Real-time predictions of pesticide runoff risk: linking multi-scale runoff models and weather data APIs to improve water quality

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Abstract

This paper describes a novel integration of soil water interaction models with open weather data. Such models require a large amount of inputs about for example describing field conditions, soil wetness and so on. Here proxies for these were developed using spatially distributed antecedent and predicted rainfall data from live APIs. A spatiotemporal data cube past and projected weather data allows the soil water interaction model to be parametrised by inferring soil water status from long runs of historical data. This research suggests that there a number of opportunities for revisiting soil-water interaction models, which are driven by soil wetness and plant-soil interactions, in conjunction with live feeds to very large datasets such as climate data, to infer soil water balance and to estimate antecedent soil conditions and thus runoff in real-time. The proposed framework is generic and can be used to model any kind of agricultural runoff with minimum model specification. It demonstrates how modified soil water interaction models can be used with real time, spatially distributed by highly localised environmental data.

Keywords: Big spatial data; soil water interactions; agriculture; spatial modelling;

1 Introduction

Runoff is the process by which water (and suspended sediment and chemical products from agricultural applications, such as fertilisers and pesticides), passes over the land surface to water bodies. Runoff is a major driver of water pollution. This paper describes recent research that has developed a generic framework for real-time predictions of agro-chemical runoff risk at two scales of decision making: field scale for on-farm decisions about agro-chemical applications risk and catchment scale for drinking water abstraction decisions.

Effective agrochemical use in modern agriculture contributes to increased yield and quality. Agro-chemicals are less effective if they are washed away soon after they are applied and negatively affect water quality and the environment if they are transferred to surface or groundwater (Mitchell et al., 2005; Gao et al., 2008; Lapworth et al., 2012). The risk of runoff is exacerbated by certain weather events, as well as plant-soil interactions. Typically, precipitation immediately following agrochemical application results in surface runoff and the risk of polluted watercourses. Runoff risk is enhanced on land that is already saturated or when rapid by-pass flow to field drains occurs. This can result in pollutant concentrations in surface waters that exceed drinking water standards (Petty et al., 2003). Better management of agrochemical applications will result in both improved agricultural productivity / profitability and improved water quality.

This paper describes the development of tools that provide real-time, spatially and temporally dynamic runoff risk information. This is demonstrated for 2 examples of agro-chemical applications at catchment and field scales to support drinking water abstraction and on-farm decision making. The tools combine live, real-time weather data on rainfall amount and probability with landscape models of underlying soil, landform, drainage, land use etc. They provide a generic framework for modelling the risk associated with *any* agricultural application to the land. The novelty of this research lies in the coupling of live spatially distributed weather data, assumed in spatiotemporal stacks or data cubes, that are interrogated and used to generate proxies for the inputs required by soil-water interaction models. This approach is facilitated by the ability to link to spatially and temporally explicit data through APIs.

2 Background

There is long standing interest in developing spatially explicit decision tools to support agriculture. Around 30 years ago, tools started to emerge that took advantage of GUI and easily programmable GISs (e.g. through ArcView 3.0 and Avenue scripting). These were developed to support farming compliance under newly legislated environmental directives; principally, the Water Framework Directive (WFD, 2000). This sought to minimise the externalities of agricultural activity on Europe's water bodies and the decision tools for use by both farmers and policy makers were developed over a range of spatial supports: nationally at typical scales of 1, 5 and 10 km^2 and Europe wide at scales of 10, 20 and 50 km^2. Examples of UK models include Webb and Misselbrook (2004) Chadwick et al. (2005), Chambers et al. (1999), Davison et al. (2008), Lord and Anthony (2000) and (Lord,

1992) many of which are summarised in Anthony et al. (2008). At the EU scales, similar models include PyCatch (Schmitz et al., 2017) and the FOOTPRINT (Functional Tools for Pesticide risk Assessment and Management) framework which integrates pesticide use information with MACRO (Jarvis et al., 2000) for drainage and leaching pathways and PRZM (Suarez, 2005) for runoff and erosion pathways.

The key and necessary characteristic of these process models was that their outputs and the scales they reported over were spatially and temporally coarse. This is because they were underpinned by highly aggregated data by way of model inputs such as underlying soil types, drainage, land use, climate, terrain characteristics, farming practice, etc. The problem was that despite the existence of very detailed and precise prediction models for soil water balances and the associated runoff, leaching and pollution risks (e.g. Morselli et al., 2018; Pullan et al., 2016), these required specific, local information that cannot be obtained from generalised GIS layers.

However, the biggest driver of runoff risk is precipitation: applications made to very wet soil (at field capacity or wetter) or just before heavy rainfall are much more likely to generate runoff, regardless of other local and catchment factors (e.g. the status of field drains, the topology of the landscape, the distance to water course, etc). In the UK, the Meteorological Office provides a free API to their weather data and weather predictions. These are spatially distributed (either at point locations or generalised over 1km^2) and temporally explicit and include a range of short term (3 hourly for 24 hours) and medium term (5 day) predictions and forecasts of precipitation probabilities, as well as actual precipitation measures. Linking live dynamic precipitation probabilities and measures to field and catchment scale runoff models provides the opportunity to develop real-time predictions of agrochemical runoff risk. Such integration goes beyond the many smartphone apps available to farmers that simply report wet weather probabilities or general guidance on farm management decisions.

3 Methods and Results

Catchment and field scale risk models were developed for 2 agricultural applications; Metaldehyde (commonly used to treat slugs on oil seed rape in arable areas) and Acid Herbicide (used to manage grassland weeds in grassland areas), in 2 contrasting catchments - the Teifi in Wales and the Wissey in the east of England. The risk of runoff, for any agrochemical application is driven by the local soil water conditions, the behaviour and movement of chemicals in each application through different types of soils, and the likelihood of precipitation in the immediate/short-term period after application. The new risk models developed here included the following components: live and historical weather data and a model of movement through the field or the catchment. These are described below.

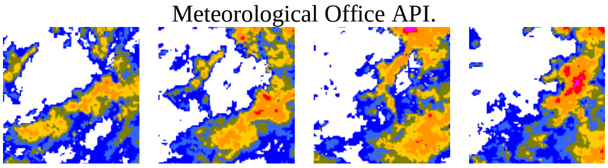
3.1 Weather data: the Met Office API

For each study catchment, a link to the Meteorological Office API was established to constantly download, 1km^2 climate data that was stored in raster stack. Having antecedent rainfall data (i.e. recent rainfall histories) allows current local water balances to be determined. An example of 15-minute data for 2017 in the Teifi study catchment is shown in Figure 1.

3.2 Catchment scale models

The catchment scale models sought to support drinking water abstraction decisions. Runoff risk models of metaldehyde in arable areas and acid herbicides in livestock farming areas considered loss from agricultural, diffuse (i.e. fields) sources only and do not include either point sources or additional non-agricultural applications of pesticides in the landscape. Absorption or desorption associated with river and groundwater biogeochemical processes are also ignored. Thus, the models are essentially minimum information requirement (MIR) only, capturing critical landscape intrinsic risks, with any potential impacts from existing uptake of on-farm mitigation measures (i.e. business-as-usual) not included in model scenarios at this stage.

Figure 1: Example of precipitation data from the Meteorological Office API.



All modelling is undertaken using a 1km^2 grid. Available information on catchment land cover from the June Agriculture Survey (JAS) is combined with survey information on crop-specific pesticide applications to generate spatially explicit pesticide loading surfaces for agricultural land. Runoff pathway apportionment (surface, drain flow, subsurface) is taken from the PSYCHIC (Phosphorus and Sediment Yield Characterisation in Catchments) process-based model (Davison et al., 2008; Stromqvist et al., 2008; Collins and Zhang, 2016). Surface runoff connectivity uses distance to river channel, downstream slope length and the proportion of terrain that has a slope >3 degrees. Drain flow connectivity uses information on the distribution (based on capital grant awards to farmers) or requirement for soil drainage (based on the HOST – Hydrology of Soil Types; Boorman et al., 1995) with estimates of drain efficiency (Zhang et al., 2016). Surface and drain connectivity combine to estimate landscape connectivity for agricultural land.

Integration of rainfall data and runoff estimates (land cover-specific SCS curve number approach) with pathway apportionment and associated pesticide loadings, taking account of organic carbon associated absorption and consequent pesticide degradation, generates spatially explicit landscape scale estimates of pesticide risk delivery to watercourses. An overview of the catchment scale model is shown in Figure 2 and Figure 3 shows some of the interim model components.

3.3 Field scale models

The field-scale runoff risk models sought to support on-farm decisions about agro-chemical applications. In this case, the model is limited to provide the farmers with a forecast of potential runoff from their fields as this is the main variable they use to make decision regarding pesticide application. Although a soil water balance model could be used to estimate runoff in real-time, data and computational requirements are an important limitation. To overcome this, a meta-modelling approach was used to estimate antecedent soil conditions combined with the SCS Curve Number method (USDA, 2004) to assess potential field runoff from forecasted precipitation (Figure 4).

Figure 2: The catchment scale runoff risk model

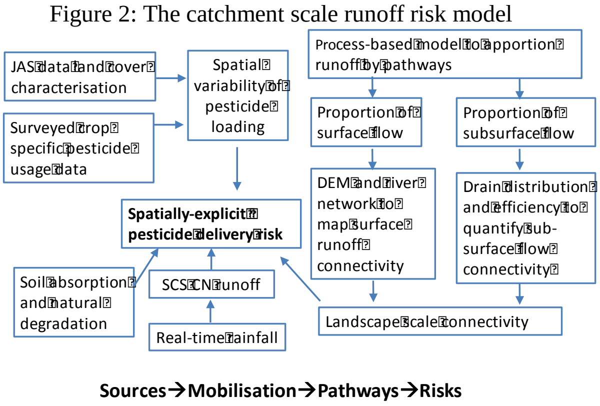
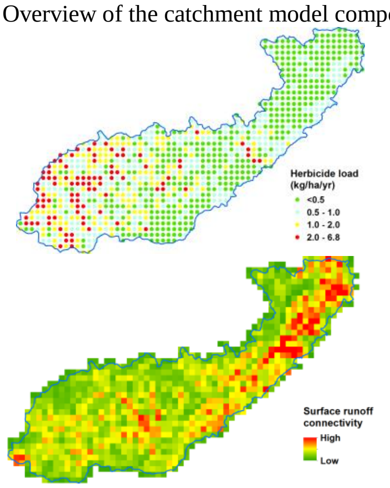


Figure 3: Overview of the catchment model components



WaSim (Hess and Counsell, 2000) was used to adjust site-specific linear regression models to estimate antecedent soil water conditions using 10 previous days' accumulated rainfall, number of days since last daily with rainfall above 2 mm and long-term average daily soil water conditions for the time of the year (calculated from historical WaSim results). WaSim is a daily soil water balance model that simulates changes in root zone soil water content and water table position in response to weather and water management. It estimates changes in soil water content by combining data on rainfall, crop specific evapotranspiration, soil characteristics and field drainage. WaSim was run for a series of soil characteristics and crop cover permutations using daily 1km^2 resolution weather time series (1961 to 2015) from the CEH CHESS dataset (Robinson et al, 2016, 2017). Daily soil water content from WaSim was used to adjust the linear regression model. The results for the meta-modelling approach show a good representation of runoff production despite different quality of estimation of antecedent soil water conditions (Figure 5). Forecast data from the Met Office API are used afterwards to project future soil water conditions and estimate runoff risk using the SCS Curve number method.

Figure 4: The field scale runoff risk model

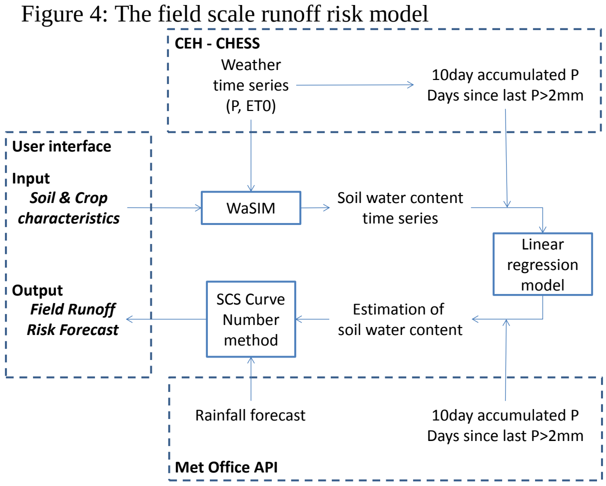
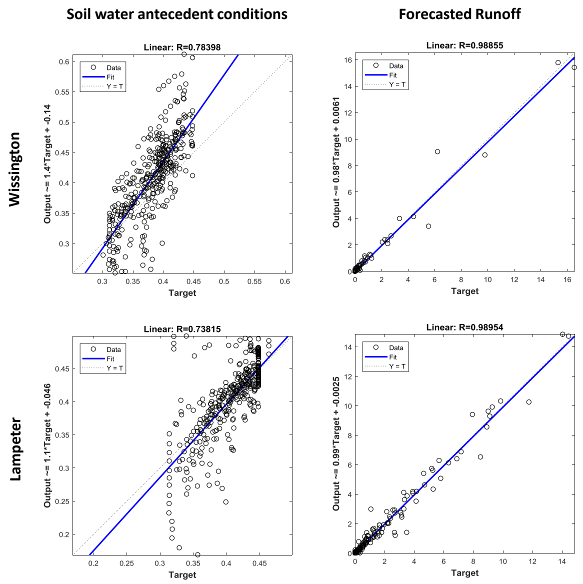


Figure 5: Comparison between WaSim and linear regression results for antecedent soil water conditions (left) and runoff (right) at two locations in the East of England (top) and Wales (bottom).



3.4 Model integration

A generic web-interface was developed to link the data and the models. The data included the static data layers for each model as well as the dynamic and antecedent rainfall data. A zoomable OSM / Leaflet interface was used to provide background mapping. For the field-scale model, a number of drop down boxes were provided for uses to enter their location either in the form of a grid reference or a post-code, and the application type they are interested in, which for this proof-of-concept project was either Metaldehyde or acid herbicide. After entering their information, the user is presented with different surfaces of field level risk relating to different timescales. The catchment scale model provides higher level synoptic information about drinking water abstraction risk across the entire catchment. It links static layers and coarser models of landscape water flows and pesticide delivery. In both cases risk predictions are made in timescales from now to 5 days' time, with associated decreasing certitude.

4 Discussion

The individual components of the tools developed by this project are not new: field and catchment scales of pesticide and herbicide runoff have existed for a long time. There are many weather forecasting websites, smartphone apps and tools. As yet, however, real-time forecasting and soil water models have not been linked. This is despite rainfall being the major dynamic (i.e. changing) factor associated with runoff and many other environmental processes. Up until now, many of the data inputs to models have been relatively static: cropping systems, measures of catchment scale field drainage, etc, which do not change much from year to year and at the field scales. Nor do soil water interactions and pesticide persistence. In both cases, the major dynamic model components are those related to rainfall (antecedent or forecast). In past models, these have had to be assumed under a suite of potential scenarios that the user has to chose from. However, the ability to link to spatially and temporally explicit data through APIs offers a new avenue for enhancing and breathing new life into the wider application and utility of soil-water interaction models. In the future, all geo-spatial data will be served to users in this way via distributed portals (rather than sitting on someone's hard drive).

This research has explored how dynamic spatio-temporal data can be linked to statistical datasets and models at farm and landscape scale to improve decision-making, using a case study of 2 agricultural applications in 2 case study areas. The method (and the underpinning models) could be used to determine the risks to water quality and the wider environment associated with ***any*** agricultural application – fertilisers, pesticides, fungicides, insecticides – at the farm decision scale or at the landscape management scale.

The next steps in this project are to liaise with famer groups and water companies responsible for ensuring drinking water quality, to refine the model outputs in order to better support on the ground decision-making.

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