Modelling Pathogen Inputs to Drinking Water Reservoirs in Australia, the UK and the USA

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EXTENDED ABSTRACT

The pathogen catchment budget (PCB) model (Ferguson et al. 2007) was developed for estimating the pathogen (*Cryptosporidium* and *Giardia*) and faecal indicator (*E. coli*) loads generated within and exported from drinking water catchments. The model uses a mass-balance approach and predicts the total loads generated and the total loads exported from each sub-catchment for the pathogens *Cryptosporidium* and *Giardia* and the faecal indicator *E. coli*. Briefly, the PCB model consists of 5 components: a hydrologic module, a land budget module, an on-site systems module, a sewage treatment plant (STP) module and an in-stream transport module.

PCB is an event-based model, representing the likely fluxes from sub-catchments in dry, wet and flood conditions. The model was developed in the Interactive Component Modelling System (ICMS), (Cuddy et al. 2002), and is freely available from the Commonwealth Scientific Information and Resource Organisation (CSIRO). Inputs to the model include GIS land use and hydrologic data as well as catchment specific information such as animal density and the location of on-site systems and sewage treatment plants (STPs) as well information on pathogen concentrations in different species, pathogen inactivation rates and mobilisation of faecal material. The hydrologic module uses the non-linear loss module of the IHACRES rainfall-runoff model described by Croke and Jakeman (2004).

The PCB model was initially applied to the Wingecarribee catchment and subsequently to the Sydney Catchment Authority (SCA) area of operations (Ferguson 2005; Ferguson and Croke 2005). As part of a project funded primarily by the American Water Works Association Research Foundation, the model has been applied to drinking water supply catchments in Australia (Googong), the UK (Thirlmere) and the USA (Kensico). This paper describes the application of the existing event-based PCB model to these catchments, and the adaptations to the model needed in each case. The influence of snow in the study catchments in the UK and USA has not been taken into account, so the model results are suitable for summer storm events only.

The higher inactivation rate for *E. coli* leads to only nearby sub-catchments contributing significantly to loads entering the dam in the Googong catchment. In comparison, *Cryptosporidium* and *Giardia* do show evidence of transport from the headwater areas in the Googong catchment even under low flow conditions. The study sites in the UK and the USA are significantly smaller, and each sub-catchment is directly connected to the reservoir so that the inactivation rates during transport are not significant. Table 3 shows the sub-catchments which the model predicts will have the largest input into the stream network (i.e. ignoring in-stream processes).

The output from the PCB model facilitates identification of those sub-catchments that represent the highest pathogen (and indicator) risk to the quality of raw drinking water supplies. This enables managers to prioritise the implementation of control measures, to inform water supply strategies and target best management practices. The outputs from the model can also be used as input data to hydrodynamic models of pathogen transport in reservoirs.

1. INTRODUCTION

Numerous papers have outlined the difficulties in quantifying diffuse sources of pollutants in drinking water catchments (Ferguson et al. 2003; Ferguson and Croke 2005; Oliver et al. 2005, Tian et al. 2002). Various models have been developed to predict nutrient and sediment loads transported from catchments e.g. CatchMODS (Newham et al. 2004). However, few models are able to predict pathogen loads transported from drinking water catchments (e.g. Ferguson et al. 2007; Hayden 2006 and 2007; Dorner et al. 2004 and 2006). Estimation of pathogen loads is further complicated by the lack of source data for the prevalence and concentration of animal and human sources of contamination and the lack of water quality data available to calibrate models.

This study describes the application of the PCB model to quantify pathogen and faecal indicator loads within Australian (Googong), UK (Thirlmere) and USA (Kensico) raw water catchments.

2. DESCRIPTION OF THE CATCHMENTS

2.1. Googong

The Googong catchment (Figure 1) is a semi-protected catchment located to the east of Canberra in South Eastern Australia. There are some livestock present in the catchment although large areas are dominated by pine forest and native vegetation. The domestic livestock include sheep, cattle, alpacas and goats. The wildlife species include kangaroos, foxes, rabbits, deer and feral cats. There are no STPs in the catchment; however there are numerous on-site systems particularly in the Burra Creek sub-catchments. The total catchment area is 890 km^2.

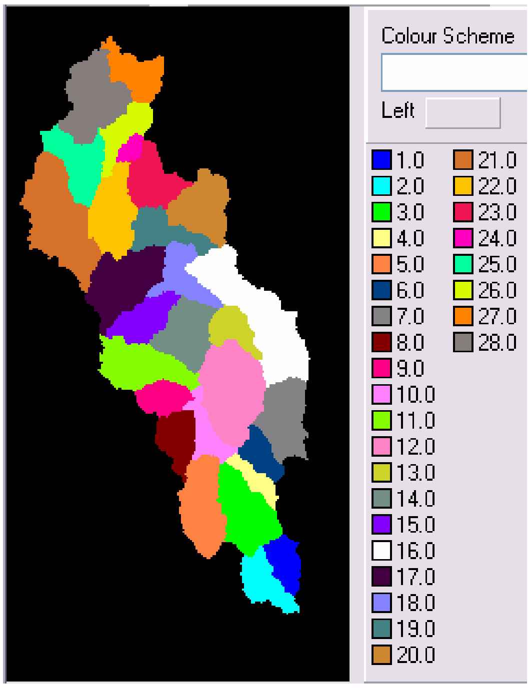

Figure 1. Googong catchment (28 sub-catchments, reservoir is in sub-catchment 28)

2.2. Thirlmere

The total catchment area comprises 41.3 km^2 and the surface area of the lake is 3.3 km^2. The catchment is divided into 6 sub-catchments, each draining directly into Thirlmere; these are (1) Raise Beck 3.7, (2) Whelpside 6.0, (3) MillGill 9.7, (4) Arnboth 6.6, (5) Old Scarf 5.6 and (6) Wythburn 6.3 km^2 (Figure 2). There is a canal in Mill Gill sub-catchment diverting water into Thirlmere, thereby increasing the size of the catchment. There are 5 tenancies (farms) in the catchment (some extend outside the catchment – the total area of farms inside the catchment is 19.5 km^2), mostly raising sheep. The total across all farms (over-estimate of animals inside the catchment) are shown in Table 1.

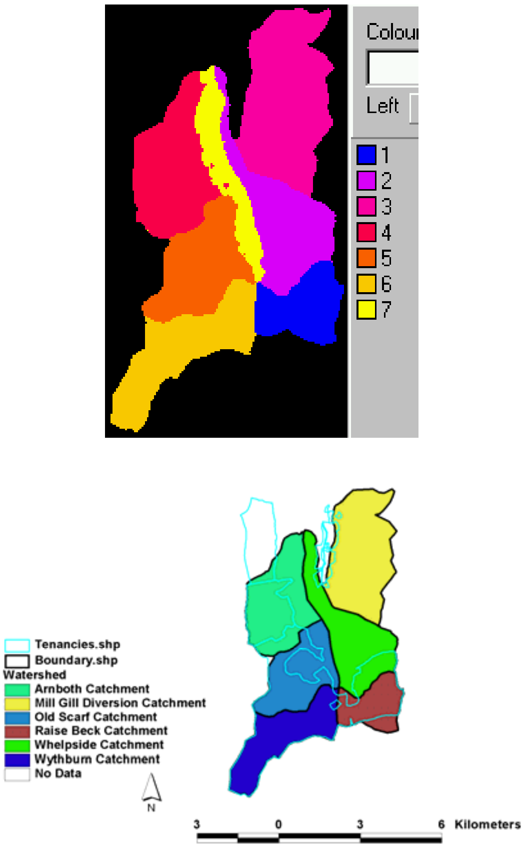

Figure 2. Thirlmere catchment (7 sub-catchments, Lake is sub-catchment 7 (yellow))

The farms are predominantly located on the west side of the lake. The east side of the lake is more mountainous, reaching an elevation of approximately 940 m about 2 km east of the lake (the lake is about 180m). Other land uses in the catchment include approximately 5 km^2 of coniferous trees (located mostly on the shores of Thirlmere). The non-farmed area on the east of the catchment is predominantly a mixture of rough grasslands and scree. The mean annual rainfall is approximately 2500 mm/yr (measured rainfall from gauge at The Nook Logger station, Thirlmere).

Table 1. Estimates of Animal densities in the Thirlmere catchment

Animal Type	Number in the catchment
Suckler cows	10
Dairy cattle	50
Other cattle (calves)	30
Ewes	4510
Gimmer hog	1200
Rams	90
Lambs	3080
Poultry	12
Horses	1
Dogs	19

2.3. Kensico

The land uses available from the New York GIS layers were re-categorised as outlined in Table 2. There were a few minor adjustments that were required, such as removing a small urban area from sub-catchment 7, which is the dam itself (Figure 3). The residential land use was put in the grass category as small amounts were found in areas without houses. The improved pasture cattle category in the model was renamed as pasture. The total catchment area is 34.3 km^2.

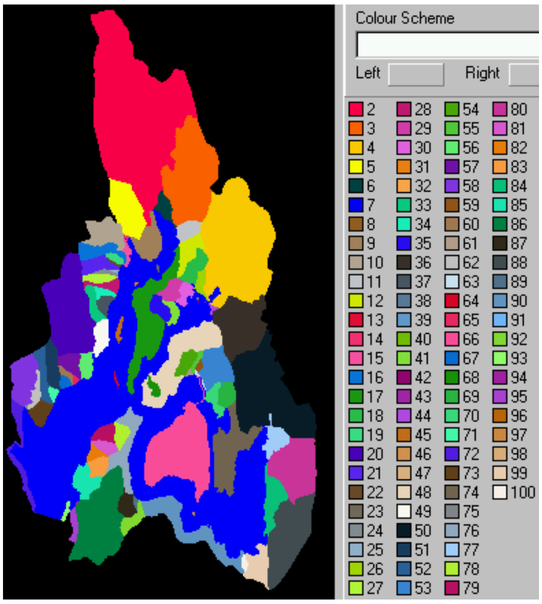

Figure 3. Kensico catchment (99 sub-catchments, reservoir is sub-catchment 7 (blue))

Table 2. Land use categories for the Kensico catchment

PCB model category	NY GIS Category
Grass	Grass hay, herbaceous, managed turf, parks and residential
Grass & Brush	Bushland, golf courses, mixed brushland, shrub and bush
Commercial & Industrial	Airports, commercial and services, industrial, office parks and institutional, impervious surfaces, roads, paths and shopping centres
Urban residential	Medium density housing, multi-family units, urban and built-up land, single-family units
Rural residential	Low-density housing, rural housing
Forestry with native fauna	Coniferous forest land, deciduous forest land, mixed forest land
Pasture	Cropland and pasture, pasture,
Intensive plants	Rotated crop lands
Wetland	Wetland
Water	Water

3. APPLICATION OF THE MODEL TO THE CATCHMENTS

Each catchment was divided into a series of unique sub-catchments based on the digital elevation data from the GIS layers. The available GIS land use data for each catchment were amalgamated into a subset of 10-13 land use classes. The specific sub-catchment characteristics of the catchments required to run the model were derived from the GIS land use layer e.g. sub-catchment area. However, other variables such as the location of the STP that an upstream sub-catchment is connected to were identified and input manually.

3.1. Googong

As there is no STP within the Googong catchment, the sources of pathogens are animals and on-site systems (mostly located in the Burra Creek sub-catchment – no. 21 and 25 in Figure 1). The animal and microorganism data files used for the Sydney catchment (Ferguson 2005) were modified to account for different animal densities in the Googong catchment reported by Starr (2006).

3.2. Thirlmere

The model uses the sub-catchments defined by United Utilities. No native or feral animals have been included at this stage, nor has the influence of humans been properly handled. Animal densities were based on reported numbers of animals on each farm, and multiple entries for the same animals have been included to permit densities to vary between farms. Local data on animal density and pathogen concentrations was substituted for those animals for which UK data was available e.g. lambs, cattle etc. to account for geographical differences in pathogen prevalence and concentration. As the catchment is small, and sub-catchments all drain directly into the lake, the drainage part of the model is not playing a significant role. The effect of snow has not been taken into account, and the model estimates should be considered as applicable for summer rainfall events only.

3.3. Kensico

For the USA catchment additional data on animal density and pathogen concentrations was required for new animal species eg. beaver, racoons etc. and to account for geographical differences in pathogen occurrence in domestic species such as cattle. As with the model for Thirlmere, the model estimates apply only for summer rainfall events.

4. OUTPUT FROM THE MODEL

Table 3 shows the sub-catchments which input to the stream network the largest amount of each pathogen in each catchment (both in terms of actual export and export per km^2). Microbial loads are reported as x $\log_{10}$ which is equivalent to 10^x. In dry weather daily *E. coli* loads exported from sub-catchments in the Googong were predicted to range from as high as 9.6 $\log_{10}$ in sub-catchments 1, 2, 4, 6, 9 and 24 to as low as 8.72 $\log_{10}$ in sub-catchment 21, and 8.2 $\log_{10}$ in sub-catchment 28, which includes Googong dam (top panel of Figure 4). The rapid inactivation of *E. coli* bacteria compared with the travel time between catchments results in no spatial correlation of the *E. coli* loads in dry weather. In wet weather, the *E. coli* loads increase to a maximum of 14.2 $\log_{10}$ for intermediate events (middle panel of Figure 4), and 15 $\log_{10}$ for large events (bottom panel of Figure 4), with the influence of the shorter travel time in wet conditions resulting in accumulation of *E. coli* load through the catchment. In comparison, the *Cryptosporidium* loads (Figure 5) show evidence of accumulation through the catchment regardless of weather conditions due to the longer inactivation time for *Cryptosporidium* oocysts.

The lack of connectivity between the sub-catchments in the Thirlmere and Kensico models (in each model, each sub-catchment drains directly to the reservoir) means that the influence of the travel time is not apparent. The exports from both Kensico and Thirlmere sub-catchments is considerably less than that for Googong, reflecting the different scales involved (average sub-catchment size for Googong is 32 km^2, Thirlmere 6.3 km^2 and Kensico 0.3 km^2.

Table 3. Sub-catchments with the highest inputs in each study catchment (second half of the table gives the top sub-catchments in terms of exports/km^2).

		Googong	Thirlmere	Kensico
Crypto	Dry	16	3	2
	Wet_I	16	6	50
	Wet_L	16	6	50
Giardia	Dry	21	6	2
	Wet_I	28	6	50
	Wet_L	21	6	50
E. Coli	Dry	16	3	2
	Wet_I	16	3	2
	Wet_L	16	3	2
Crypto	Dry	1	6	59
	Wet_I	23	6	59
	Wet_L	20	6	59
Giardia	Dry	5	6	10
	Wet_I	23	6	59
	Wet_L	28	6	59
E. Coli	Dry	1	3	10
	Wet_I	23	3	10
	Wet_L	20	3	10

Under dry conditions, the largest potential source of pathogens in Thirlmere is Mill Gill, while in wet conditions; the largest potential export is from the Wythburn sub-catchment. For Kensico, the largest potential sources of pathogens under wet and dry conditions are the larger sub-catchments in the north and north east of the catchment, driven at least partially by the size of these sub-catchments.

The exported load from the reservoirs has been modelled for Googong and Kensico but not Thirlmere. Googong reservoir is included in sub-catchment 28, but is not limited to the dam. The lowest sub-catchment of both Kensico and Thirlmere are limited to just the reservoirs.

5. CONCLUSIONS

The output from the PCB model facilitates identification of those sub-catchments that represent the highest pathogen (and indicator) risk to the quality of raw drinking water supplies. This enables managers to prioritise the implementation of control measures, to inform water supply strategies and target best management practices.

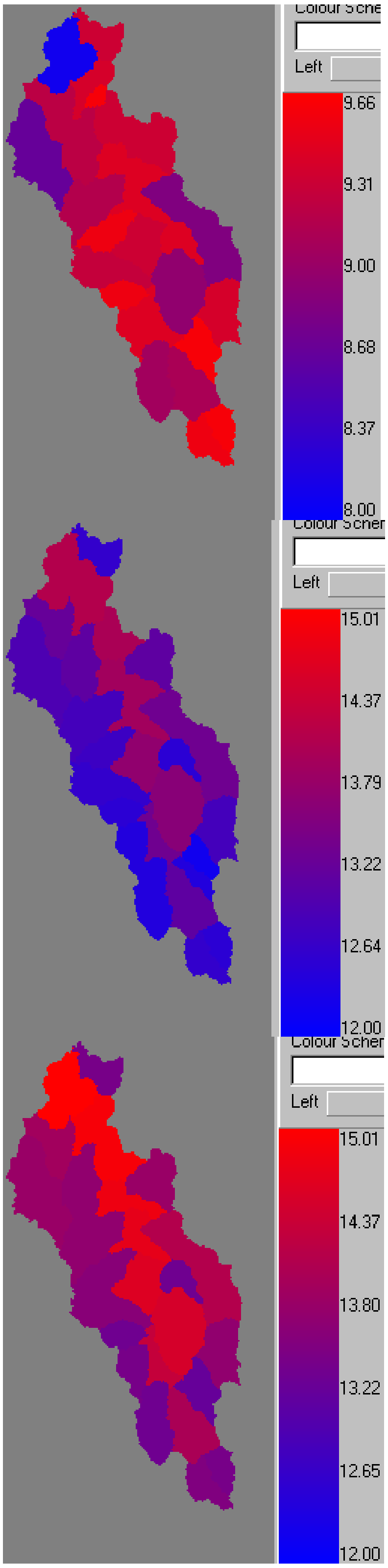

Figure 4. Estimated *E. coli* loads cfu ($\log_{10}$ day) exported from the Googong sub-catchments in dry weather (top), intermediate wet weather (<30 mm rainfall in 24 h) (middle), large wet weather event (100 mm rainfall in 24 h) (bottom).

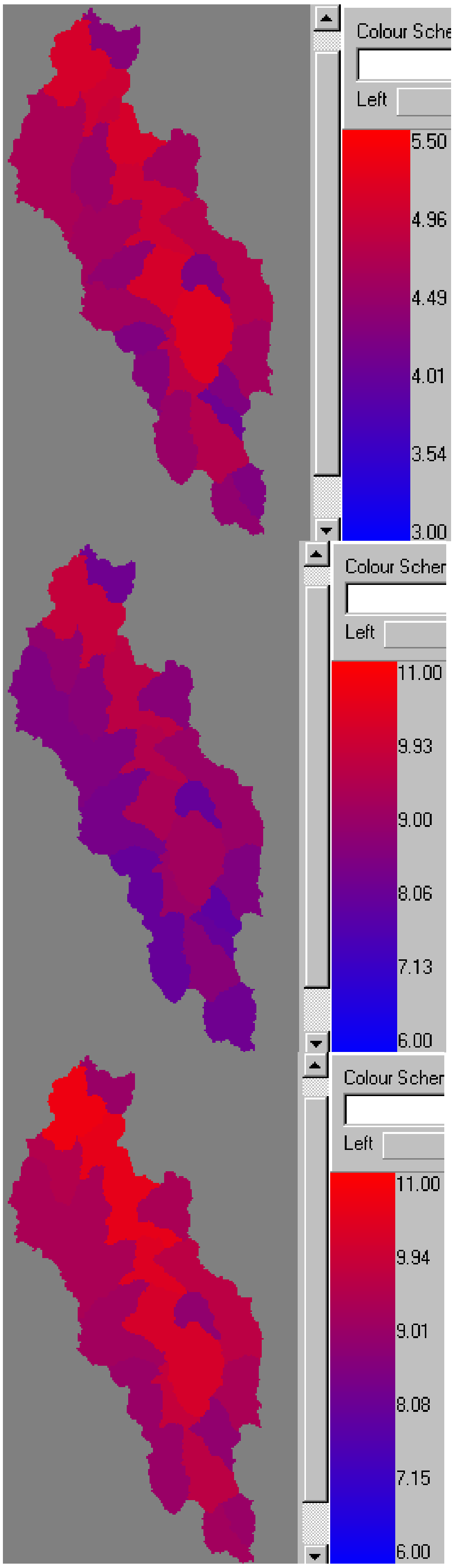

Figure 5. Estimated *Cryptosporidium* oocyst loads ($\log_{10}$ day) exported from the Googong sub-catchments in dry weather (top), intermediate wet weather (<30 mm rainfall in 24 h) (middle), large wet weather event (100 mm rainfall in 24 h) (bottom).

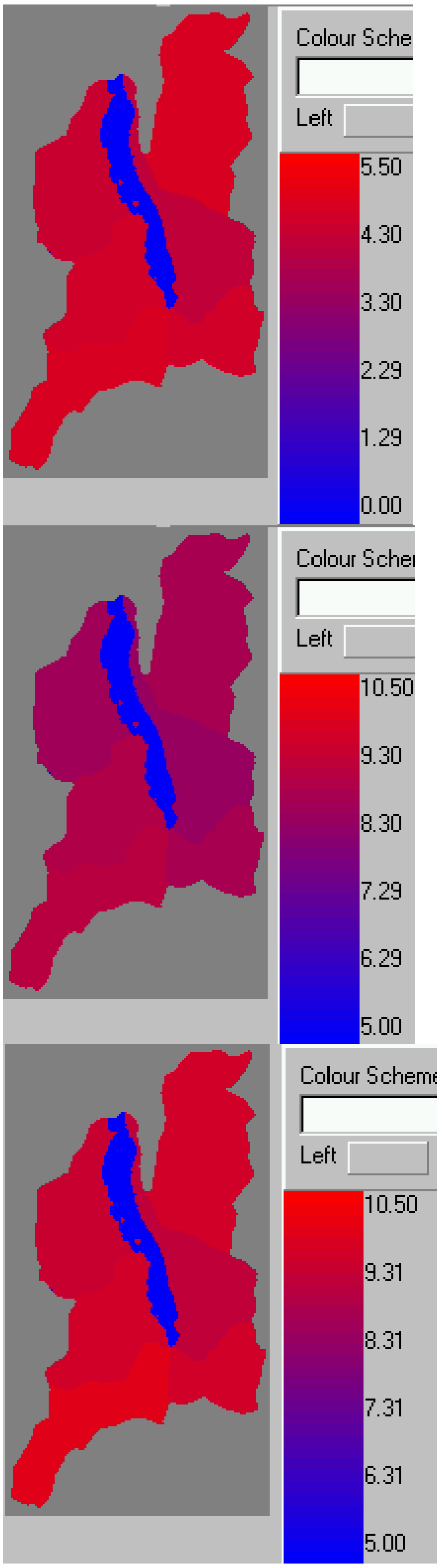

Figure 6. Estimated *Cryptosporidium* oocyst loads ($\log_{10}$ day) exported from the Thirlmere sub-catchments in dry weather (top), intermediate wet weather (<30 mm rainfall in 24 h) (middle), large wet weather event (100 mm rainfall in 24 h) (bottom).

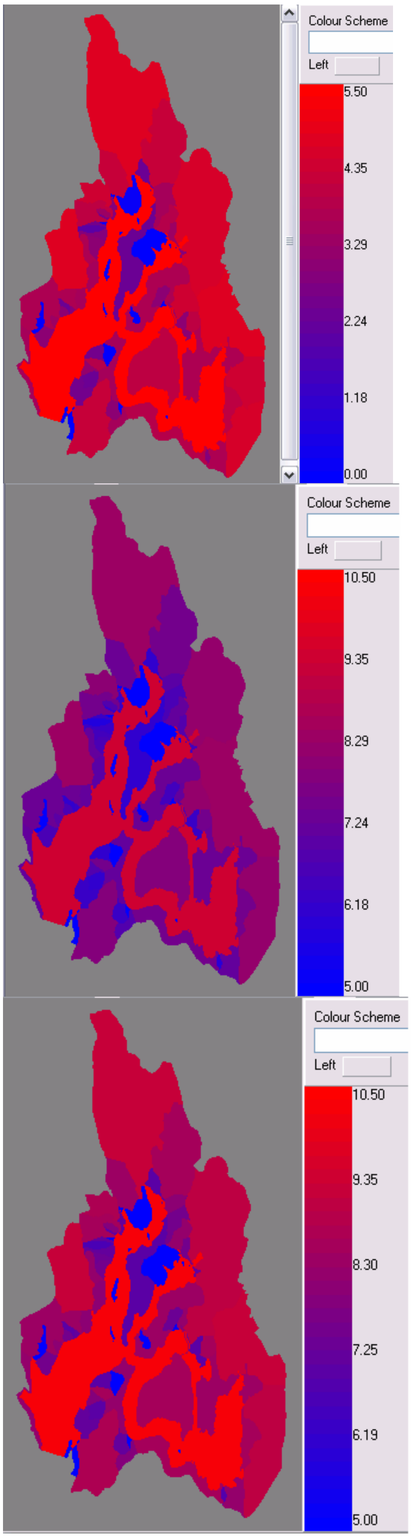

Figure 7. Estimated *Cryptosporidium* oocyst loads ($\log_{10}$ day) exported from the Kensico sub-catchments in dry weather (top), intermediate wet weather (<30 mm rainfall in 24 h) (middle), large wet weather event (100 mm rainfall in 24 h) (bottom).

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