What can legacy datasets tell us about soil quality trends? Soil acidity in Victoria

What can legacy datasets tell us about soil quality trends? Soil acidity in Victoria

B P Marchant[1]**, D M Crawford**[2] **and N J Robinson**[3]

[1] British Geological Survey, Nicker Hill, Keyworth Nottingham, UK
[2] Department of Economic Development, Jobs, Transport and Resources, Ellinbank, Victoria, Australia
[3] Department of Economic Development, Jobs, Transport and Resources, Bendigo, Victoria, Australia

E-mail: benmarch@bgs.ac.uk

Abstract. Purpose-built soil monitoring networks have been established in many countries to identify where soil functionality is threatened and to target remediation initiatives. An alternative to purpose-built soil monitoring networks is to use legacy soils information. Such information yields almost instant assessments of soil change but the results should be interpreted with caution since the information was not collected with monitoring in mind. We assess the threat of soil acidification in Victoria using two legacy datasets: (i) the Victorian Soils Information System (VSIS) which is a repository of the results of soil analyses conducted for scientific purposes since the 1950s and (ii) a database of 75 000 routine soil test results requested by farmers between 1973 and 1993. We find that the VSIS measurements are clustered in space and time and are therefore suitable for local rather than broad-scale assessments of soil change. The farmers' results have better spatial and temporal coverage and space-time models can be used to quantify the spatial and temporal trends in the pH measurements. However, careful validation of these findings is required since we do not completely understand how the measured paddocks were selected and we cannot be certain that sampling or laboratory protocols have not changed with time.

1. Introduction

Around the world there are threats to soils and the important functions which they perform. These include loss of organic matter, erosion, sealing, compaction, loss of biodiversity, contamination, landslides and salinization. There is concern that these threats are increasing in intensity and number, perhaps as a result of climate change. The soil must be monitored to determine when and where these threats are emerging and remediation is required. Much of this monitoring is initiated locally by farmers and other land managers who use the resultant information to decide what measures are required to maintain the productivity of their soils. There is also an important role for broader-scale soil monitoring networks to determine more general trends. Such information permits governments to devise targeted policies to maintain soil quality where it is under threat and to test whether such policy measures have been effective. Governments might provide education, resources and other support to land owners so that they can effectively protect their soils or introduce legislation to prevent practices which harm the wider environment.

For these reasons many countries have introduced national-scale soil monitoring networks (SMNs). These are designed to ensure that unbiased estimates can be made of both the status and change of soil properties. There are costs associated with the implementation of a SMN although they are small in

comparison to productivity loses and environmental damage that can result from soil degradation. Changes in soil properties are often slow and it is generally necessary to wait a decade or more before resampling the networks and testing whether relatively stable properties such as soil organic carbon content have undergone change that is large enough to be reliably detected. For this reason few SMNs have currently completed their second phase of sampling. One exception is the National Soil Inventory of England and Wales [1] which has been used to quantify the decreases in soil acidity that have resulted from decreased acid deposition.

Policy makers are aware of the long-term need for purpose-built SMNs (e.g. [2]) but they require immediate information about the rate of soil change and given that many soil changes are irreversible, policy-makers cannot afford to wait more than a decade until newly implemented SMNs have been resampled. Therefore many countries are exploring what they can learn about soil change from legacy soil information (e.g. [3]). This might involve the resampling of soil inventory sites that were used for past mapping exercises or the interrogation of other databases of soil information such as the results of soil analyses requested by farmers. Some caution is required when using this legacy information. In general the data were not collected with monitoring in mind. Soils exhibiting certain characteristics could have been preferentially sampled and these preferences might vary in time. For example a farmer might focus his soil sampling efforts where he thinks nutrient inputs are required and he might change where he samples within his farm as he learns more about the management of soils and fields on his farm. Therefore, there is potential for naïve analyses of such information to lead to biased results.

We illustrate these points with reference to the problem of soil acidification in Victoria, Australia. In 2004 the Environment and Natural Resources Committee of the Parliament of Victoria conducted an inquiry into the impacts and trends in soil acidity [4]. The inquiry estimated that soil acidification was leading to an annual loss of AU$ 470 million of agricultural production in Victoria. At that time approximately 23 % of Victoria's agriculturally productive soils were thought to be affected by acidity and it was forecast that this area could double over the next 20 years. Therefore a number of initiatives were implemented to reverse the trend. These included a campaign to raise awareness of the problems of acid soils, attempts to reduce the costs of soil tests in regions most affected by acid soils, efforts to ensure consistency between soil analysis laboratories and research into how intensive agricultural practices can impact on soil pH. The estimates and forecasts contained in the report were uncertain. The enquiry highlighted that a scarcity of data hampered their efforts to quantify the threat of acidification. Therefore, as part of their Understanding Soil and Farming Systems project (http://vro.depi.vic.gov.au/dpi/vro/vrosite.nsf/pages/lwm_usfs), the Victorian Department of Environment and Primary Industries (DEPI; formerly DPI) explored the potential to use legacy information to quantify soil acidification. In this paper we discuss two sources of legacy information. The first is the Victorian Soils Information System (VSIS), a repository of soil pit data collected since the 1950s by Victorian Government soil surveyors. The second is a dataset of 75,000 soil analyses requested by farmers in Victoria between 1973 and 1993 [5]. We explore the extent to which these data might be used to map the status and change of topsoil pH across Victoria.

2. Background

2.1. Soil Monitoring Networks
Arrouays et al. [6] describe how many countries (e.g. France, UK, Denmark, Austria, Switzerland and Germany) have adopted national-scale purpose-built SMNs. There are two distinct types of design for these purpose-built networks. In *probabilistic designs* the sampling locations are selected randomly and independently of each other whereas the locations for a *purposive design* are selected to best serve a specific objective. Often a purposive design consists of a regular grid since this ensures that the samples are evenly dispersed over the study area and are hence suitable for producing maps.

The main advantage of probabilistic designs is that they can be analyzed by classical statistical methods which require very few assumptions and lead to unbiased estimates of the mean and variance

of the status or rate of change of property of interest. If these classical methods are applied to data collected according to a purposive design then biased estimates can occur. For example, if a soil property is sampled on a regular grid then the sample variance is likely to be an inflated estimate of the actual variance of the property within the study region. This is because the grid design does not include any points that are located less than the grid-spacing apart. Hence for a purposive design, it is necessary to estimate a statistical model of the spatial correlation of the property so that such a bias can be removed. Any inferences or conclusions drawn about the variation of the soil property are only reliable if the statistical model is an appropriate representation of the soil property. Therefore thorough validation of the statistical model is required. Note that in the case of a regular grid the average of the collected data is an unbiased estimate of the mean of the soil property because locations are not preferentially sampled according to any attribute of the soil.

Arrouays et al. [6] listed examples of legacy data being used to monitor soil change. These involved either the resampling of inventory sites or the use of soils information that was collected for another purpose (e.g. measurements to assist farmers make fertiliser management decisions). However, the original purposes for collecting legacy data are not necessarily the same as purposes for which SMN are established. For instance, farmers might focus their soil analyses where they expect there to be a deficit of nutrients. Such preferential sampling could lead to a bias in classical statistical estimates of both the mean and the variance of the property of interest. One might hope to remove such biases through the use of a suitable statistical model but this is only possible if the criteria used to select the locations of samples are well understood. Often this information is not recorded.

2.2. The threat of soil acidity and soil acidification
Soil pH is a measure of the acidity or alkalinity of the soil. It is either measured in water or a weak solution of calcium chloride using one part soil to five parts aqueous solution. Measurements made in calcium chloride are less affected by seasonal variations. They can be 0.6-0.8 units lower than measurements made in water although this difference can be less in saline soils. In this paper we generally quote calcium chloride values unless we state otherwise.

The ideal soil pH for plant growth is between 5.5 and 6.5. Outside this range the pH influences availability of elements such as phosphorus, molybdenum, zinc, aluminum and manganese and can lead to toxic levels or deficiencies. Soil acidity can adversely affect plant production and limit a farmer's choices when sowing crops or pastures to acid tolerant plant species. Soil acidity can also have a wider effect on the environment. Reduced vegetative cover can lead to increased leaching, runoff and erosion, with concomitant off-site effects such as increased ascensions to groundwater and increased movement of nitrates leading to contamination of groundwater and surface water. Soils tend to be more acidic in high rainfall regions due to increases leaching of nitrates and other ions.

When undesirably low soil pH is measured, the acidity can be ameliorated by applying lime. Soil acidification can be moderated through balancing inputs and outputs of organic matter such as hay, the selection of crop and pasture species and careful fertilizer management to improve nitrogen cycling. These measures are mainly implemented by land managers at the farm- or paddock-scale but policy makers can facilitate them through the provision to farmers of incentives such as subsidized soil testing, and education.

2.3. The Victorian Soils Information System (VSIS)
The Victorian DEPI has recently collated soil pit data collected for various projects and research purposes into a repository known as VSIS. This database is currently available to DEPI staff and in the future will be made available to natural resource managers, scientists and modellers outside DEPI. The location of each soil pit has been recorded. The VSIS contains 1415 observations of topsoil pH that are comparable with the farmers data described below. These samples extend from the surface to between 8 and 12 cm and were extracted between 1958 and 2011. Figure 1 (left) shows the temporal and spatial coverage of these samples. Samples from each time period tend to be clustered in space reflecting the

local focus of the different research projects (such as the Victorian pasture portion of the National Soil Fertility Project, NSFP, shown in figure 1 right) which contributed to VSIS.
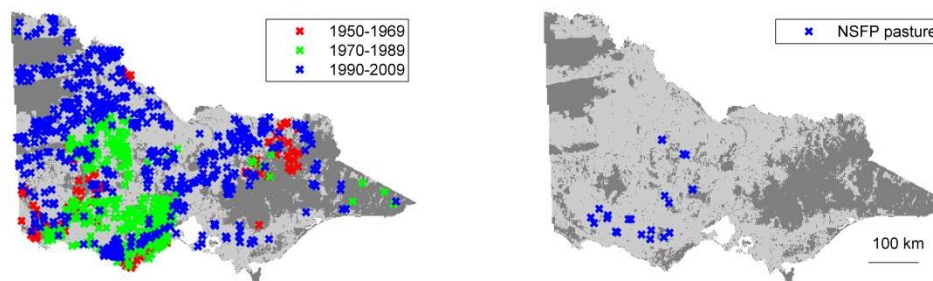

Figure 1. (left) Locations of VSIS measurements of topsoil pH across Victoria sorted according to sampling date; (right) locations of NSFP pasture sites where pH topsoil is measured in 1970-72, 1993 and 2011-13. Public land is coloured dark grey.

2.4. Farmer requested soil analyses from Victoria Australia

MacLaren et al. [5] collated a dataset of 75 000 soil analyses requested by farmers in Victoria between 1973 and 1993. For each analysis, the soil submitted to the laboratory was a bulked sample judged to be representative of the 0-10cm layer of a particular paddock. The bulked soil samples were air dried and sieved to less than 2mm and then soil pH was measured in water with a soil to water ratio of 1:5. The site information recorded included the year of sampling, the nature of the next enterprise scheduled to use the paddock (pasture, horticulture, cereal, row crops or forestry), and the nearest location. The locations were geo-referenced using the Government of Victoria's gazetted place names. Since the precise coordinates of the sampled area in the field, are unknown it is not possible to pair observations made at the same location at different times.

The sampling intensity and the enterprises requesting tests varied in both time and space (Figure 2) since they are controlled by the requirements of farmers and land managers rather than statistical considerations. However, in comparison to VSIS there is reasonable spatial and temporal coverage of samples from pastures across Victoria (Figure 2a & 2c). The only possible exception to this is in the northwest of the state where crops are more prevalent. Cereal soils were only widely sampled from the late 1980s and these samples were predominantly taken from the northwest of Victoria (Figure 2b).

Soil tests are likely to have been requested for one of three reasons: (i) to optimize fertilizer additions (ii) to identify reasons for poor plant growth (iii) to monitor soil quality. The reason for requesting a particular test is not recorded and there is potential for soils portraying particular characteristics (e.g. poor plant growth) to be preferentially sampled. No tests were requested from public land which is coloured grey in figure 2.
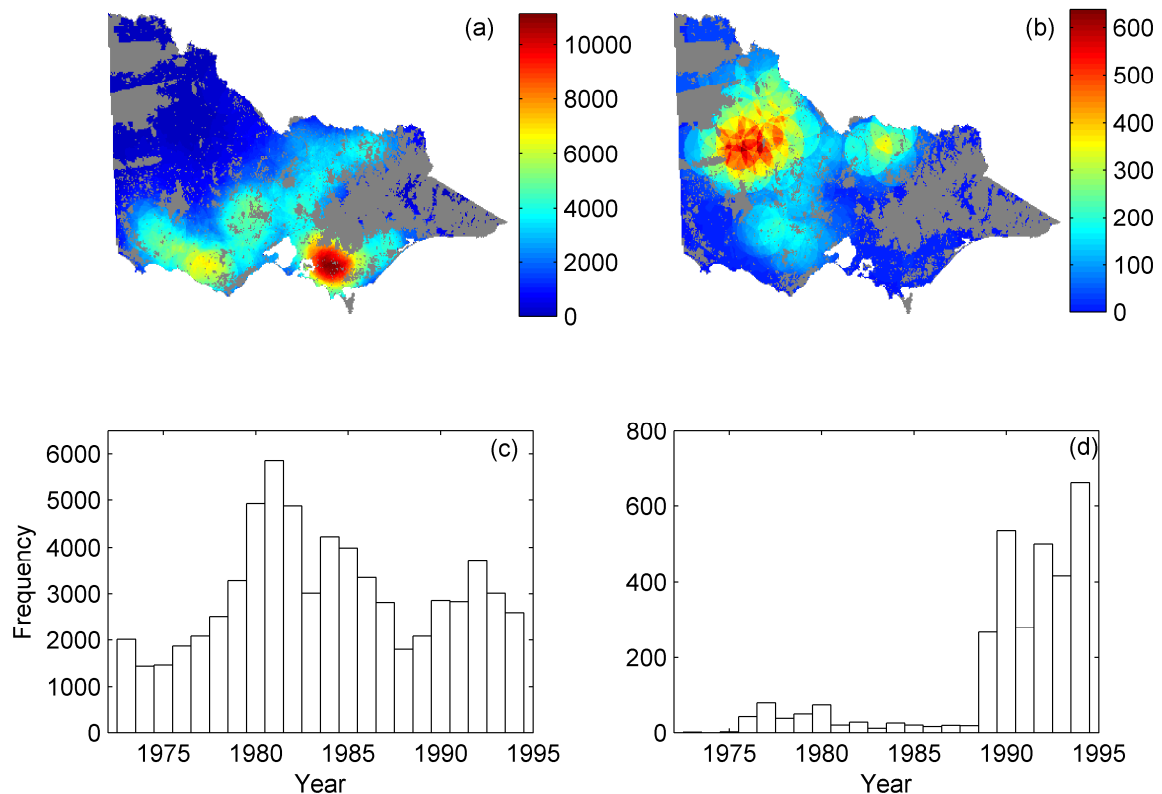
Figure 2. (a) Number of pasture soil samples requested within 50 km; (b) number of cereal soil samples requested within 50 km (c) histogram of pasture soil samples each year; (d) histogram of cereal soil samples each year.

2.5. Primary Production Landscapes

An important consideration in any spatial study of a soil property is the support size or coverage of each prediction of the property. For example the measurements within the farmers' dataset each had a support of a single paddock. It might be considered natural to therefore report predictions of topsoil pH with the same support. However, it is questionable whether this is the most meaningful support size given that different schedules of soil management practices such as liming are likely to lead to large variations in pH for paddocks in the same locality. These variations due to management schedules could hide the variations due to larger-scale factors such as climate. At the other extreme, one might predict the temporal variation of the mean topsoil pH value across the whole state. However Victoria covers an area of 227 000 km^2 and contains vastly different soil types and climatic conditions (Figure 3b) and therefore a single state-wide value would fail to recognize important regional variations. MacEwan et al. [7] addressed this problem by dividing Victoria into 22 Primary Production Landscapes (PPLs; Figure 3a). These landscapes were regions of relatively constant climate, dominant soil types and management practices and were considered suitable areas over which variability in agricultural productivity could be assessed and advice could be given.
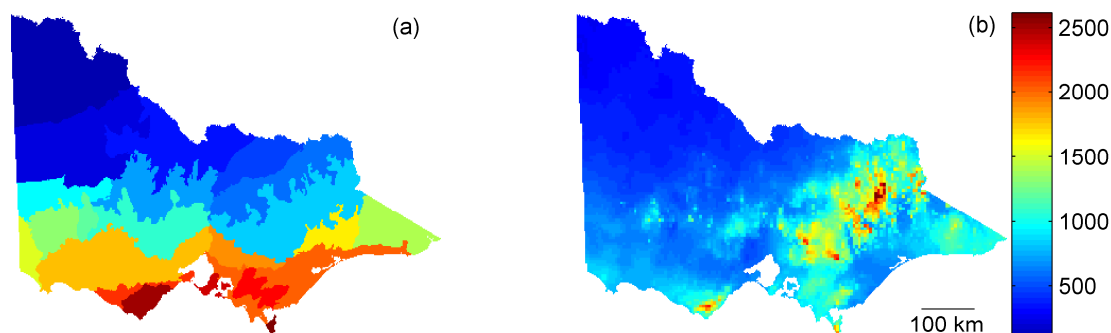
Figure 3. (a) The 22 PPLs of Victoria as designated by MacEwan et al. [7]; (b) mean annual rainfall (mm) across Victoria between 1973 and 1994.

2.6. Overview of this paper

We are interested in the state-wide mapping of topsoil pH status and its variation in time and space. We have seen that the data contained in VSIS tend to be spatially clustered for each time period. Thus these data are not suitable for state-wide mapping since variations in time are confounded with variations in space. There is much more potential to use these data to quantify the status at the same or a smaller spatial scale as the original projects which contributed to the database. In cases where sites or regions have been re-visited it is also possible to assess the local change in pH that has occurred between visits. Examples of such re-visits within the database are rare but new survey efforts could be arranged at the sites of VSIS soil sites. Crawford and Robinson [8] describe a pilot study which uses this approach to assess change in topsoil pH at sites in the west of Victoria where pH was measured between 1968-72 as part of the National Soil Fertility Project (NSFP; [9]). Crawford et al. [10] had previously re-measured topsoil pH in 1993 at 31 NSFP sites (Figure 1 right). A further possible use of the VSIS data is to validate models of soil variation inferred from other data sources. In particular the NSFP data were collected and analyzed according to a similar protocol as the farmers' data.

   In this paper we focus on the farmers' data collected from pastures since these data have good spatial and temporal coverage between 1973 and 1994. Preliminary analyses suggest that pH measurements amongst the farmers' data that were collected from cereal enterprises were significantly higher than those collected from pastures in the same locality. Therefore we do not combine different enterprise types within our analyses. We describe the statistical models that are required to account for the uneven sampling intensity evident in figure 2. Then we present predicted maps of topsoil pH status in 1973 and 1994 and the change in pH that occurred between these dates across Victoria. Finally we discuss the extent to which these predictions can be trusted and the model validation that is required. This includes validation using the NSFP data.

3. Methods

3.1. Spatio-temporal modelling of the Victorian Farmers' data

A statistical model is required to infer trends in the observations gathered from any non-probabilistic or purposive sample design [6]. Figure 2 shows that this issue is particularly pertinent for the farmers' dataset since the samples are unevenly distributed across Victoria. Therefore a linear mixed model (LMM) of the space-time correlation between the pH observations within the farmers' dataset was estimated. Note that such a model can account for the uneven distribution of samples in space and time. It cannot account for any preferential sampling (e.g. if a farmer is more likely to request an analysis of fields he expects to be acidic).

   The complete farmers' dataset consists of 75 000 observations. Such a large dataset can be cumbersome to analyze and therefore we focus on measurements made at the start and end of the

survey period. We treat the $n_1 = 4\,125$ measurements made between 1973-75 (time period t_1) and the $n_2 = 9\,307$ measurements made between 1992-94 (time period t_2) as two spatially correlated variables denoted z_1 and z_2 respectively. The location recorded for each observation corresponds to the nearest gazetted place name. There were $n_p = 1\,988$ unique combinations of place name and time periods at which pH observations were recorded. The LMM is written:

$$\begin{bmatrix} \mathbf{z}_1 \\ \mathbf{z}_2 \end{bmatrix} = \mathbf{M\beta} + \mathbf{DU} + \boldsymbol{\varepsilon}. \tag{1}$$

Here $\mathbf{z}_1$ and $\mathbf{z}_2$ are the vectors of observations of z_1 and z_2. $\mathbf{M}$ is a fixed effects design matrix. It consists of q columns and is of length $n = n_1 + n_2$. Each column of $\mathbf{M}$ contains a factor which explains some of the variability in topsoil pH. $\boldsymbol{\beta}$ is a length q column vector of fixed effects coefficients. In our model, $q = 2$. The first column of $\mathbf{M}$ consists of ones and the first entry of $\boldsymbol{\beta}$ corresponds to the space-time mean of topsoil pH across Victoria within the two time periods. The second column of $\mathbf{M}$ contains the natural logarithm of the mean annual rainfall between 1973 and 1994 at the site of each observation and thus the fixed effects are linearly related to this factor. Note that the fixed effects vary in space but not time. This is to ensure that the fixed effects did not lead to temporal trends within the predicted maps in regions where there were too few data to infer this trend. $\mathbf{D}$ is a $n \times n_p$ fixed effects design matrix. For $i = 1, \dots, n$, the ith row of $\mathbf{D}$ contains a 1 in the column corresponding to the place and time period combination of observation i. The other entries of the row are zero. $\mathbf{U}$ is a length n_p vector which contains the spatially and temporally correlated random effects associated with each place and each time period combination. The entries of $\mathbf{U}$ are realizations of a Gaussian random function with mean zero and covariance matrix $\mathbf{C}$. Finally, $\boldsymbol{\varepsilon}$ is a vector of independent and identically distributed Gaussian random effects associated with each observation. The inclusion of this term permits different observations recorded at the same location and in the same time period to have different values. The entries of $\boldsymbol{\varepsilon}$ have mean zero and variance σ_ε^2.

The covariance matrix of the correlated random effects, $\mathbf{C}$, was determined from a linear model of coregionalization (LMCR) of the random effects of z_1 and z_2 (see [11]). This model has three components: an autovariogram which describes the spatial dependency amongst the random effects for measurements made in period t_1; an autovariogram which describes the spatial dependency amongst the random effects for measurements made in period t_2 and a cross-variogram which describes the spatial dependency between the random effects of an observation made at time t_1 and the random effects of an observation made at time t_2. The parameters of the LMCR and the independent variance parameter σ_ε^2 were fitted to the available data and by the method of moments [12]. Matérn models, [13], were used to represent each variogram.

When we use the LMM to simulate soil pH measurements (see Section 3.3) we assume that the random effects of each variable are a realization of a Gaussian random function. The observed data were skewed (skewness=1.93) and inconsistent with this assumption. Therefore prior to model estimation the observed pH measurements were log-transformed and shifted and this reduced the skewness to 0.7 (Figure 4).
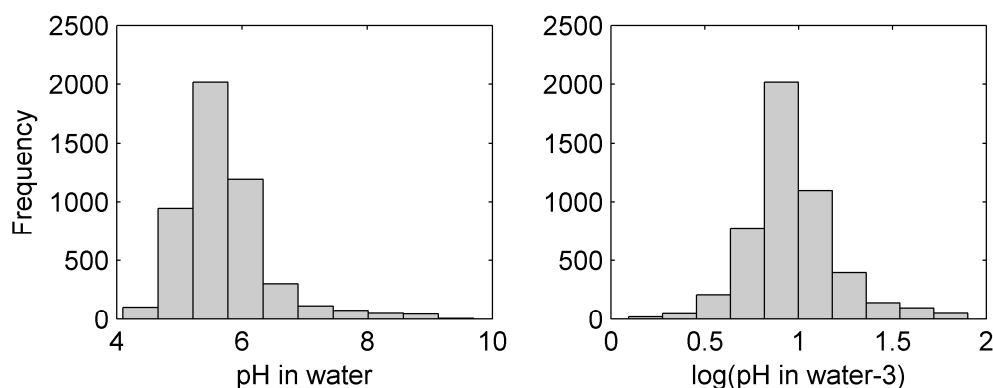
Figure 4. (left) Histogram of 1973 measurements pH in water on pasture; (right) histogram of 1973 log (pH in water − 3) on pasture.

3.2. Validation of the linear mixed model
The estimated LMM was validated by leave-one-out cross-validation. In this procedure an observation is removed from the dataset and the remaining data are used to predict that observation by co-kriging [12] and to calculate the co-kriging variance for that prediction. Then the standardized prediction error – the squared difference between the predicted value and the observed value all divided by the co-kriging variance – is calculated. The procedure is repeated removing each observation in turn. If the prediction errors are normally distributed then the standardized prediction errors will be realizations of a first order chi-squared distribution. This distribution has mean 1.0 and median 0.45. The farmers' data and the fitted LMM were also used to predict topsoil pH at the NSFP pasture sites shown in figure 1. These predictions were compared with the values observed in the NSFP survey.

3.3. Mapping the status and change in topsoil pH
The estimated LMM of (transformed) topsoil pH was used to simulate 1000 realizations of z_1 and z_2 at the nodes of a regular 2 km grid which covered Victoria using the conditional LU simulation algorithm [12]. Each simulated value was back-transformed and the average simulated pH value at each node in each time period and the average change in pH values between time periods at each node were calculated. The use of a stochastic simulation algorithm meant that the probability of the status or change exceeding a particular threshold could be extracted from the histograms of the simulated values. Each realization was up-scaled to the PPL-scale by calculating the average of the simulated values within each PPL.

4. Results
The auto and cross variograms of the LMM of transformed pH are shown in Figure 5. Substantial spatial correlation in transformed pH measurements is evident at distances up to 100 km. The estimated β value corresponding to the log rainfall factor amongst the fixed effects was -1.07 ± 0.16 log-pH units which indicated a significant and negative correlation between rainfall and soil pH. The independent random effects contributed 33% of the total variance of the transformed pH in the 1970s and 37% of the total variance in the 1990s.
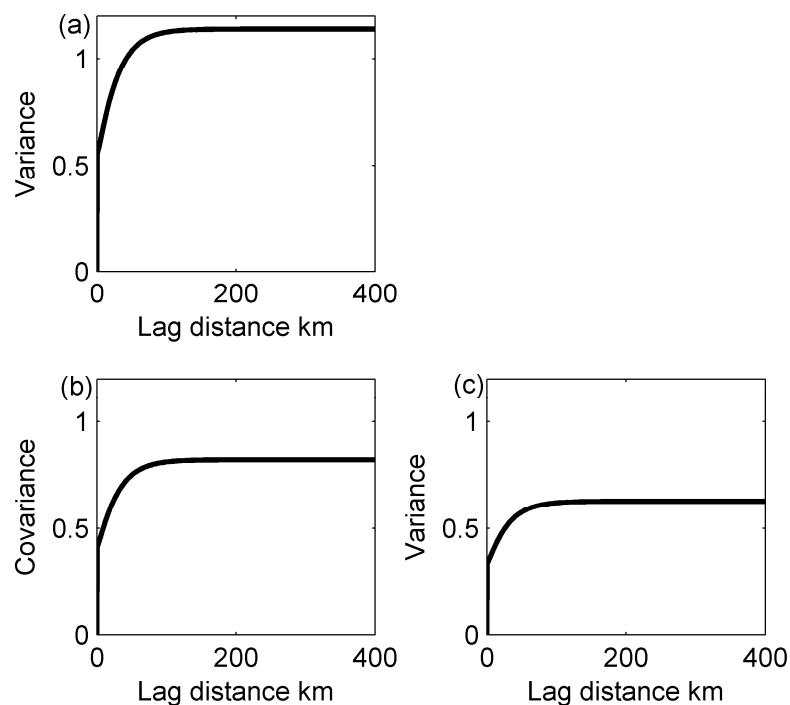
Figure 5. (a) Auto-variogram for transformed pH on pastures in 1973-75; (b) cross-variogram for transformed pH on pastures in 1973-75 and 1992-94 and (c) auto-variogram for transformed pH on pastures in 1992-94.

Clear spatial trends are evident in the maps of pH status on pastures in the early 1970s and early 1990s (Figure 6). The lowest pH values are in the highest rainfall areas. A substantial and increasing proportion of the state (23% in the early 1970s and 29 % in the early 1990s) has expected topsoil pH<4.8 implying that large areas of soil have acidified. The expected pH is greater than 4 at all locations in the Victoria in both time periods. However, the local variation between paddocks means that in each time period an average of 2% of the paddocks in each realization had pH < 4 and therefore have productivity compromised by extremely acidic soil (Figure 7).
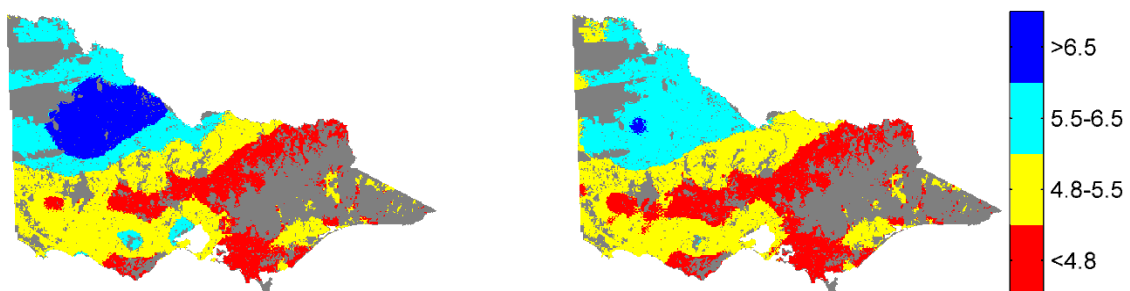

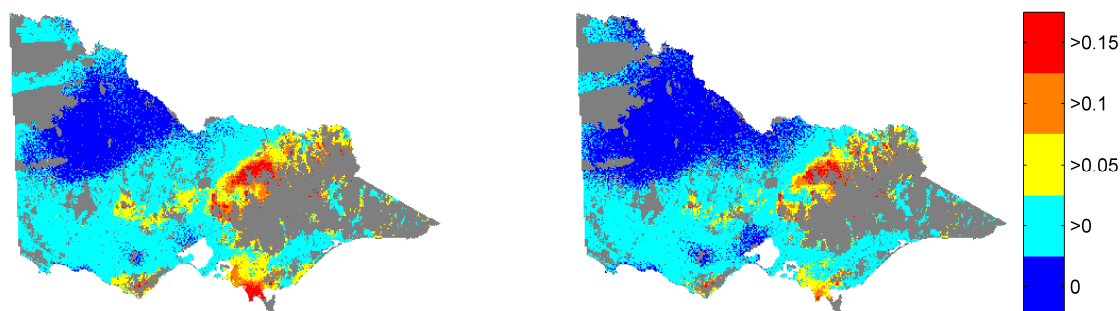**Figure 6.** Predicted status of topsoil pH on pastures in 1973-75 (left) and 1992-94 (right).

Figure 7. Map of the probability of a paddock having pH<4 in 1973-75 (left) and 1992-94 (right).

The expected change in topsoil pH on pastures over the duration of the farmers' data survey is negative for the majority of Victoria (Figure 8). Figure 8 (right) assesses where the predicted changes are statistically significant. The changes recorded in figure 8 (left) are the average change that is expected to have occurred within a paddock at a particular site. However this change will be uncertain. This uncertainty can be assessed by looking at the range of different changes that were recorded for the site amongst the 1000 simulated realizations. The dark blue portions of the map signify where more than 90% of the simulated realizations recorded an increase in soil pH during the course of the survey. Similarly the red portions signify where 90% of realizations recorded a decrease in soil pH. There is a small region in the southeast of the state where the probability of an increase is greater than 0.9. There are other small regions in the southwest where the probability of a decrease in pH is greater than 0.9. There is also a large region in the northwest where a decrease appears to be similarly certain. However it should be recalled that the samples were relatively sparse in this region.
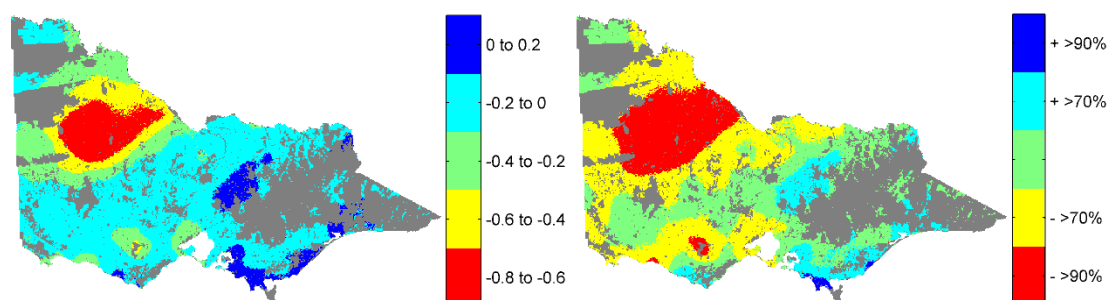

Figure 8. (left) Predicted change in topsoil pH on pastures from 1973-75 to 1992-94 at the paddock-scale; (right) Percentage of simulations where a local increase occurred '+' or decrease occurred '−' in topsoil pH on pastures at the paddock-scale.

The support of the predictions in figure 8 is a single paddock. Hence the local variation between paddocks means there are relatively few areas where a significant change is predicted. When this prediction support is increased to the PPL this local variability is smoothed over the larger area and the probability of a decrease in pH is greater than 0.9 for 11 of the 22 PPLs (Figure 9).
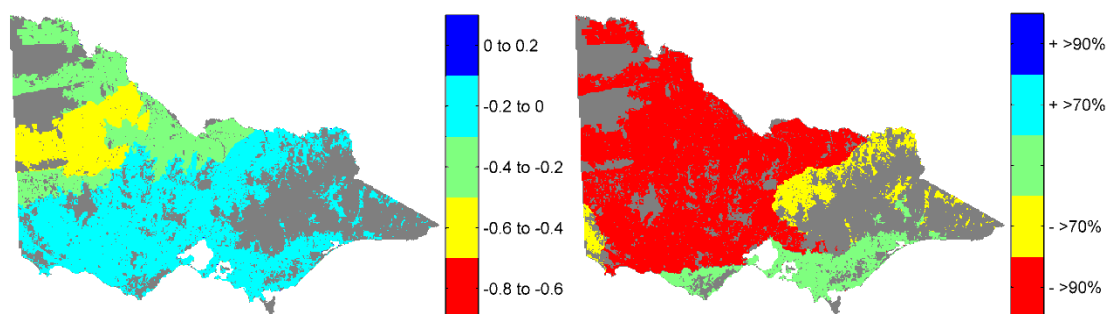
Figure 9. (left) Predicted change in topsoil pH on pasture between 1973-75 and 1992-94 at the PPL support; (right) likelihood of increase '+' or decrease '−' in topsoil pH on pasture at the PPL support.

When the same modelling procedure was applied to the farmers' samples from cereal enterprises rather than pastures a similar pattern of pH variation was evident (Figure 10). However pH values were larger in the croplands in the northwest of Victoria. The map of topsoil pH status for cereal enterprises in the 1970s (Figure 10 left) was based on a relatively small number of observations. Therefore this map is uncertain and no statistically significant temporal trends in pH for cereals were observed.
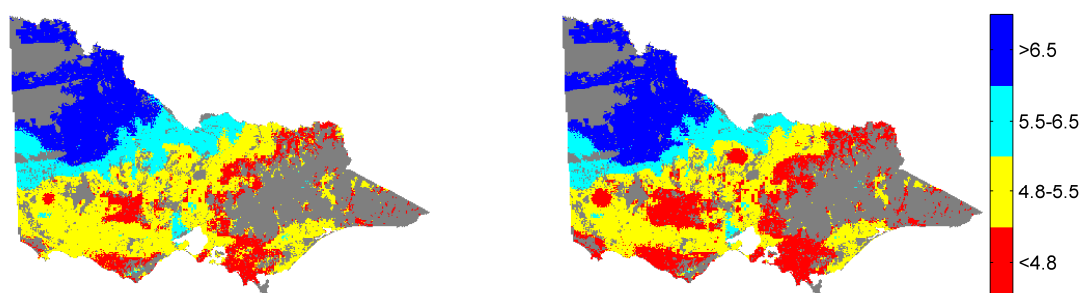

Figure 10. Predicted status of topsoil pH under cereals in 1973-75 (left) and 1992-94 (right).

When cross validation of the LMM for pastures was performed the mean and median standardized prediction errors were reasonably close to their expected values (mean =1.07; median =0.35). Figure 11 demonstrates that the LMM reliably predicted the spatial trends in the NSFP observations made in each of the two time periods.
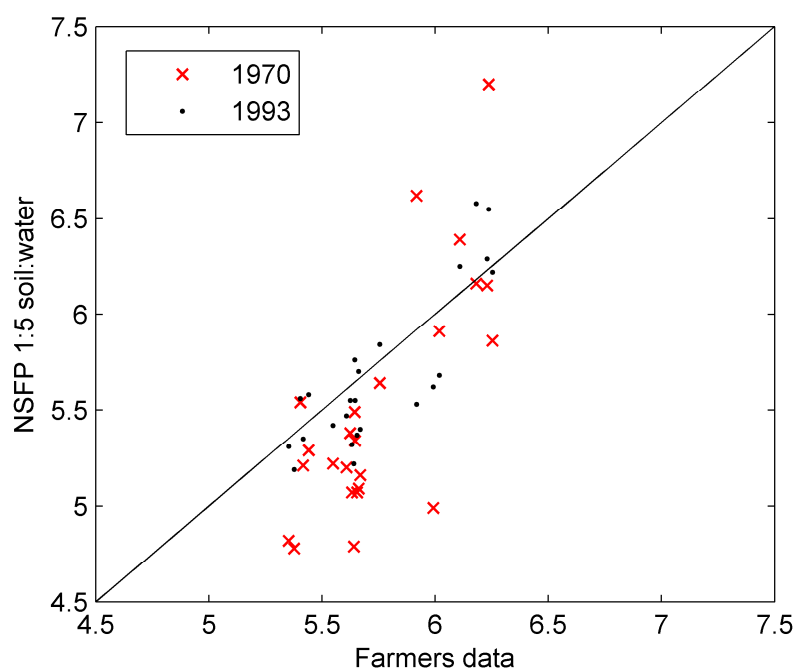
Figure 11. Validation of model of topsoil pH at NSFP pasture sites.

5. Discussion and Conclusions

In this paper we have seen evidence that the levels of acidity measured in farmers' soil samples in Victoria increased between 1973 and 1994. According to our space-time model of the variation of topsoil pH, in the early 1970s samples from 23% of Victoria were expected to have a pH of less than 4.8. This percentage increased to 29% by the early 1990s. Such levels of acidity are known to lead to severe productivity losses. The space-time models lead to maps which identify where the acidity threat is emerging and can be used by policy makers to focus remediation efforts.

Although the expected topsoil pH was never less than 4, the large component of local variation meant that in some areas the probability that paddock-scale acidity would exceed this threshold was as high as 0.2. Thus broad-scale soil monitoring can only be used to look at underlying trends in properties. Further soil sampling is required to inform paddock- and farm-scale soil management decisions.

Leave-one-out cross-validation suggests that the space-time models adequately represent the variation of measured pH values. However we have stressed the need to apply caution when interpreting these results. It is vital to consider whether the trends observed in the farmers' samples are necessarily representative of the soils of Victoria because some farmers may have preferentially sampled soils with particular characteristics. For example a farmer might focus his sampling in fields where he thinks that pH is changing rapidly or where he suspects it might be limiting crop production. Also, laboratory methods might evolve during the course of the survey and the absence of exact locations for each sample hinders the modelling. Such issues cannot be identified by internal cross-validation exercises. Validation exercises which use reliable data from other sources (e.g. the NSFP measurements) can give a better indication of whether the model predictions are consistent with the actual variation of Victorian soils. Such independent validation data is unlikely to be available throughout the state and often it is necessary to use expert opinion to validate the predicted maps. Experts might identify regions where the predicted behavior does not conform to their expectations. For example, the large decreases in pH on pastures in the northwest of Victoria were surprising.

Further examination of the predictions suggested that the large decreases might be artefacts caused by there only being a small number of gazetted place names for samples from this area and by some of these locations changing during the course of the survey. Such artefacts are unlikely to have substantial effects further south where the sampling is much more intensive and consistent in time and space.

The results of purpose-built SMNs might be expected to be more reliable than studies which use legacy data. SMNs with a probabilistic design do not require a model to quantify the variability amongst the data. Although a model is required for purposive designs we can generally be confident that these SMNs have not been preferentially sampled. That is not to say that the interpretation of purpose-built SMNs is not without challenges, for example the study of Chapman et al. [14] demonstrated the difficulties in ensuring that soil measurements made decades apart were equivalent.

Using legacy data to monitor soil does have its advantages. It is generally cheaper and quicker to yield results than a newly implemented purpose-built SMN. Often legacy data is the only source of information about the past state of soils. However this convenience comes at a cost since it is not generally possible to control the design of legacy datasets and therefore they might not be suitable to monitor a particular property of interest. For example we found that the VSIS data did not have sufficient spatial and temporal coverage to permit state-wide monitoring and the farmers' data only covered the period 1973-94 and had insufficient samples to monitor pH on croplands. Furthermore legacy datasets often fail to document exactly how the sampled locations were chosen which can hinder the correction of any sampling biases. If the exact locations are not recorded then it is not possible to identify cases where the same location has been re-sampled and to use these measurements from the same site as a direct measurement of change. Also the legacy data might require pre-processing before they can be used. For example the collation of the farmers' data took 15 months since handwritten reports had to be digitized.

Some countries are currently implementing more carefully organized soil monitoring efforts using farmer requested soil analysis results [3]. In France, analytical laboratories are given financial incentives to provide data. In such a monitoring effort there is potential to have more control over the collected data through requests to the laboratory to collect information on the reason why an analysis was requested, to remove measurements which result from preferential sampling for a particular soil attribute and to provide information on the exact laboratory protocols used. Also it might be possible to record when the same field has been resampled. Collecting data on management schedule could also be undertaken if this is provided with the documents accompanying the submitted sample. Critically this would provide an opportunity to elucidate the effects management on soil tests and more broadly inform on the effect of policy makers' and farmers' responses to the information gained from monitoring.

References
[1]   Kirk G J D, Bellamy P H and Lark R M 2010 Changes in soil pH across England and Wales in
        response to decreased acid deposition *Global Change Biology* **16** 3111-3119
[2]   European Commission 2006 Proposal for a Directive of the European Parliament and of the
        Council. Establishing a Framework for the Protection of Soil and Amending Directive
        2004/35/EC.COM(2006)

[3]   Arrouays D, Saby N P A, Swiderski C, Chauveau D, Marchant B P, Orton T G, Lemercier B, and Walter C 2014 A soil test database for French agricultural soils. State of progress, advantages and limits for monitoring soil changes. Proc. of *Soil Change Matters* workshop, Bendigo, Australia, March 2014

[4]   Environment and Natural Resources Committee 2004 Inquiry on the Impact and Trends in Soil Acidity. Parliamentary Paper No. 59 of session 2003-2004. Parliament of Victoria, Australia.

[5]   MacLaren G S, Crawford D M, Brown A J and Maheswaran, J 1996 Temporal and spatial changes in soil chemistry: (I) pH and electrical conductivity In 'Australian and New Zealand National Soils Conference 1996: Soil Science - Raising the profile, 1st - 4th July 1996 University of Melbourne' (Melbourne, Australia: Australian Soil Science Society)

[6]   Arrouays D, Marchant B P, Saby N P A, Meersmans J, Orton T G, Martin M P, Bellamy P H, Lark R M and Kibblewhite M 2012 Generic issues on broad-scale soil monitoring schemes: A review *Pedosphere* **22** 456-469

[7]   MacEwan R, Robinson N, Imhof M, Rees D, Sposito V and Elsley M 2014 Primary Production Landscapes of Victoria *Proc. of 14th Australian Agronomy Conf.* http://regional.org.au/au/asa/2008/poster/agronomy-landscape/6250_macewanrj.htm

[8]   Crawford D M and Robinson N 2014 A pilot survey of change in soil pH using legacy sites. Proc. of *Soil Change Matters* workshop, Bendigo, Australia, March 2014.

[9]   Colwell J D 1977 'National Soil Fertility Project. Vol. 1, Objectives and procedures.' (Adelaide, South Australia: CSIRO Division of Soils)

[10]   Crawford D M, Baker T G, and Maheswaran J 1994 Soil pH changes under Victorian pastures *Aust J Soil Res* **32** 105-115

[11]   Marchant B P and Lark R M 2007 Estimation of linear models of coregionalization by residual maximum likelihood *Eur J Soil Sci* **58** 1506-1513

[12]   Webster R and Oliver M 2007 *Geostatistics for Environmental Scientists*. 2nd Edition, (United Kingdom: John Wiley and Sons Ltd Chichester)

[13]   Marchant B P and Lark R M 2007 The Matérn variogram model: Implications for uncertainty propagation and sampling in geostatistical surveys *Geoderma* **140** 337-345

[14]   Chapman S J, Bell J S, Campbell, C D, Hudson G, Lilly A, Nolan A J, Robertson A H J, Potts J M and Towers W 2013 Comparison of soil carbon stocks in Scottish soils between 1978 and 2009 *Eur J Soil Sci* **64** 455–465