Deterministic Model To Quantify Pathogen And Faecal Indicator Loads In Drinking Water Catchments

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EXTENDED ABSTRACT

Catchments are the first potential barrier to pathogen hazards in the water supply system. Reducing pathogen loads exported from catchments to drinking water reservoirs is thus an important priority in applying a risk-based approach to managing water supplies. Although predictive models are available to estimate sediment and nutrient loads, few models are available to predict either bacterial indicator or pathogen loads exported from catchments. This paper describes the application of a process-based mathematical model to predict pathogen (*Cryptosporidium*) and faecal indicator (*E. coli*) loads generated within and exported from the Sydney drinking water catchments. The model was derived from a conceptual model that identified key processes for microbial sources from animals, on-site systems and sewage treatment plants (STPs) and their subsequent transport within drinking water catchments (Ferguson et al. 2003). Inputs to the model include GIS land use and hydrologic data and catchment specific information. The model was initially applied to the Wingecarribee catchment in the Sydney drinking water catchment and a sensitivity analysis of the model was undertaken to determine components of the model that required further investigation (Ferguson et al. submitted). The model was then applied to all 27 individual catchments (and the 196 sub-catchments) within the Sydney Catchment Authority (SCA) area of operations. The model predicts pathogen catchment budgets (PCB) and ranks the sub-catchments that generate the highest loads of pathogens and indicators (per km^2), as well as the sub-catchments that export the greatest load of pathogens to the downstream storages. Ranking the sub-catchments enables quick identification of those areas that are generating the highest pathogen and indicator loads facilitating the implementation of control measures.

The outputs from the model show that in dry weather the highest daily loads of *Cryptosporidium* were predicted to be generated in Kellys Creek and Mittagong Creek sub-catchments in the Wingecarribee catchment. These sub-catchments are heavily impacted by the effluent discharged from Bowral and Moss Vale STPs, respectively. However, in wet weather the wash off of faecal material into surface runoff predicts that large loads of *Cryptosporidium* are generated in sub-catchments dominated by improved pasture grazed by cattle. The slow decay of protozoan pathogens combined with their rapid transport in water during wet weather events results in a cumulative export of *Cryptosporidium* to downstream sub-catchments. For example, the PCB model predicts that Warragamba reservoir would receive 4 x 10^{11} *Cryptosporidium* oocysts following a 100 mm in 24 h rainfall event in the Sydney catchment. The model predicts that in dry weather approximately 1 x 10^{11} *E. coli* per day were generated in sub-catchments that contain improved pasture with agricultural livestock with additional inputs from sub-catchments receiving STP effluent. The rapid die-off and limited transport of this microorganism in dry weather results in fairly localized impacts. However in wet weather significant loads of faecal indicator bacteria are mobilised to the stream network and transported to downstream sub-catchments with Warragamba reservoir and the Lower Wollondilly predicted to receive up to 5.4 x 10^{15} *E. coli* following a 100 mm in 24 h rain event in the Sydney catchment. The pathogen and indicator wet weather export loads predicted by the PCB model can be used as input variables to the hydrodynamic reservoir model developed by Hipsey *et al.* (2005) thus enabling the estimation of the risk of their subsequent transport to the water storage offtake point in Warragamba Reservoir.

1. INTRODUCTION

The wide variety of pathogenic microorganisms that can contaminate source waters and the lack of quantitative data concerning their origin and distribution within drinking water catchments has hindered the development of predictive models of pathogen loads from catchments. One of the first attempts to predict pathogen loads from drinking water catchments was a model developed by Walker and Stedinger (1999). This model used diffuse pollution inputs to predict *Cryptosporidium* concentrations in the raw water supplied to New York City from the Catskill-Delaware catchment. In the Netherlands, Medema and Schjiven (Medema and Schijven 2001) modelled the discharge of *Cryptosporidium* and *Giardia* into surface water and the dispersion into rivers and streams using an emission model (PROMISE) and a dispersion model (WATNAT). However, the authors noted that the model was unable to account for the impact of diffuse agricultural pollution. Several other faecal indicator models have also been developed recently (Collins and Rutherford 2004; Crowther et al. 2003; Tian et al. 2002) and at least one other pathogen model is currently under development (Dorner, Huck and Slawson 2004). None of these models are yet commercially available.

This study describes the application of a process-based mathematical model or pathogen catchment budget (PCB) to quantify pathogen and faecal indicator loads within the Sydney drinking water catchments. The model is based on a conceptual model that identified key processes for microbial sources and transport within drinking water catchments (Ferguson et al. 2003). The model uses a mass-balance approach and predicts the total loads generated and the total loads exported from each sub-catchment for the pathogen *Cryptosporidium* and the faecal indicator *E. coli.*

2. DESCRIPTION OF THE MODEL

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. The model is coded using the Interactive Component Modelling System (ICMS) software (Cuddy, Letcher and Reed 2002) freely available from the Commonwealth Scientific Information and Resource Organisation (CSIRO). The software can be requested from the website (www.clw.csiro.gov.au/products/icms). Inputs to the model include land use and hydrologic flow data and catchment specific information to predict pathogen loads. The hydrologic module uses the non-linear loss module of the IHACRES rainfall-runoff model described by Croke and Jakeman (2004). Briefly, this model assumes an initial catchment moisture deficit and using the distribution of surface rainfall (GIS layer) an amount of rainfall is converted into a depth of effective rainfall (rainfall that ends up as stream flow) for each sub-catchment. The effective rainfall is used to estimate the wet weather mobilisation of faeces that have been deposited on the land (as described in the land module). The depth of effective rainfall depends only on the amount of rainfall and the soil moisture. The antecedent dry period is adjustable (30 days used in this study). The amount of rainfall is adjustable (30 mm and 100 mm in <24 h for intermediate and large events respectively, in the current simulations).

The land module calculates the number of microorganisms leaving the sub-catchment as the sum from all animal species present in the sub-catchment. Animal species are assigned as present or absent for a particular land use at a defined density. Animal density per sub-catchment is calculated from the GIS layers. Faecal material deposited on the land surface decays at the rate for microbial inactivation in soil. Faecal material, mobilised to the stream in wet weather or deposited in the stream, decays at the inactivation rate for each microorganism in water. Decay is calculated based on the estimated travel time to reach the sub-catchment outlet. In dry weather, the only linkage between the land budget module and the in-stream transport module was through direct input into the stream (i.e. animals defecating directly into the stream). This is calculated based on an estimate of the access to streams (wild animals have unrestricted access; domesticated animals may be prevented from accessing streams). In addition to access, an estimate of the likelihood of a particular species defecating into the stream is included. The wet weather budget includes the build up of material on the land, and the likelihood of mobilisation to the stream. The build up of the store of microorganisms on the land depends on the length of the antecedent dry period, the assumed storage at the start of the antecedent dry period, and the decay rate for each microorganism in soil. The mobilisation rate of manure assigned to each species is a considered estimate based on the size, shape and consistency of faecal material. Mobilisation varied with effective rainfall.

STP and on-site system impacts were estimated using effluent water quality and population data. Selection of sub-catchments connected to STPs was based on proximity to a STP, and spatial connection of urban areas. STP connectivity was calculated based on the proportion of the total population located in urban land use areas compared to the total sub-catchment population. In urban areas 98% of the population was assumed to be connected to the STP. The dry weather budget was simply the product of the population connected to the STP, the volume of water used per person per day and the post treatment microorganism concentration measured in the water released by the STP. The volume of effluent produced per person per day is adjustable (160 L in this study). In wet weather the volume of effluent that may be released during an event can be allocated based on the buffer capacity for each STP and available data on overflow volumes. The microbial load excreted per person per day was calculated by multiplying the percent prevalence of infection in the community by the concentration of microorganisms excreted per infected person per day. The wet weather budget was the load of microorganisms entering the STP (population connected multiplied by the number of microorganisms.person^{-1} day^{-1}) buffered by the available storage at the STP. Any water entering in excess of the buffer was assumed to leave the STP without treatment.

The input of microorganisms to the stream from on-site systems is assumed to depend on the population using on-site systems; an estimate of the number of microorganisms excreted per person per day; and the fraction of on-site systems connected to the stream. The only difference between wet and dry conditions for the on-site systems module is the level of connectivity to streams. In dry weather 1% of on-site systems were assumed to be connected to the stream and in wet weather this was assumed to increase to 20%. The model assumes that there was no decay of microorganisms between on-site systems and the stream network.

In-stream routing effects were calculated using stream order, the length of the stream reach, flow velocity and settling factors. In dry weather, all microorganisms bound to sediment were assumed to settle out, and there was no resuspension of settled material in either dry or wet weather. A fixed rate of 50% of *E. coli* were assumed to be bound to sediment and thus lost through settling. *Cryptosporidium* primarily remain in the water column with only 5% becoming bound and lost through settling. The stream reach (km) was divided by the flow velocity to estimate the loss due to settling per km for each sub-catchment. Microbial inactivation was calculated using the microorganism specific decay rate for water and an estimated travel time. There was no decay of microorganisms entering the river network from the STPs before reaching the outlet of each sub-catchment due to the STP being located near the sub-catchment outlet. During dry weather (low flow conditions), the flow velocity was assumed to be 0.1 m s^{-1}. During intermediate wet weather events flow velocity was assumed to be 1 m s^{-1} and for the larger wet weather event flow velocity was assumed to be 3 m s^{-1}. All flow velocity values are adjustable for each sub-catchment. Further detail of the model functions are described in Ferguson et al. (submitted).

3. APPLICATION OF THE MODEL TO THE SCA CATCHMENTS

Each sub-catchment was identified with a unique 4 digit number. The first two digits represented the catchment (1 to 27) and the second two digits represent the sub-catchments within that catchment (Figure 1). The available GIS land use data for the Sydney drinking water catchment were transformed into a subset of 13 land use classes. The same assumptions were made regarding the density of the human population as described for the Wingecarribee catchment (Ferguson et al. submitted). These were 2400 people km^{-2} for urban residential, 100 people km^{-2} for rural residential, and 10 people km^{-2} for agricultural land uses. 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. The animal and microorganism data files for the model were the same as used for the Wingecarribee catchment based on results from studies by Cox et al. (in press) and Davies et al. (2005).

In dry weather the STP loads were calculated using the arithmetic mean concentrations of the microorganisms in the post-treatment effluent for each STP. These inputs to the model were calculated from the existing data on microbial quality of sewage effluent (Krogh and Paterson 2002; Paterson and Krogh 2003) combined with new data. In wet weather the volume of effluent that may be released during an event was based on the buffer capacity for each STP and available data on overflow volumes (Paterson and Krogh 2003). There are approximately 18 000 on-site systems in the Sydney drinking water catchment (Charles et al. 2001). The total catchment population was estimated based on land use type, and then the proportion of the population that was not located in an urban area and thus not connected to an STP were assumed to be using on-site systems.

4. OUTPUT FROM THE MODEL

In dry weather daily *Cryptosporidium* loads generated within sub-catchments were predicted to range from approximately 4 log_{10} in Katoomba (0602) and Bindi Creek (1401) to as high as 6.3 and 7.8 log_{10} in Mittagong (2504) and Kellys Creek (2503) sub-catchments, respectively (Figure 2). These latter sub-catchments are located downstream of Moss Vale and Bowral STPs, respectively, in the Wingecarribee catchment. In intermediate (<30 mm in 24 h) and large (100 mm in 24 h) wet weather events daily *Cryptosporidium* loads generated in all sub-catchments increased by 3-5 log_{10} (Figure 2). Wet weather *Cryptosporidium* loads generated within sub-catchments were predicted to range from 7-7.5 log_{10} in Berrima (2506) and Covan (1603) sub-catchments to as high as 10.6 log_{10} in Warragamba reservoir (1001) and 10.4 log_{10} in Upper Kowmung (0904). Similar trends were predicted for the exported loads of *Cryptosporidium* with most sub-catchments predicted to export approximately 5 log_{10} oocysts per day in dry weather (Figure 3). The exported loads of *Cryptosporidium* during wet weather again showed similar trends to the predicted input loads except that the exported loads were spread over a slightly wider range than the input loads with the highest exported loads reaching 11.6 log_{10} in Warragamba reservoir (Figure 3).

E. coli loads generated daily in dry weather were predicted to range from 9 log_{10} mpn (most probable number) in an Unnamed Ck in Werri Berri sub-catchment (2404) and Woronora R (2702) to 12 log_{10} in Bundanoon Ck (803) and Lower Mulwaree (1608). Generally there was little variation between sub-catchments within a catchment, with most sub-catchments predicting source loads of approximately 11 log_{10} mpn per day. Export loads of *E. coli* during dry weather were usually 3 log_{10} lower than the input load, with most sub-catchments predicting export loads of approximately 8 log_{10} mpn per day. The lower predicted export loads reflect the rapid die-off of *E. coli* in dry weather conditions compared to the more robust survival of *Cryptosporidium* oocysts. In wet weather the predicted daily *E. coli* source loads ranged from 11.5 log_{10} mpn in Berrima (2506) and Katoomba (602) to 14.5 log_{10} mpn in Warragamba reservoir (1001), Upper Kowmung (904) and Bundanoon Ck (803). The predicted daily export loads of *E. coli* during wet weather ranged from 12-15 log_{10} mpn compared to the source loads which ranged from 12-14 log_{10} mpn per day.

5. DISCUSSION

The model predicts that daily *Cryptosporidium* and *E. coli* loads generated during dry weather have mainly localised impacts on a few SCA sub-catchments, primarily the Mittagong and Kellys Creek sub-catchments downstream of Moss Vale and Bowral STPs and also those sub-catchments that are impacted by agricultural activities associated with improved pasture land use. However, following rainfall events the rapid transport of microorganisms mobilised from the land surface results in a cumulative impact on downstream sub-catchments. The effect is more pronounced for *Cryptosporidium* than *E. coli* bacteria due to its slow inactivation rate.

While it was acceptable to apply some assumptions and default values across the whole Sydney catchment, e.g. microbial decay rates, further work should replace other parameters with data that are more appropriate for the different sub-catchments. Parameters that should be reviewed for each sub-catchment include; the fraction of urban areas connected to the sewerage system, flow velocities in dry, intermediate and large wet weather events, the level of stock access to streams and animal density estimates by land use type. For example, the default flow velocities could be replaced with measured values for those sub-catchments that have flow gauging equipment installed. Also, the current model does not account for the potential resuspension of microorganisms from the sediment during wet weather events, indicating that current model outputs may underestimate the total loads generated during wet weather.

6. CONCLUSIONS

The application of the PCB model to the entire SCA catchments represents the first quantitative identification of those sub-catchments that represent the highest pathogen (and indicator) risk to the quality of Sydney's raw drinking water supply. The outputs of the model should be used as first cut budgets to enable catchment managers to prioritise the implementation of control measures, to inform public education strategies and drive best management practices. However, the model should not remain static, incorporation of new data and replacement of default values with actual data will reduce the level of uncertainty of the outputs. The ongoing drought conditions in the catchment prevented the collection of wet weather water quality data. Collection and analysis of additional water samples during wet weather events is essential to properly test the outputs of the model.

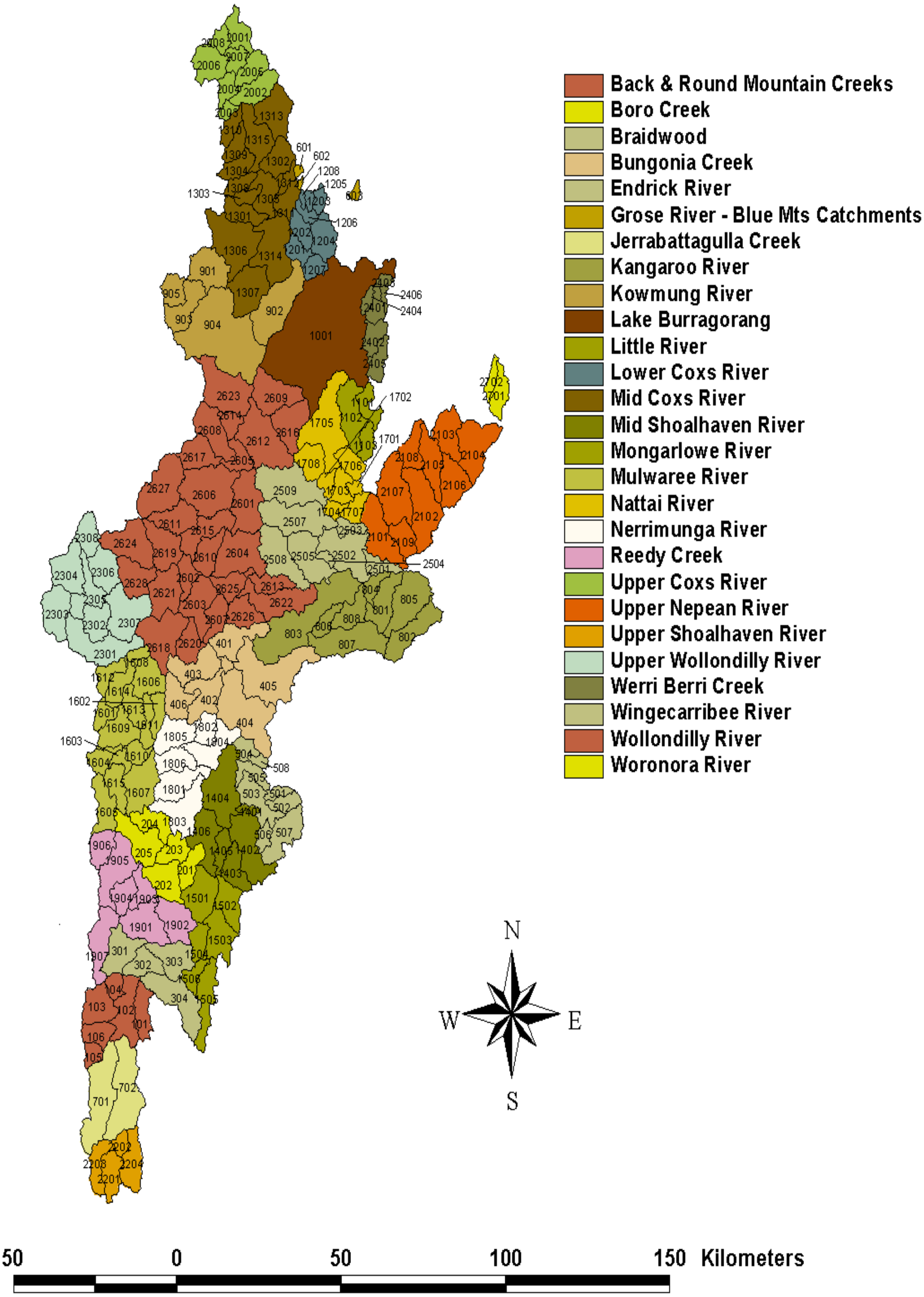

Figure 1. Map of the Sydney drinking water catchment.

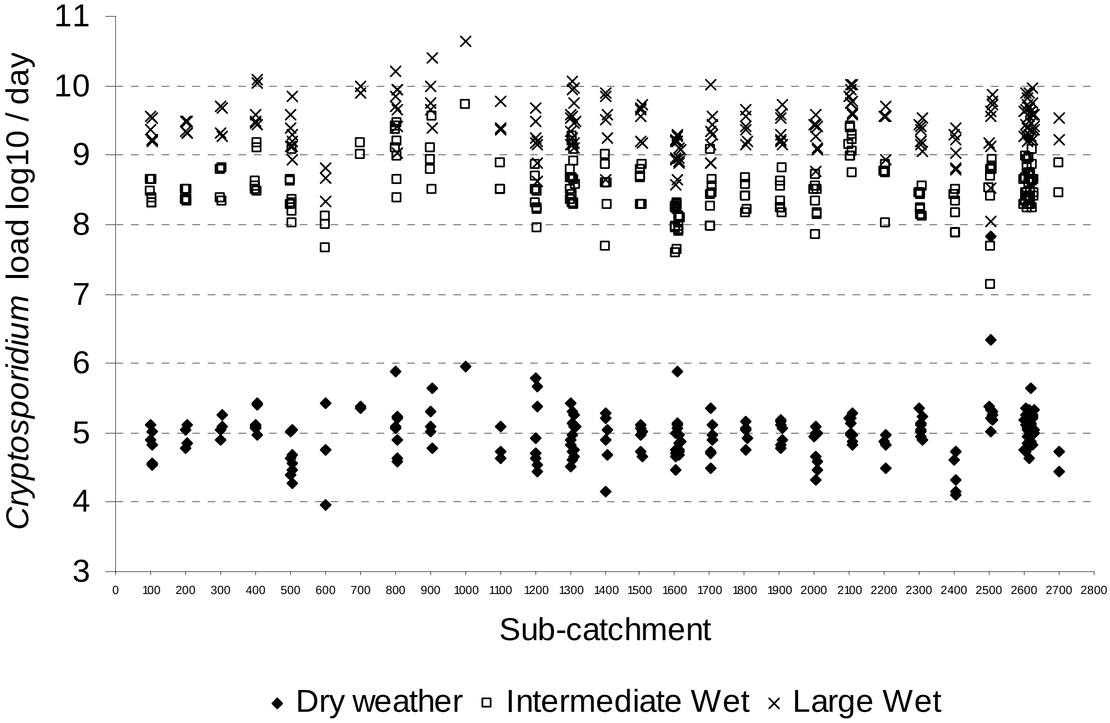

Figure 2. *Cryptosporidium* oocyst loads ($\log_{10}$ day) generated within SCA sub-catchments per day. Sub-catchments are not in sequential downstream order.

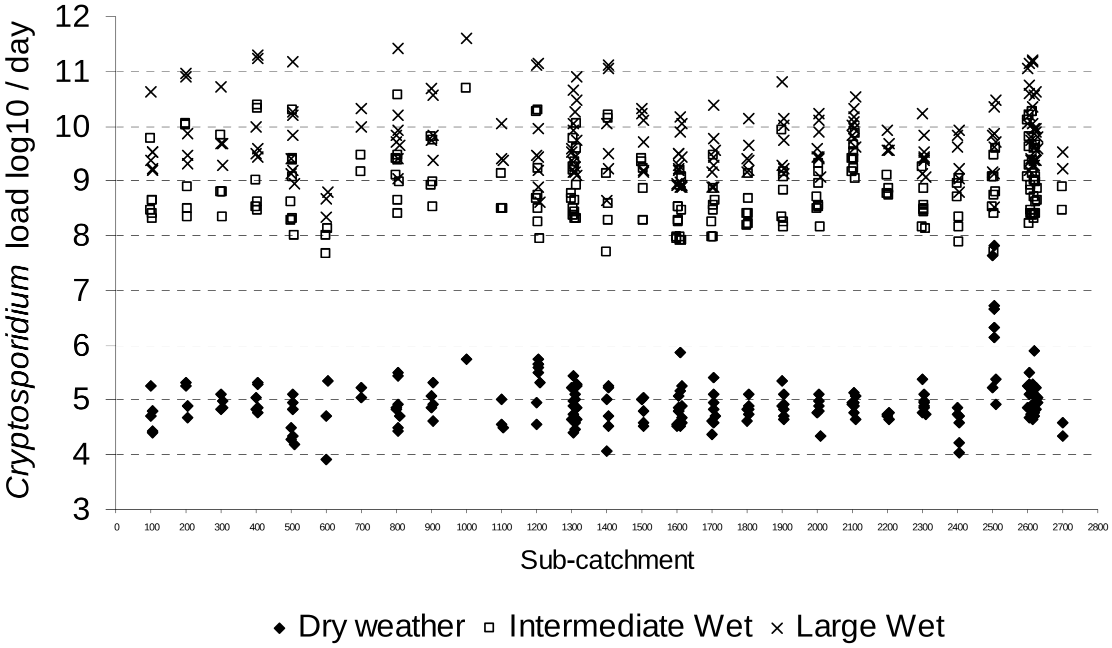

Figure 3. *Cryptosporidium* oocyst loads ($\log_{10}$ day) exported from SCA sub-catchments per day. Sub-catchments are not in sequential downstream order.

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