Quantifying and tracking drought and intermittence patterns in the groundwater-fed streams of the East Chilterns

A collaboration using the Springs and Sources dataset of Hertfordshire and North London Area of the Environment Agency

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Executive summary

Intermittent rivers and ephemeral streams (IRES) are hydrologically dynamic and ecologically diverse, under pressure from water resources and climate change, but underrepresented in protective legislation and monitoring programmes. The Springs and Sources dataset of Herts and North London Area is an internationally rare dataset of observations along intermittent rivers that has good resolution in hydrological state (flowing, ponded, dry), time (approx. monthly) and space (between 18 and 32 sites per river). The results delivered by this collaboration were threefold.

Firstly, the development of the current water situation on the chalk streams of the East Chilterns was tracked throughout the project. There was a marked lack of network expansion through the winter months in comparison with expected long term average recovery (March 2004 – March 2019). The proportion of dry reach in March 2019 was comparable with that of March 2006, most notably on the groundwater-dominated rivers (Misbourne, Chess, Bulbourne, Gade, Ver and Mimram).

Secondly, metrics have been provided that quantify the long term temporal availability of flowing, ponded and dry states at biological sampling sites to facilitate hydroecological assessment. Further metrics, quantifying the consecutive months of flow preceding a biological sample, and the distance from the site to flowing water in connectivity with the perennial reach have also been provided.

Thirdly, visualisations have been designed for characterising IRES and communicating their behaviour with a view to future facilitation of assessing their response to climatic and artificial drivers. Heat maps using an extracted monthly dataset show the annual pattern of summer contraction and winter expansion on groundwater-dominated rivers such as the Chess, Bulbourne and the Gade and the greater frequency of flowing state along the whole survey length apparent on flashier rivers, such as the Rib and the Stort. Long term permanence is presented in graphical and map form revealing local augmentations and losing reaches.

Challenges to the work highlight the need to infill gaps in the data. The accuracy of the statistical modelling techniques investigated was high for flowing and dry states, but limited for ponding, probably due to the small availability and the diversity of ponding observations on which to train the model. Further modelling work is recommended to infill the gaps, and explore the research potential and operational application of this rare and valuable dataset. Its value was highlighted by the launch, in April 2019, of a citizen science initiative (https://crowdwater.ch/) to collate similar data across Europe.

Acknowledgements

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Contents

1 Introduction

Intermittent rivers and ephemeral streams (IRES) are ecologically diverse because of their dynamic behaviour, transitioning between aquatic and terrestrial habitats (Stubbington et al. 2017), and drying is a primary hydrological determinant of biodiversity (Leigh & Datry 2016). However, with under-representation in monitoring programmes and protective legislation (Acuña et al. 2014; Fritz et al. 2017), IRES are at risk of deterioration as the pressures of climate change and local artificial influences change the natural variability in their hydrological behaviour. Hydrological data are required at good resolution and over sufficient duration to capture this variability in time and space, and must include standing as well as flowing water for ecologically meaningful assessments.

The Springs and Sources dataset collated in Herts and North London Area (HNL) of the Environment Agency is a rare resource, because it comprises multiple observations of hydrological state per year, at multiple sites along ten rivers and spanning a period of 22 years. The surveys monitor hydrological state using an eightfold classification of hydrological state: dry bed, wet bed, ponded, very low flow (trickle), low flow, medium flow, high flow and overbank flow. The study area in the East Chilterns includes both groundwater-dominated rivers (Misbourne, Chess, Bulbourne, Gade, Ver and Mimram) and those more influenced by superficial deposits (Beane, Rib, Ash and Stort).

In a recent collaboration between the Centre for Ecology & Hydrology and the Environment Agency, heat maps visualising this dataset demonstrated the greater occurrence of ponding and more rapid transitioning between states on those rivers more influenced by superficial deposits. Seasonal patterns in the proportion of flowing, ponded and dry states and in the spatial fragmentation of hydrological states along the rivers were quantified (report Sefton et al. 2017, paper Sefton et al. 2019).

Recent developments in the hydrological study of IRES that recognise flowing, ponding and dry states include monitoring in Switzerland (unpublished study involving paired sensors in experimental catchments), and an initiative to establish a European citizen science network of observers (SMIRES, 2019). The HNL dataset allows the development of techniques for categorical, ordinal data of this type to track drought, and quantify intermittent behaviour at site-scale for water resource and ecological assessments. Furthermore, the co-location of gauging stations and boreholes in the same catchments presents an opportunity to investigate the relationship between intermittence patterns and environmental drivers.

1.1 Project aims

The aims of the collaboration, building on the quantification of spatial patterns in intermittence, were twofold. Firstly, to apply the spatial metrics developed to track the water situation arising from long term rainfall deficits. Secondly, to adapt the methodology in the dimension of time instead of space to develop metrics that quantify temporal patterns in intermittence at a given site.

Three objectives were defined to address the aims:

1. Improve our understanding of drying/wetting cycles e.g. the duration, timing and longitudinal connectivity of flow and pooling, of ten Chalk streams in Hertfordshire.

2. Update and refine a quality assured Spring and Sources dataset, with two components:

    i) extraction of a monthly dataset to remove the inherent bias in irregular observations;
    ii) exploration of methods for infilling gaps in the dataset.

3. Develop temporal site metrics to link hydrological change and ecological response.

Data deliverables consist of the monthly dataset, and derived spatial, site and sample metrics.

2 Methods

2.1 Drought tracking

A consistent visualisation was required for the tracking of changes in the composition of hydrological state on each river with time and provide context. This was required to be suitable for presentation at drought meetings, for swift assimilation by management and decision makers.

Stacked bar charts showing the abundance (proportion) of each survey length observed to be in dry, ponded, moderate flow and high flow states were prepared and iterative improvement made to their format, month by month. Considerations included the number of panels showing reference years and long term average conditions for comparison with the current water situation, the criteria and suitability of potential dry reference periods, and the number of months shown in the development of the water situation. Inclusion of future months beyond the current month was also considered and rejected, despite its potential usefulness in comparing years, to avoid the misleading suggestion that the methodology was providing a forecast. The final format comprised four panels, the top one showing the development of the current water situation over the current and preceding five months, and three others providing the selected historical comparisons for context, as described in Table 1. The graphics were produced by R code reading directly from the Springs and Sources Survey spreadsheets updated by Environment Agency hydrologists. Where multiple surveys were undertaken in response to the dry weather, the mid-month survey conducted by HNL water resources hydrologists was used.

Table 1 Period of hydrological state proportions shown in each of the drought tracking panels

Panel	Period
Panel 1	The current and preceding five months.
Panel 2	The corresponding six month period in the previous year.
Panel 3	The corresponding six month period in the dry reference period of August 2005 – December 2006.
Panel 4	Average conditions in each of the corresponding six months during the period March 2004 to March 2019.

The dry reference period in Panel 3 was selected using the minimum proportion of flowing state over 17 consecutive months during the period of record. Both 2005-2006 and 2011-2012 were commonly identified using this criterion on the study rivers, the former on seven of the ten rivers.

2.2 Refinement of the dataset

2.2.1 Extraction of a monthly dataset

For quantifying patterns in intermittence as they vary with time, a dataset with regular intervals is required. This is because of the intensification of survey frequency during a dry period which, although desirable from an operational point of view, introduces bias towards dry conditions and probable overestimation of non-flowing states. An automated extraction of a monthly dataset, retaining one observation per month, was conducted using updates to the quality controlled dataset delivered as part of the earlier collaboration (Sefton et al. 2017). Where there were two or more observations in a month, the one nearest the middle of the month was again used for consistency with the monitoring protocol. Where two were equidistant, the survey used was that which gave the more consistent duration between survey dates across the months either side.

The fourfold classification of hydrological state used in the earlier work was reduced to three by the merging of moderate and high flow in order to address the likely underestimation of high flows and uncertainty associated with assigning high flow events to a whole month. The rationalisation also maximised confidence in the identification of hydrological state for application in hydroecological analysis. A monthly extracted dataset is provided as a data deliverable from the project (D1, Appendix A), with threefold classification of hydrological state, flowing, ponded and dry. The monthly dataset for each river is visually presented using heat maps, with time along the horizontal axes at monthly resolution, distance from the confluence along the vertical axis, and flowing, ponded and dry states colour coded blue, brown and pink, respectively, with missing months grey.

2.2.2 Exploring infilling of the monthly dataset

For operational reasons, there were months during which no surveys were conducted. There was an extended period without surveys from 2002-2003, with the Beane a notable exception (Figure 2 of Sefton et al. 2017).

An incomplete dataset poses issues for the quantification of temporal metrics, and methodologies were therefore explored for infilling both short gaps and longer gaps in the dataset. Buffering was explored for short gaps of up to two consecutive months in the period from January 2004 to October 2018, only. Statistical modelling was explored for longer gaps, with no such restriction on period. Modelling, whilst more complex than buffering, offers the potential for extrapolation, subject to the impact of artificial influences.

The extracted monthly dataset included 202 months without a survey, out of a possible 1780 survey months (10 rivers, 178 months) between January 2004 and October 2018. The percentage of missing survey months during this period varied between catchment, from 3.4-5.1% for the Colne, to 13.5-16.9% for the Lee (11.3% overall).

2.2.2.1 Buffering

Missing observations were infilled with unused survey data collected within a predefined number of days of the middle of the missing survey month; 18 and 22 day buffers were explored. Surveys conducted up to a week outside of a given month were thus included, without the introduction of bias by replicating data.

This method is limited by the assumption that hydrological state did not change between the missing survey month and the neighbouring month; the likelihood of this assumption being violated increases as the buffer is extended. Whilst no attempt was made to statistically test the assumption in order to assess the accuracy of such an approach, its effectiveness was evaluated using the reduction in missing data as a measure.

It is also recognised that the degree to which this assumption is invalidated varies spatially and temporally. Variability with time is more likely in flashier catchments (Beane, Rib, Stort, and Ash) than in those more dominated by baseflow (e.g. Gade, Chess and Mimram). The flashier catchments also exhibit temporally varying degrees of state transitioning, and the validity of the assumption will therefore vary with time and between sites.

2.2.2.2 Modelling

The potential for using models to estimate the hydrological state along the rivers for those months without observations was explored (Eastman, 2018). This poses a significant advantage over buffering in its suitability for infilling gaps in the record, as it considers the relationships between hydrological state and the surrounding environment, as well as the preceding hydrological conditions. The modelling involved training a series of six statistical models to estimate hydrological state (dry, ponded and flowing), a more complex approach than buffering but more robust in handling hydrological state variability.

Since the data are ordinal (falling into ordered categories of wetness, from dry to flowing) the approach selected was cumulative logit models (CLMs). This is an ordinal regression approach that does not require a value to be assigned to each state, but retains the inherent ordering between them (dry < ponded < flowing). More commonly used regressions requiring numerical data were rejected as they require a value to be assigned to each state (for example, flowing = 3, ponded = 2, dry = 1). This is inappropriate as it infers, for example, that the differences between flowing and ponded (3 minus 2) and ponded and dry (2 minus 1) are the same, and equate to half of the difference between flowing and dry (3 minus 1).

The models make use of input data (covariates), that quantify expected drivers of intermittence such as rainfall and groundwater level. This enables inferences to be made regarding drivers of hydrological state. Some covariates, specifically percolation, flow and groundwater level were included in all of the models. However, the way in which they were included and additional covarites such as the distance of the site from the confluence of the river, varied between models. The variation between the models is detailed below, and summarised in Table 2.

Inter-site variation

Model 1 did not account for inter-site variation, other than the sequence of the sites along the river. The probability of each state was calculated for the river as a whole and then assigned to sites according to their ordering alone. For example, if the model predicts that on a river with 20 sites, 20% of those sites will be dry, 30% ponded and 50% flowing, sites 1 to 4 at the upstream end would be assigned dry, sites 5 to 10 in the mid-reaches ponded, and 11 to 20 at the downstream end flowing.

Models 2 & 3 accounted for inter-site variation by training models on each site, allowing the relationships between hydrological state and environmental covariates to be independent from the site. Models 4 & 5 included a distance to confluence variable, allowing the probability of each state being estimated to change with the distance to confluence. Model 6 consisted of the best performing of Models 1-5.

Flow

Models 1-5 related hydrological state to the average monthly flow. However, Model 6 utilised functional data analysis to gather more information from the available daily flow data. Monthly B-splines were fit to daily flow data, and functional principal components analysis (FPCA) performed to determine how the corresponding month of flow varied from other B-splines. FPCA scores from the primary principal component were then used with other environmental covariates to train models.

Proportional Odds

Models 1, 2, 5, and 6 do not allow the regression coefficient to vary with hydrological state. They rely on the assumption that the relationship between the environmental covariate and each hydrological state is consistent, and are thus termed proportional odds models. By contrast, Model 3 is a non-proportional odds model, which means that the proportional odds assumption is removed, allowing the regression coefficients, and thus the relationships, for each environmental covariate to vary by hydrological state. Model 4 is a partial proportional odds model, allowing the regression coefficients to vary for some covariates.

The models were evaluated according to their success in estimating each of the three hydrological states, and also of the three combined for an overall evaluation. Successful model outcomes for each state comprise both true positives (correctly simulating its presence) and true negatives (correctly simulating its absence). These are summarised in two performance metrics; sensitivity, which is the proportion of actual positives correctly simulated by a model, and specificity, the proportion of actual negatives correctly simulated.

Table 2. Brief description of each model and covariates included in estimation of hydrological state

Model Identifier	Model Description	Covariates
Model 1	Proportional Odds CLM trained and tested on each river. No site-specific variation incorporated; probability of each state assigned according to site ordering.	Flow (average) Month index Percolation (average and frequency) Precipitation (average and frequency) Groundwater (average)
Model 2	Proportional Odds CLM trained and tested on each site.	Flow (average) Month index Percolation (average and frequency) Precipitation (average and frequency) Groundwater (average)
Model 3	Non-Proportional Odds CLM trained and tested on each site.	Flow (average) Month index Percolation (average and frequency) Precipitation (average and frequency) Groundwater (average)
Model 4	Partial Proportional Odds CLM trained and tested on each river, with distance to confluence included as a covariate.	Flow (average) Month index Percolation (average and frequency) Precipitation (average and frequency) Groundwater (average) Distance to confluence
Model 5	Proportional Odds CLM trained and tested on each river with distance, and the product of distance and other covariates included as additional covariates.	Flow (average) Month index Percolation (average and frequency) Precipitation (average and frequency) Groundwater (average) Distance to confluence Products of distance to confluence and each of the above
Model 6	Proportional Odds CLM trained and tested on each river. Replacement of average monthly flow data with primary functional principal component of average daily flow observations.	Flow (PC1) Month index Percolation (average and frequency) Precipitation (average and frequency) Groundwater (average) Distance to confluence

2.2.2.3 Observation bias

The models were trained using 75% of the data, and tested on the remaining 25% and state estimations can be made with the greatest confidence when covariate conditions in the testing dataset are similar to those in the training dataset. An important element of this similarity is the absence of observational bias. This would exist in the dataset if for example, monthly surveys were often missed during times of high flow because of operational commitments elsewhere. Since accurate extrapolation of state estimations to infill missing data is dependent upon the absence of observation bias, its assessment is an important precursor to interpretation of model results.

The presence/absence of observation bias was evaluated using logistic regression models. Each record in the monthly time series from 05/1997 – 05/2018 was assigned a value (1 or 0) based on whether or not an observation was made. Subsequently, the covariates used to train the models presented in Chapter 2.2.2.2 were regressed against this binary response variable.

$$\Pr(Y = 1) = \frac{e^{\beta_0 + \sum_{i=1}^{N} \beta_i x_i}}{1 + e^{\beta_0 + \sum_{i=1}^{N} \beta_i x_i}}$$

where Y represents whether or not an observation was made (1 = TRUE, 0 = FALSE) and where x_i is equal to:

$$\begin{aligned}
&x_{1:11} = Month \\
&x_{12} = Flow\ rate \\
&x_{13} = Percolation\ average \\
&x_{14} = Percolation\ frequency \\
&x_{15} = Precipitation\ average \\
&x_{16} = Precipitation\ frequency \\
&x_{17} = Groundwater\ level
\end{aligned}$$

Logistic regression models were also trained using a single covariate (precipitation average or groundwater level, dependent on location) to prevent the influence of multicollinearity on results.

The method identifies significant relationships between covariates (x_i) and whether an observation was made. This suggests the missing data is not random in terms of covariates, which may influence the accuracy of extrapolation.

2.3 Metrics

2.3.1 Spatial metrics

Metrics quantifying the spatial composition and configuration of hydrological states along the river that were selected in the earlier collaboration (Sefton et al. 2017; Section 2.3.2) were derived from the monthly dataset to produce time series. Mean metrics across the period of record (March 2004 to March 2019), broken down by river, allow comparisons within and between the sub-catchments of the Colne and the Lee. Distribution plots for the same period show the median, centiles and range of metrics across all rivers, and allow comparison between rivers free from the bias of irregular surveying.

The spatial metrics derived from the extracted monthly dataset are provided as a data deliverable from the project (D2a), with threefold classification, as detailed in Appendix A.

2.3.2 Spatial and temporal equivalence

The metrics used to quantify the composition and configuration of hydrological state along a river on a given date may be applied in the temporal dimension to describe the composition and configuration of hydrological state over a period of time at a given site (Sefton et al. 2017; Table 3). Conceptually, the spatial metrics describe a vertical slice of the heat map that was described in Section 2.2.1, that is, they summarise the observations along the whole survey length during a given monthly survey. Similarly, the temporal metrics describe a horizontal slice, that is, they summarise all monthly observations through the period of record at a given site. For example, dry state as a spatial metric describes the proportion of a river's study length that was dry in a given month, and as a temporal metric describes the proportion of time for which a given site was dry. Similarly spatial fragmentation describes the number of changes of state observed along a river, and temporal fragmentation the number of changes at a given site.

The derivation of the metrics was adapted in the temporal dimension because, although the observations are irregularly spaced in both space and in time, the processing requirements are not the same. Spatially, interpolation was used, with reach boundaries equidistant between the sites and the state observed at each site assigned to the reach that it represents. Temporally, however, a monthly time series was required, with twelve equally-distributed observations per year. An extraction methodology was therefore used, in preference to interpolation, whereby the observation closest to the middle of each month was used to represent that month. If two observations were equidistant from the middle of the month, e.g. 13 and 17 April, the date that was furthest from the adjacent month's observation was used to represent the target month. In this example, if the adjacent months' surveys were on 19 March and 17 May, then 17 April (30 days before May survey) would be used in preference to 13 April (26 days after March survey).

Table 3 Spatial and temporal equivalence for metrics describing the composition and configuration of hydrological state

Dimension	**Spatial (all reaches, single time step)**	**Temporal (all months, single site)**
Proportion	Relative abundance distance (proportion of survey length)[1]	Permanence (proportion of all months)
	Evenness[1] (from distance)	Evenness (from months)
	Fragmentation[1] (all states, derived from number of sites not reach length)	Fragmentation (all states)
	Single state fragmentation (derived from number of sites not reach length)	Single state fragmentation (frequency)
Absolute	Abundance distance[1] (km)	Abundance (number of months)
	Mean patch length[1] (all states, km)	Mean patch length (all states, months)
	Single state mean patch length (km)	Single state mean patch length (months)
	Edge density[1] (changes of state per km)	
	Lotic connectivity[1] (km upstream)	Lotic connectivity (months back from present date)
	Richness[1]	Richness

[1]Spatial metrics provided for each of the ten rivers by Sefton et al. 2017.

Both dimensions require an assessment of consecutive observations in the same state. Spatially, contiguous (neighbouring) reaches in the same state are called a "patch", and the results presented in a way that allows interpretation of the assumption of reach-representation. Temporally, consecutive months in the same state are termed a "period" in preference to "duration" to avoid the implication of continuous observation from discrete data.

The temporal equivalent of each spatial metric is defined in Table 3. Most of these are temporal equivalents of the spatial metrics provided by Sefton et al. 2017, denoted by the superscript [1], however, two additional metrics were derived because, although not identified as significant in the spatial dimension, they were now of interest in the temporal dimension. For completeness, however, they were derived in both time and space.

The first new metric is single state fragmentation which in the temporal dimension is the number of onsets of flowing/ponded/dry state across the period of record and may be thought of as frequency. This was not previously calculated in the spatial dimension as the requirement was for a measure of the overall fragmentation of states along the river. The second new metric is mean patch length for each of the three hydrological states in turn. In the spatial dimension this was previously calculated only as a summary metric for all states together, characterising the connectivity of hydrological states along the river. In the temporal dimension it is also calculated for each state in turn to provide a measure of the average periods in which the site is in each of the flowing, ponded or dry states. Thus, a “flow period” is one during which consecutive records in the monthly dataset are of the flowing state.

2.3.3 Temporal metrics

The temporal metrics in Table 3 describe long-term average conditions at each given site and full definitions for selected metrics that are thought to be of ecological relevance are given in Table 4. These quantify, for example, the proportions of each state present at a site over a given period of time, their duration, their timing and their fragmentation in time. The metrics were quantified for the period of record, starting March 2004, which sacrifices the 1997-1998 drought from the analysis but removes the likely inconsistency in the earlier recording of ponding, resulting from the standardisation of the monitoring protocol when surveys were resumed in 2004 after a two-year break.

The long-term temporal metrics derived from the extracted monthly dataset are provided as a data deliverable from the project (D2b), with threefold classification (Appendix A).

2.3.4 Sample metrics

For hydroecological analysis, metrics describing short-term temporal conditions preceding biological samples taken at observation sites, and short-reach spatial conditions in their vicinity were required.

Short-reach spatial metrics

A new metric, **Indicative Distance to Flow**, quantifies the distance to the flowing state from the biological sampling site (Figure 1, Table 5). This was defined as the difference between the distance to confluence and the lotic connectivity metric; positive results indicate if the flow is downstream of the sampling site, and negative if the flow is upstream (with the sampling site in a flowing state). It is recognised that the assumptions made regarding the state between sampling sites are harder to justify considering a short reach and this metric is therefore indicative.

Table 4 Long-term temporal metrics for a given site

Type	Metric	Definition	Interpretation
Composition	Permanence [Flowing/ponded/dry]	Proportion of monthly observations in each hydrological state	At a site that is flowing for six months of the year and dry for six, flow permanence is 0.5, pond permanence zero and dry permanence 0.5.
	Temporal evenness	Standardised measure of state diversity	If equal to one, each of the states observed at this site was equally abundant during the period of record. If close to zero, one of the states was very dominant e.g. mostly moderate flow.
Configuration	Temporal fragmentation [all states]	Number of changes in state (edges) as a proportion of the total number of months	One means there is a change of hydrological state every month, zero means there are no changes of state, (e.g. perennial.)
	Frequency (temporal single-state fragmentation) [Flowing/ponded/dry]	Number of onsets of a given state	
	Mean period (number of months) [Flowing/ponded/dry]	Mean number of consecutive monthly observations in a given hydrological state	At a responsive site, the mean period will be of the order of months, at a slower site, years.
	Lotic connectivity	Number of consecutive months observed flowing preceding current date	Lotic connectivity of 24 months means that all observations in the extracted monthly dataset before the current month were of flowing state

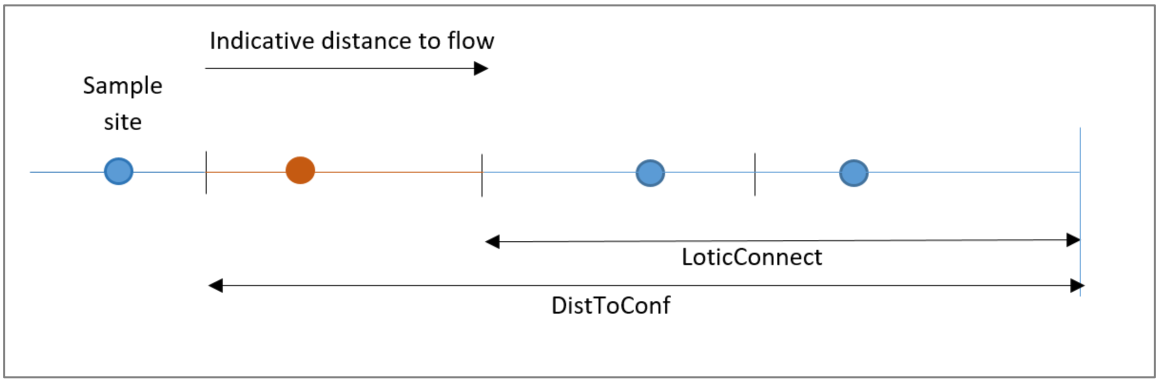


Figure 1 Schematic illustrating short-reach spatial metrics of hydrological state for biological samples

Short-term temporal metrics

As for the short-reach metric, it is recognised that the use of a single observation within each month is harder to justify when considering the short-term conditions preceding a sample date. For this reason, no attempt has been made to infill the dataset, rather, three subsets of the dataset unaffected by missing data have been recommended and provided for hydroecological analysis. These datasets consist of metrics unaffected by missing data, or with Mon.Flow uninterrupted by missing data for more than 12, 24, or 36 consecutive observations (Figure 2, Table 5). This is to allow for the development of ecological communities with no known interruptions to flowing conditions for one, two and three years preceding the sample.

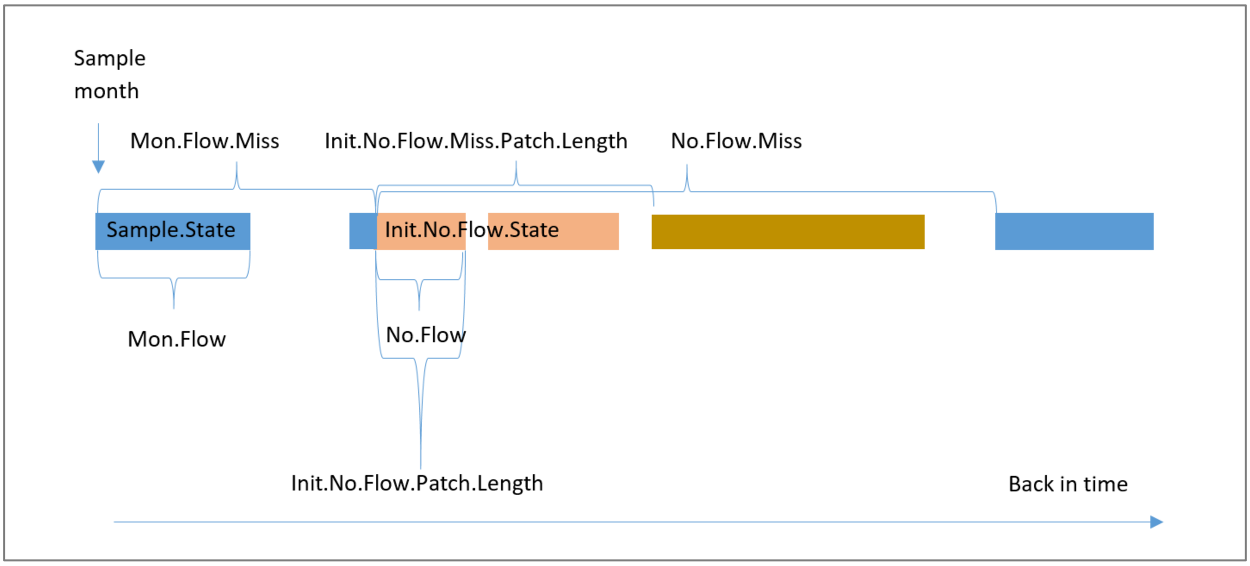


Figure 2 Schematic illustrating short-term temporal metrics of hydrological state for biological samples

Table 5 Short-reach spatial (top three) and short-term temporal metrics of hydrological state for biological samples (Data Deliverable D2c, see Appendix A)

Reference	Type	Description
DistToConf	Distance	Distance to confluence from the downstream boundary of the reach. Reach boundaries are equidistant from adjacent sites.
LoticConnect	Distance	Lotic connectivity (to upstream boundary of contiguous flow) derived from hydrological survey for month of biological sample.
Indicative Distance to Flow (DTC_LC)	Distance	Difference between DistToConf and LoticConnect. Defined as positive if the connected flow is downstream of the sample site; conceptually, the distance to flow.
State	State	The flow state of the hydrological survey for the month in which the biological sample was taken.
Mon.Flow	Period	The number of consecutive months in which flowing state was observed before, and including, the month in which the sample was taken.
Mon.Flow.Miss	Period	The number of consecutive months in which flowing state was observed or the data was missing, before, and including, the month in which the sample was taken. *The state of the missing data cannot be assumed to be flowing.*
Init.No.Flow. State	State	The state (dry or ponded) that immediately preceded Mon.Flow.Miss.
Init.No.Flow. Patch.Length	Period	The number of consecutive months in which Init.No.Flow.State was observed.
Init.No.Flow. Miss.Patch. Length	Period	The number of consecutive months in which either Init.No.Flow.State was observed or the data was missing. *It is not known whether or not the missing observations were of Init.No.Flow.State.*
No.Flow	Period	The number of consecutive months prior to Mon.Flow.Miss in which a non-flowing state (dry/ponded) was observed.
No.Flow.Miss	Period	The number of consecutive months prior to Mon.Flow.Miss in which a non-flowing state (dry/ponded) was observed or the data was missing. *It is not known whether or not the missing observations were flowing or non-flowing states.*

The sample metrics (short-reach spatial and short-term temporal) derived from the extracted monthly dataset are provided as a data deliverable from the project (D2c), with threefold classification as detailed in Appendix A.

3 Results

3.1 Drought tracking

An example of a drought tracking graphic is presented for the River Bulbourne, for March 2019 (Figure 3) and a full set is presented in Appendix B. The winter of 2018-2019 began with around 50% of the survey length in a dry state (Panel 1), which was comparable with the long-term average for October (Panel 4), and somewhat less than the autumns of 2017 (Panel 2) and 2005 (Panel 3). However, in contrast to the usual recovery seen through the winter months (Panel 4), and evident in the winters of 2017-2018 (Panel 2) and 2005-2006 (Panel 3), the proportion of dry survey length was sustained through the winter months and was still around 50% in March 2019. The water situation on the Bulbourne at the start of the spring is therefore comparable with that of 2018 and 2006.

The lack of recovery through the winter months is similarly apparent on the Misbourne, Chess, Gade, Ver and Mimram (Appendix B). Significant rainfall would be needed through the spring to sustain the winter recharge period and allow recovery to average conditions.

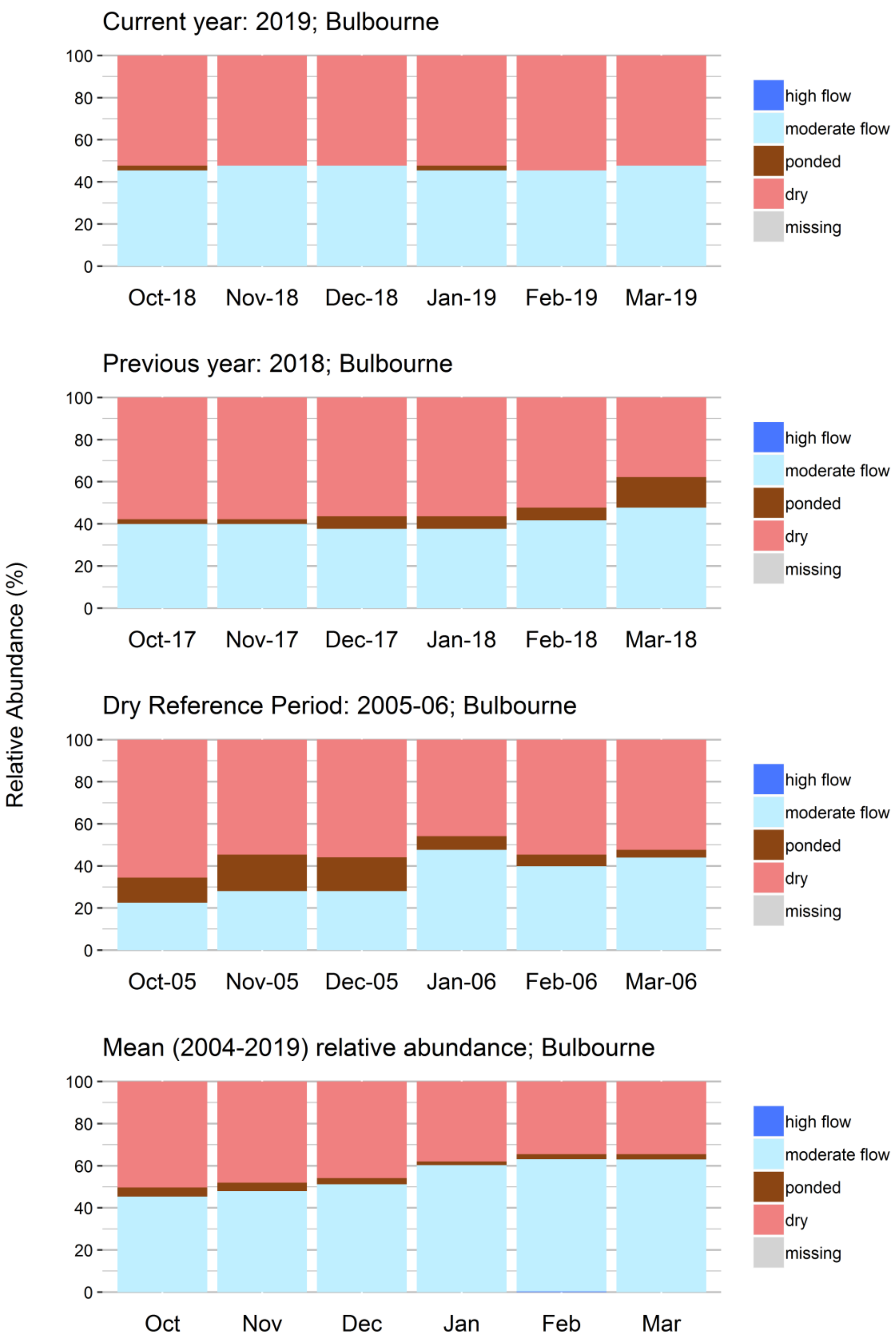


Figure 3 Drought tracking for the River Bulbourne, updated March 2019

3.2 Refinement of the dataset

3.2.1 Extraction of a monthly dataset

Using the Bulbourne as an example, heat maps visualising the raw data (Figure 4; Sefton et al. 2017) and monthly data (Figure 5), demonstrate the value of extracting the monthly dataset (D1).

The annual pattern of summer contraction and winter expansion of the river network is visible in both heat maps from 2007 until 2017. However, the monthly extracted data removes the bias towards dry conditions that distorts the time axis, most noticeably during the 1997-1998 and 2004-2006 droughts. This means that the eye can more readily identify perturbations of the typical drying/wetting cycle, such as the lack of upstream source migration during the winter of 2011-2012 when low recharge suppressed the seasonal recovery of groundwater levels. The other notable improvement made possible by the monthly extraction is representation of missing data which is shown only indicatively in the raw data using missing seasons (three consecutive months starting January, April, July, and October).

A full set of heat maps for the extracted data is presented in Appendix C. The source migration is also seen on other groundwater-dominated rivers such as the Chess and the Gade, and the greater frequency of flowing state along the whole survey length apparent on flashier rivers, such as the Rib and the Stort.

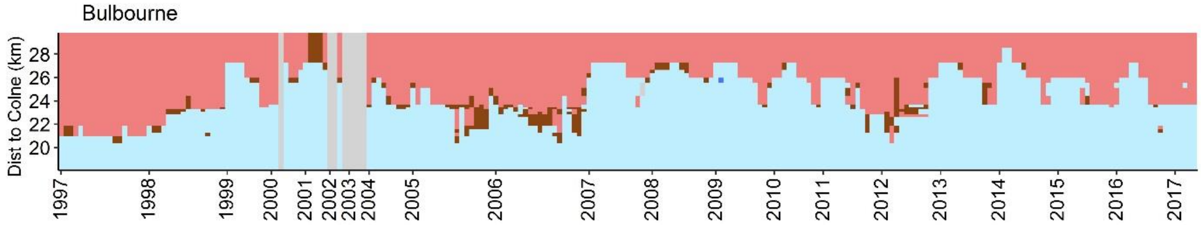


Figure 4 Heat map showing the raw dataset for the River Bulbourne (May 1997 - June 2017)

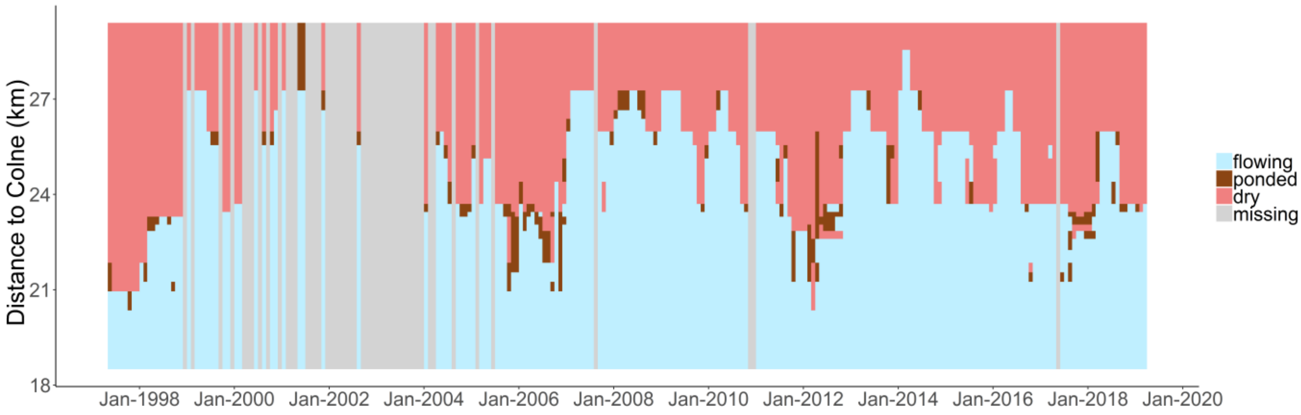


Figure 5 Heat map showing the extracted monthly dataset for the River Bulbourne (May 1997 - March 2019)

3.2.2 Exploring infilling of the monthly dataset

Buffering

The number of missing survey months was reduced from 202 (11.3%) to 179 (10%), and 171 (9.6%) using an 18- and 22-day buffer, respectively and the effect on spatial metrics was found to be minimal. This was also the case for temporal composition metrics that calculate proportions based on the full period of record. For example, flow permanence increased from 60.4 to 61.3 and 61.6% using 18- and 22-day buffers, respectively.

However, the configuration metrics, temporal lotic connectivity, mean patch length, and fragmentation, were sensitive to infilling. Lotic connectivity increased from 5 km to 13.9 km, and 14.2 km using 18-day and 22-day buffers, respectively. Mean patch length increased from 5.3 km to 5.8 km, and 6.3 km, respectively, and fragmentation decreased from 0.25 to 0.23 and 0.22, respectively

Modelling

The true positive rate of the CLMs varied considerably between rivers, models, and hydrological states (Table 6). Model 6 (the principal components model) had a sensitivity of 91.6%, 92.9%, 93.6%, and 93.9% for the Bulbourne, Mimram, Chess, and Gade, respectively. These impressive results reflect the high accuracy of the model with both flowing and dry states but mask a widespread inaccuracy in the estimation of ponded conditions. Only 2.4%, 0.0%, 18.2%, and 0.0% of ponded observations were estimated correctly using Model 6 for the Bulbourne, Mimram, Chess, and Gade, respectively.

The Model 6 overall true positive rate of groundwater-dominated rivers (Misbourne, Chess, Bulbourne, Gade, Ver and Mimram) varied from 84.2% (Misbourne) to 93.9% Gade. Rivers more influenced by superficial deposits (Beane, Rib, Ash and Stort) varied from 70.5% (Stort) to 81.5% (Beane). This is likely to be due to the slower response of groundwater-dominated rivers.

Inter-model variation enabled inference regarding hydrological state drivers, and their relative importance. Model 1 generally performed poorly, with an average true positive rate of 70.3% (rivers weighted equally). Model 2, which incorporated site-specific variation by training individual proportional CLMs on each site, had an average sensitivity of 83.6%.

Training individual non-proportional CLMs on each site (Model 3) led to an overall decrease in sensitivity. This suggests that the effect of covariates on hydrological state does not vary enough between states to increase performance.

Model 4 had an average true positive rate of 81.2%, suggesting that whilst the incorporation of site variation using distance to confluence increased the sensitivity, it did not fully account for site-specific variation. However, Model 5 resulted in a modest increase in sensitivity, to 81.8%, further accounting for site variation.

Model 6 had the highest average true positive rate between rivers (equally weighted) at 84.4%. This demonstrated the importance of flow data when estimating hydrological state, as well as accounting for flow variation effectively.

In general, the sensitivity of the modelling was high for flowing and dry states, and limited for ponding, a result that is likely to arise from both the small availability and the diversity of ponding observations on which to train the model.

Table 6 Total and individual state model sensitivity (true positive rate) for each river.

		Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Ash	**Overall**	**65.1**	**73.7**	**71**	**71.8**	**72.8**	**73.7**
	Flowing	86.6	86.3	85.4	90.9	67.6	86.3
	Ponded	0	34.8	28.6	11.6	20.5	34.8
	Dry	48.5	74.3	71.3	58.4	53.8	74.3
Beane	**Overall**	**74.6**	**81.4**	**76.6**	**78.9**	**78.8**	**81.5**
	Flowing	98	95.5	89.4	96.9	96	95.8
	Ponded	0	23.4	29.2	8	15.2	25.8
	Dry	9.6	56.3	55.1	39.5	37.7	54.5
Bulbourne	**Overall**	**67.8**	**90.8**	**87.3**	**90.3**	**91.3**	**91.6**
	Flowing	91.6	96.5	93	96.1	97.1	97.4
	Ponded	0	9.5	9.5	0	2.4	2.4
	Dry	34.2	92.7	88.8	90.9	92.4	92.7
Chess	**Overall**	**74.9**	**93.6**	**91.8**	**92.6**	**93.2**	**93.6**
	Flowing	87.6	97	96.1	97	97.6	97
	Ponded	0	15.4	30.8	0	0	15.4
	Dry	48.7	94.8	89.2	90.9	91.4	94.8
Gade	**Overall**	**69**	**92.8**	**80**	**93.9**	**93.1**	**93.9**
	Flowing	96.7	97.5	77.6	99.2	97.9	99.2
	Ponded	0	13.8	17.2	0	10.3	0
	Dry	12	93.1	93.5	93.5	92.6	93.5
Mimram	**Overall**	**79.1**	**92.9**	**88.7**	**85.4**	**89.5**	**92.9**
	Flowing	99.2	96.1	90.3	94.5	93.1	96.1
	Ponded	0	0	10	0	0	0
	Dry	9.8	88.6	89.4	57.6	82.6	88.6
Misbourne	**Overall**	**72.6**	**84.2**	**76.9**	**72.5**	**72.2**	**84.2**
	Flowing	88.8	88.1	79.6	89.5	89.2	88.1
	Ponded	0	16.1	22	0	0	16.1
	Dry	53.1	85.7	78.7	51.6	51.2	85.7
Rib	**Overall**	**67.3**	**67.7**	**66.3**	**74**	**74.4**	**74.8**
	Flowing	98.7	84	81.3	93.2	94	94
	Ponded	0	13.8	22.8	0	0.8	0.8
	Dry	4.1	74	67.5	59.2	57.4	59.8
Stort	**Overall**	**67.6**	**71.1**	**69.2**	**67.9**	**68.5**	**70.5**
	Flowing	95.4	86.9	85.9	94.1	93.3	86.2
	Ponded	0	20.2	23.4	0	6.4	18.1
	Dry	25.9	63.6	57.1	30.8	32.4	64.1
Ver	**Overall**	**65**	**87.4**	**83.4**	**84.3**	**84.6**	**87.4**
	Flowing	86.4	93.2	86.7	90.5	90.3	92.9
	Ponded	0	6.3	6.3	0	0	6.3
	Dry	36	90.7	89.4	84.2	85.4	91.1

Observation bias

Significant sets of environmental covariates ($p < 0.05$) were identified, suggesting whether or not an observation was made was related to the covariates used to estimate hydrological state in the models described in Chapter 2.2.2.2. Models using single covariates also approached significance ($p < 0.1$), increasing the confidence in these results. There is thus some evidence that there is a relationship between the timing of observations and the environmental conditions. This is a source of uncertainty in the infilling of the dataset.

3.3 Metrics

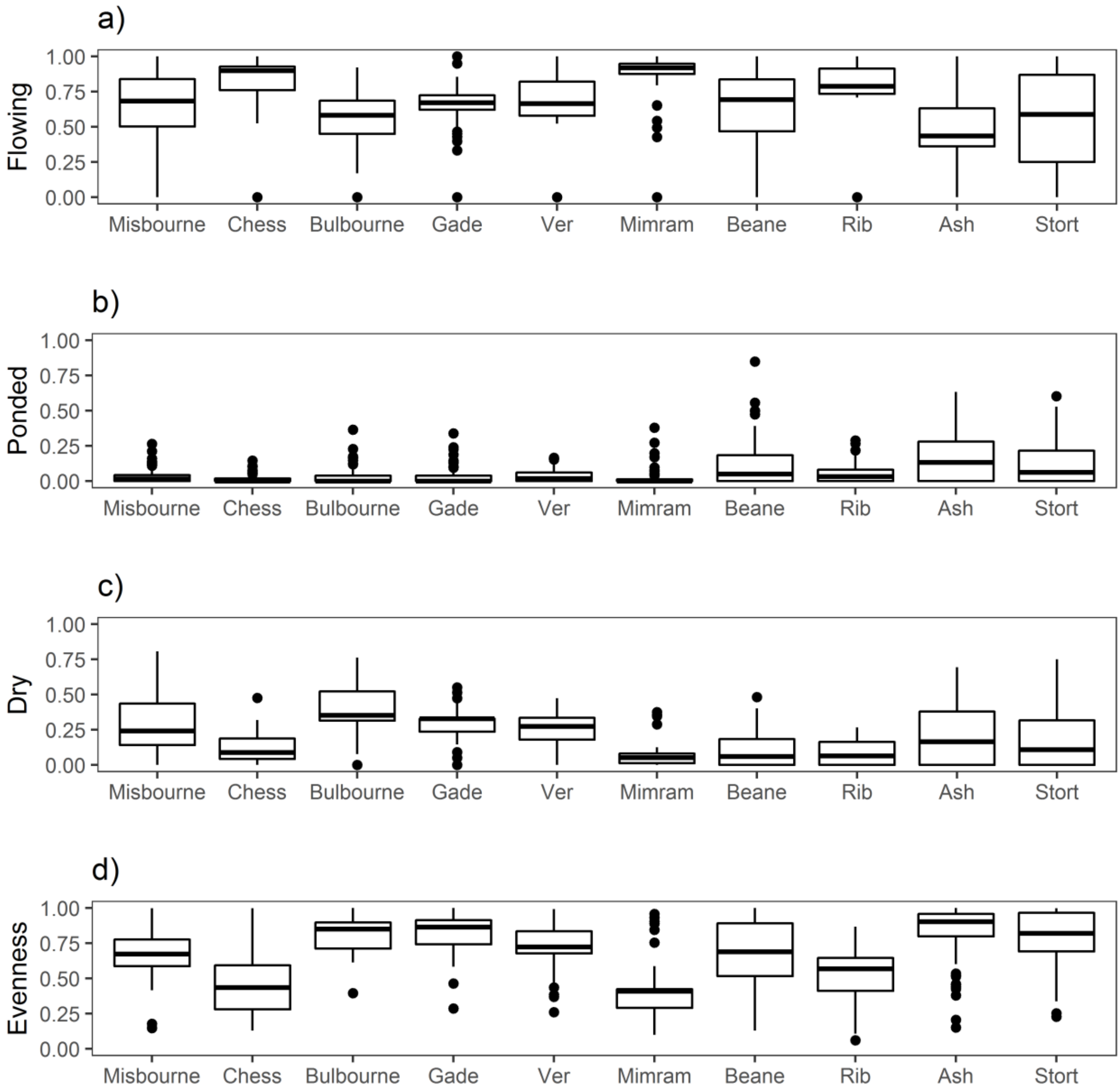
3.3.1 Spatial metrics

The mean proportions of flowing, ponded and dry states present along the survey length in the monthly data across the period of record are shown in Table 7, with their evenness, mean patch length, fragmentation and lotic connectivity (Deliverable D2a, Appendix A). Flowing states are the most dominant, and ponding the least, and there is more ponding in the Lee catchment than in the Colne. The fragmentation scores are also higher in the Lee catchment, because the ponding is often distributed along the channel, separating dry reaches, as seen in the heat maps (Appendix C).

Table 7 Mean spatial composition and configuration metrics by river from monthly data (Mar 2004 – Mar 2019); the proportion of the surveyed river length that is in each of the flowing, ponded and dry states, evenness (of the three state proportions), mean patch length (of contiguous reaches in any single state), fragmentation (of states along the survey length), and lotic connectivity (the length of flowing water in connectivity with the perennial reach downstream.)

	Proportion of survey length flowing	Proportion of survey length ponded	Proportion of survey length dry	Evenness	Mean patch length (km)	Fragmentation	Lotic connectivity (km)
Misbourne	0.63	0.03	0.28	0.68	8.3	0.10	9.2
Chess	0.83	0.01	0.11	0.45	3.9	0.08	7.2
Bulbourne	0.55	0.03	0.38	0.83	4.7	0.08	6.2
Gade	0.66	0.03	0.28	0.82	4.8	0.07	6.7
Ver	0.65	0.04	0.26	0.73	7.7	0.10	16.0
Mimram	0.76	0.01	0.06	0.37	8.4	0.06	13.4
Beane	0.60	0.11	0.11	0.68	11.3	0.12	15.8
Rib	0.72	0.05	0.08	0.52	15.4	0.12	27.8
Ash	0.49	0.16	0.21	0.84	9.9	0.16	12.1
Stort	0.54	0.12	0.17	0.79	11.5	0.12	10.1

More information on the distribution of the metrics for each river through the period of record is given by Figure 6 which shows the 25th, 50th (median) and 75th centiles, and indicates the presence of tails and outliers. For example, the Beane flowed along at least two thirds of its survey length for half of the time (flowing median 0.69, Figure 6a) and occasionally along its whole length (flowing max 1.0).


a)
Flowing
1.00
0.75
0.50
0.25
0.00
Misbourne
Chess
Bulbourne
Gade
Ver
Mimram
Beane
Rib
Ash
Stort
b)
Ponded
c)
Dry
d)
Evenness

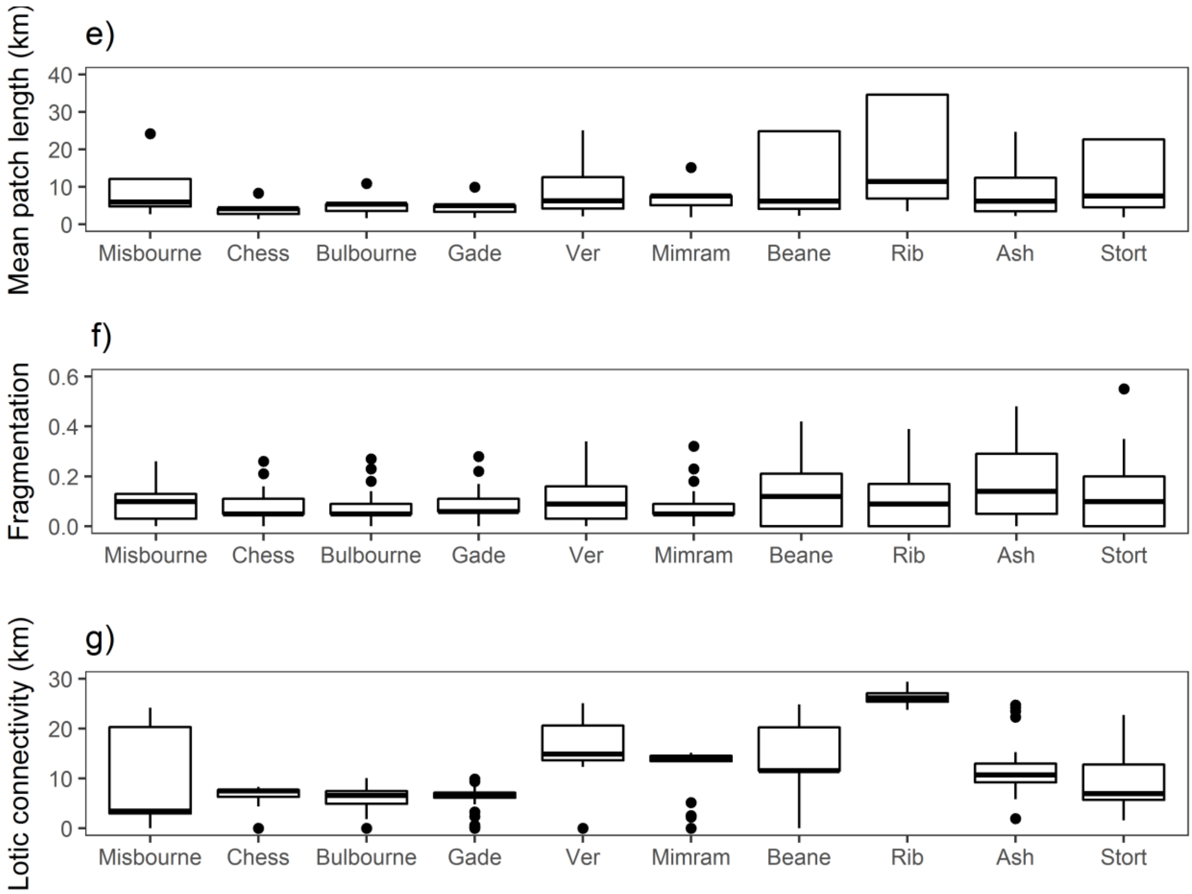


Figure 6 Distribution of metrics of spatial composition and configuration for each of the ten study rivers (Mar 2004 – Mar 2019)

3.3.2 Temporal metrics

Two visualisation methods for relative permanence (Deliverable D2b, Appendix A) are shown for the River Bulbourne below, with full sets of charts presented in the appendices. The first (Figure 7, Appendix D) is a stacked bar chart showing flowing, ponded and dry permanence at each site longitudinally along the river. The second (Figure 8, Appendix E) is a stacked bar chart showing the distance between sites longitudinally along the river in addition to the flowing, ponded and dry permanence. A third map-based method is shown for the Colne (Figure 9) and Lee catchments (Figure 10) as a whole.

While similar visualisations are possible for configuration metrics, these are more adversely affected by missing data than the composition metrics. For example, the known perennial sites at the bottom of the Rib should have fragmentation scores of zero, and lotic connectivity equal to the period of record, but interruptions to the flow result in a fragmentation of 0.2 and lotic connectivity of just 10 months. The composition metrics are less affected as they are not concerned with the arrangement of hydrological states but their relative abundance, and missing data can therefore be readily quantified and removed from analysis.

Relative permanence by site (longitudinal)

See Appendix D

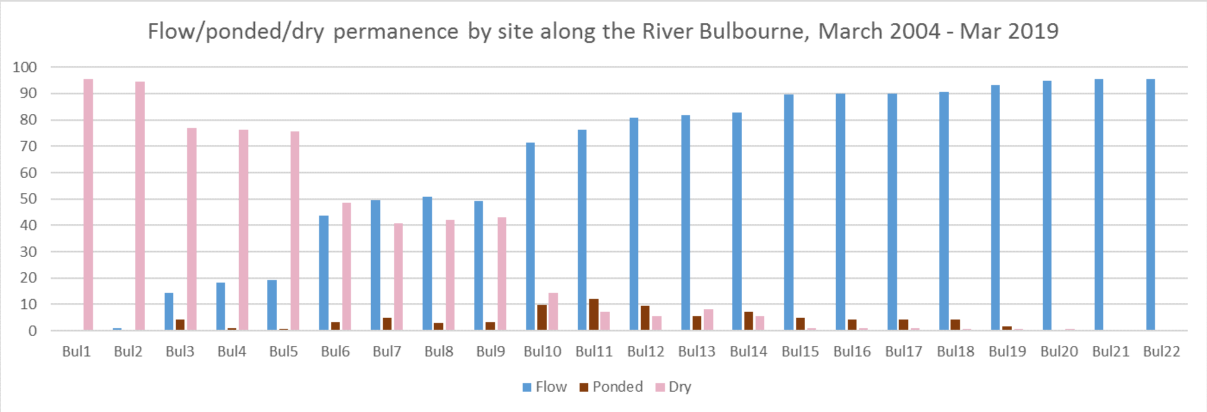


Figure 7 Flow/ponded/dry permanence by site along the River Bulbourne, March 2004 - Mar 2019. NB missing data records are excluded from the graph.

Relative permanence with distance (longitudinal)

See Appendix E

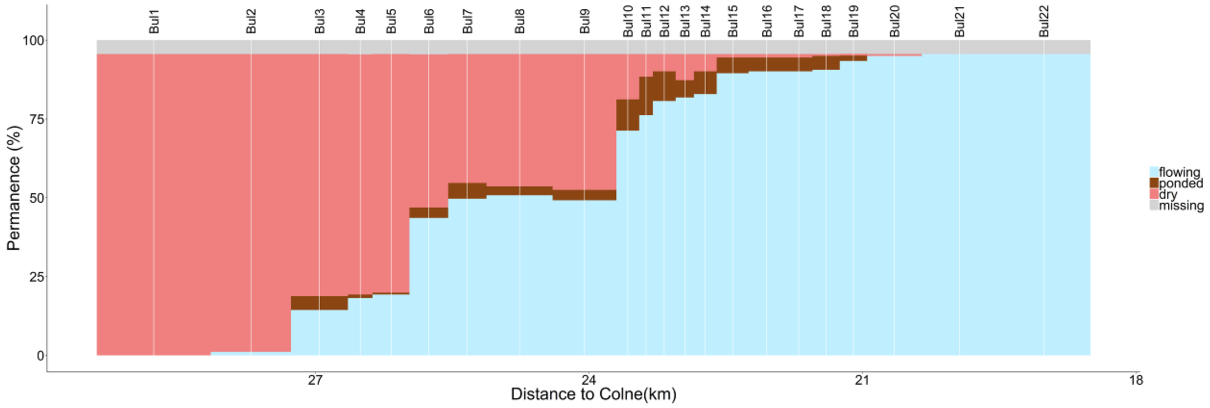


Figure 8 Flow/ponded/dry permanence by distance along the River Bulbourne, Mar 2004 – Mar 2019. Vertical white lines represent the observation site distance to Colne (km).

The pattern of reducing dry permanence, giving way to increasing flow permanence at successive sites downstream that is seen on the Bulbourne (Figure 7) is typical of the groundwater-dominated streams (Chess and Gade, Appendix D), with the introduction of the spatial component (Figure 8; Appendix E) illustrating that the number and distribution of sites is adequate for characterising the intermittent behaviour. The surge in dry permanence in the mid-reaches of the Misbourne (Appendices D and E), where natural loses to the aquifer compounded by historical mill workings cause the channel to lose contact with groundwater, is a marked interruption to the longitudinal gradient. In the Lee catchment, the greater occurrence of ponding is apparent but long term average pond permanence does not vary between sites as much as visual inspection of the heat maps might suggest.

Permanence map

Snapshots of the interactive map tool, showing every third site, provide contextual information for variability in relative abundances along the survey lengths. The dry reach that develops in the lower reaches of the Misbourne during average and dry years is apparent, and an artificially near-perennial reach in the headwaters of the Ver, with dry state observed for a greater proportion of the time both upstream and downstream (Figure 9).

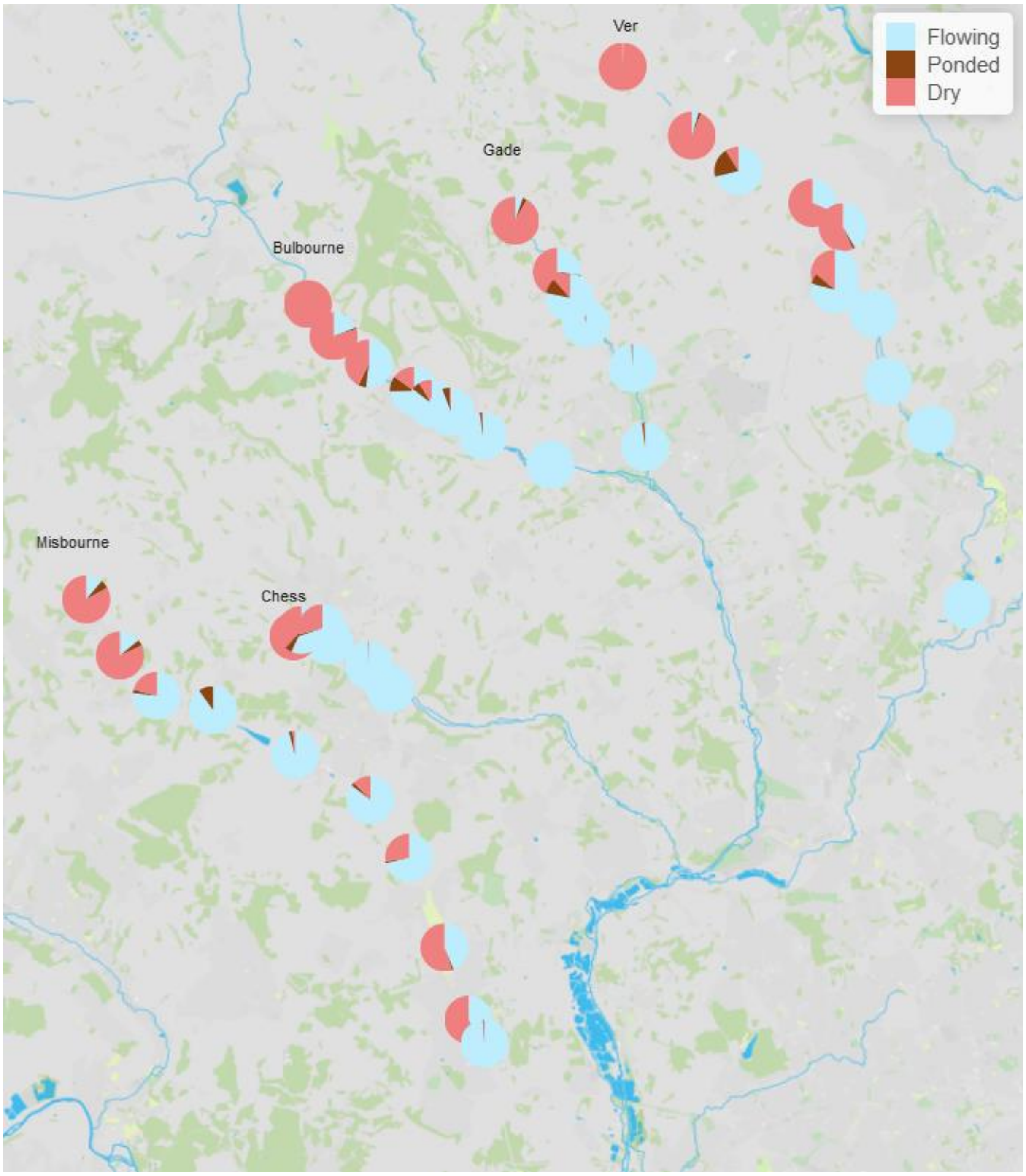


Figure 9 State permanence (the proportion of months in which in site is in each of the flowing, ponded and dry states) at a subset of sites along rivers within the Colne catchment, March 2004 – March 2019

In the Lee catchment, the greater occurrence of ponding is again apparent, without clear spatial patterns (Figure 10).

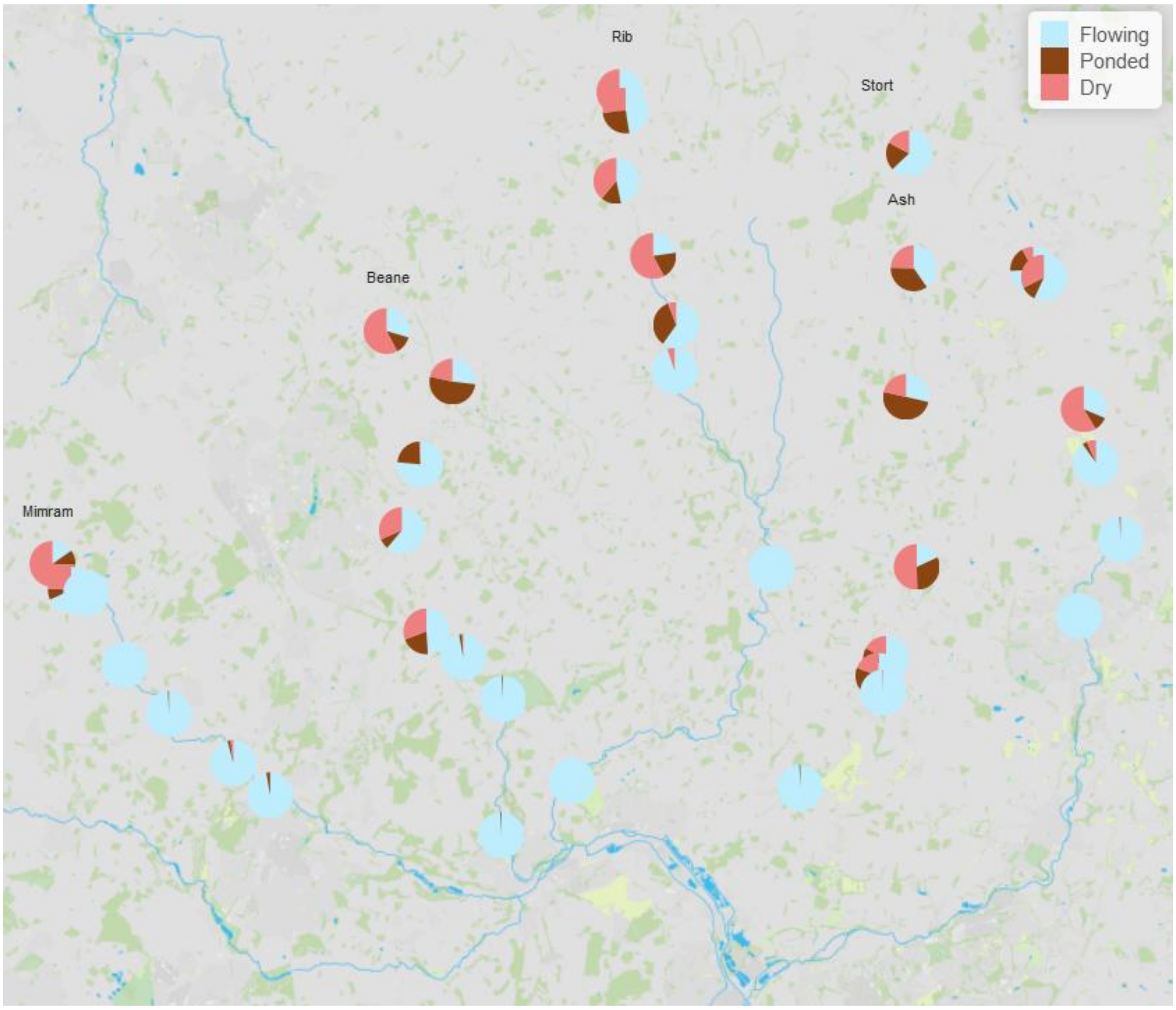


Figure 10 State permanence (the proportion of months in which in site is in each of the flowing, ponded and dry states) at a subset of sites along rivers within the Lee catchment, March 2004 - March 2019

3.3.3 Sample metrics

The sample metrics (short-term temporal and short-reach spatial, D2c) present an opportunity for hydroecological assessments, when the sites and dates of the hydrological surveys are concomitant with those of a biological sampling programme. Analysis of the relationships between biological communities and metrics, and the hydrological metrics provided can take account of the preceding conditions as well as the distance to connected flow.

4 Discussion

4.1 Spatial and temporal intermittence for the East Chilterns streams

The first and third objectives of the project were to improve our understanding of the drying/wetting cycles of the ten study streams and develop site metrics which could be used to evaluate intermittence along the rivers. The metrics and charts facilitate discussion both of the response of the rivers to drought and patterns in their spatial and temporal intermittence.

Cycling in the expansion and contraction of the network in response to drought was investigated using the proportion of hydrological state as in index. The long term average behaviour was network expansion – an increase in the relative abundance of flowing survey length – through the winter months on each of the rivers (Panel 4, Appendix B). However, during the winter of 2018-2019 there was no such recovery on the Misbourne, Bulbourne or Ver, and the Gade and Chess continued to contract. Only the Stort and the Rib, with near-average conditions, and to a lesser extent the Ash, saw some expansion of the network (Panel 1, Appendix B). In comparison with the previous winter (2017-2018), the Beane, Rib, Ash and Stort were more contracted in 2018-2019, whilst the more groundwater-dominated rivers further west were broadly similar in both winters (Panel 2, Appendix B). In comparison with the dry reference period, the network was less contracted in March 2019 than in March 2006 on the Misbourne or Beane, Rib, Ash and Stort but comparable on the Chess, Gade, Ver, Mimram and Bulbourne (Panel 3, Appendix B). The development of the spring conditions was markedly different between the two events on the Bulbourne, which was more contracted in October 2005 than in October 2018, but saw some recovery through the winter of 2005-2006. On the other groundwater-dominated rivers, as in 2018-2019, there was limited if any recovery through the winter months of 2005-2006.

Intermittence patterns on the groundwater-dominated and flashier rivers are revealed by the charts of relative permanence by site (Appendix D). On 'classic' chalk streams like the Gade, Chess and Mimram, flow permanence (the proportion of time for which there was flowing water at the site) increases downstream, from almost zero at the uppermost site, to almost 100% at the perennial sites downstream (left to right). The inverse pattern is seen in dry permanence with a small amount of ponding at those sites where transitioning occurs; the Bulbourne has four sites at which the dry and flowing permanences are approximately equal. The same pattern is seen in the headwaters of the Misbourne, however the dry reach downstream causes an increase in dry permanence between sites 15 and 26, with flow once again predominating further downstream. On the Ver, the pattern is interrupted by local augmentation of flowing and ponded state and suppression of dry state between sites 6 and 9. On the flashier rivers (Beane, Rib , Ash and Stort), the pattern is different, with higher evenness of states in the upper reaches revealing local effects, such as the increase in flow permanence at the confluence of the Beane with Ardeley Brook (between Beane4 and Beane5) and Stevenage Brook (Beane13 and Beane14). Artificial local augmentation is seen on the Rib which is near-perennial downstream of Buntingford sewage treatment works (Rib15). Conversely, local drying is seen on the Stort at Clavering (Stort8) where a swallowhole causes an increase in dry permanence at the next five sites downstream, before reliable springs bring perennial flow.

With the addition of distance between sites to the charts, the spatial resolution of the observations can be interpreted (Appendix E). For example, the reason that the Ash is very similar from sites 11-14 is that they are very close together – within 0.6km. The assumption that a site represents its reach is supported on the Misbourne, where sites are well spaced and temporal dynamics captured, and less justified on the Ash, where Ash6 represents a reach of 2.9km on a river where there are frequent changes of hydrological state along the channel, as seen in the heat map. Nonetheless, local features such as augmentation of flow permanence by the confluences with Ardeley Brook and Stevenage Brook are clearly seen on the Beane, with an unexplained decreasing trend in flow permanence over the 8km between the two confluences. On the Ver, conversely the sewage treatment works augments flows for around 2km downstream.

4.2 Infilling gaps in monthly hydrological state data

The second objective, of updating and refining the hydrological state dataset, required the extraction of a monthly dataset to remove the inherent bias in irregular observations and exploration of methods for infilling gaps in the dataset. Pending the future development of remote sensing techniques, hydrological state data of the required resolution in time and space is likely to have such gaps, and although this dataset is the best known of its type for duration and regularity of observations, significant gaps are revealed by the heat maps (Appendix C). It is important that gaps are infilled in order to facilitate calculation of composition and, in particular configuration metrics with an acceptable level of uncertainty. For example, a dry period interrupted by a month of “missing” state will present as two shorter periods.

However, the respective limitations of the proposed alternative infilling techniques need to be considered, as does the potential presence of observation bias in the dataset. Both of these factors influence the level of confidence in hydrological state observations, and therefore need to be considered in all future attempts to infill the monthly dataset.

Alternative infilling techniques

In addition to the buffering and modelling techniques described, a variety of other infilling methods of varying complexity were considered (Figure 11).

By eye

Estimation of each missing observation using expert judgement is appealing due to its operational simplicity, especially on slower responding catchments, but was dismissed due to its inherent subjectivity. The difficulties associated with sites exhibiting transitioning between states on the more rapidly responding rivers (Beane, Ash, Stort) were considered to be prohibitive.

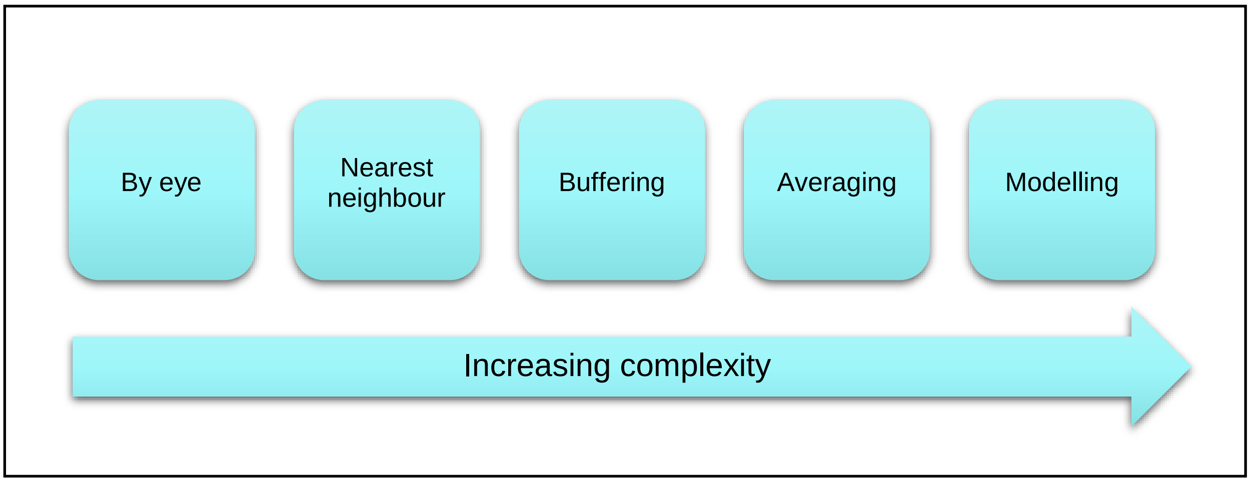


Figure 11 Schematic of potential methods for infilling gaps in the extracted monthly dataset

Nearest neighbour

Estimation of missing values based on the observations in the neighbouring months according to predefined conditions was proposed to reduce the inherent subjectivity in estimation by eye. However, this method is limited by the assumption that hydrological state did not change between neighbouring months and the missing survey month, or that the change can be described by simple rules. For example, if a missing observation occurs between flow and dry, it is unclear whether it should be assigned flow, ponding, or dry. Finally, the replication of data required by this method poses the potential to introduce bias to the dataset, and subsequently derived metrics.

Averaging

Averaging could also be applied to the Springs and Sources dataset to infill missing data. This involves assignment of empirical values to hydrological states, and subsequent averaging of a predefined neighbouring state period surrounding the missing survey month. This method was proposed to appeal to the period of record consideration advantage of the By Eye method, whilst removing its inherent subjectivity.

However, whilst considered, this method was not applied due to the complexity of assigning empirical values, and thus distances between hydrological states. Alternatively, this method could be applied to periods of consistent hydrological state, removing the requirement of empirical value assignment. However, this would introduce observation, and subsequent metric, bias toward stable conditions.

Finally, the assignment of the most commonly observed hydrological state at a site during the whole period of record, or individual months, was proposed to avoid these limiting assumptions. However, this method was dismissed due to the lack of incorporation of temporal variation, as well as poor justification for sites with relatively low dominant state permanence.

Further modelling work

A number of opportunities for further modelling arise from this work, and their development should seek to balance scientific rigour (particularly their justification on the quicker responding catchments) with the operational considerations of survey timing and other demands on staff time. The priority is evaluation of the potential to increase ponding estimation accuracy with the inclusion of site-specific topography, geology and land-use variables. Exploration of other methods is also suggested, given the limitations imposed by the small number of ponding observations, for example, the incorporation of neighbouring state observations using nearest neighbour approaches and the exploration of machine learning techniques. However, further investigation into observation bias is required to increase infilling confidence. Any such approaches must also consider the potential to extrapolate results beyond the HNL Springs and Sources dataset, capitalising on its value in the development of tools and techniques to protect IRES in the both UK and further afield.

5 Conclusions and recommendations

Metrics quantifying the spatial intermittence of hydrological state have been used to track the development of the current water situation. The cumulative effect of two dry winters between October 2017 and March 2019 was partially offset by late recharge in April 2018. However, conditions for the groundwater-dominated rivers in March 2019 were nevertheless similar to March 2006 and the continued dry conditions in April and May, despite a wetter than average June, means that groundwater resource will be under pressure during the summer and autumn of 2019.

Temporally equivalent metrics quantifying the long term intermittence of hydrological state at sites along IRES have been identified and used to characterise the behaviour of the ten study rivers in the East Chilterns. A strong pattern of increasing flow permanence and decreasing dry permanence downstream was apparent on the chalk streams, with both natural disturbances from tributaries and a swallowhole and unnatural, from sewage treatment works, apparent. On those rivers in the east more influenced by superficial deposits, localised ponding caused greater evenness in hydrological states, dominating the longitudinal picture.

Exploration of infilling techniques has shown that the impact of missing data is significant in characterising the configuration of hydrological state across a period of time at a site. The challenge of infilling is greatest on the rapidly responding catchments of the Lee tributaries. Relationships developed using environmental drivers have been used to simulate flowing and dry state with a high degree of accuracy.

However, the importance of ponded observations makes it imperative to increase the estimation accuracy of this state before modelling can be applied as an infilling method. Causes for the poor ponded estimation performance may include the smaller number of ponding observations, the range of conditions included in the ponded category and the need for additional covariates to capture its drivers such as superficial geology, topography, land-use, and higher resolution environmental covariates.

With a complete dataset, the metrics presented would provide characterisation of the hydrological behaviour of intermittent rivers needed for effective water resource and hydroecological assessment. Artificial influences would also need to be addressed if the relationships are to be effective tools for infilling the longer gaps of a year or more. There is potential for future adaptation of the modelling methodology, for example, before and after a known change such as a sustainability reduction in abstraction, to investigate the impact of artificial influences.

Despite the challenges associated with using the dataset, it remains the best of its type in the academic literature, and has provided a benchmark for the establishment of a citizen science network across Europe, under EU-funded COST Action [CA15113] on the Science and Management of Intermittent Rivers and Ephemeral Streams (European Cooperation in Science and Technology). The window of opportunity to further demonstrate the potential of such data in the monitoring, assessment and protection of these diverse and dynamic systems remains open at this time.

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7 Appendices

Appendix A. Data deliverables

A spreadsheet of data deliverables is provided for each of the ten study rivers with an introductory tab (Table 8) and four further tabs, as described. All data deliverables have a threefold classification of hydrological state: flowing, ponded and dry. Full listings of deliverables D2a and D2b are provided in Table 9 and Table 10 respectively, including references to column headings in the data deliverable spreadsheets. A full listing of metrics in D2c is provided in Table 5.

Table 8 Data deliverables provided in electronic form, one spreadsheet for each of the ten study rivers

Tab name	Data deliverable	Description	Notes
Monthly_data	D1	Extracted monthly dataset of hydrological state, site by site	May 1997 to March 2019
Monthly_spatial_metrics	D2a	Metrics describing the spatial composition and configuration of hydrological state along the whole survey length of the river, derived from the extracted monthly dataset (D1)	March 2004 to March 2019
Temporal_metrics	D2b	Metrics describing the long-term temporal composition and configuration of hydrological state at each site, derived from the extracted monthly dataset (D1)	March 2004 to March 2019
Sample_metrics	D2c	Metrics describing the conditions in the short-term or short reach pertaining to a biological sample, derived from the extracted monthly dataset (D1)	May 1997 to December 2018, biological sampling sites and dates only

Table 9 Listing of monthly spatial metrics provided in Data Deliverable D2a

Reference	Metric	Units	Description
AbundanceSites_Flowing AbundanceSites_Ponded AbundanceSites_Dry AbundanceSites_Missing	Abundance	count ranges from - to max no of sites	Total number of sites having each hydrological state
RelativeAbundanceSites_Flowing RelativeAbundanceSites_Ponded RelativeAbundanceSites_Dry RelativeAbundanceSites_Missing	Relative abundance	dimensionless ranges from 0 to 1	Proportion of total number of sites having each hydrological state
AbundanceDistance_Flowing AbundanceDistance_Ponded AbundanceDistance_Dry AbundanceDistance_Missing	Abundance	km	Total length of surveyed channel of each hydrological state
RelativeAbundanceDistance_Flowing RelativeAbundanceDistance_Ponded RelativeAbundanceDistance_Dry RelativeAbundanceDistance_Missing	Relative abundance	dimensionless ranges from 0 to 1	Proportion of surveyed channel length of each hydrological state
Richness	Richness	dimensionless - ranges from 1 to 4	Number of hydrological states present along the surveyed channel length
Evenness	Relative evenness	dimensionless - ranges from 0 to 1	Diversity of hydrological states present along the surveyed channel length

Fragmentation	Relative edge density	dimensionless - ranges from 0 to 1	Number of changes of state as a proportion of the total number of reach boundaries
RelativeFragmentation_Flowing	Single state spatial fragmentation	dimensionless ranges from 0 to 1	Number of patches in each hydrological state as a proportion of the total number of patches
RelativeFragmentation_Ponded			
RelativeFragmentation_Dry			
RelativeFragmentation_Missing			
MeanPatchLength	Mean patch length	km	Average length of consecutive reaches having the same state
MeanPatchLength_Flowing	Mean flowing patch length	km	Average length of patches in each hydrological state
MeanPatchLength_Ponded	Mean ponded patch length		
MeanPatchLength_Dry	Mean dry patch length		
MeanPatchLength_Missing	Mean missing patch length		
edgeDensity	Edge density	km-1	Number of changes of state per km
loticConnect	Lotic connectivity	km	Total length of flowing surveyed channel that is connected to the farthest downstream site

Table 10 Listing of long-term temporal metrics provided in Data Deliverable D2b

Reference	Metric	Units	Description
SiteMetricsAbundance_Flowing SiteMetricsAbundance_Ponded SiteMetricsAbundance_Dry SiteMetricsAbundance_Missing	Temporal abundance	months	Total number of months having each hydrological state
SiteMetricsRelativeAbundance_Flowing SiteMetricsRelativeAbundance_Ponded SiteMetricsRelativeAbundance_Dry SiteMetricsRelativeAbundance_Missing	Permanence	dimensionless ranges from 0 to 1	Proportion of total number of months having each hydrological state
SiteMetricsRichness	Temporal richness	dimensionless - ranges from 1 to 4	Number of hydrological states present during the period of record
SiteMetricsEvenness	Temporal evenness	dimensionless - ranges from 0 to 1	Diversity of hydrological states present during the period of record
SiteMetricsFragmentation	Temporal fragmentation	dimensionless - ranges from 0 to 1	Number of changes of state as a proportion of the total number of months
SiteMetricsFragmentation_Flowing SiteMetricsFragmentation_Ponded SiteMetricsFragmentation_Dry SiteMetricsFragmentation_Missing	Frequency (temporal single state fragmentation)	dimensionless ranges from 0 to 1	Number of flow periods as a proportion of total number of periods of any state
SiteMetricsMeanPatchLength	Mean period	months	Average number of months in all periods of any state
SiteMetricsMeanPatchLength_Flowing	Mean flow period	months	Average number of months in periods of

SiteMetricsMeanPatchLength_Ponded	Mean ponded period		each hydrological state
SiteMetricsMeanPatchLength_Dry	Mean dry period		
SiteMetricsMeanPatchLength_Missing	Mean missing period		
SiteMetricsLoticConnect	Temporal lotic connectivity	months	Flow period preceding the final month in the period of record

Appendix B. Drought tracking

Panel 1	Proportion of study length observed in each hydrological state from October 2018 until March 2019 for the a) Misbourne, b) Chess, c) Bulbourne, d) Gade, e) Ver, f) Mimram, g) Beane, h) Rib, i) Ash and j) Stort.
Panel 2	Proportion of study length observed in each hydrological state from October 2017 until March 2018 for the a) Misbourne, b) Chess, c) Bulbourne, d) Gade, e) Ver, f) Mimram, g) Beane, h) Rib, i) Ash and j) Stort.
Panel 3	Proportion of study length observed in each hydrological state from October 2005 until March 2006 for the a) Misbourne, b) Chess, c) Bulbourne, d) Gade, e) Ver, f) Mimram, g) Beane, h) Rib, i) Ash and j) Stort.
Panel 4	Long term average proportion of study length observed in each hydrological state by calendar month (March 2004 – March 2019) for the a) Misbourne, b) Chess, c) Bulbourne, d) Gade, e) Ver, f) Mimram, g) Beane, h) Rib, i) Ash and j) Stort.

Appendix C. Heat maps

Hydrological state observed in each month at each reach during the period May 1997 to March 2019 for the a) Misbourne, b) Chess, c) Bulbourne, d) Gade, e) Ver, f) Mimram, g) Beane, h) Rib, i) Ash and j) Stort.

Appendix D. Relative permanence by site

Flow/ponded/dry permanence by site for the period March 2004 to Mar 2019 along the a) Misbourne, b) Chess, c) Bulbourne, d) Gade, e) Ver, f) Mimram, g) Beane, h) Rib, i) Ash and j) Stort. Missing data records are excluded from the graph.

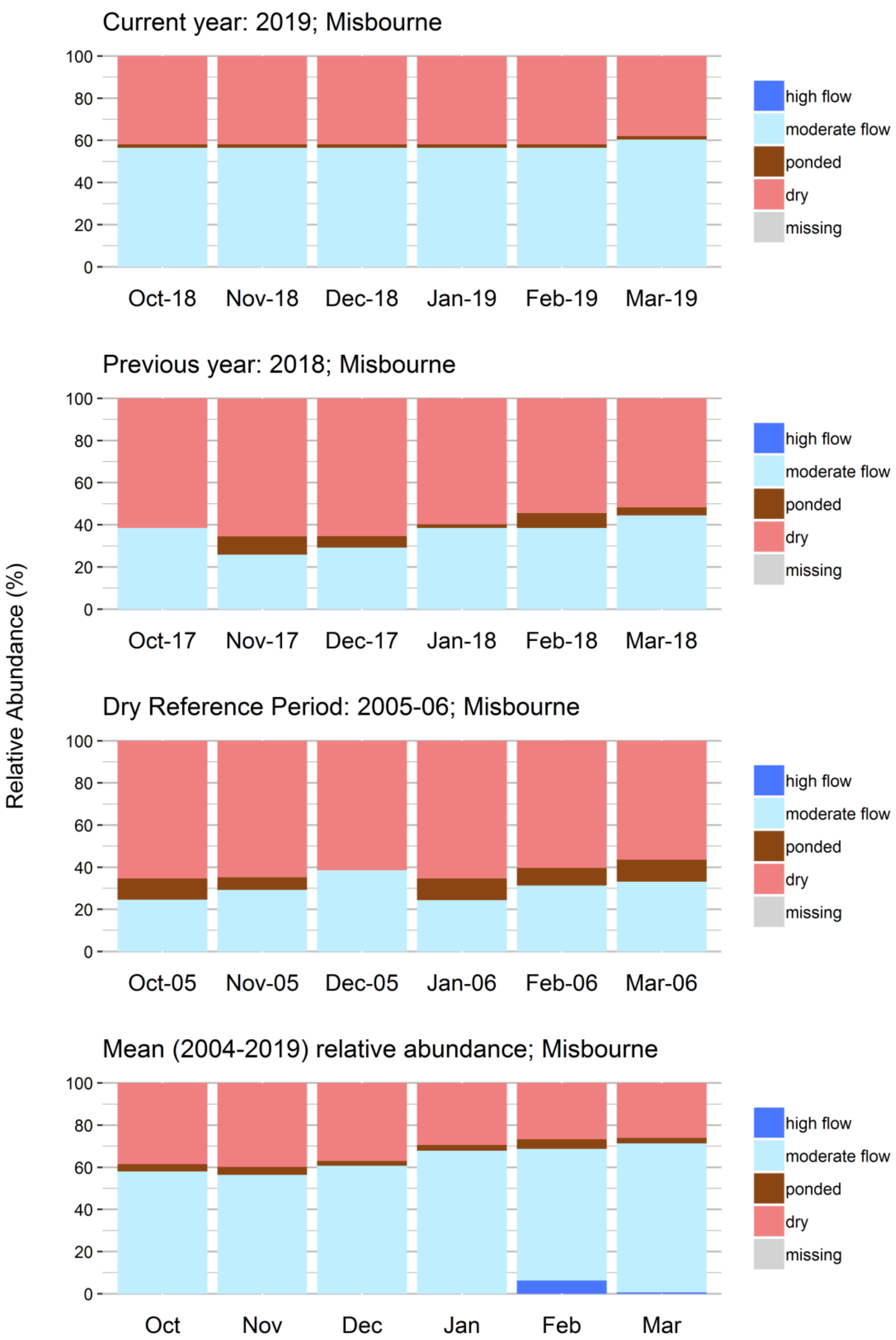
Appendix E. Relative permanence with distance

Flow/ponded/dry permanence by distance for the period March 2004 to Mar 2019 along the a) Misbourne, b) Chess, c) Bulbourne, d) Gade, e) Ver, f) Mimram, g) Beane, h) Rib, i) Ash and j) Stort.

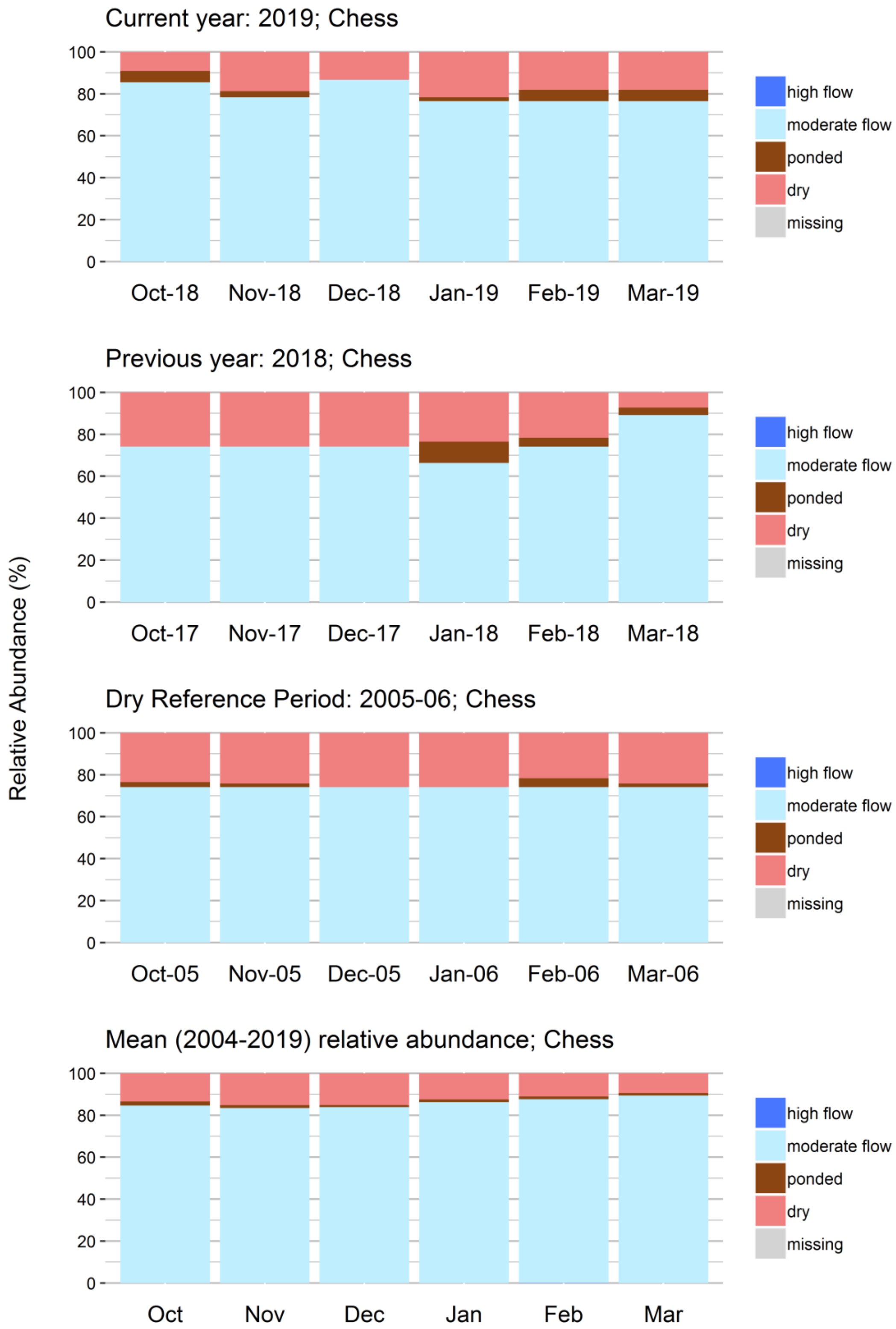
Appendix B. Drought tracking

Colne Catchment

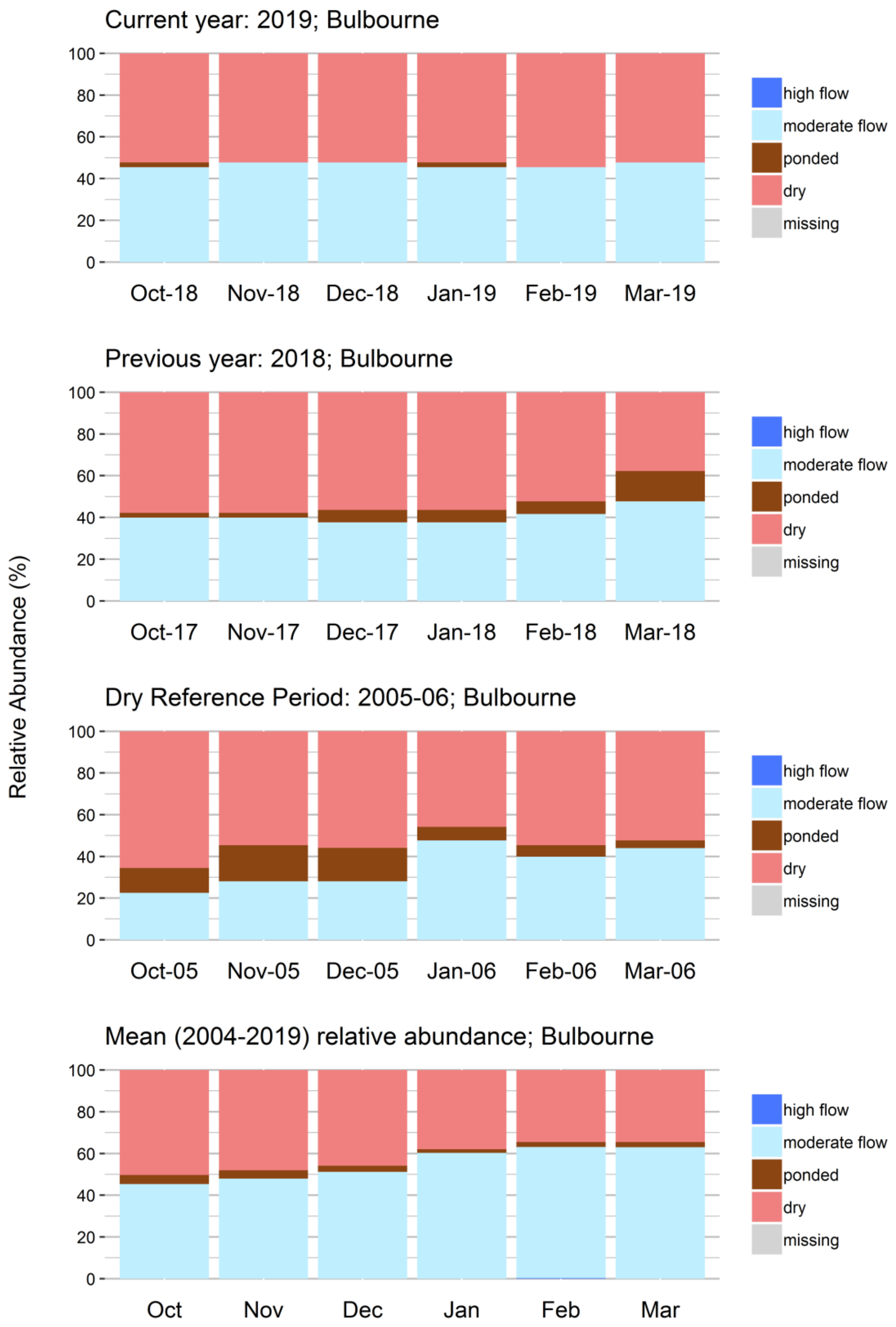
a) River Misbourne



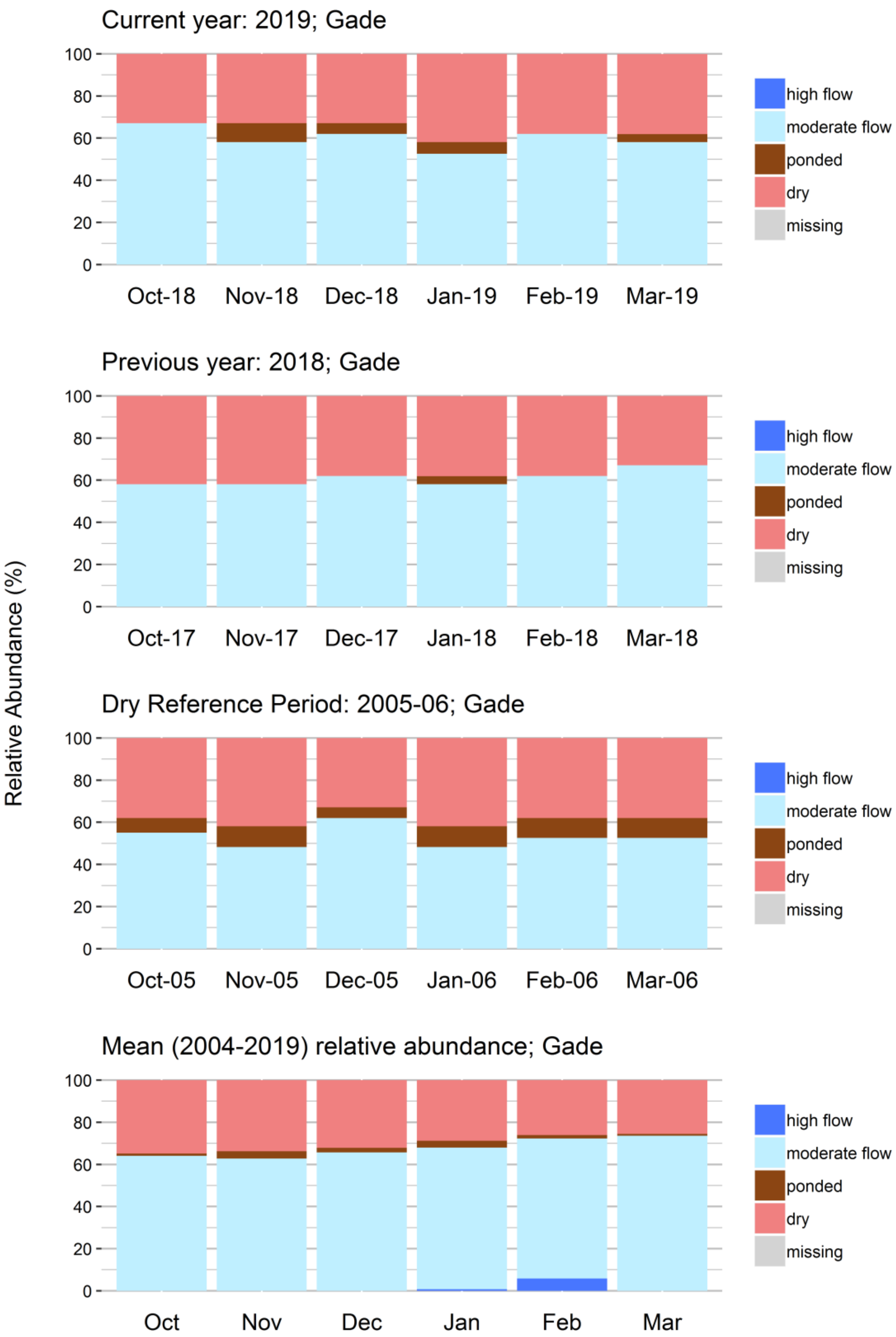
b) River Chess



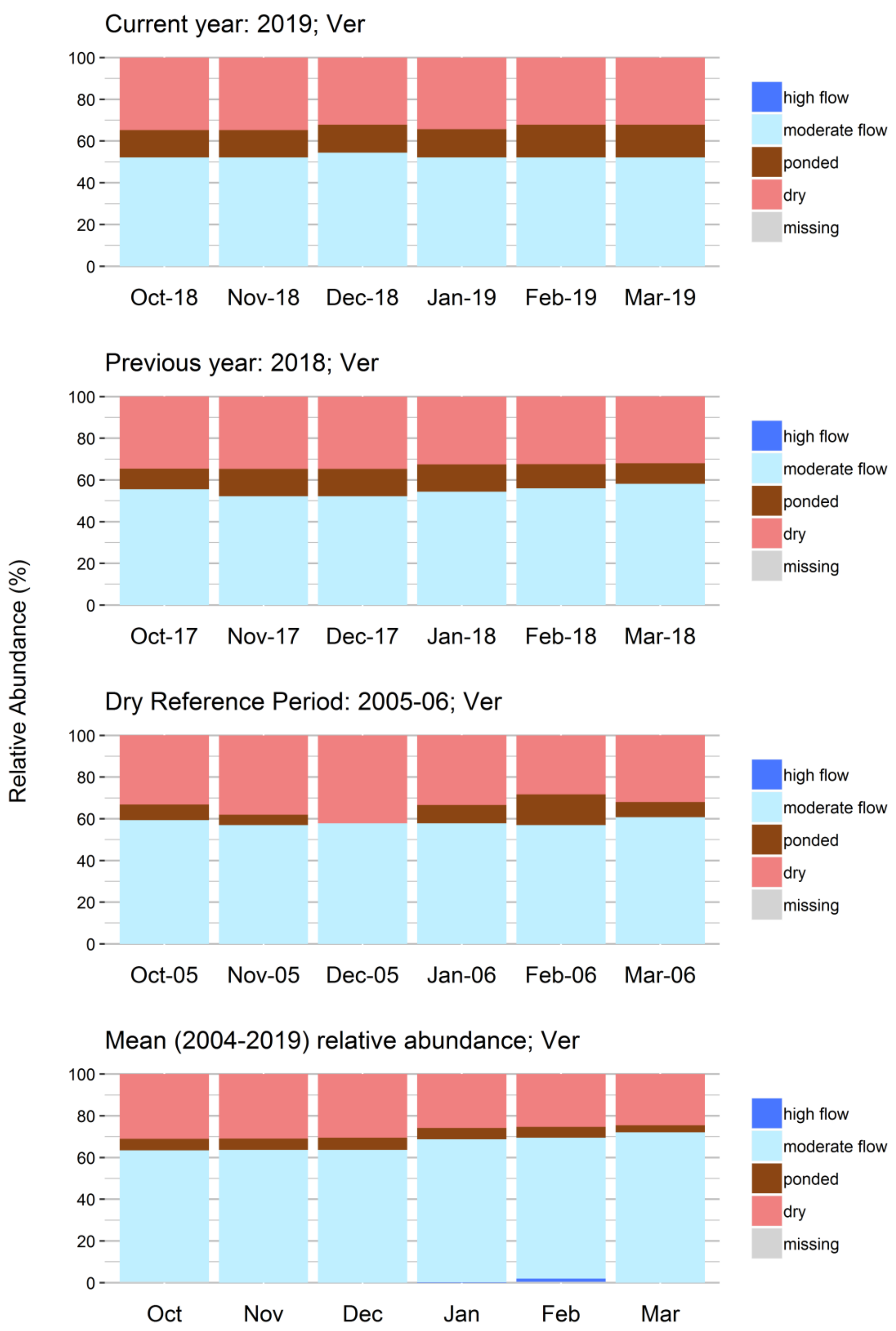
c) River Bulbourne



d) River Gade

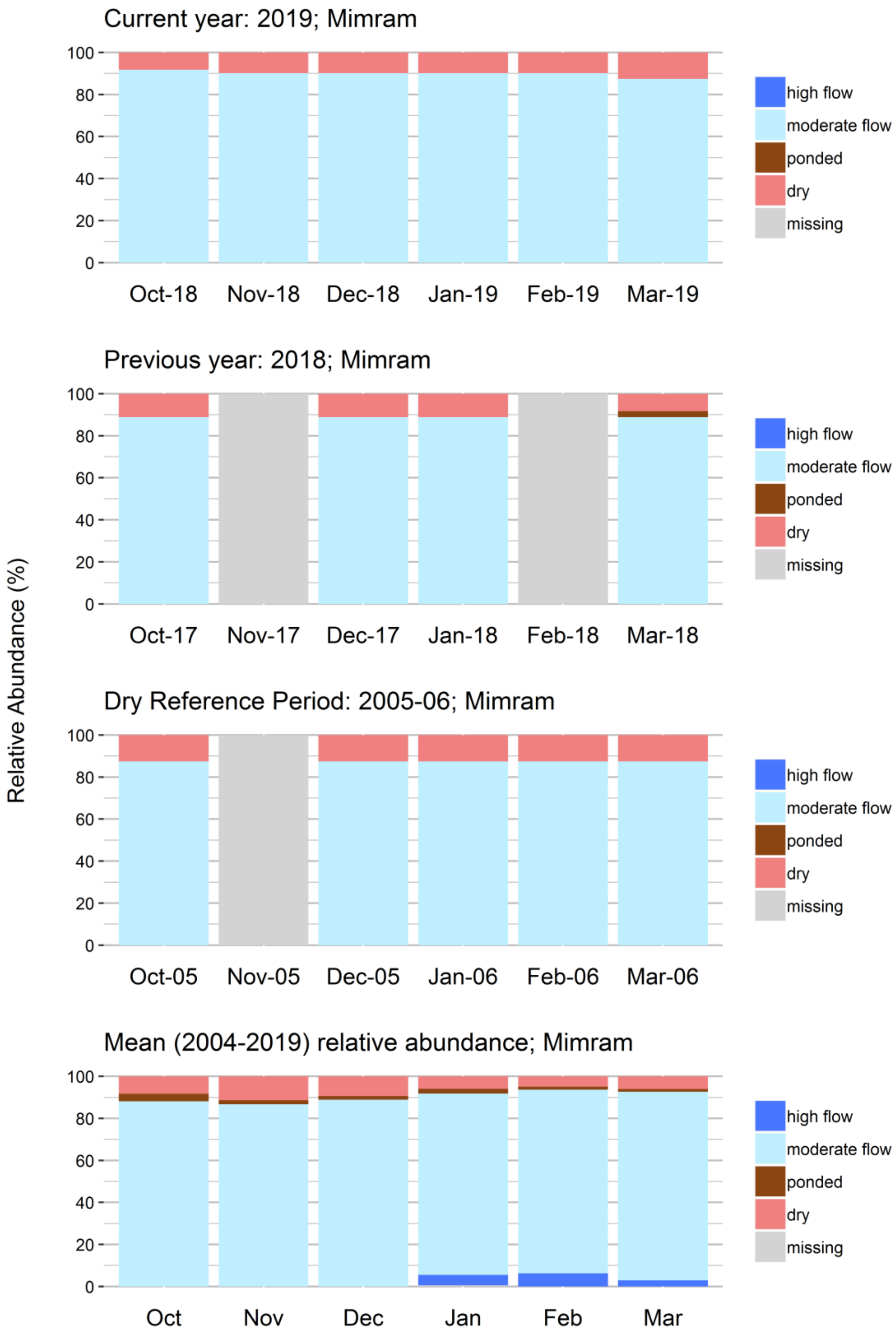

Current year: 2019; Gade
Previous year: 2018; Gade
Dry Reference Period: 2005-06; Gade
Mean (2004-2019) relative abundance; Gade
Relative Abundance (%)
Oct-18 Nov-18 Dec-18 Jan-19 Feb-19 Mar-19
Oct-17 Nov-17 Dec-17 Jan-18 Feb-18 Mar-18
Oct-05 Nov-05 Dec-05 Jan-06 Feb-06 Mar-06
Oct Nov Dec Jan Feb Mar
high flow
moderate flow
ponded
dry
missing

e) River Ver

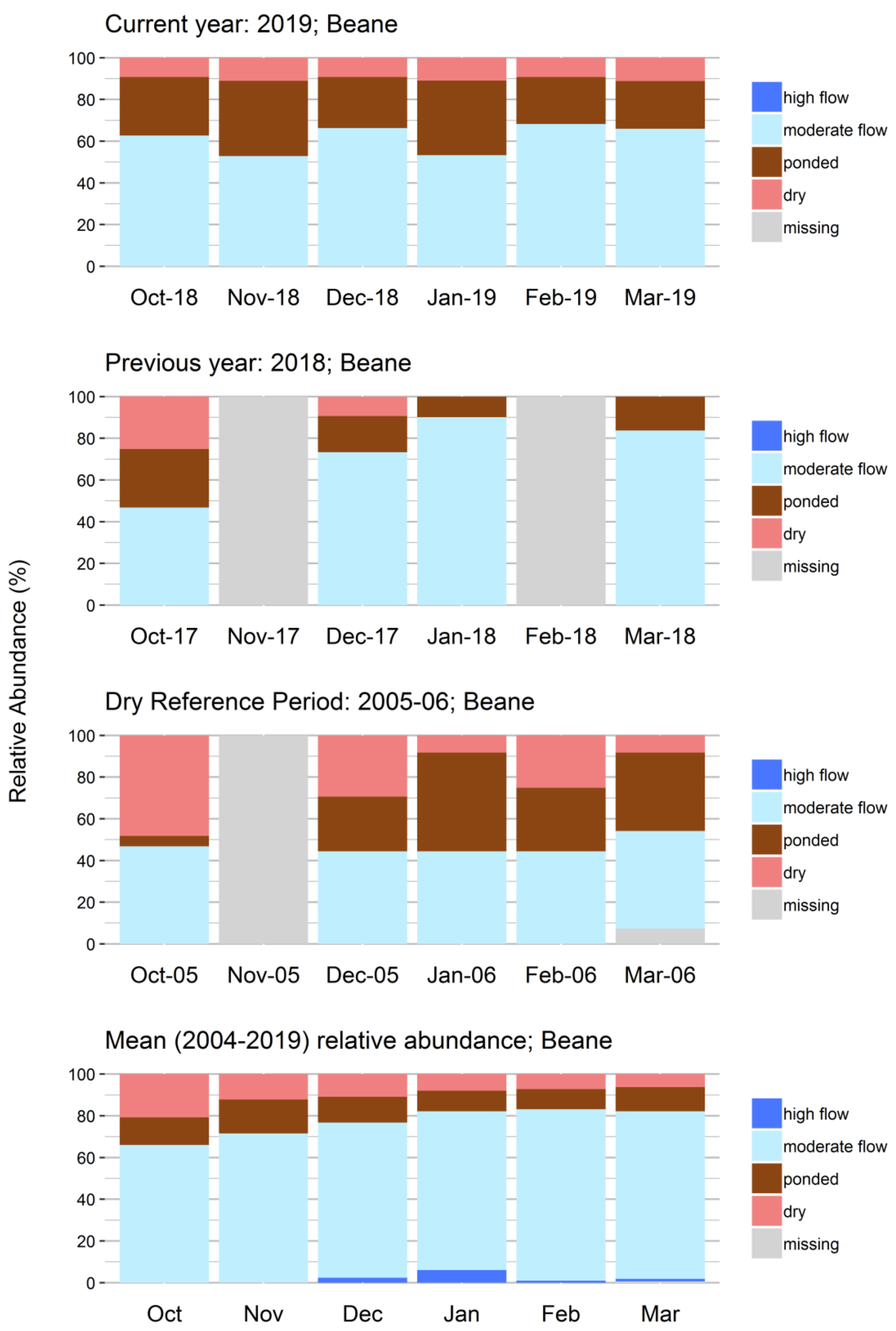

Current year: 2019; Ver
100
80
60
40
20
0
Oct-18
Nov-18
Dec-18
Jan-19
Feb-19
Mar-19
high flow
moderate flow
ponded
dry
missing
Previous year: 2018; Ver
Oct-17
Nov-17
Dec-17
Jan-18
Feb-18
Mar-18
Dry Reference Period: 2005-06; Ver
Oct-05
Nov-05
Dec-05
Jan-06
Feb-06
Mar-06
Mean (2004-2019) relative abundance; Ver
Oct
Nov
Dec
Jan
Feb
Mar
Relative Abundance (%)

Lee Catchment

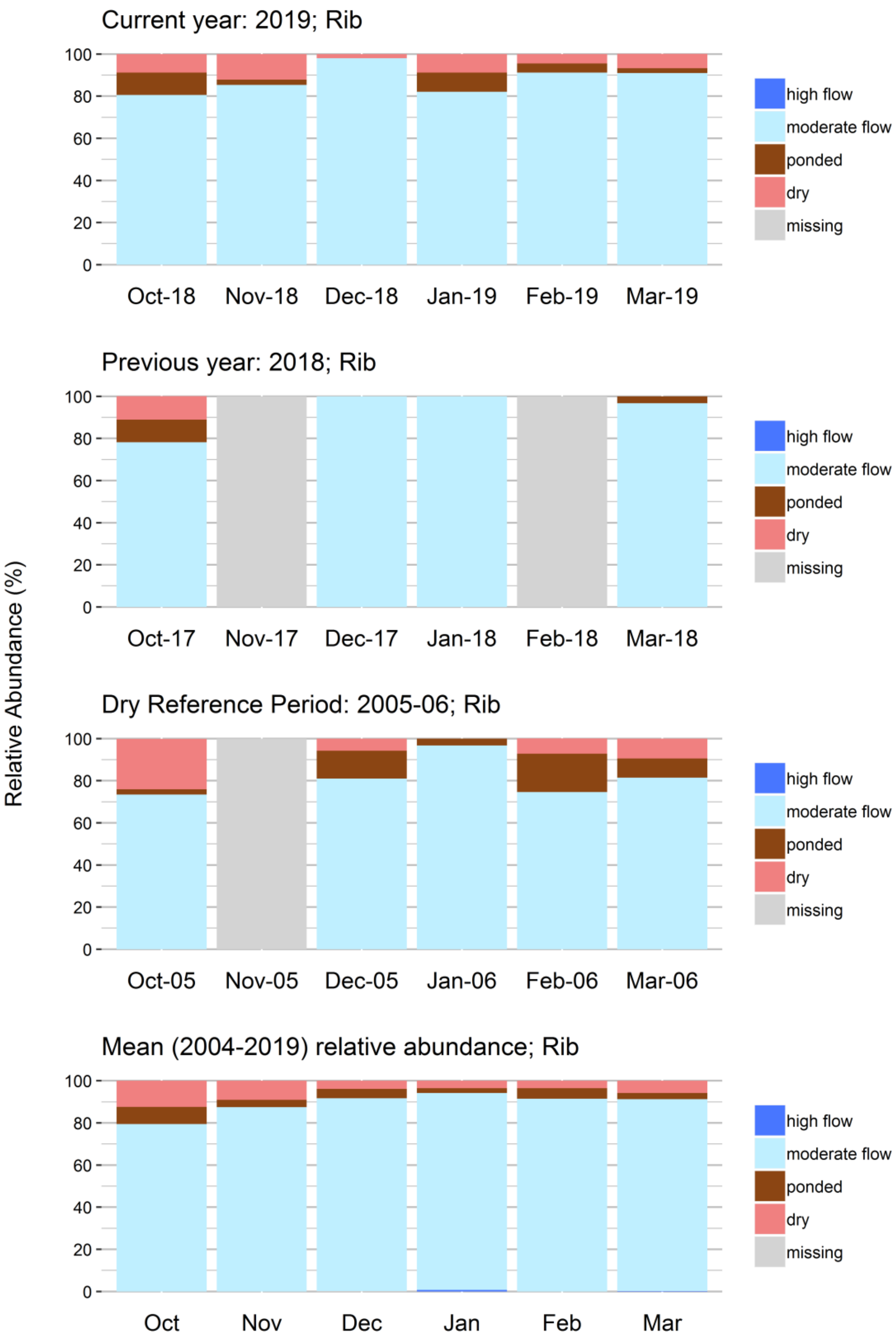
f) River Mimram



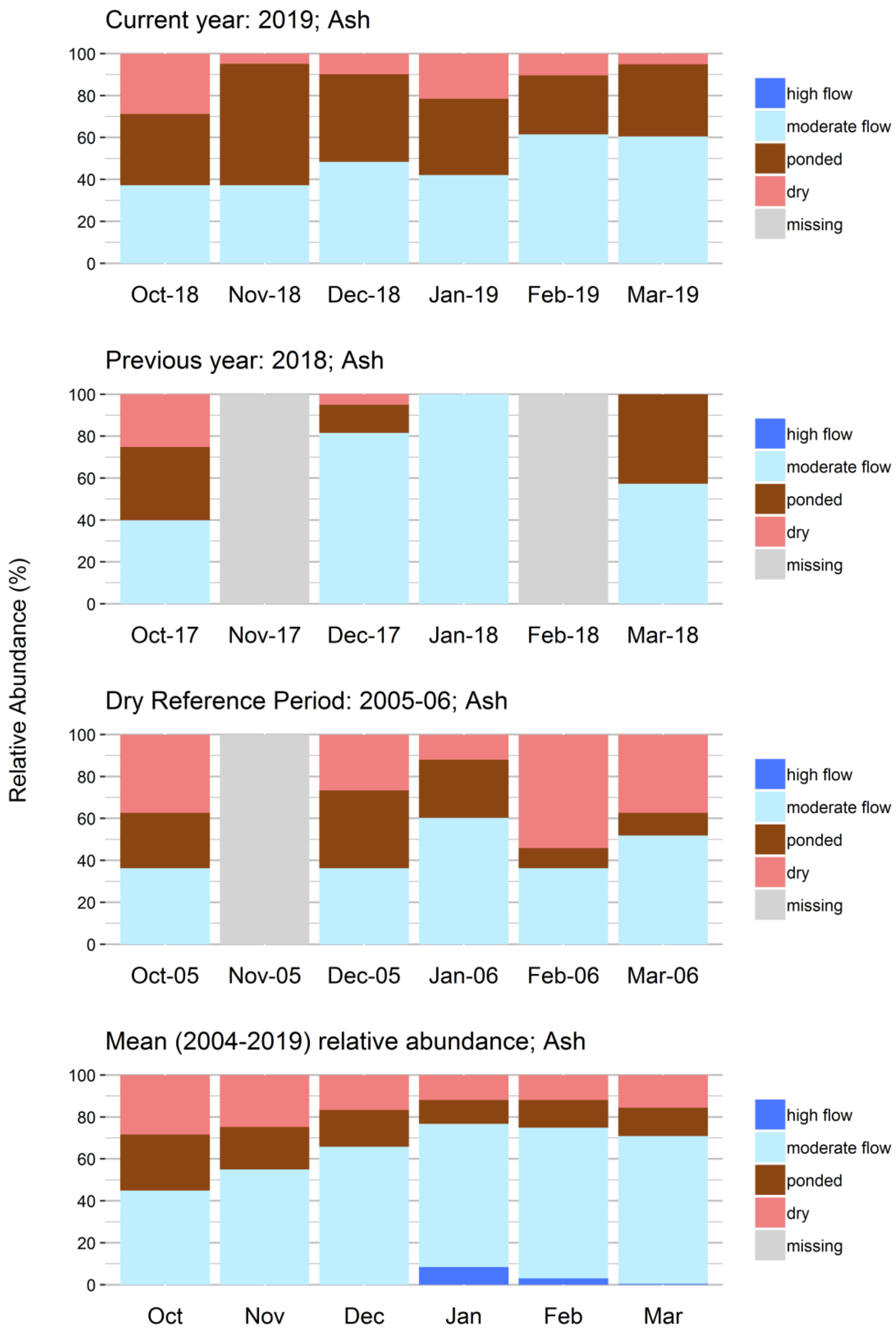
g) River Beane



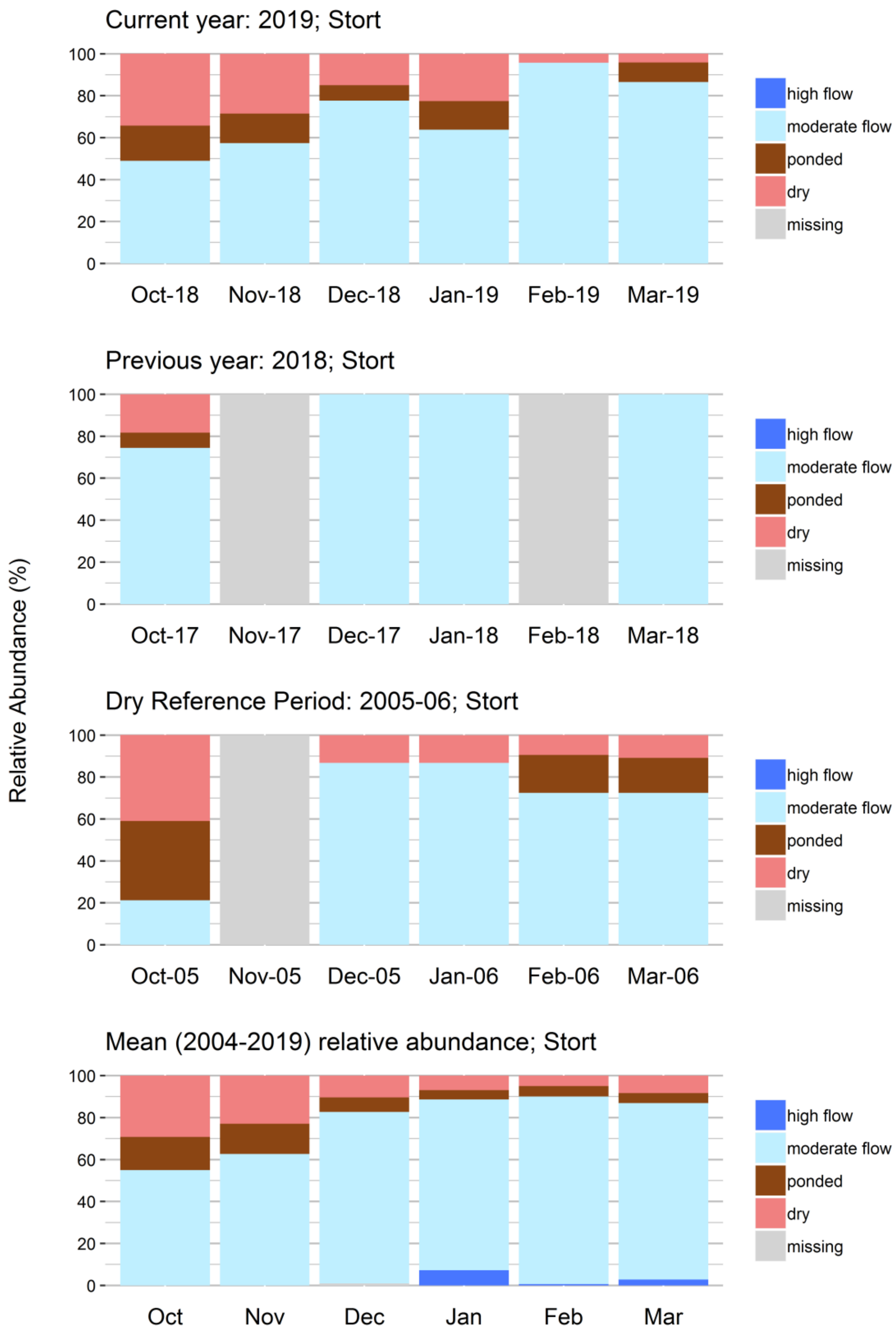
h) River Rib


Current year: 2019; Rib
100
80
60
40
20
0
Oct-18
Nov-18
Dec-18
Jan-19
Feb-19
Mar-19
high flow
moderate flow
ponded
dry
missing
Previous year: 2018; Rib
Oct-17
Nov-17
Dec-17
Jan-18
Feb-18
Mar-18
Dry Reference Period: 2005-06; Rib
Oct-05
Nov-05
Dec-05
Jan-06
Feb-06
Mar-06
Mean (2004-2019) relative abundance; Rib
Oct
Nov
Dec
Jan
Feb
Mar
Relative Abundance (%)

i) River Ash


Current year: 2019; Ash
100
80
60
40
20
0
Oct-18
Nov-18
Dec-18
Jan-19
Feb-19
Mar-19
high flow
moderate flow
ponded
dry
missing
Previous year: 2018; Ash
Oct-17
Nov-17
Dec-17
Jan-18
Feb-18
Mar-18
Relative Abundance (%)
Dry Reference Period: 2005-06; Ash
Oct-05
Nov-05
Dec-05
Jan-06
Feb-06
Mar-06
Mean (2004-2019) relative abundance; Ash
Oct
Nov
Dec
Jan
Feb
Mar

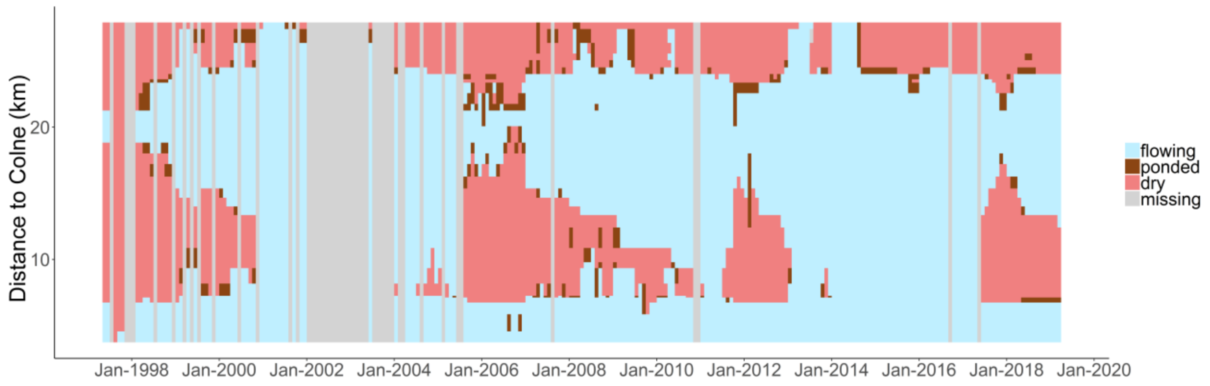
j) River Stort



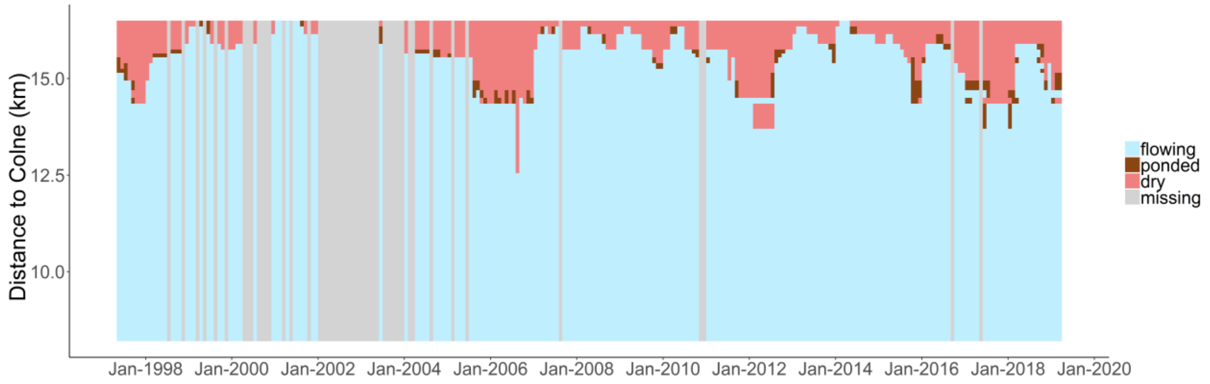
Appendix C. Heat maps

Colne Catchment

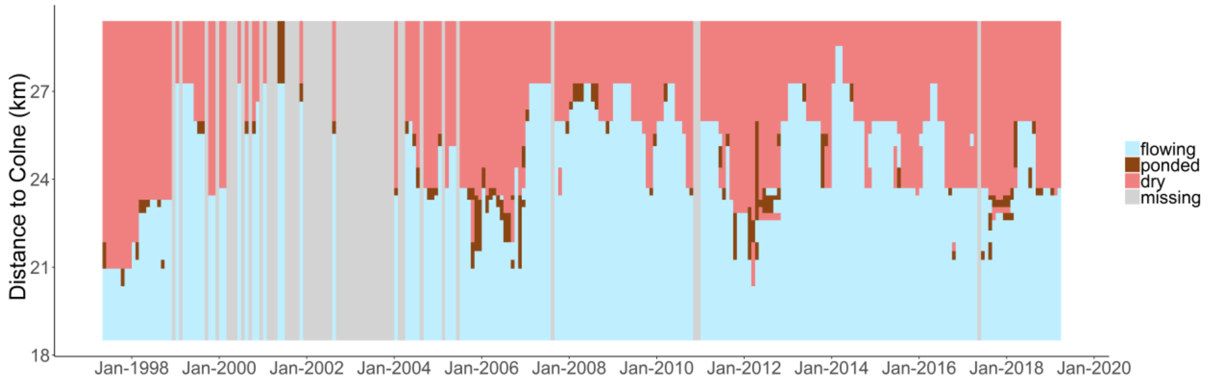
a) River Misbourne



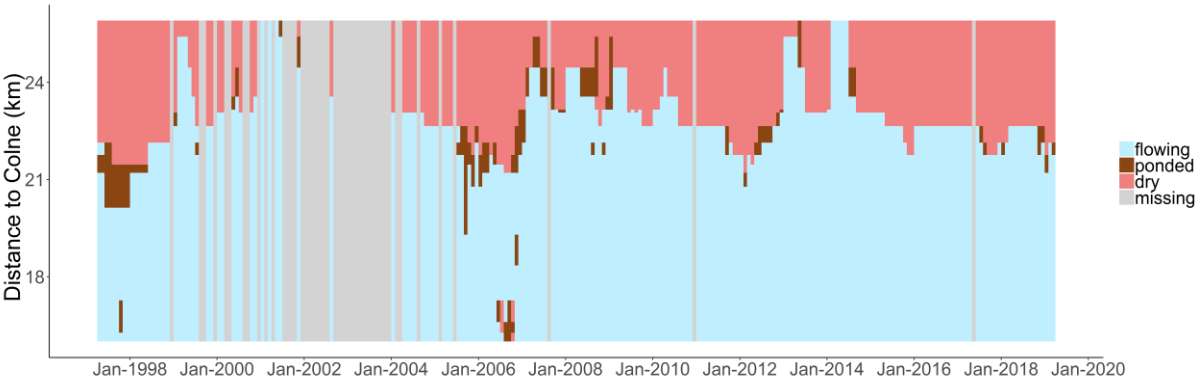
b) River Chess



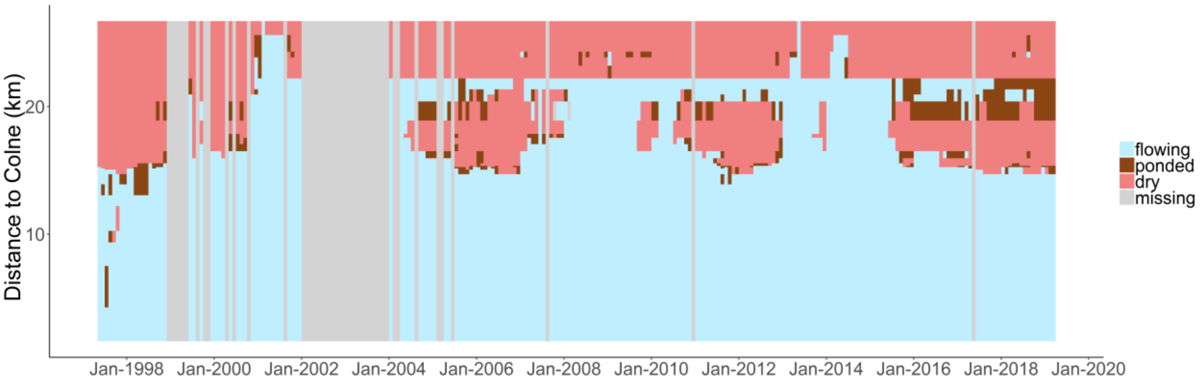
c) River Bulbourne



d) River Gade

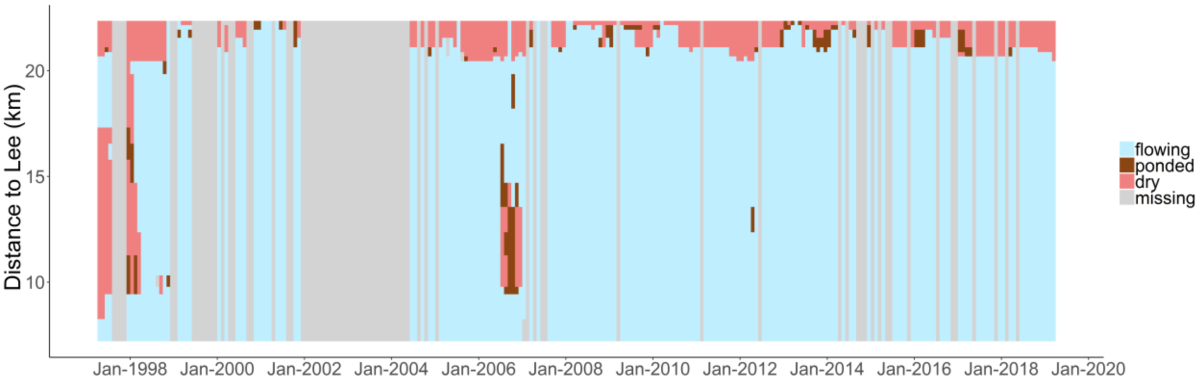


e) River Ver

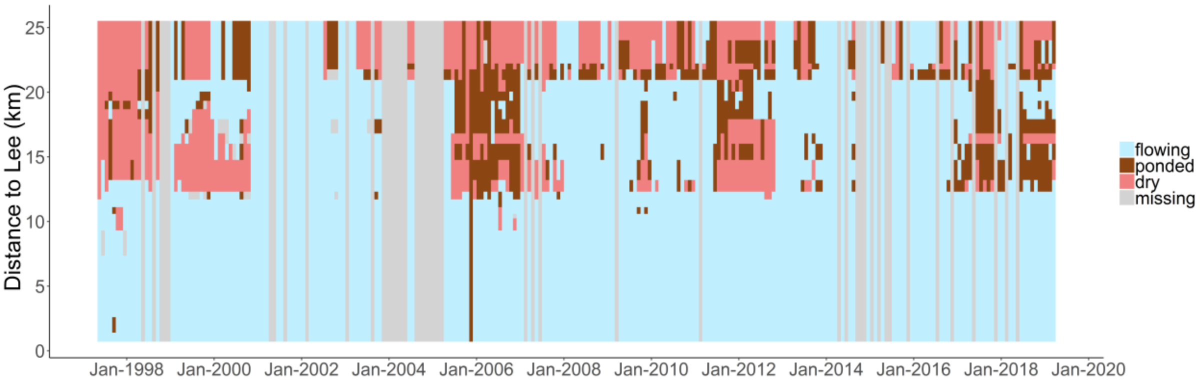


Lee Catchment

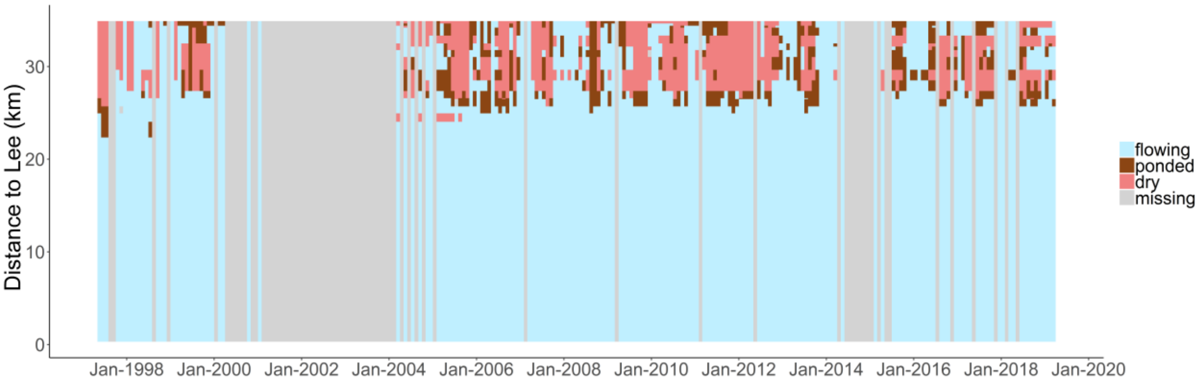
f) River Mimram



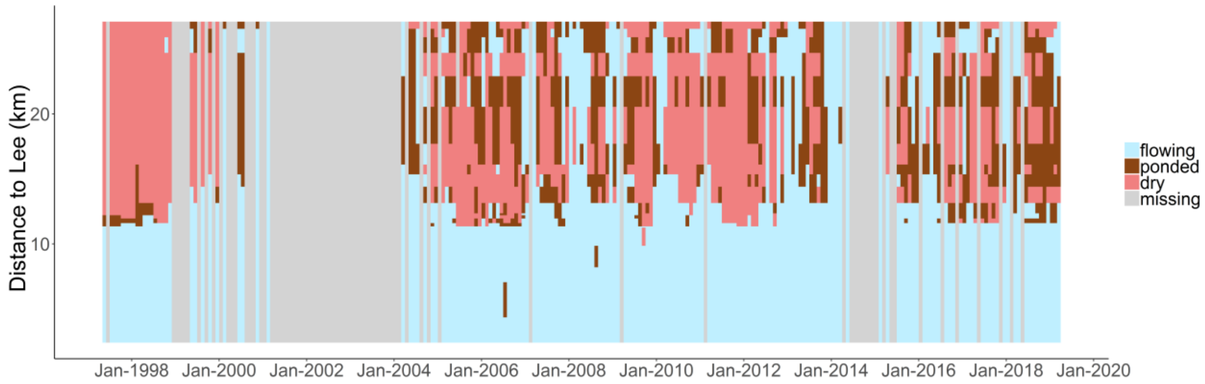
g) River Beane



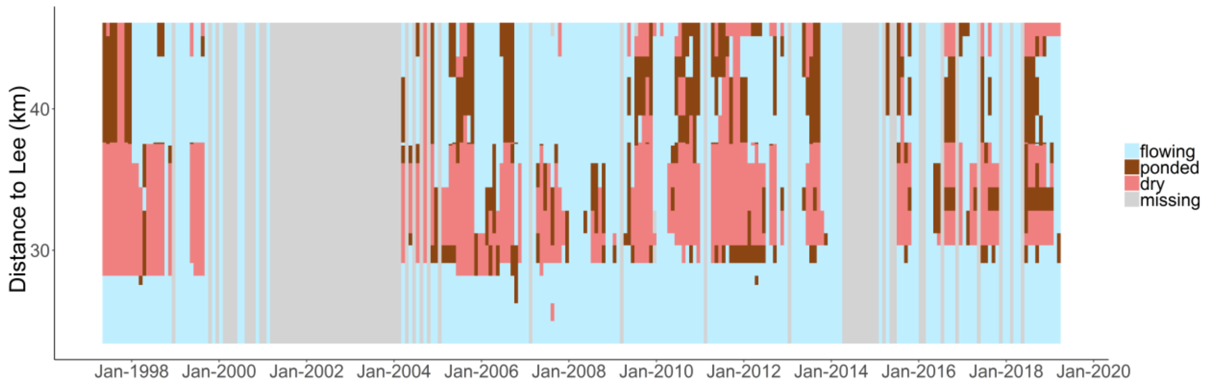
h) River Rib



i) River Ash



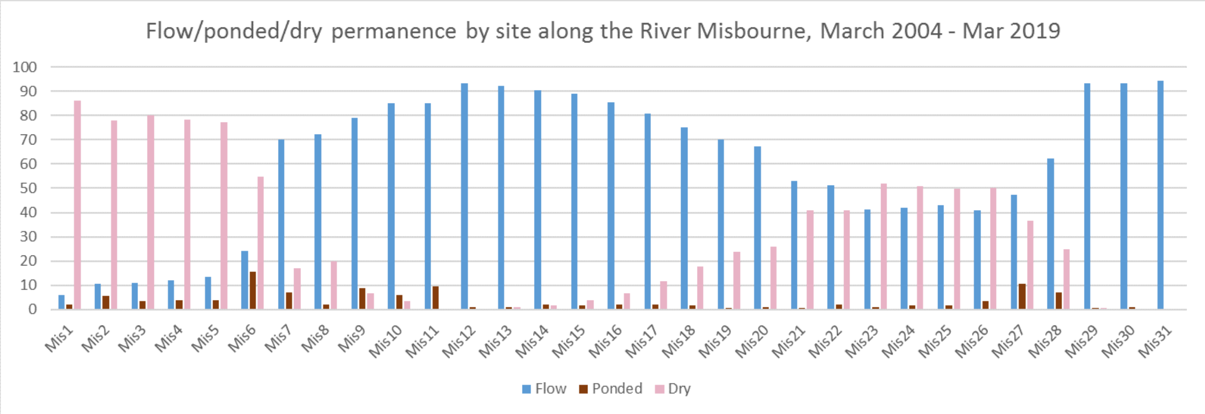
j) River Stort



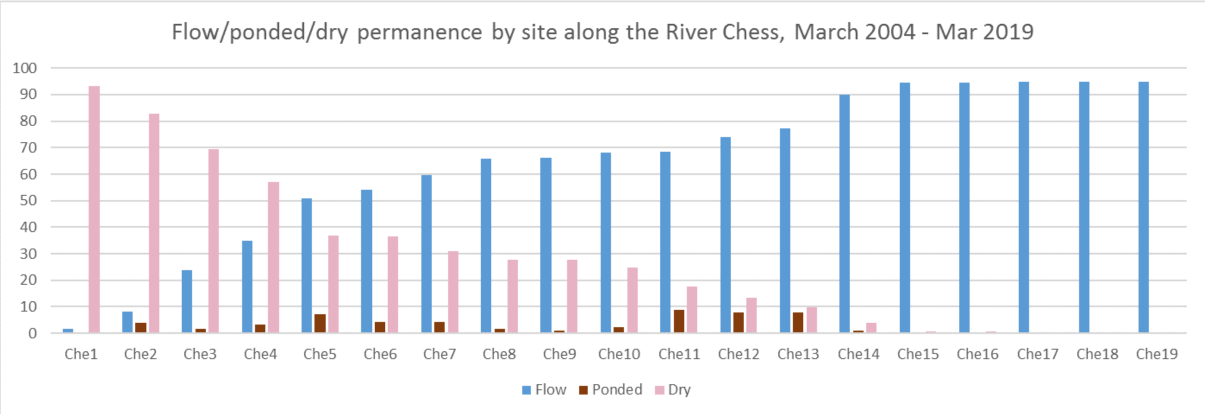
Appendix D. Relative permanence by site

Colne Catchment

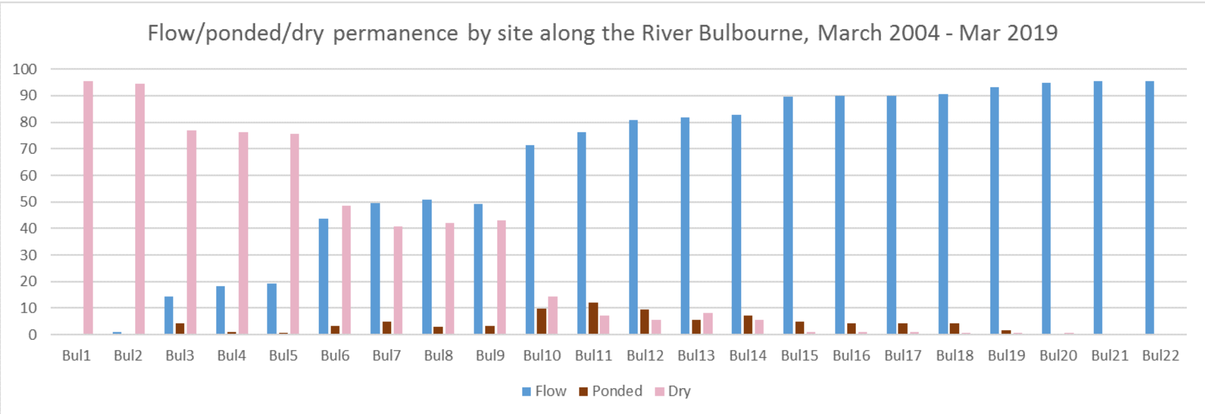
a) River Misbourne



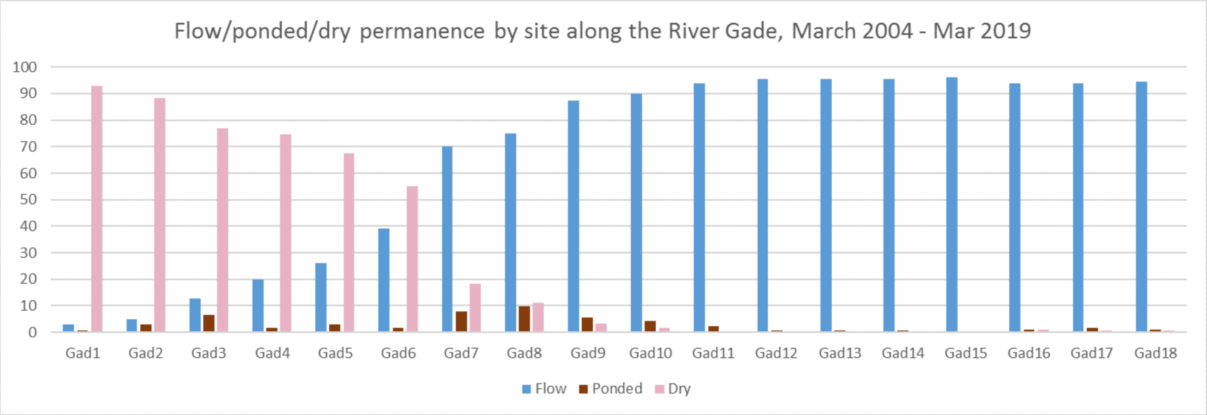
b) River Chess



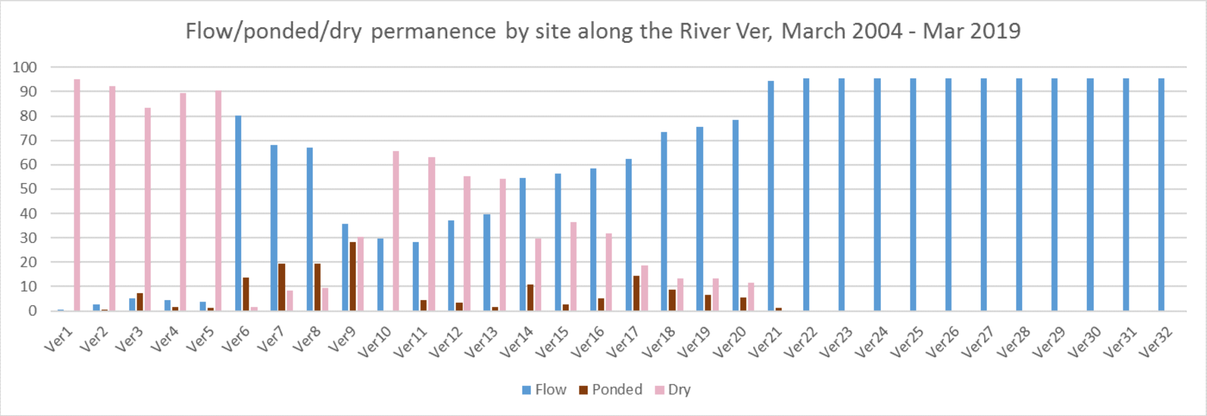
c) River Bulbourne



d) River Gade

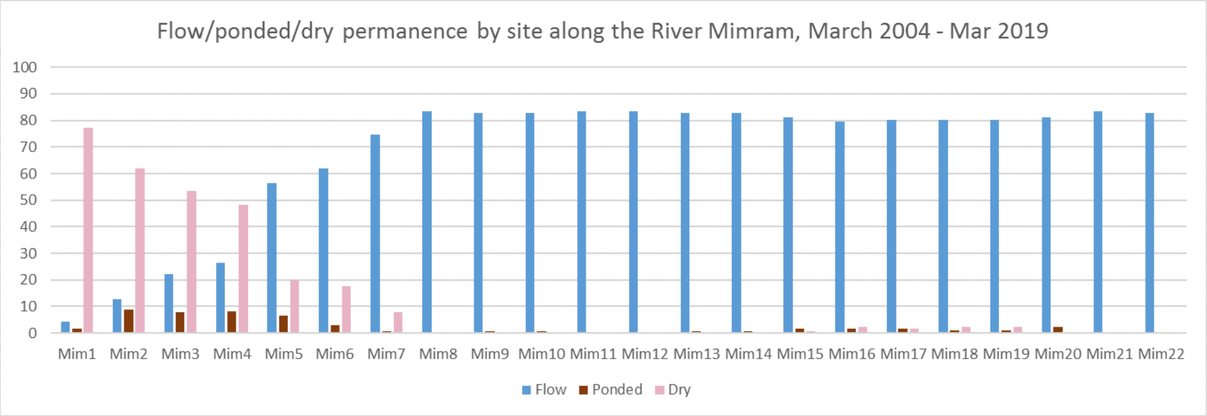


e) River Ver

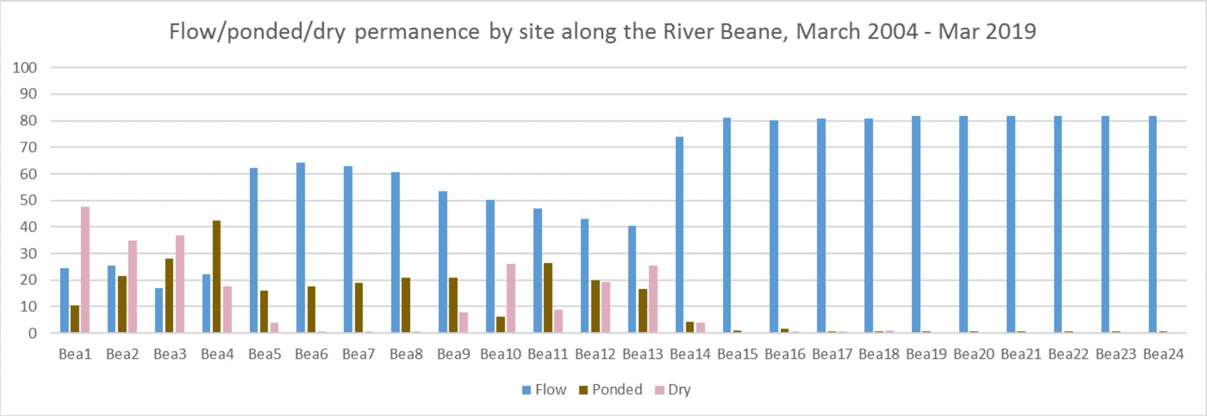


Lee Catchment

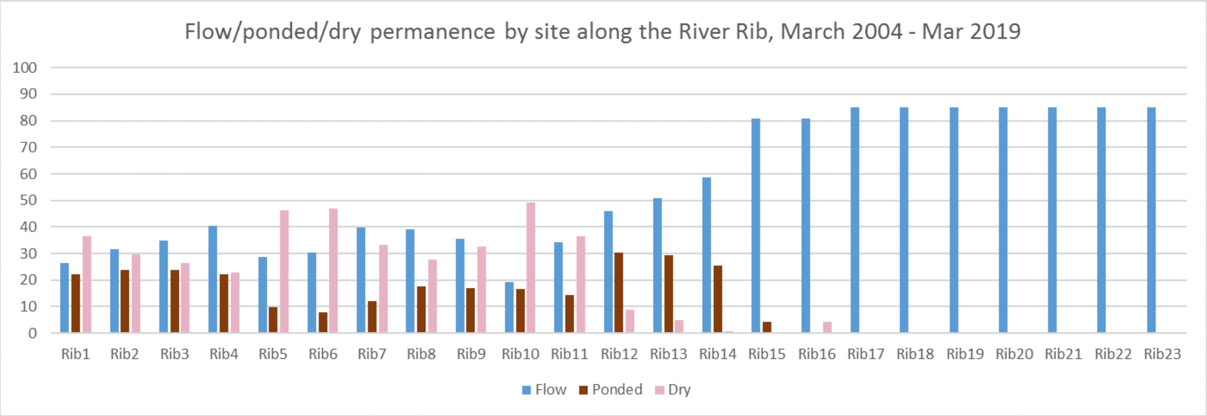
f) River Mimram



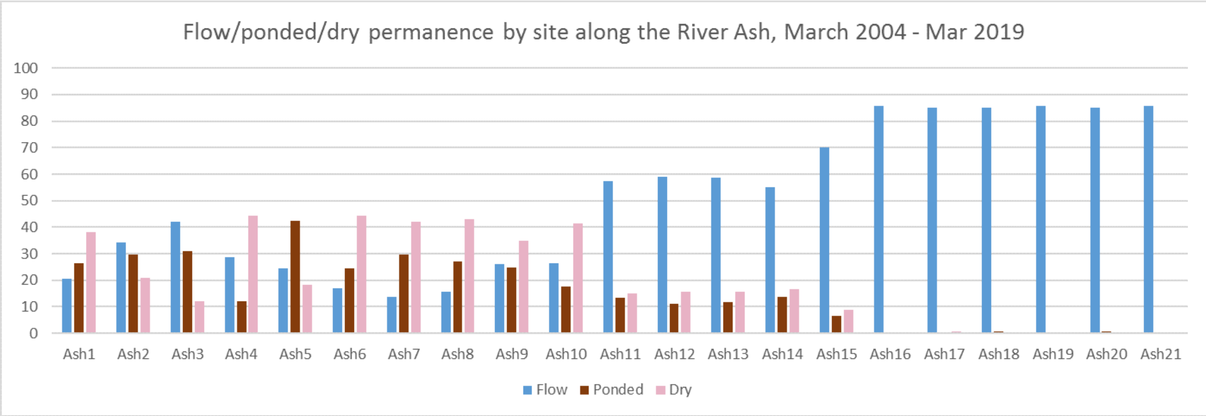
g) River Beane



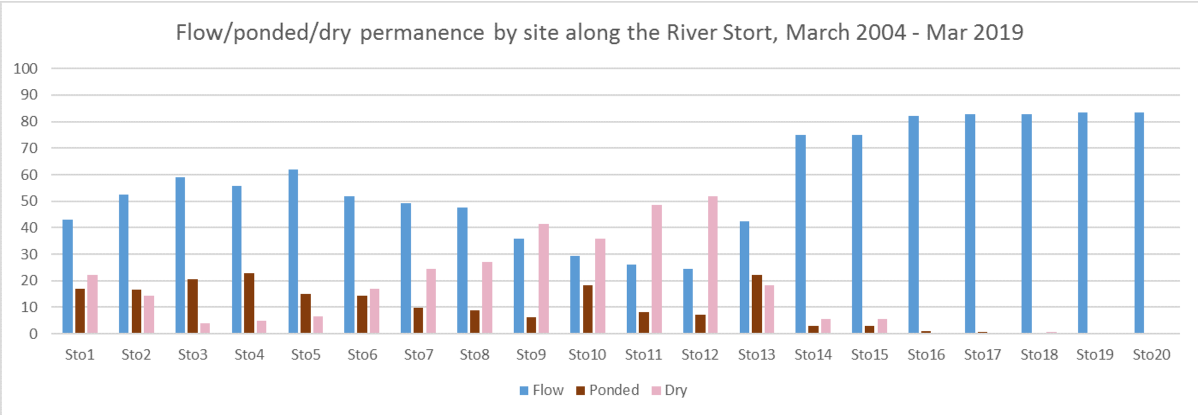
h) River Rib



i) River Ash



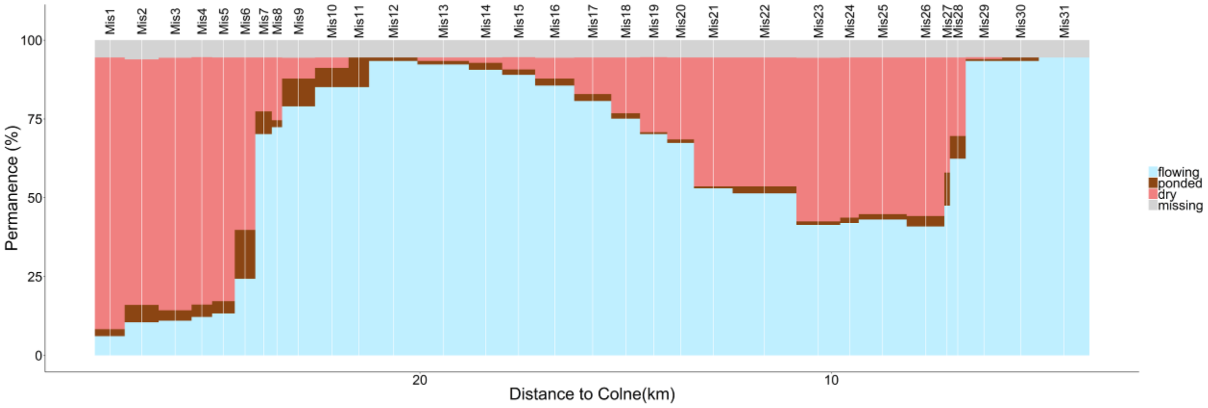
j) River Stort



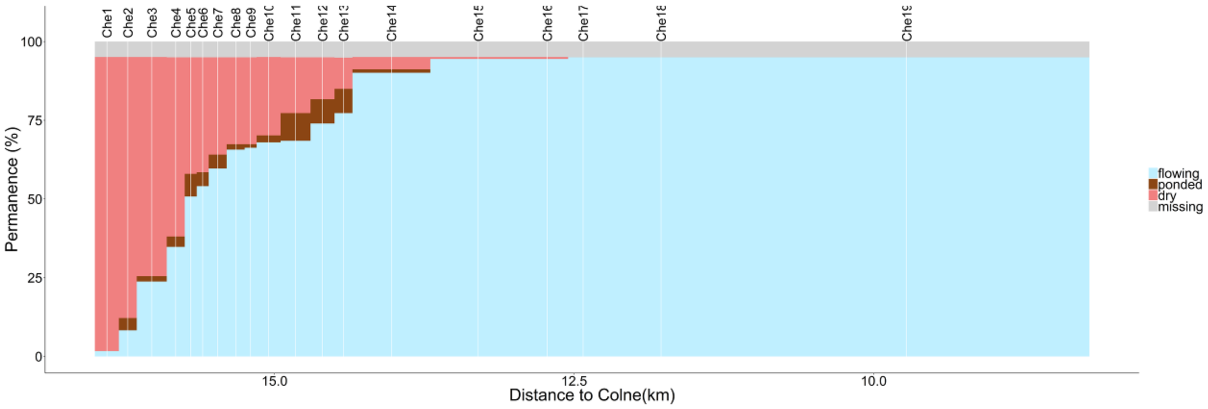
Appendix E. Relative permanence with distance

Colne catchment

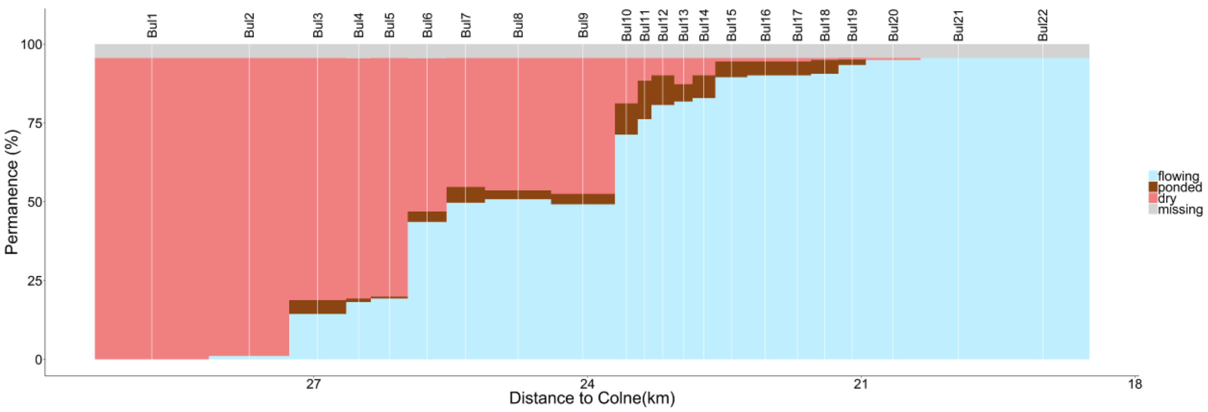
a) River Misbourne



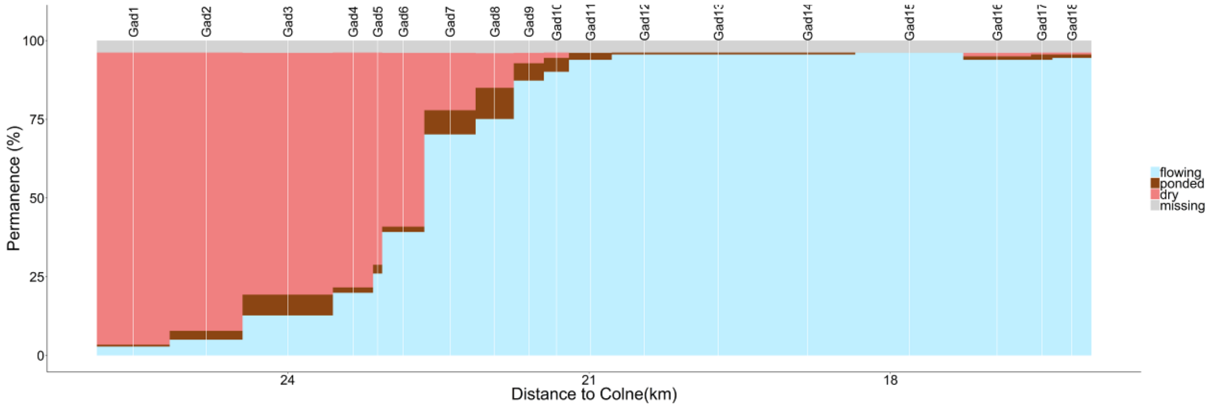
b) River Chess



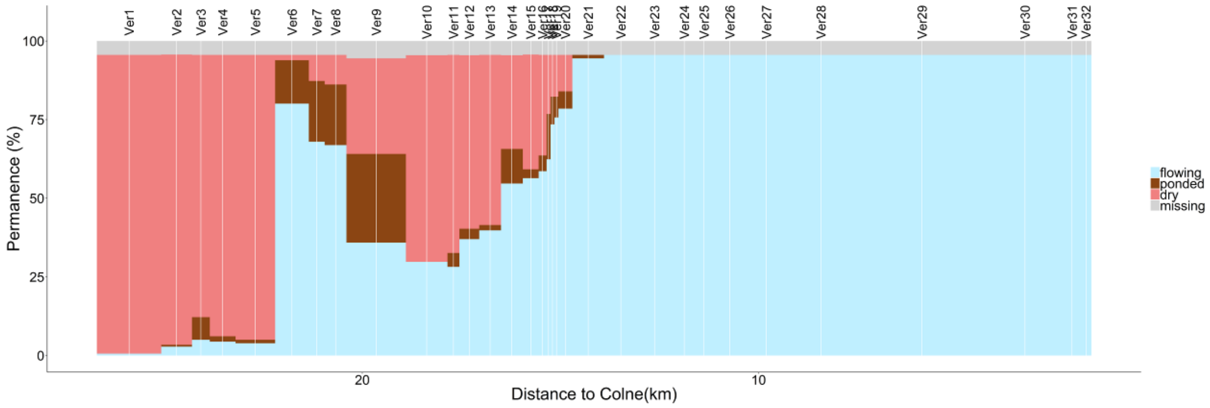
c) River Bulbourne



d) River Gade

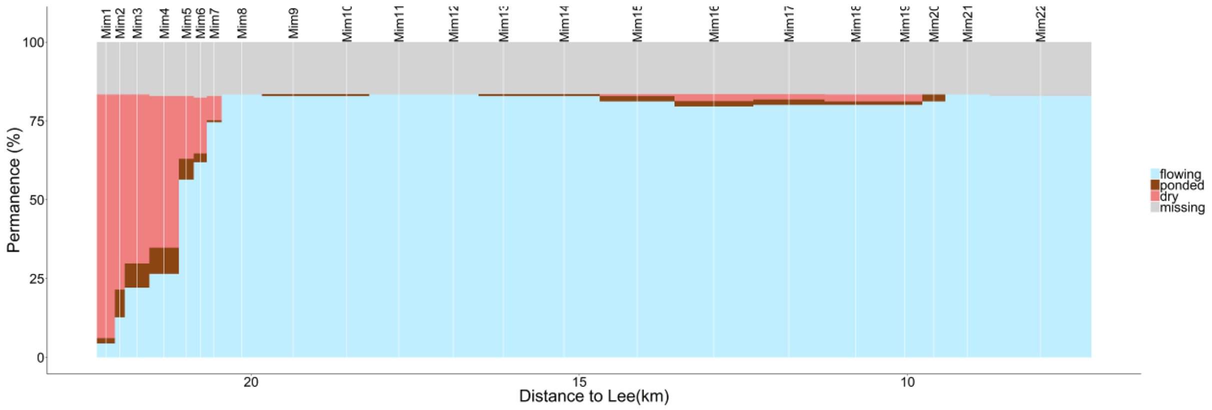


e) River Ver

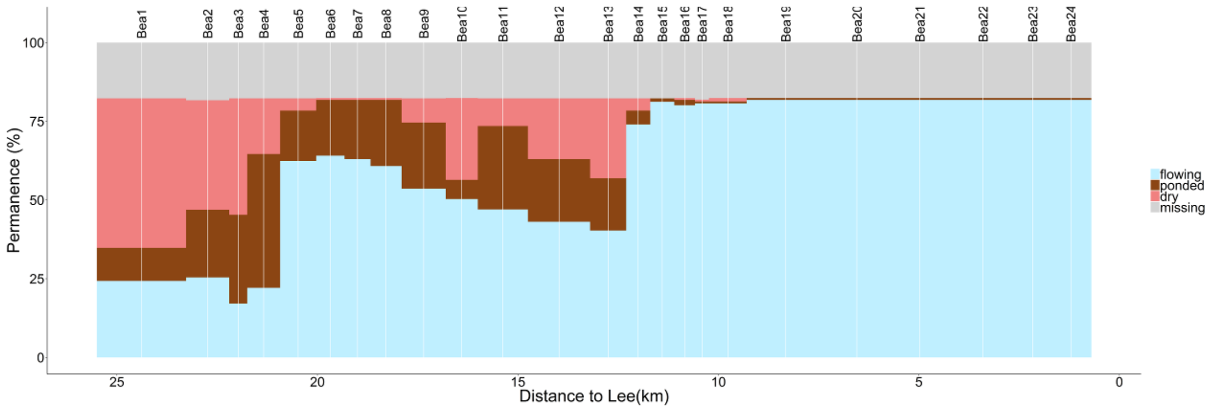


Lee catchment

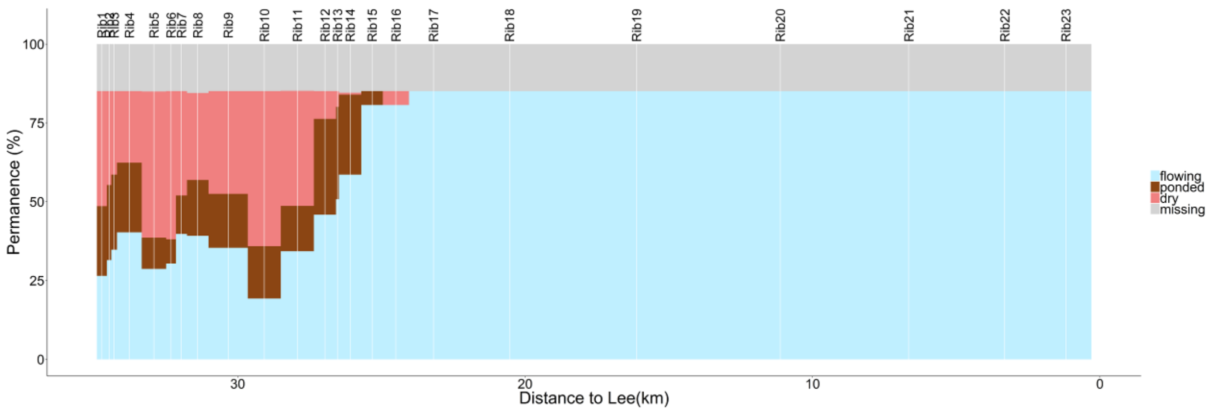
f) River Mimram



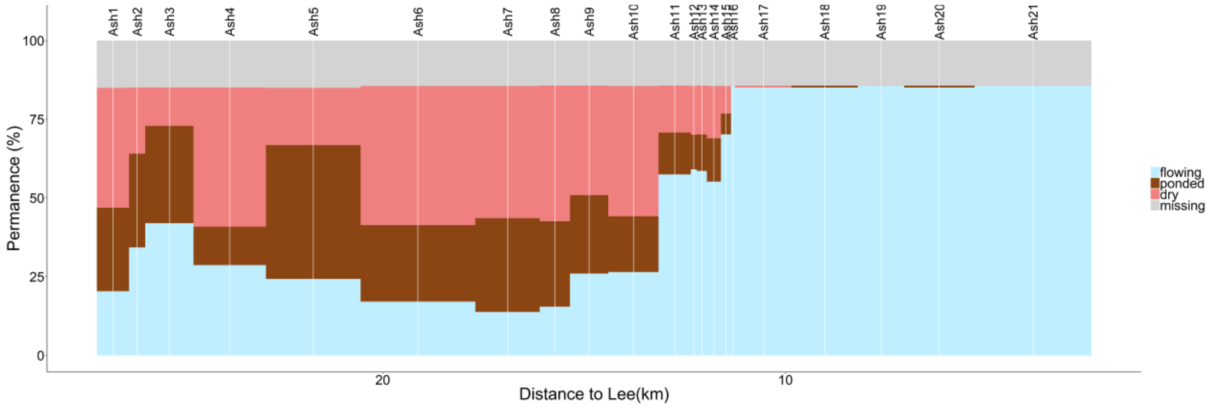
g) River Beane



h) River Rib



i) River Ash



j) River Stort