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Towards understanding links between rural land management and the catchment flood hydrograph

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The nature of causal links between land management in rural river catchments and the flood hydrograph is investigated. A catchment can be represented as a mosaic of tiles with different land use, land management, and soils. Over the mosaic, the causal links vary with the physical properties of the land and channel drainage network, and with the management practices and space–time variations in rainfall and evaporation. The river Hodder catchment in northwest England is represented using a custom-designed semi-distributed rainfall-runoff model. An adjoint, reverse algorithmic differentiation, version of the model is then used to find the sensitivity of the peak flow rate at the catchment outlet to the model parameters controlling runoff generation. Using this novel approach, the links between changes in land management and the impact on the peak flow rate are investigated by decomposing the impact in space to give maps that show the sources of impact, tile by tile. The method works quite well for the Hodder catchment, especially for rainfall events in the autumn and winter. Its strengths and weaknesses are discussed. Copyright © 2012 Royal Meteorological Society

Key Words: adjoint modelling; algorithmic differentiation; anthropogenic change; rainfall-runoff modelling

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1. Introduction

There is a fundamental need to understand the causal link between land management in rural river catchments and the rate of inflow to flood sites downstream. This understanding is needed when assessing the role played by land management practices in historical floods, and when land management interventions are proposed as a contribution towards flood risk management. Extensive reviews of the links between land management and flooding in the United Kingdom (e.g. O’Connell et al., 2005, 2007; Pattison and Lane, 2012) concluded that the links are complicated and that there is a need for more and better field data and models. Of central importance in studying causal links is the role of scale: there is substantial evidence for changes to local runoff generation associated with modern land management practices (e.g. soil compaction leading to more flashy runoff), but a major gap in understanding exists on the link between local changes and the resulting effect on the catchment flood hydrograph. Accordingly, the key question explored in the Flood Risk from Extreme Events (FREE) research project ‘Land Use Management Effects in Extreme Floods’ was the following: ‘How do the effects of land use management propagate from the local scale (∼ 1 ha, and below) to that of mesoscale catchments (∼ 100 km²) and affect extreme floods?’

The research conducted to explore the above research question was built around an integrated programme of multiscale field studies and distributed/semi-distributed numerical modelling, funded from FREE, the Engineering and Physical Sciences Research Council (Flood Risk Management Research Consortium) and the UK Environment Agency. These multiscale field studies focus on recent land management changes implemented at Pontbren in the upper Severn catchment (Marshall et al., 2009), and in the
Hodder sub-catchment of the River Ribble, northwest England. In the Hodder catchment (260 km$^2$) extensive upland restoration work covering approximately 25 km$^2$ within a wider area of 58 km$^2$ (Figure 1) has been carried out under the United Utilities Sustainable Catchment Management Plan, SCaMP (McGrath and Smith, 2006). The modelling in this article is based on an interpretation of the effect of two of the several types of land management interventions made under SCaMP: blocking gullies and grips (open drains) to increase the water levels in blanket peat, and reducing or relocating sheep grazing. A programme of field monitoring and numerical modelling for SCaMP has been running since 2008 (Ewen et al., 2010; Geris et al., 2010; Geris, 2012).

The Pontbren and Hodder multiscale field studies have provided unique datasets through which to explore new modelling and impact assessment methods. Inevitably, however, the results are specific to the catchments and the land management changes implemented, and are limited in scope by the effort required to instrument and monitor the locations undergoing change and the flows downstream. Distributed numerical modelling is therefore the only practical tool for generalizing the results and studying causal links in detail. This has known limitations (O’Connell et al., 2005, 2007), especially in that there is no guaranteed or agreed way to create accurate models for the small runoff elements in a distributed model. Sometimes several models are used simultaneously (ensemble modelling), especially when no single candidate model performs best in all the performance tests run against observations (e.g. Breuer et al., 2009). Typically, the small runoff elements in distributed models have areas measured in hectares rather than square kilometres, and often they take the form of squares on a grid or a mosaic with tiles representing small areas of land that have some common properties, such as tiles for agricultural fields, hillslopes, or simply for patches of land with specific combinations of land use, soils and vegetation. A further difficulty is that the models must accurately represent the sensitivity of the runoff to changes in land management, which is a poorly understood problem that has had little study (Ewen et al., 2006). These limitations, though, should not be cited as a reason for inhibiting the development of new methods of analysing the responses of models, such as the method described here, because these have the potential to lead to general improvements in rainfall-runoff modelling and to practical tools useful to land managers and regulators.

The research conducted to explore the FREE research question had three stages. (Stage 1) Local-scale runoff generation models were developed that capture the key features of how land management changes affect runoff (Bulygina et al., 2010, 2011, 2012; Ballard, 2011; Ballard et al., 2011a, 2011b). Small-scale detailed physically-based models were used to characterize runoff generation, as evidenced by field data, and simple lumped metamodels were parametrized/regularized using the detailed physically-based responses and regionalized indices such as Hydrology Of Soil Types (HOST: Boorman et al., 1995) and the Soil Conservation Service Curve Numbers (SCS-CN: USDA Soil Conservation Service, 1986). One outcome from this is multiple sets of equally-likely parameters for runoff generation at small scales, for use in the analysis of uncertainty. (Stage 2) An integrated model was developed, containing the metamodels, in which the simulated runoff is fed into a channel network flow routing model (based on a solution of the Saint Venant equations), and routed through the network to the catchment outlet. (Stage 3) Causal links were studied using the integrated model.

1.1. Causal links

The subject of this article is Stage 3, specifically the analysis of spatial and temporal variations in the causal links between changes in land management and the impact on the flow at the catchment outlet. A new method is used, based on applying algorithmic differentiation (Griewank, 2000; Hascoët and Pascual, 2004) to the integrated model. One hundred parameter sets from Stage 1 are used in extensive testing, each set giving all the necessary parameters for modelling the catchment under pre-change and post-change land management. Using multiple parameter sets in this way allows a much wider range of hydrological states and responses to be covered than would be possible if using only a single parameter set. Uncertainty could be analysed using the multiple sets, but that is beyond the scope of this article.

There are other ways to analyse causal links, including the analysis of routed flows, for example by mapping the source of flood water in geographical information system (GIS) based rainfall-runoff models (e.g. de Smedt et al., 2000) or channel network models (O’Donnell, 2008). The approach taken here, however, is fundamental in that the causal links are established by estimating the sensitivity to the parameters of the models that simulate the runoff from the small tiles on a mosaic. The approach is demonstrated for the Hodder catchment. Given the novelty of the method, the article concentrates heavily on testing the method rather than on the practical interpretation of the predictions made for the catchment. Note that although the testing is for the effect of change in land management on peak flow rates at the catchment outlet, the method can be used for any measure of flow anywhere downstream, including flow volumes and flow rates at flood sites. Its potential practical relevance is that it can show where, within a catchment, land management...
interventions are likely to affect the flow downstream, and how the flow can be affected by any prescribed programme of interventions.

2. Method

Algorithmic differentiation involves mathematically differentiating, line by line, the source code for an algorithm or an entire model. If a model written in source code (e.g. Fortran) has two parameters, \(a\) and \(b\), and has a single value output \(f\), algorithmic differentiation can be used to create a new source code which gives two sensitivities: \(\delta f/\delta a\) and \(\delta f/\delta b\) (for convenience represented by \(f_a\) and \(f_b\)). If the parameters undergo small changes \(\delta a\) and \(\delta b\), then the change in output can be estimated as \(f_a\delta a + f_b\delta b\). The accuracy of this estimate depends on several factors, including the magnitude of the changes and the degree of nonlinearity in the model.

This simple approach can be applied to an entire semi-distributed model to calculate the sensitivities of the peak flow rate downstream to changes in the parameters controlling runoff generation from the mosaic tiles. For example, in the model of the Hodder catchment there are 2634 tiles and 8 parameters per tile, so a total of 21,072 parameters, and hence sensitivities, per simulation. Because the sensitivities for a semi-distributed model correspond to tiles, a mosaic map can be drawn showing the variation of sensitivity over the catchment.

Sensitivity mosaic maps show the tendency for the peak flow rate to change as the tile parameters change, but even more useful would be estimates for the actual change (i.e. impact) caused by a given spatial pattern of change in land management, as represented by a spatial pattern of finite changes in the tile parameters. This could, for example, represent a real programme of changes in land management made in the field. Returning to the simple example, if the parameter values change from \(a\) to \(A\) and \(b\) to \(B\) then the impact \((I)\) can be estimated as:

\[
I = (A - a)(f_a + f_A)/2 + (B - b)(f_b + f_B)/2,
\]

where the adjoint model is first run to obtain \(f_a\) and \(f_b\) and then run to obtain \(f_A\) and \(f_B\). This assumes that the ‘effective’ sensitivities are means. For example, the effective sensitivity for a change from \(a\) to \(A\) is the mean of the sensitivities \(f_a\) and \(f_A\). It will be shown here that ‘effective sensitivity’ is a workable and useful concept, and that the mean is a reasonable choice (as a result of several factors, including nonlinearity, the ‘effective’ value could in fact lie anywhere between \(f_a\) and \(f_A\), or even outside this range). Impact can be mapped in the same way as sensitivity, so mosaic maps for a semi-distributed model can be drawn that show the sources of impact, tile by tile.

Here is a simple hypothetical example in which Eq. (1) is applied to semi-distributed modelling. It is assumed there are only four tiles, each with eight runoff parameters, and that simulations run for a rainfall event give peak flow rates of 90 cumecs (m\(^3\)s\(^{-1}\)) and 100 cumecs, corresponding to the current land management condition and altered conditions, respectively. The simulated total impact is therefore 10 cumecs. A set of eight sensitivities for each tile are obtained by setting the parameter values to their current values and applying the adjoint version of the semi-distributed model. A further set of eight sensitivities for each tile are then obtained after changing the parameter values to those for the altered conditions. The impact for each tile is then calculated using Eq. (1), extended to have one term per parameter (i.e. eight terms). Each term has the form \((P - p)(f_p + f_P)/2\) where \(P\) and \(p\) are the tile’s parameter values for the current and altered conditions, respectively, and \((f_p + f_P)/2\) is the mean of the corresponding sensitivities from the current and altered adjoint simulations. If, for example, the estimated tile impacts are 7.5, 2.3, 1.1 and \(-1.2\) cumecs, this gives a total of 9.7 cumecs which is in good agreement with the result from the direct simulations. These tile values give quite a lot of information about the source of the total impact: (i) by far the largest contribution comes from the changes in land management made to the first tile; (ii) the changes made in the first three tiles increase the peak flow rate; and (iii) the effect from the first three tiles is partly offset by the effect of the changes made in the fourth tile.

The accuracy of impact maps depends on the accuracy of the effective sensitivities. The nature of ‘effective’ sensitivities is therefore investigated and the accuracy of the maps tested. When analysing the overall uncertainty in impact maps, the error in the effective sensitivities must be combined with other uncertainties, such as the uncertainty in the parameters of the semi-distributed model. This combination is beyond the scope of this article. Sensitivity depends not only on the parameters of the model, but on the hydrological state. For example, the sensitivity to a change in the value of a drainage parameter can depend on the wetness of the tile and the hydrological state in the river channel network in the period leading up to the time of peak discharge. It is therefore important in the testing to sample many different hydrological states, and that is one of the reasons for using 100 different parameter sets (the other reason simply being to test repeatability).

3. Hodder catchment and modelling

The upland areas in the Hodder catchment have rich organic soils supporting grassland and moorland vegetation, and receive in excess of 1500 mm rainfall annually. In general, these soils are shallow, seasonally waterlogged, and poorly drained. There are small areas of arable farming in the main Hodder valley and the River Loud catchment (Figure 1), where the annual rainfall is typically 1100 mm. Approximately half the catchment has permanent grassland, improved by drainage and the application of fertilizer and lime, and the half at higher elevations (mainly peatland) has rough grazing and is also used for game rearing. Pockets of native woodland are scattered throughout the lower Hodder Valley, and there are a few small commercial coniferous forests. The land lying upstream of Stocks Reservoir is not included in the modelling (Figure 1) because the reservoir breaks the direct connection between the changes in land management upstream of the reservoir and the flows downstream of the reservoir (reservoir catchment area is 37 km\(^2\), including the water surface area of 1.4 km\(^2\)).

There are three intrinsic scales in the modelling (Table 1). A considerable effort was spent on characterising a dendritic channel network that drains the 500 m cells, using a combination of information from: a digital elevation model; field surveys for channel location, profiles and friction conditions; hydraulic geometry equations from a nearby research catchment (the Eden catchment: Mayes et al., 2006); and literature reviews for suitable values for Manning’s friction factor. Within the network, there are 28
stations for river gauging, using automatic logging. There are a total of 2634 mosaic tiles lying within the 500 m cells, each selected such that it has a uniform land use and HOST class. A 500 m cell receives rain from the nearest of seven rain-gauges (Figure 1) and each tile it contains is allocated a potential evaporation rate calculated using the Penman–Monteith equation with data from an automatic weather station (Figure 1) and Penman–Monteith parameters from Allen et al. (1998). Land use was classified as: deciduous trees; coniferous trees; agricultural land; grazed grassland; and rough grazing plus shrubs etc. This classification was based on data from Fuller et al. (2002).

The runoff metamodel (Figure 2) is the same for all tiles, but its parameters vary with three properties: land use, HOST class, and land condition (land condition represents the effect of land management practices). For peatland, the classes for land condition correspond explicitly to different land use and HOST class, and land condition, and runoff for some patterns of land condition some changes made uniformly over one or more squares. For peatland, the classes for land condition correspond explicitly to different land use and HOST class. A change from poor condition was used for the regeneration of severely degraded areas, and a change from fair to good for less degraded areas. This is based on knowledge from small-scale experiments and monitoring that intensive upland grazing causes a loss of plant species, increased erosion, and decreased infiltration (Meyles et al., 2006; O’Connell et al., 2007). A deterioration in condition from fair to poor was used for small inbye areas (enclosed fields). As part of the overall set of interventions, the inbys are being used more intensively than in the past, for lambing and the overwintering of sheep, giving a risk of soil compaction (Drewry, 2006). Blocking of grips and gullies implemented over an area of approximately 2.5 km² of peatland around coordinates (800, 1950) was represented as a change from ‘drained land’ to ‘drained land where the drains have been blocked’.

The tile runoff model has eight parameters (Table 2), which define the behaviour of a soil–moisture bucket that passes water to a set of three parallel linear reservoirs via overflow and drainage which is linearly proportional to the current storage. The runoff is the total output from the reservoirs. The channel network model solves the non-inertial Saint Venant equations (Yen and Tsai, 2001) using a custom-designed finite-difference approach involving a combination of local and global iteration algorithms to give accurate fully-implicit solutions at all scales within the network. In particular, it is designed to give perfect mass balance throughout the network and to give accurate solutions at junctions (requirements for successful algorithmic differentiation).

The length of run-up period for the simulations was restricted severely because each adjoint simulation was limited to two hours of processing time on the PC cluster available for the work. This is important for the summer events, because of the time needed for moisture deficits to
build up. After some experimentation, the simulations for the summer events were started from a saturated condition at the end of the winter. A full year or more of run-up would have been better for these, in case the initial condition has some subtle effects on the details of the sensitivity and impact maps.

4. Results

Seven rainfall events from the period 2008 to 2010 have been analysed. The results here are for an autumn event (4 October 2008) and a summer event (20 July 2010). Daily summaries from the UK Meteorological Office show there was an active frontal system for the October event and occasional rain, often heavy, for the July event. The observed peak flows for the events are 217 and 93 cumecs, respectively. This autumn event was chosen because it gave test results that are typical for the autumn and winter events; and this summer event was chosen because it gave the poorest results seen for any of the seven events. For a given rainfall event and spatial pattern of land condition, the full set of 200 simulations (100 pre-change and 100 post-change) gives 1600 sensitivity mosaic maps for the sensitivity of the peak flow rate at the catchment outlet to the tile runoff parameters. Figure 3 shows typical maps for sensitivity to the fast partition coefficient for the pre-SCaMP land conditions. In sensitivity maps, positive values show that an increase in the parameter value would cause the peak flow rate to increase, and negative values show it would cause a decrease. Each set of 1600 sensitivity maps gives 100 impact maps, derived by applying Eq. (1). For a typical change in the fast partition coefficient (e.g. a change of 0.1) the sensitivities shown in Figure 3 will generate only modest contributions to impact, which will be proportionally larger for the summer event because that event has a smaller peak flow rate. There are several competing patterns visible in the sensitivity maps: a rainfall pattern that is quite coarse and blocky because each 500 m square uses the data from the nearest rain-gauge; gradual variations associated with distance from the catchment outlet, associated with flood wave travel times and amplitude attenuation in the channel network; and patterns associated with land use (defined on the 500 m squares) and HOST class (defined on the tiles, which comprise clusters of 10 m cells).

A typical mosaic map for impact, derived from sensitivity maps using the simple method described in the hypothetical example in the Methods section, is shown in Figure 4. Many of the changes in land condition were specified for 500 m squares, including for the inbye areas which show up in the maps as squares with positive impact (i.e. increased peak flow rate). Generally, the impact is negative (i.e. decreased peak flow rate). The impact for the area undergoing grip blocking (light grey area around coordinates (800, 1950) in the right-hand plot in Figure 4) is quite small.

4.1. Testing

Tests were run in which impact was calculated by two methods: (i) using the sensitivities from the adjoint simulations; and (ii) directly as the difference between the peak flows simulated for pre-change and post-change land conditions. The aim in these tests is to see if the impact maps are accurate in that they can be used reliably to estimate the impact for any given spatial pattern of change in land management. For example, if the maps produced using method 1 (which is a linear method) are greatly affected by nonlinearity, then the resulting estimates for the total impact at the catchment outlet will disagree with the results from method 2, which takes the effect of nonlinearity fully into account. In these tests, three patterns of change were considered, each with a different spatial scale: the catchment scale (approximately 25 km²), where there was a mixed pattern of change based on actual interventions made in the field, as described earlier; and the cell scale (0.25 km²), where the land condition for a single 0.25 km² square lying within the 25 km² area. The results for this test are in Figures 5 and 6, because the cell-scale impacts in turn for one set of parameters.

Examples have been shown of mosaic maps derived using an adjoint (reverse algorithmic differentiation) version of a semi-distributed rainfall-runoff model applied to a landscape comprising a mosaic of land use, soils and land management in the Hodder catchment in northwest England. One form of these maps, impact mosaic maps, is sampled at the catchment scale than at the smaller scales, which helps explain the variations in the lengths of the grey lines in Figures 5 and 6. The main cause of the poorer result in Figure 6 (e.g. the scatter for the SCaMP results) is sensitivity to the evaporation multiplier ε and the effect it has on moisture deficit and the nonlinear overflow behaviour of the soil moisture bucket in the runoff model. For some tiles, in extreme cases, the main process contributing to runoff might be overflow for the pre-change conditions but drainage for the post-change conditions, or vice versa. For these tiles, the change in process can give a large change in sensitivity, and this will contribute to the length of the grey lines and the magnitude of scatter.

It would be a great simplification in the analysis of the link between land management and flooding downstream if general-purpose impact maps could be created, which would avoid the need to create new maps for every new spatial pattern of land condition. This is beyond the scope here, but a simpler related problem has been studied: it was tested whether maps created for SCaMP, which are for changes made over an area of 25 km², give accurate results when applied to changes made over only one 0.25 km² square lying within the 25 km² area. The results for this test are in Figures 5 and 6, because the cell-scale impacts shown there are for a change made only at the highlighted inbye square, and these were calculated using the SCaMP sensitivity maps. Wider tests were also successful, in which all the 0.25 km² squares in the SCaMP area were considered in turn for one set of parameters.

5. Discussion and conclusions

Examples have been shown of mosaic maps derived using an adjoint (reverse algorithmic differentiation) version of a semi-distributed rainfall-runoff model applied to a landscape comprising a mosaic of land use, soils and land management in the Hodder catchment in northwest England. One form of these maps, impact mosaic maps, shows the contribution that would be made to the peak flow rate at the catchment outlet by a change in land management. These maps show there are strong spatial patterns in the links between land management and flow rates downstream, including patterns related to land use,
land condition, soil type, rainfall and evaporation fields, and travel distance to the catchment outlet. Some of the spatial patterns and intensities vary from rainfall event to rainfall event.

The impact maps are based on sensitivity maps which show the sensitivity of the peak flow rate to the model's 2,415 parameters for runoff generation. Algorithmic differentiation proved very accurate and efficient for calculating the sensitivities. Standard tests of the outcome from algorithmic differentiation, carried out when the adjoint model was developed, showed that the calculated sensitivities are accurate to better than one part in a billion. Also, adjoint simulations run several hundreds of times faster than the equivalent corresponding sets of difference simulations, because they calculate all the sensitivities simultaneously within a single simulation. The development of the adjoint model took several months of effort, which included the design of suitable iterative algorithms for the local and global conservation equations for flow in the channel network. Algorithmic differentiation is not limited to finding sensitivities to model parameters; it can find sensitivities to any of the numbers that are entered into the model, including the numbers in a rainfall time series. Now that the semi-distributed model exists, it would be relatively easy to create other adjoint models for investigating other types of causal links (e.g. giving mosaic maps related to the effect of timing, amplitude and spatial errors in rainfall records and their use). One important use for further adjoint modelling would be to check the sensitivity to initial conditions, and it would be good practice in future to included the sensitivity to the initial conditions as an output from the adjoint modelling as a check on whether the initial model run-up times are sufficiently long for all the effects of the initial conditions to decay sufficiently.

The work involved analysing the responses produced by a semi-distributed model for 100 sets of equally-likely parameter sets. It would therefore be possible to derive mosaic maps for the uncertainty in sensitivity and impact. This is beyond the scope of this article, but it is noted that for any specified spatial pattern of change in land management the sets of 100 estimates for sensitivity and impact tend to cover a considerable range.

It is a general limitation of the method that the sensitivity and impact maps produced will vary between rainfall events and with the spatial pattern of land management interventions. There are many aspects of this limitation that deserve further study, such as how the maps actually vary between rainfall events. An element of simplicity was found in the analysis of the spatial pattern of land management interventions carried out under the United Utilities Sustainable Catchment Management Plan (SCaMP), which simplifies the estimation of the impact of programmes of interventions made over any land area from the SCaMP area (25 km²). Rather than each programme requiring its own mosaic maps, it was found that, for a given rainfall event, the impact map created for the full extent could be used when estimating the impact for smaller extents. This suggests that local decisions about land management can be made within this area without considering interactions with changes made elsewhere within the area, which gives a limited basis for the development of design rules for use in flood risk management (albeit rules that must take into account spatial and event-to-event variability). It is not known, however, if similar simplicity would be found for other catchments, or even when using other semi-distributed models for the Hodder catchment. The main problem is that impact mapping will tend to break down when large nonlinear effects are simulated, such as threshold effects from soil-moisture deficit, groundwater recharge and discharge, and changes in river flow regime. When impact mapping does break down, this still leaves sensitivity mapping. This has the potential to be used in a variety of other novel ways to help understand the behaviour of rainfall-runoff models and study the links between land management and flooding downstream in river catchments (e.g. O'Donnell et al., 2011).

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