution argument does suggest a multiplicative term may be appropriate for the temporal component of a simple water quality model. If precipitation is uniform over a wide area, then dilution may be regionally similar. An extension of the SPARROW modelling framework to include a multiplicative temporal effect has been described by Wellen *et al*.[20].

We apply a simplified version of Wellan *et al*'s[20] spatio-temporal model in which the spatial component is additive and the temporal component a seasonal multiplier of the spatial component. We examine the performance of the model in describing the variability in concentration changes measured in headwater subcatchments of the Conwy catchment, North Wales. Our model excludes point sources, which are largely absent from the headwater subcatchments sampled. The influence of any instream processes is assumed to be accounted for through their influence on the estimated drainage concentrations from the landscape classes used at the scale of the headwater subcatchments. The model can be interpreted as assuming simple mixing of end-members generated by a small number of landscape classes, with equal dilution or proportionate generation at equal times, for all end-member sources.

We consider three different landscape classification schemes as potential end-member sources for the spatial component of the model. Each scheme is derived from national UK databases. On any sampling occasion, each landscape class is assumed to generate an end-member runoff component with characteristic water quality. Downstream water quality is taken to be a mixture of end members, according to the upstream proportion of each class under the selected classification scheme. The model does not allow interaction between time and space, so that concentrations may not stay fixed for one landscape class while varying in another class. Interaction between landscape classes and temporal effects may be tested through residual analysis. The model is applied individually to a range of variables, so that proportional changes in concentration over time may vary between water quality variables.

In our application of the model to the Conwy catchment, water quality is measured quarterly through two years, and given this limited number of sampling occasions, we estimate a seasonal effect only, recognising that this will be influenced by hydrological and other conditions at the time of sampling.

## 2 Methods

The spatio-temporal model expresses concentration of a single water quality variable as the product:

$$y_{s,t} = c_s \lambda_t \tag{1}$$

In equation (1), $y_{s,t}$ is a concentration measurement at location $s = 1,...,n_s$ and field excursion $t = 1,...,n_t$. The parameters $c_s$ and $\lambda_t$ represent the spatial and temporal components of the model. The time parameter $\lambda_t$ adjusts simulated concentrations $c_s$ as they are influenced by such factors as hydrological conditions and season at the time of sampling.

We extend the model of equation (1) to allow $c_s$ to be a function of the configuration of landscape classes within the catchment, which are assumed to be available as a complete fine-scale spatial coverage. In particular, where a catchment property is distributed upstream of a sampling point, we assume simple mixing of upstream contributions by landscape class, so that

$$c_s = \sum_j p_{s,j}\vartheta_j \qquad (2)$$

where in equation (2) $p_{s,j}$ is the proportion of the headwater subcatchment covered by landscape class $j = 1,...,m$ and $\vartheta_j$ is the concentration in water draining landscape class $j$ at the defined reference sampling time. This is the functional form of the spatial representation used by Cooper *et al.*[13] and in terms of fluxes assumes simple mixing of contributions from each class, under the condition that the flow from each class is area-proportional.

We further extend the model to allow $\lambda_t$ in equation (1) to be a function of time-varying covariates, so

$$\lambda_t = f_t(\varphi) \qquad (3)$$

In equation (3), $f(\varphi)$ is some function whose value at any point in time depends on the parameter array $\varphi$. Combining equations (1), (2) and (3) gives

$$\begin{aligned} y_{s,t} &= \left(\sum_j p_{s,j}\vartheta_j\right)\left(f_t(\varphi)\right) \\ \log\left(y_{s,t}\right) &= \log\left(\sum_j p_{s,j}\vartheta_j\right) + \log\left(f_t(\varphi)\right) \end{aligned} \qquad (4)$$

Our hypothesis is that equation (4) explains sufficient of the variability in concentrations to be useful for estimating of water quality in headwater streams at large temporal and spatial scales. We include random terms in the logarithmic form of equation (4), giving

$$\begin{aligned} \log\left(y_{s,t}\right) &= c_s + \lambda_t + \eta_{s,t} \\ c_s &= \log\left(\sum_j p_{s,j}\,\vartheta_j\right) + \varsigma_s \\ \lambda_t &= \log\left(f_t\left(\varphi_k\right)\right) + \xi_t \end{aligned} \qquad (5)$$

In equation (5) $\varsigma_s$ is a random site effect, $\xi_t$ a random sampling occasion effect, and $\eta_{s,t}$ a residual error term assumed uncorrelated in time and space. Wellen *et al.*[20] also include temporal correlation in their model through a random walk structure for the temporal parameters. Because we apply the model only to independent headwater subcatchments for we ignore instream losses (Wellen *et al*'s[20] $H^S_{i,j}$ and $H^R_{i,j}$). While equation (5) is the most complete form of the model used, we also consider sub-models which excluding the fixed effects $\vartheta_j$ and $\varphi_k$.

The models are applied to a number of measured water quality variables, and inferences made on the relationship between these variables through studying both estimated model parameters and residual series.

# 3 Application

## 3.1 Spatio-temporal survey

We sampled stream water from 39 independent headwater subcatchments of the Conwy catchment in North Wales (Fig 1).

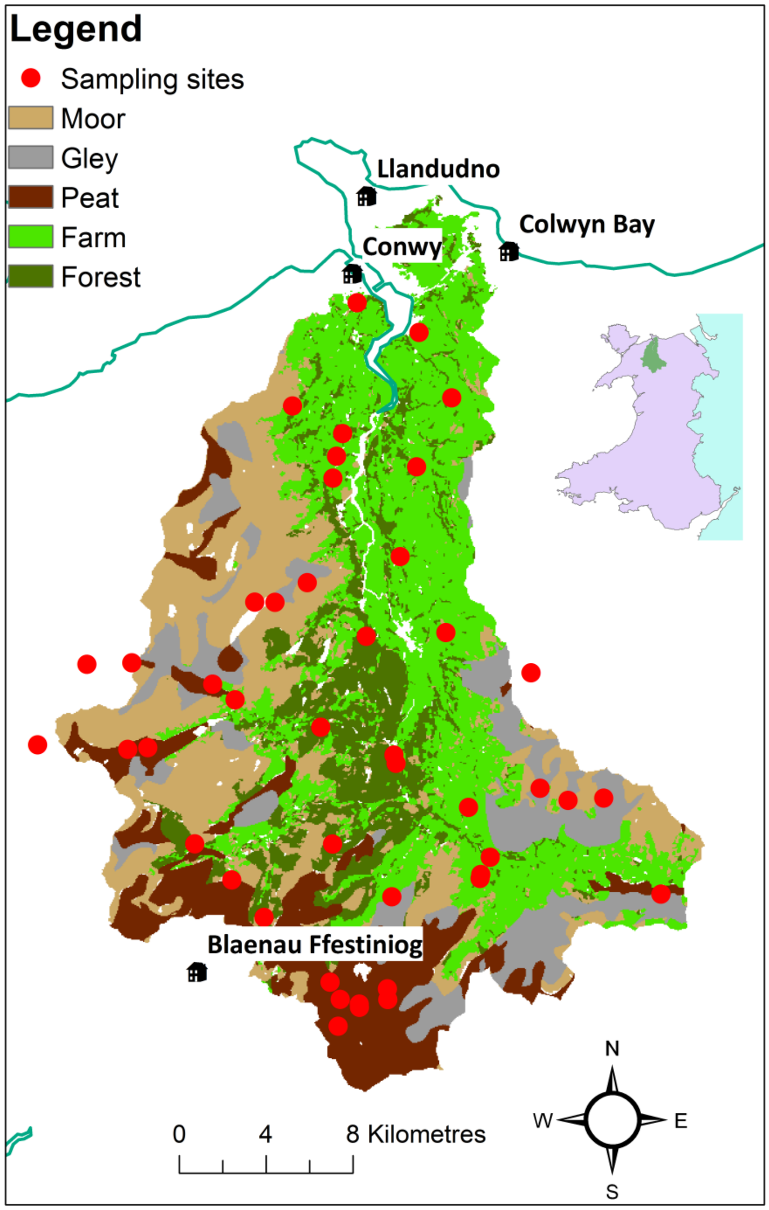


**Figure 1. The Conwy catchment, North Wales**

The Conwy catchment (3$^{o}$50W 53$^{o}$N) includes a range of common upland UK landscapes (73% of the catchment is above 200m compared with 28% of the UK) with the main components being the mountains and moorland of Snowdonia, plantation forestry with non-native coniferous species, and enclosed improved grazing land for sheep and cattle. There are smaller areas of broadleaved woodland and little urbanisation. Elevation varies from sea level to 1060m, with rainfall between 600 and 3000 mm $yr^{-1}$. The catchment above the tidal limit is described in detail by Evans *et al.*[14].

The subcatchments monitored are upstream of registered point sources such as sewage treatment works or industrial effluent discharge, most draining uninhabited moorland or forest. A small number of farmed subcatchments included farm buildings where washings from yards or seepage from septic tanks. Such indeterminate sources are taken as contributing to the overall diffuse source contribution for the purposes of this analysis. Samples were collected at each subcatchment site on eight occasions at three-monthly intervals between September 2008 and June 2010.

Headwater subcatchments were chosen with the aim of providing good estimates of model parameters rather than to estimate population values of variables. To this end they were selected where possible to be dominated by a single landscape class expected to strongly influence water quality as defined and identified from maps and a field visit. Simple random sampling of first order streams would include numerous very mixed subcatchments with little information for the estimation of parameters associated with landscape differences in drainage water quality. The purpose here is to demonstrate a modelling approach at an example catchment, rather than to attempt to provide a fully parametrised model which can be applied without modification throughout the United Kingdom. The modelling approach may be applied elsewhere, with estimation of local parameters. If used elsewhere with the parameter values estimated for the Conwy, residual analysis would provide some insight into differences between the study catchment and the Conwy. eThe three landscape classifications used in modelling were based on:

1. Soil class
2. Land cover
3. Dual soil/land cover ("landscape", cf Evans *et al.*[14] )

### *Soil class*

We use the England and Wales National Soil Resources Institute **(**NSRI**)** LandIS soil classification http://www.landis.org.uk/index.cfm, combining some soil classes which are either poorly represented or distributed in the catchment. The final classes used are shown in Table 1.

**Table 1. Soil classification**

| Soil class | LandIS soil association |
|---|---|
| Humic ranker | 311 |
| Brown soil | 541, 561 |
| Brown podzolic soil | 611, 612 |
| Stagnopodzol | 654 |
| Stagnogley | 713 |
| Stagnohumic Gley | 721 |
| Peat | 1013 |

### *Land cover (LCM)*

The UK 2007 Land Cover Map (LCM2007, http://www.ceh.ac.uk/LandCoverMap2007.html) includes 23 classes at UK scale. After some consolidation of major land cover groups in to account for poor representation in the Conwy catchment, we use the classes shown in Table 2.

**Table 2. Land cover class**

| Land cover class | LCM 2007 class |
|---|---|
| Broadleaved Woodland | 1 |
| Coniferous Woodland | 2 |
| Arable and Horticulture | 3 |
| Improved Grassland | 4 |
| Unimproved Grassland | 5,6 |

| | |
|---|---|
| Acid Grassland | 8 |
| Heather | 10 |
| Heather Grassland | 11 |
| Bog | 12 |
| Montane  and Rock | 13,14 |
| Fresh water | 16 |
| Built up | 22, 23 |

## *Dual soil/land cover (“ landscape”)*

In a previous study of the Conwy catchment, Evans *et al*[14] identified five major landscape classes, defined by combining soil and land cover classes. They started from a landscape division based on all soil and land cover combinations present and clustered these into five classes based on available stream water quality data The grouped landscapes are defined as “Mountain”, “Peat”, plantation coniferous forestry (“Forest”), gley moorland (“Gley”) and enclosed farmland (“Farm”), and used these to model water quality in the catchment. The combination of class groups used in the landscape definition is shown in Table 3.

**Table 3. Combined landscape classification**

| LandIS soil association | LCM2007 land cover class | Combined landscape class |
|---|---|---|
| | 1,2 | “Forest” |
| | 3,4,5,23 | “Farm” |
| 1013 | | “Peat” |
| 721 | | “Gley” |

| | | |
|---|---|---|
| All present except 721 and 1013 | 8,10,11,13,14 | "Mountain" |

This choice of grouping is also supported by evidence from other studies of enhanced atmospheric deposition of some water quality variables, differences in soil processes in different soil types, particularly between peat and mineral soils, and the strong association between water quality and farming, where the fertility of the soil is artificially influenced by farming practices [12,21,11].

The three classifications do not explicitly include a number of covariates which are likely to influence water quality, including topography, slope and precipitation. However, these covariates are highly correlated with catchment characteristics and their influence is therefore partly accounted for within the classification schemes.

## 3.2 Sample collection and chemical analysis

Field samples of stream water were collected in polypropylene bottles and stored at $4^0$C prior to analysis. Major ions sodium, potassium, calcium, magnesium were analysed using ICP-OES; chloride and sulphate using ion chromatography; nitrate colorimetrically using a SEAL AQ2 discrete analyzer; pH by pH electrode and non-purgeable organic carbon (NPOC), taken to be equivalent to dissolved organic carbon (DOC), using a Skalar

Formacs analyser. The data and details of the chemical analysis methods used may be accessed at Cooper *et al.*[22].

### 3.3 Model implementation

We used the `nlmer` routine in the `R` package (http://www.r-project.org/) `lme4` for non-linear model fitting. We fitted seven models of increasing complexity. We used the model shown by equation (5) as the most complex, with sub-models as shown in Table 6.

**Table 6. Model components (cf. Equation (5))**

| Model no. | Model | Spatial effect $C_s$ | Temporal effect $\lambda_t$ |
|---|---|---|---|
| **1** | Simple mean | - | - |
| **2** | Random spatial only | $\varsigma_s$ | - |
| **3** | Random temporal only | - | $\xi_t$ |
| **4** | Random spatial and temporal | $\varsigma_s$ | $\xi_t$ |
| **5** | Random and fixed spatial; random temporal | $\log\left(\sum_j p_{s,j}\vartheta_j\right)+\varsigma_s$ | $\xi_t$ |
| **6** | Random and fixed temporal; random spatial | $\varsigma_s$ | $\log\left(f_t(\phi_k)\right)+\xi_t$ |
| **7** | Random and fixed temporal and spatial | $\log\left(\sum_j p_{s,j}\vartheta_j\right)+\varsigma_s$ | $\log\left(f_t(\phi_k)\right)+\xi_t$ |

# 4 Results

## 4.1 Differences between models and choice of spatial covariates

Model performance is first assessed using AIC (Akaike Information Criterion) values. The lowest AICs for the 3 spatial classifications were given by model 7 for most water quality variables, with the combined landscape classification in most cases giving the lowest AIC. Exceptions were potassium, for which model 5 was preferred. For both nitrate and potassium, the land cover classification gave lower AIC than the combined landscape. This is thought due to greater resolution of agricultural land using LCM2007 land cover, where the leaching of these two nutrients varies considerably within different crop and grazing regimes. The apparent superiority of Model 5 for potassium is due to the lack of a consistent seasonal pattern in measured concentrations. With the exception of DOC and nitrate, the poorest model fit in terms of AIC was for the soil classification. For the major cations Na, K, Mg, Ca fitting a random temporal effect (Model 3) gives an estimated variance of the random effect of zero, indicating that there is no detected seasonal variability between sites. With the exception of K, a seasonal effect is detectable for these variables when explicitly parametrised (Models 6 and 7). DOC, NO3 and pH show both seasonal effects and differences between classes within classification schemes. Results are summarised graphically in Figure 2 for models 4 to 7. Note that models 4 and 6 include no spatial component, so their AIC is the same for all choices of spatial classification.

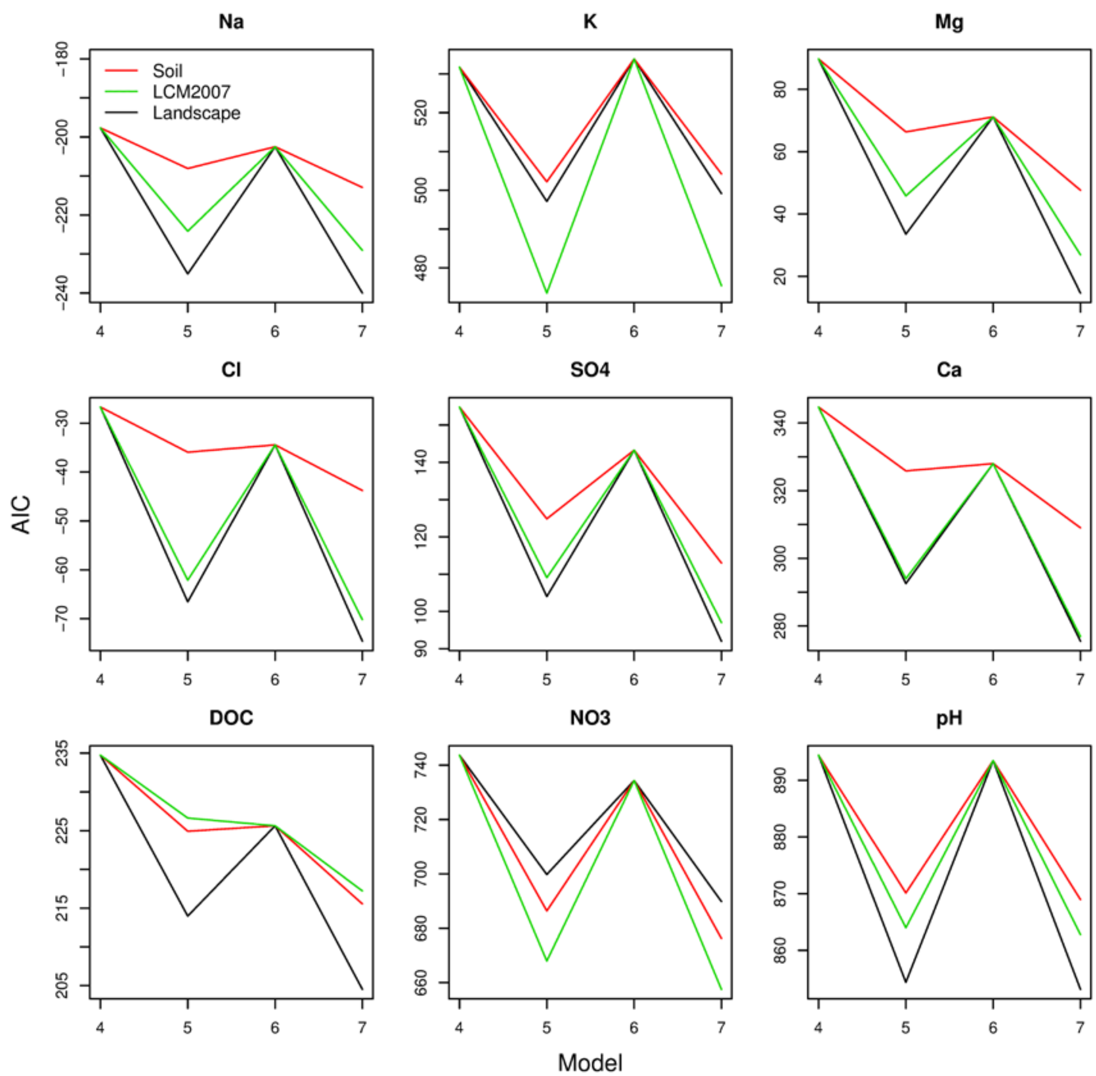


**Figure 2. AIC values by determinand and model**

Model 4 includes spatial and temporal effects as random only. For models 5 to 7, some of this variability is accounted for by fixed effects and some by random effects, but the total spatial and temporal variability accounted for remains the same as for model 4. The variance proportions associated with the application of model 4 to each water quality variable are shown in Figure 3. The dominant source of variability is spatial rather than temporal for all variables. The seasonal effect is greatest for DOC, nitrate and pH.

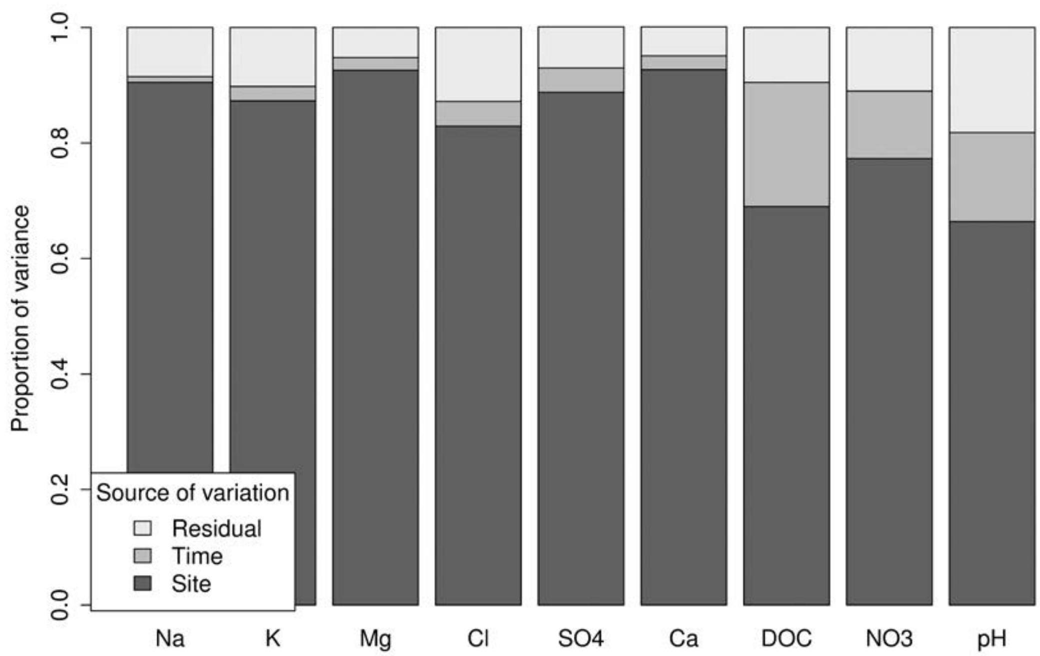


**Figure 3. Proportions of variance accounted for by site, sampling time and residual for Model 4**

## 4.2 Differences between choice of spatial and temporal covariates

Figures 4 and 5 show the spatial and temporal variability accounted for by the fixed effects model, as a proportion of the variability accounted for by a random effect alone. The figures suggest that the quality of fit between variables is quite consistent within landscape classifications. Both the land cover and the landscape classification give similarly high explanatory power. However, the landscape classification has fewer parameters and therefore tends to have lower AIC values. Figure 5 shows the very high proportion of the temporal variability which is accounted for by the seasonal model. The data for these variables suggest that spatial class influences concentrations, but that there is consistency between sampling times at individual sampling points. That is to say, site effects within spatial classes are significant and persistent. Differences between sampling occasions tend to be consistent regardless of site or spatial class.

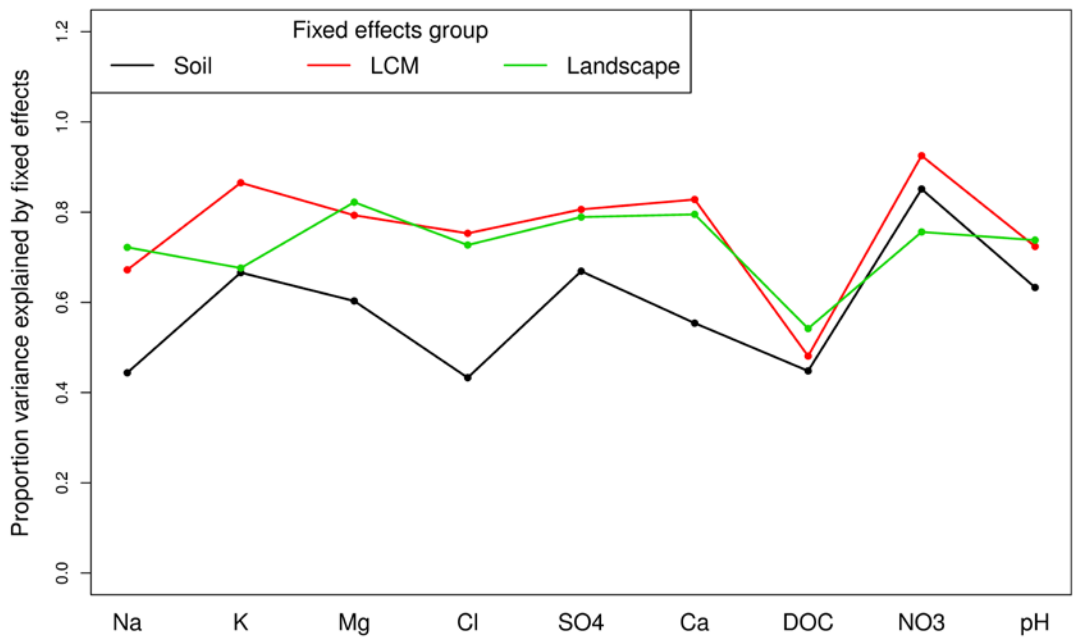


**Figure 4. Performance of fixed effects groups in terms of site variance accounted for**

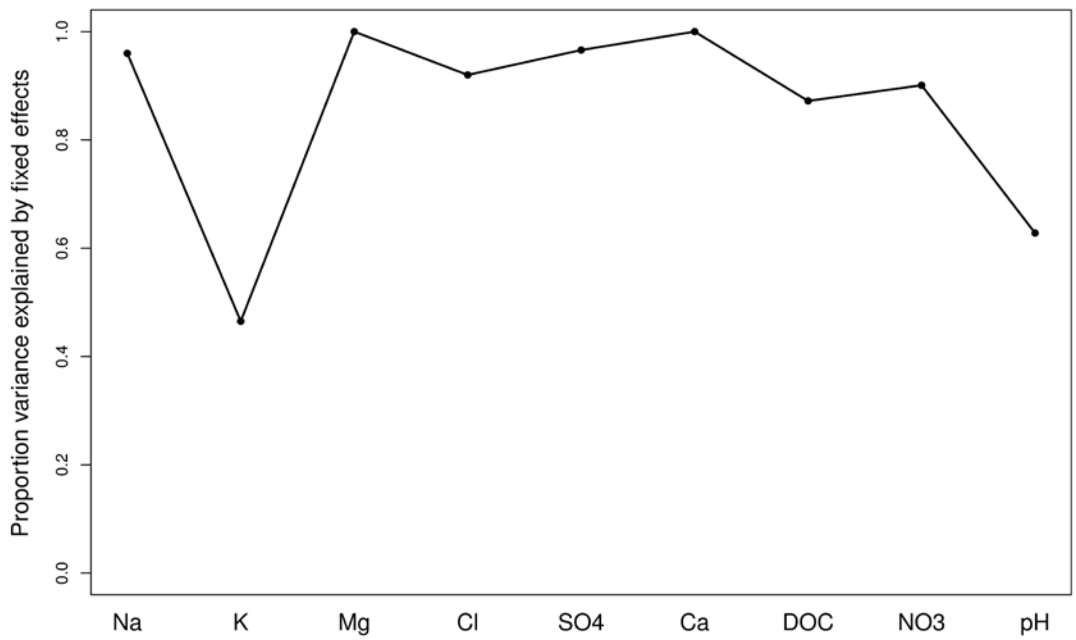


**Figure 5. Performance of seasonal fixed effect in terms of time variance accounted for**

## 4.3 Residual analysis

Our analysis has been applied to individual water quality variables without accounting for any correlation structure between them. Even if the model gives an excellent fit for individual variables, the residual sequences for variables which are strongly related may still show strong correlation. First ignoring between-site correlation we consider the residual between-variable relationships. Returning to the logged raw data, the first two scaled principal components are plotted in Figure 6.

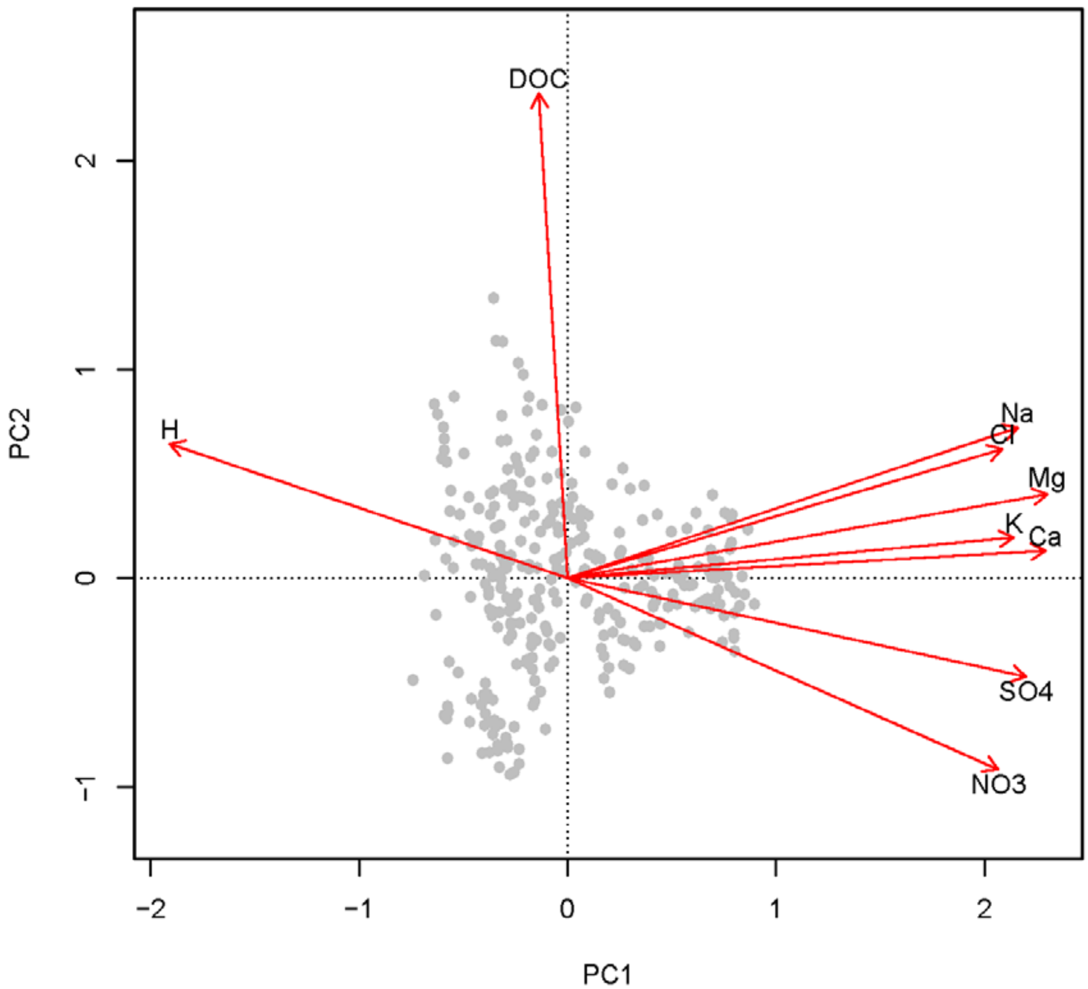


**Figure 6. Scaled principal components plot for log(raw data)**

Figure 6 is strongly influenced by the agricultural component of water quality, which tends to show high concentrations of all major ions apart from hydrogen and dissolved organic carbon. Sulphate and nitrate are included amongst these major ions, and appear to be inversely related to hydrogen ion concentration, despite being acid anions. These two major anions are associated with the major cations rather than hydrogen in satisfying a change balance in stream water.

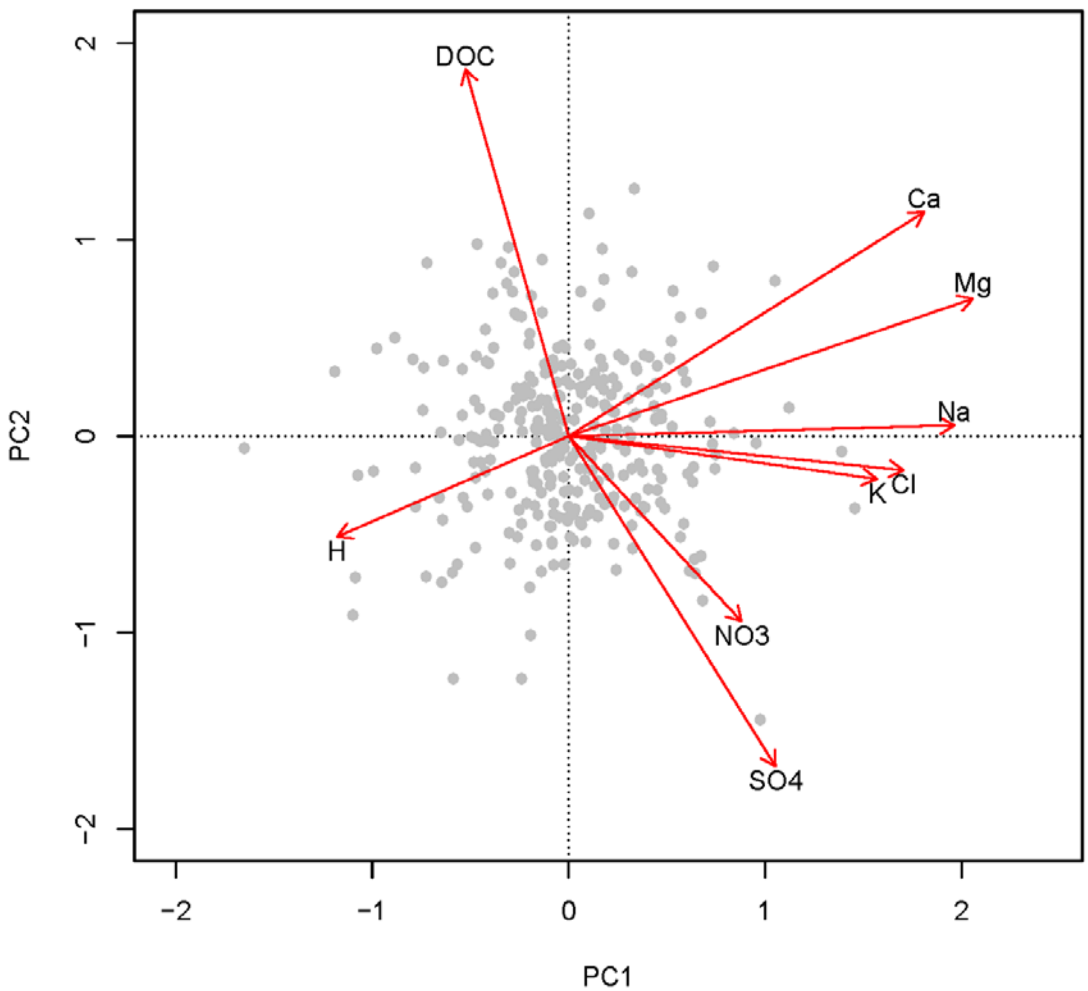


**Figure 7. Scaled principal components plot for residuals**

Figure 7 shows scaled principal components of the residual series. One of the main effects of model fitting is to reduce the strong influence of agriculture. The remaining variability shows the strongest inverse relationships between DOC and sulphate/nitrate and between hydrogen and calcium/magnesium. Plots of DOC against sulphate residuals for individual sites suggest that the relationship is strongest for those sites with high concentrations of peat. The inverse relationship between DOC and sulphate in upland waters has been noted and explained elsewhere[23]. Our results show that the inverse relationship holds at catchment scale. The inverse relationship with nitrate is believed to be related to an unaccounted site by time interaction associated with seasonal differences between these two variables. In peat subcatchments, high DOC is measured during summer when nitrate concentrations are low due to plant uptake.

To examine clustering of residual behaviour by site, we first take principal components of the (39 site x 8 field excursion) row x (9 determinand) column matrix of residuals. Each principal component then represents an independent linear combination of determinands having diminishing influence on the overall variance of the residuals. We then reconfigure the principal components matrix to give a 72 x 39 matrix, each column of which comprises 8 values over time x 9 principal components. We can then cluster the sites using these data to investigate relationships between sites, associated with interaction terms related to site and time. We use the `hclust` routine of R to generate clusters.

Cluster analysis of the transformed residuals generates 7 natural clusters of sites. The interpretation of these clusters is that the chemistry of cluster members has similar site by time interactions unaccounted for by the model. A comparison of the locations of cluster members with the original dominant landscape classes suggests some correspondence (Table 7).

## Table 7. Relationship between residual clusters and landscape classes – allocation by site

| | | Residual cluster | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | Farm 1 | Farm 2 | Margi-nal farm | Peat/ Gley | Mountain | Outlier 1 | Outlier 2 |
| Dominant Landscape | Farm | 7 | 6 | 0 | 0 | 0 | 0 | 0 |
| | Forest | 2 | 0 | 2 | 0 | 2 | 0 | 0 |
| | Gley | 0 | 0 | 1 | 3 | 0 | 0 | 1 |
| | Mountain | 0 | 0 | 3 | 0 | 5 | 0 | 0 |
| | Peat | 0 | 0 | 1 | 3 | 1 | 2 | 0 |

Two clusters of residuals correspond approximately to the single original "farm" landscape classification. A comparison of the raw data suggests that this split is based on higher Na, Mg and SO4, and lower DOC in one group. Of the remaining clusters, it is not possible to identify one associated with forest, though mountain and peat clusters are identifiable, and an additional cluster associated with subcatchments at the upper extreme of enclosed agriculture (marginal farm). Three outlier sites are identified, two of which are adjacent subcatchments. Within clusters, there is some evidence that nearby sites (on a 1km scale) have more similar chemistry than more distant sites within the same cluster. Table 7 indicates that the simple spatio-temporal model fails to capture some interactions between season and landscape class, particularly associated with agricultural land use. This suggests that there would be benefit in modelling these landscapes separately.

# 5 Discussion

The analysis confirms that most of the variability in water quality can be described by the spatial component of the model. This is no doubt partly because of the wide range of landscapes present in the catchment, and the absence of hydrological extremes from the limited sequence of measurements made. Clearly longer time series of data would provide greater opportunities for identifying temporal relationships between water quality variables and covariates. For base cations there is either little seasonal variability, or it is not consistent across landscapes. The greater seasonal variability in pH, nitrate and DOC is interpretable in terms of known biogeochemical processes. DOC concentrations are higher in summer when there is greater microbial activity, while nitrate is higher in winter when there is less uptake. The pH is higher is summer when flow is lower and weathering effects on stream water quality are greater.

The principal components analysis of residuals between variables shows how the remaining interactions between variables splits into an inverse relationship between DOC and sulphate and nitrate, and an inverse relationship between hydrogen ion concentration and calcium and magnesium, with sodium, potassium and chloride grouped together. These relationships are interpretable as due to differential weathering in deeper soils, and an interchange between sulphate and DOC particularly in peaty soils.

Cluster analysis of residuals by site suggests that many of the original landscape classification units are still distinguishable. This is consistent with there being important landscape by time interactions which are unaccounted for by the model. The lack of an apparent forest cluster suggests the model has successfully accounted for any distinguishing characteristics of this landscape. The subcatchments formerly classified as forest are now grouped according to the pre-forest landscape. The cluster analysis also suggests peat and gley residuals are not distinguishable. There are close field similarities between these two landscapes; both are upland and poorly drained, with the gley generally having less development of peat. Both are nutrient poor with high DOC concentrations. The suggested new cluster of marginal farmland corresponds to a recognised landscape in upland Wales named ffridd. This is a region characterised by bracken, coarser grasses and scattered bushes between the enclosed fields and the open hill. The two separate clusters for farmland suggest a need for a further split based on DOC concentrations. Of the three outliers, two show unusually high sodium and chloride concentrations. The sodium to chloride ratio is consistent with a sodium chloride source in the subcatchment. A marine source would be indicated by raised concentrations of magnesium, which are not observed. Since both subcatchments receive drainage from a road which is salted in winter, we assume that road salt is the source of the elevated sodium and chloride concentrations. The third outlier is believed to be both misclassified and to include an unidentified point source. While the mapped soil classification is gley, field evidence suggests the soil is largely peat. Elevated concentrations of Ca and Mg at this site at low flows suggest the existence of a point or geological source of base-rich weathering.

Water quality monitoring programmes generate large volumes of multivariate spatio-temporal data. While these can be used to calibrate models, a relatively simple statistical analysis of the data can aid in the interpretation of such data by identifying common features between sites, between sampling occasions and between variables. The framework used here is an example of how such a model can be used to identify proportions of variability attributable to various sources; identify outlier sampling sites; identify likely additional diffuse or point sources and identify features common to particular landscapes.


# 6 Acknowledgements

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