

Catchment scale land use optimisation using genetic algorithm to mitigate acute diffuse pollution

Vaida Suslovaite¹, Dr James Shucksmith¹, Professor Vanessa Speight¹, Laura Flower²

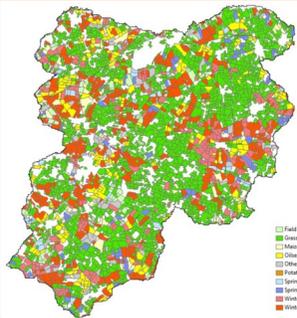
Background

Acute diffuse pollution resulting from rainfall runoff processes is known to adversely affect surface water quality, including in areas where surface water is used for drinking water supply. Designing and implementing targeted mitigation measures to reduce peak concentrations of specific contaminants such as pesticides is challenging due to the spatial and temporal variability of rainfall-runoff processes.



Past work has developed a validated, travel time based, physically distributed model³ used to predict pesticide levels after a rainfall event accounting for variations in rainfall and distribution of land use. However, targeted field scale mitigation measures require an understanding of how different land use distributions affect pollutant concentrations in river water over a representative number of rainfall events.

Project Aims



Adopt an inverse modelling approach in which a pesticide runoff model is used in conjunction with spatial and temporal distributions of rainfall data spanning over a number of years to carry out land use optimization and explore catchment management options.

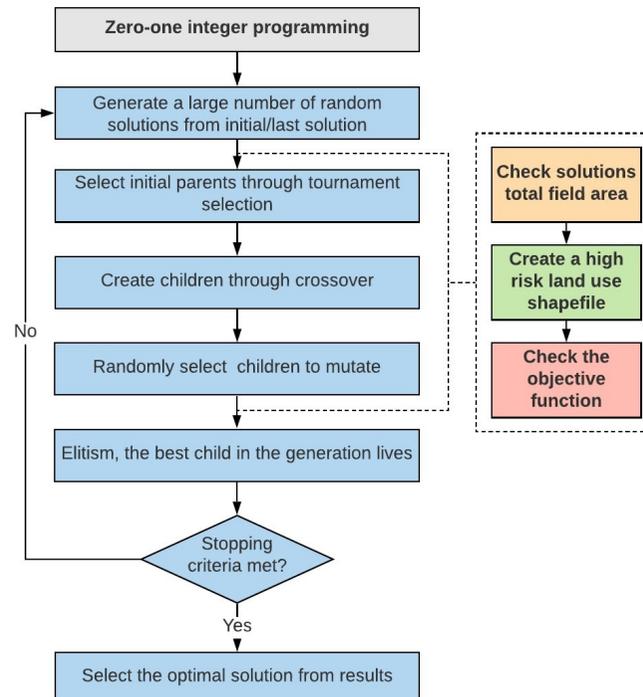
Methodology

Genetic algorithm(GA) technique was used to determine distributions of land use that minimises the total number of predicted hours that pesticide levels exceeded the EU and UK threshold of $0.1 \mu\text{g L}^{-1}$ for pesticides in drinking water following given rainfall events.

Catchment: River Leam, England

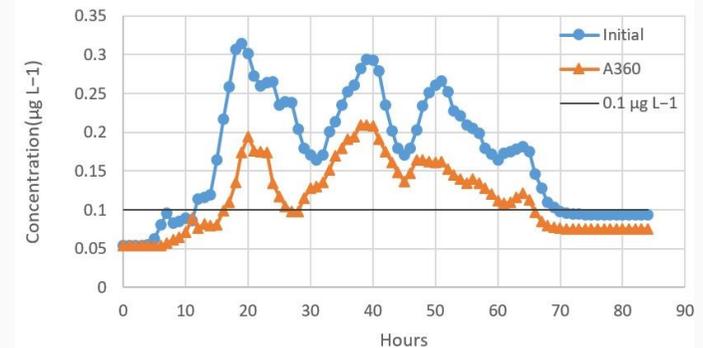
Catchment area: 300km^2

Initial Objective Function: 58 hours



Initial Results

Simulated total metaldehyde concentrations



The initial, single rainfall event analysis have demonstrated the effectiveness of GA technique in reduction of total hours pesticide levels exceeded the threshold of $0.1 \mu\text{g L}^{-1}$. Initial results returned a reduction of 11 hours, to 47 hours above threshold and reduced peak concentrations. GA ran the model 989 times. First minimum reached on run 360 and subsequently on runs 628, 631, 646, 706, 718, 771, 945 and 987.

Future work

- Use the GA method over a representative number/combination of historical rainfall events
- Show how the removal of specific high risk fields will affect pesticide concentrations as well as
- Rank and prioritise specific catchment areas to inform catchment management groups of the most effective locations for the implementation of mitigation measures.

1: Department of Civil and Structural Engineering, University of Sheffield

2: Senior Catchment Management Scientist, Severn Trent Water

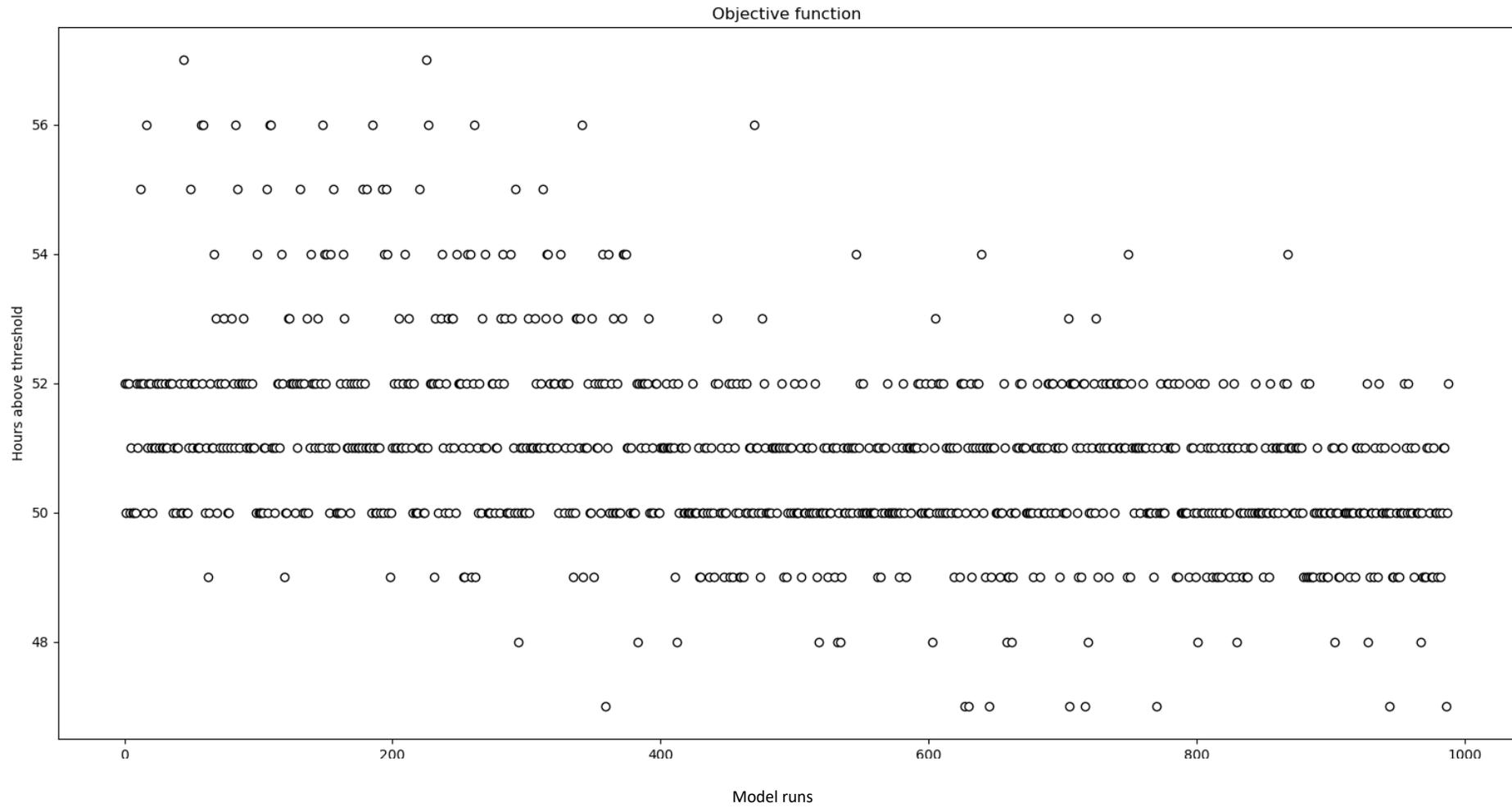
3: A. Asfaw, K. Maher, J.D. Shucksmith, 2018. Modelling of metaldehyde concentrations in surface waters: A travel time based approach, *Journal of Hydrology*, Vol. 562, 397-410

Further information: vsuslovaite1@sheffield.ac.uk

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Additional presentation materials



Rainfall event selection

A representative number/combination of rainfall events will be selected from several years of data to reduce computational time of the large amount of model runs.

Python code was written to read in rainfall data and automate identification and selection of storm events. An event was described as any rainfall in between two no-rainfall data points.

Each event was assigned an event ID, start and end date and time. Event length in hours, total event rainfall (catchment average), average standard deviation and 15 day antecedent moisture condition were also calculated for each event. Sample output table, top right. These variables will help filter out the events that are too small/short and enable selection of a variety of rainfall events that are representative of catchment rainfall.

Sample graph of automated rainfall event recognition, bottom right. The rainfall time series plotted in grey, the identified rainfall events superimposed in black.

EventID	Start Date	End Date	Event length/h	Total Rainfall	Av S Dev	AMC 15d
0	16/09/2017 03:35	16/09/2017 03:50	0.25	0.00023181	0.000879	31.995
1	16/09/2017 04:00	16/09/2017 06:20	2.333333333	0.176461884	0.016117	31.99524
2	16/09/2017 07:05	16/09/2017 07:10	0.083333333	1.97E-05	0.000453	32.1717
3	16/09/2017 07:30	16/09/2017 10:15	2.75	0.024211845	0.00484	32.17172
4	16/09/2017 11:10	16/09/2017 11:15	0.083333333	9.86E-06	0.000226	32.19593
5	16/09/2017 11:20	16/09/2017 11:25	0.083333333	5.43E-05	0.000758	32.19594
6	16/09/2017 12:35	16/09/2017 19:30	6.916666667	2.592926334	0.085167	32.19599
7	16/09/2017 19:40	16/09/2017 19:45	0.083333333	4.93E-06	0.000113	34.76506
8	17/09/2017 15:30	17/09/2017 17:45	2.25	0.362018624	0.034354	33.76506
9	17/09/2017 17:50	17/09/2017 17:55	0.083333333	6.90E-05	0.000918	34.12708
10	17/09/2017 21:00	17/09/2017 21:10	0.166666667	0.001104798	0.004036	34.12715
11	17/09/2017 21:15	17/09/2017 21:20	0.083333333	0.000147964	0.002273	34.12826
12	18/09/2017 11:45	18/09/2017 12:10	0.416666667	0.005045573	0.007776	33.80101

