River water temperature projections for English Chalk streams

Chief Scientist's Group report

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Dr Robert Bradburne
Chief Scientist

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Executive Summary

The future impacts of climate change on aquatic ecosystems remain uncertain. Strong links between surface water temperature, water quality and ecological response show that changes in water temperature are likely to be of critical importance. Quantifying the amount and timing of warming in rivers can inform the targeting of adaptation measures to reduce adverse changes and protect vital functions they provide. While projections of river water volumes and flows have been developed for England there are currently no national projections of river water temperature. This limits our understanding of future risks and management choices that can improve resilience to the impacts of climate change.

Chalk streams are a globally unique habitat restricted to England and north-west Europe. These groundwater-fed streams exhibit a stable, cool water temperature profile supporting rich biodiverse ecosystems including important salmonid fish species: Atlantic salmon (*Salmo salar*) and brown trout (*Salmo trutta*). This group of rivers was selected as a pilot for temperature projections in all rivers because of their similar morphology, uniqueness, their importance in water supply and in support of a national effort to protect these important habitats.

Chalk stream water temperature and future projections are modelled, following a previously identified framework, using historical Environment Agency water temperature records along with environment variables (air temperature, land cover and river network properties). Sufficient water temperature data were identified at 92 sites to create a ***monthly mean daytime*** water temperature model, which was then validated at 893 sites across the English chalk stream network.

This 'global' model was used to make monthly mean daytime river water temperature projections to 2080 – the temporal extent of existing climate change projections that provide future warming information. Based on a 'high emissions scenario', ecologically significant increases in water temperature were projected with summer maxima rising by 0.58°C per decade above reference levels (1981 to 2005) to 2080. These values indicate change in summer monthly mean daytime maximum water temperatures over the next 60 years and allow spatial comparisons. Regional differences are seen with sites in the north-east of England (Lincolnshire and Yorkshire Wolds) projected to experience the lowest increases whereas those in the vicinity of London (rivers Colne, Lee, Hogsmill, Mole and Wandle) are projected to experience the highest. Some 'hotspots' as well as 'cold spots' can also be identified amongst the sites. Monthly daytime projections are particularly affected by the amount of urban land in the catchment. An important temperature threshold for salmonid egg survival during the winter spawning period of 12°C will likely be exceeded at over 85% of sites by 2080 and adult brown trout will continue to be under threat from high summer temperatures with all sites exceeding that species' upper critical temperature range of 19.5°C by 2080.

The historic water temperature readings provide a 'snapshot' temperature value for water from various sources (e.g., upstream flow, precipitation, surface water runoff, groundwater influx) all of which will have different temperature profiles and volume contributions which will vary through the seasons and between years. The seasonal aspect of the relationship between air and water temperature was essential in model development. To account for this variation a minimum of five years monthly mean water temperature data is considered an absolute minimum to reflect meaningful interannual water temperature variation.

While the available historical water temperature records facilitated estimation of monthly mean daytime water temperatures for rivers under the influence of climate change, the coarse nature of the data (i.e., in space and time) limit the ability to draw conclusions about water temperature at specific sites. Mean monthly estimates also disguise the influence of short-term climatic fluctuations (e.g., heatwaves) which may have ecological implications ahead of the timelines outlined here. The monthly mean maximum temperature is therefore likely to underestimate daily maximum temperatures that could be experienced. More detailed projections (e.g., daily or along river channels) would be possible with higher sampling frequency or a specifically designed temperature monitoring network.

Introduction

Overview

Climate projections for England suggest there will be an increase of warmer, wetter winters and hotter, drier summers along with more frequent and intense extreme weather events, including short duration, high magnitude precipitation events (UKCP18: Met Office, 2019). Understanding the consequences of these changes on water quality and aquatic biota is important to inform the targeting of management actions and adaptation measures to help maintain the integrity of the river ecosystems and the services they provide.

Flow and water temperature (*Tw*) are considered important variables having an influence on river ecosystems and water quality (Poff et al., 1997, Woodward et al., 2010). There is a broad consensus of how the climate is changing including information about how river flows will alter. There is much less clarity about how and where *Tw* may change. Previous modelling exercises assessed how water quality and eutrophication risk could change in the future, highlighted the sensitivity of future risk to projections of *Tw* (Environment Agency, 2019). Understanding potential changes in thermal regimes will help identify priority areas for action (Knouft et al., 2021). Adaptation measures, such as tree planting for shade, can reduce thermal maxima but careful targeting is needed as the thermal benefit of riparian shade depends on physical location within the river network and on prevailing climate conditions (Garner et al., 2017, Wilby and Johnson, 2020). Models to identify where rivers are hottest and most sensitive to climate change in Scotland (Jackson et al., 2018) are being used to target riparian tree planting to protect cold water dependent species such as Atlantic salmon and brown trout.

River water temperature is controlled by a complex interaction of hydrological, climatological and landscape characteristics and previous models for predicting water temperature have utilised variables from all three of these categories (e.g., Jackson et al., 2018). Climatological influences are reflected in air temperature readings which have long been recognised as having a strong positive correlation with surface water temperatures.

Quantifying the amount and timing of future warming in rivers will provide more robust evidence to inform where to target measures to adapt to these changes. To understand how best to develop future projections of river *Tw*, Environment Agency (2021) reviewed potential modelling approaches and produced a robust framework for doing so. This study applied the framework to develop *Tw* projections for English chalk streams.

Chalk streams are watercourses dominated by groundwater discharge from chalk geology. The chalk has a strong influence on the flow regime and chemical properties supporting characteristic assemblages of plants and animals (Berrie, 1992; Sear et al., 1999). Groundwater has a stable temperature, resulting in a warming effect in winter and a cooling effect in summer (compared to air temperature), and historically, river temperatures have appeared stable between 5 and 17°C (Mackey and Berrie, 1991). Previous river temperature modelling studies have demonstrated the importance of river shading and water flow characteristics (water flow, volume, residence time) in modulating river water temperatures (Jackson et al., 2020).

Using chalk streams as a test case allows the modelling approach recommended in the scoping project to be tested, applied, and refined. It will demonstrate the effectiveness of the modelling approach, develop the specific tools for producing and updating projections elsewhere, and produce a specific set of projections that can be immediately used for understanding future impacts and how to manage them.

Project aim and objectives

The aim of this project was to develop *Tw* projections for English chalk streams using the framework developed in an earlier project (Environment Agency, 2021). *Tw*, corresponding air temperature (*Ta*) and associated catchment data were collated from available sources (Task 1; Figure 1) and assessed for their application to chalk stream catchments and the potential modelling options they could support (Task 2). A global model and catchment specific models were then developed, tested, and refined (Task 3) before making projections of *Tw* under climate change conditions (Task 4). Both global and catchment specific models were developed in Task 3 to help understand how different predictor variables influenced the projections at different spatial scales and whether the predictive ability of the models could be improved.

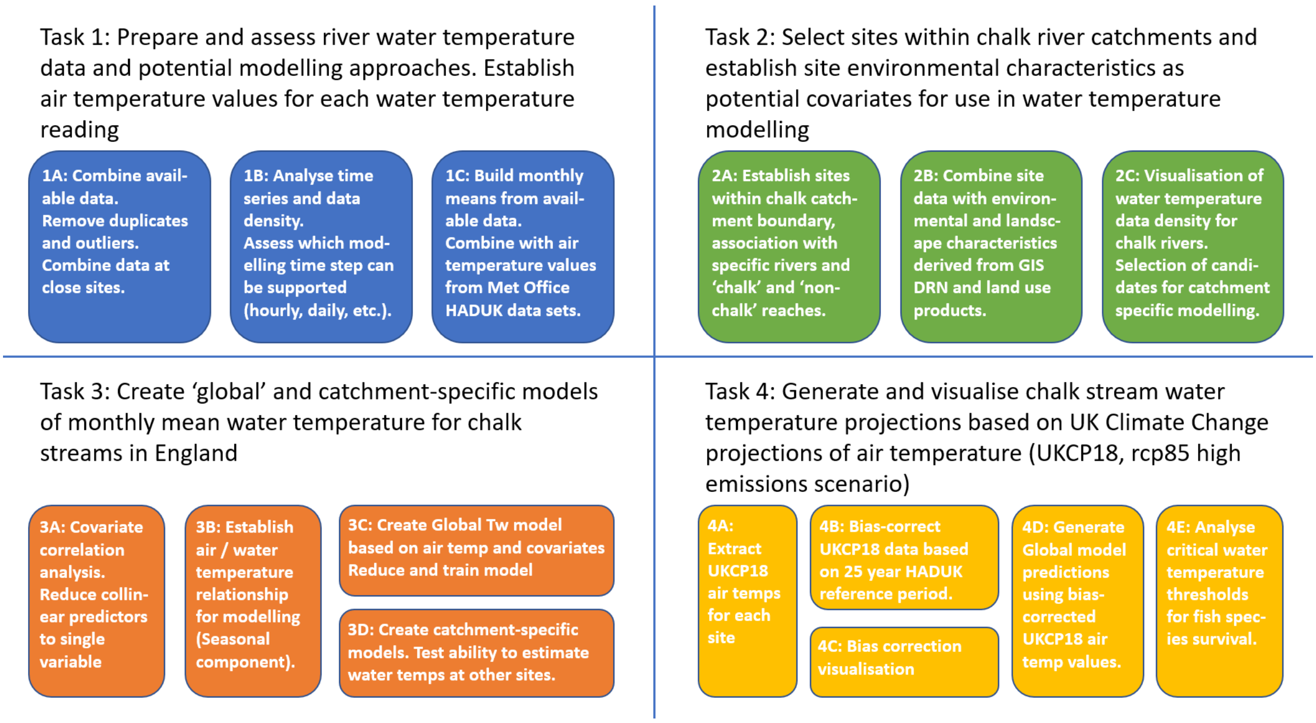

Figure 1: Task outline followed to generate models and predictions of chalk stream water temperature from available data. Task and subtask numbering relates to respective R code scripts developed to complete analysis (R code availability information needed here).

Methods

An overview of the data sets used, and the modelling approaches employed are presented here. Detailed methods are provided in the appendix.

Data for modelling and projections

Observed water temperature readings

River water temperature (*Tw*) data from the Environment Agency's Surface Water Temperature Archive up to 2007 (Orr et al., 2015) and Water Quality Data (WIMS) archive were combined (referred to herein as the 'combined *Tw* dataset'). Values above 30 (range = 30.2 to 100; 208 records) and below 0 (range = -0.02 to -2.0; 51 records) were removed as deemed erroneous and unrealistic for English rivers (Orr et al., 2015), observations grouped by unique site identifier and any duplicate measurements (by location, time, and water temperature reading) removed, leaving 3.22 million unique *Tw* records across England. Sites were further grouped into clusters if within 20 meters of each other and samples combined (1577 close sites combined into 689 clusters). Record length and sampling frequency at each of the 28,214 unique sites/clusters were assessed and sequences of *Tw* values sufficient for the generation of monthly mean water temperatures were identified that could support model generation (see Appendix – Table A1). It should be noted that there is a clear sampling bias with spot measurements almost exclusively collected during working hours (median sample time = 11:00, main range = 06:00 – 18:00, Monday - Friday), hence, this should be considered as an estimate of monthly mean daytime water temperatures (*MdTw*).

The boundary of English chalk stream catchments was identified using published chalk stream data (Environment Agency's Catchment Data Explorer; Rangeley-Wilson, 2021) and river courses within that boundary identified. Sub-catchments and tributaries were grouped into 59 major river catchments (see Appendix for catchment groupings) and known chalk stream courses used to split this river network into 'chalk' and 'non-chalk' sections. Sampling sites/clusters associated with a 100-meter buffer of these sections were labelled accordingly, and sites falling outside the buffer region were discarded.

To ensure only robust *MdTw* estimates were used for model development a site had to meet specific data criteria, the minimum criteria of three samples per month with a record length of five years to account for interannual variability. Of the 1727 sample locations identified within the chalk boundary, 92 sites representing 21 of the 59 chalk river catchments met these minimum criteria. A large proportion of sites ($n = 801$) had some months with 3+ *Tw* measurements but not for the required five-year duration; these sites were retained for checking the developed model's performance (= 'Validation dataset'). The 893 sites (92 + 801) participating in model development and validation covered 57 of the 59 chalk river catchments in England.

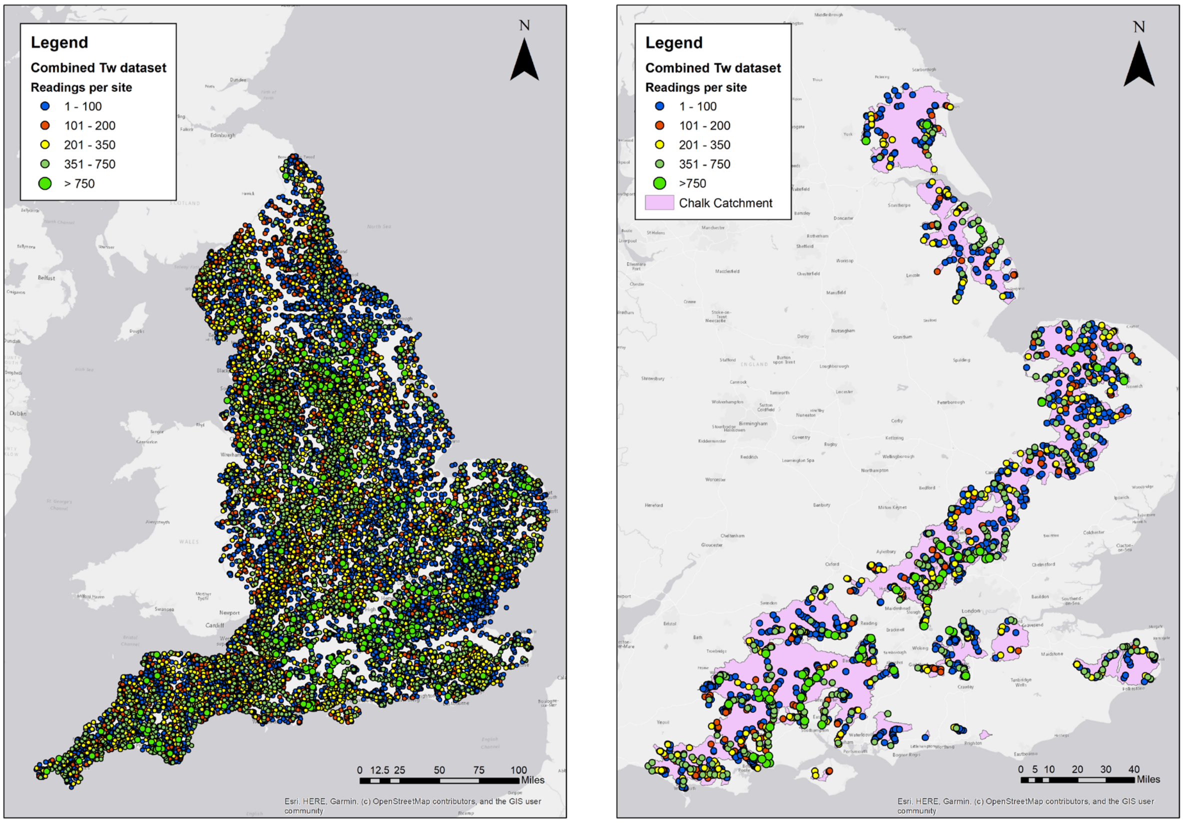

Figure 2: Combined *Tw* dataset sample sites in England (left) and in chalk catchments (right). Point colours indicate the number of temperature readings available at each site and pink polygons indicate the extent of chalk catchments

Datasets used for model development

Observed air temperature data was obtained from 1 km gridded datasets of climatological data available from the Met Office (HadUK-Grid products; Met Office 2018). Both the monthly mean (temperature at surface; *tas*) and the monthly mean of daily maximum (*tasmax*) air temperatures were extracted for each sample date and site as potential surrogates for the daytime water temperatures used in this study.

To ensure the developed models were practical and suitable for use in a management context, covariates that could be derived solely from available GIS sources were used. Indicators of upstream land-use, geology and sample site characteristics were selected, along with potential proxies for hydrological regime (e.g., river width, river gradient, Strahler stream order; See Table 1).

Landscape characteristics considered included land cover information maintained by the Centre for Ecology and Hydrology (CEH; Land Cover Map 2000 (LCM2000) datasets), topographical information derived from a Digital Elevation Model (Nextmap 50m DEM hydromodel) and LIDAR data, and watercourse characteristics from the Environment Agency's Detailed River Network GIS layer (Coley et al., 2018).

Table 1. List of covariates selected for water temperature model development. The acronym is displayed along with description and data source.

Covariate acronym	Description	Data source
USFarmland	Upstream land dedicated to farming (Arable and improved grassland; %)	CEH; Land Cover Map 2000
USUrbSub	Upstream land dedicated to urban and suburban development (%)	CEH; Land Cover Map 2000
USWoodland	Upstream land covered in broadleaf and conifer woodland (%)	CEH; Land Cover Map 2000
USWildgrass	Upstream land covered in undisturbed natural grassland (+ set-aside; %)	CEH; Land Cover Map 2000
Geo_calc_us	Upstream calcareous hard geology (%)	British Geological Survey
Geo_sili_us	Upstream siliceous hard geology (%)	British Geological Survey
Cat_size_km2	Size of upstream catchment (km^2)	Environment Agency's Detailed River Network GIS layer
Altitude_m	Altitude of sampling point (m)	Nextmap 50m DEM hydromodel
Av_Alt_US_m	Average altitude of upstream catchment (m)	Nextmap 50m DEM hydromodel
DRN_WIDTH_M	River channel width (m)	Environment Agency's Detailed River Network GIS layer
DRN_GRAD_MKM	Gradient of river section (m/km)	Environment Agency's Detailed River Network GIS layer
DRN_MEAN_ALT	Mean altitude of river section (m)	Environment Agency's Detailed River Network GIS layer
DRN_DIST2MTH	Distance downstream to the end of the DRN (m)	Environment Agency's Detailed River Network GIS layer
DRN_US_ACCUM	Total length of the river upstream of section (m)	Environment Agency's Detailed River Network GIS layer
DRN_STRAHLER	Strahler river order at site	Environment Agency's Detailed River Network GIS layer

Future climate projections

The Met Office UKCP18 datasets provide probabilistic projections of environmental variables (air temperature, rainfall, etc.) based on a range of potential future climate outcomes. A range of future emissions scenarios are considered, and each dataset comprises an ensemble of 12 potential outcomes representing the uncertainty introduced by perturbation of climate model parameters. The UK regional model projections provide access to spatially coherent 'raw' climate projection data at the highest resolution (12km grid) for the years 1981 to 2080 and were used in this study. These projections are based on the high emissions ‘RCP8.5’ scenario and are considered a basis for precautionary planning for climate change impacts (Met Office, 2019).

Projected monthly mean air temperature values for the years 1981 to 2080 and for each of the 12 potential outcomes mentioned above were extracted from the 12km RCP8.5 regional UKCP18 gridded dataset for each *Tw* sampling site. Values falling in the date range January 1981 to December 2005 (25-year reference period) were compared to observed air temperature readings for the same period and differences summarised into a set of monthly bias corrections which were then applied across each Ta projection dataset (Lenderink et al., 2007). This bias correction aligns modelled datasets with a known set of values and improves reliability of subsequent modelling outputs. These bias correction adjustments are summarised in Figure 3 and, while the majority are small (± 0.5°C), an underestimate of springtime air temperatures in the UKCP18 data require more of an uplift to align with observed values.

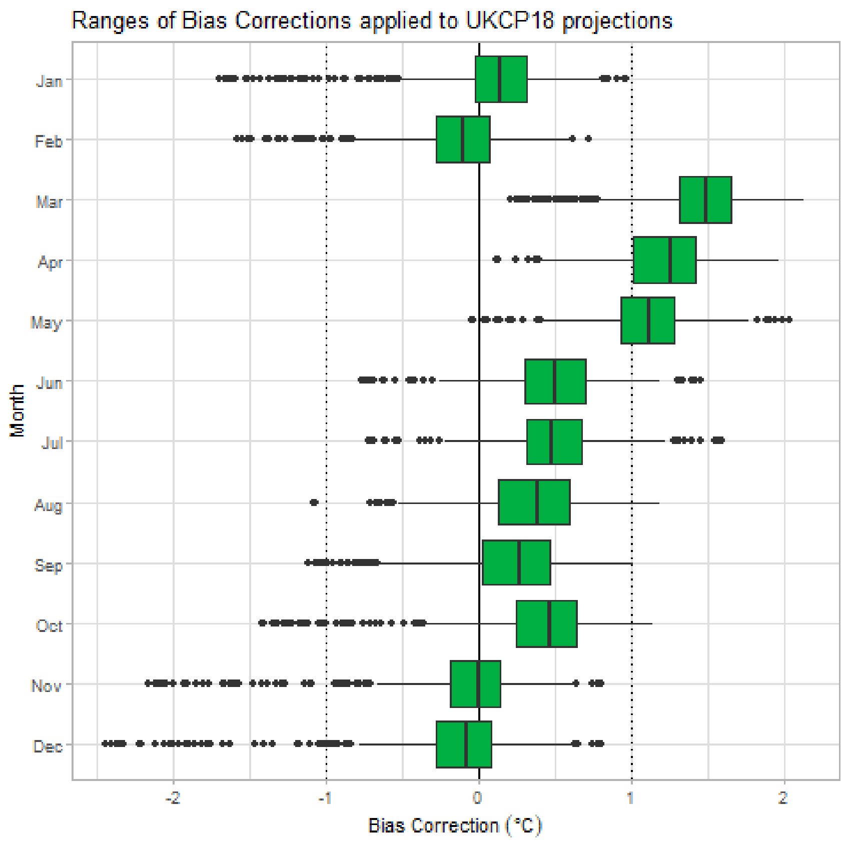

Figure 3: Ranges of bias corrections applied to the UKCP18 monthly mean air temperature projections prior to calculation of water temperature using developed models.

Model development and generation of projections

Selection of water temperature model

The river water temperature modelling process was guided by the previously established framework developed by the Environment Agency (2021). While the availability of historical monthly mean water temperature data placed this study outside the recommended bounds (daily to weekly model output), the decision-making process followed a similar series of steps (flowcharts reproduced here in Appendix; Figures A4 and A5). A mixed effect, regression-based approach was selected as most appropriate for multi-site, repeated measurement data. This option also maintained visibility of any influential covariates allowing an assessment of their physical plausibility to take place.

Model development and validation

The strength of the relationship between the observed water temperature values and both the mean and maximum air temperature values was assessed. As both relationships were statistically equivalent ($r^2 = 0.86$), the mean air temperature was selected for use in the model development process (see Appendix for further rationale). Seasonal variability in the air-water temperature slope was identified (Figure 4) and retained as a required element in model development (Mohseni and Stefan, 1999; Webb et al., 2008).

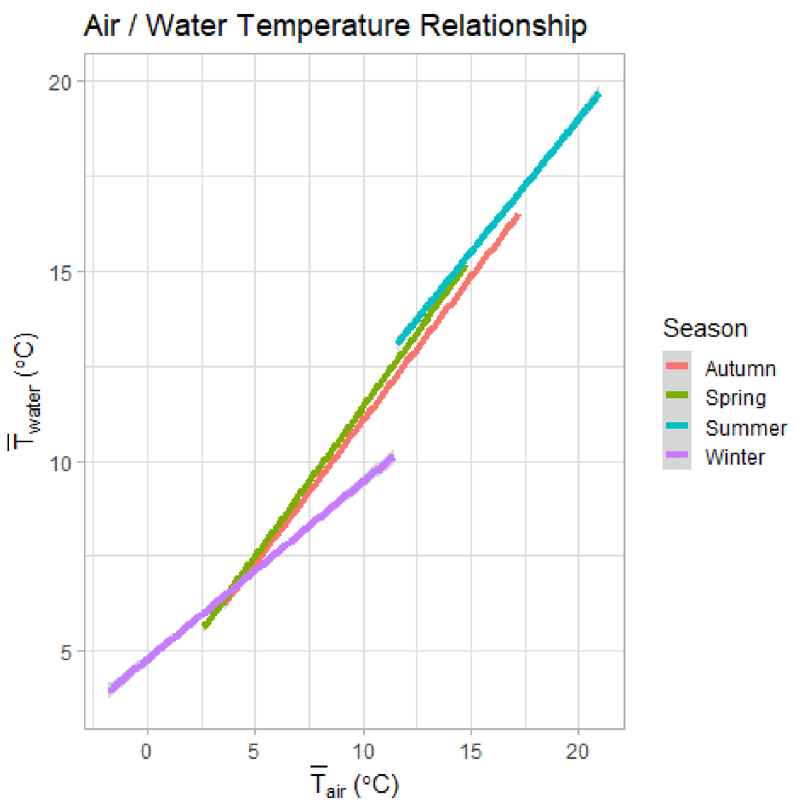

Figure 4: Seasonal variation in air temperature / water temperature relationship across chalk catchment *Tw* sampling sites. Lines fitted using ordinary least squares regression.

Collinearity between predictor variables, the tendency for one variable to change in a very similar way to another, can lead to the development of overly complex models with compounded errors that limit predictive capability (Dormann et al., 2013). Landscape and river channel covariates that displayed strong correlations with each other (Pearson correlation coefficient; $r > 0.8$) were rationalised (Appendix; Figure A7). The covariates taken forward to the modelling stage were:

- Land cover – percentage upstream farmland, urban development, woodland, and wild/natural grassland (USFarmland, USUrbSub, USWoodland and USWildgrass)
- Percentage upstream hard calcareous geology (geo_calc_us)
- Upstream catchment size (cat_size_km2)
- Channel characteristics – river width, river gradient, mean altitude, distance to river mouth, Strahler river order (DRN_WIDTH_M, DRN_GRAD_MKM, DRN_MEAN_ALT, DRN_DIST2MTH and DRN_STRAHLER)

All models were developed using R (R core team, 2021) using functions from the base, lme4 and MuMin packages. A linear mixed-effects model for chalk stream water temperature was developed based on 81 sites and 9521 observations (note the lower number of sites due to missing covariate data). Based on exploratory data analysis the following features formed the basis of model development:

- The model must include the seasonal air / water temperature relationship
- All selected covariates would initially be included to create a 'full' model which would then be simplified to contain only the most influential factors
- A spatial component would be included to represent the west-east hydro-climatic gradient (Easting value used)
- Variation between sample sites, catchments and to allow the water/air temperature relationship to vary between sites would be permitted, with the variation following a 'normal' distribution (= 'random effects' elements)

The 'full' model which included all the available covariates selected above was first fitted to available data ('lmer' command, lme4 R package) and took the form using the R syntax:

```
MdTw = Tair: Season + cat_size_km2 + DRN_WIDTH_M + DRN_GRAD_MKM +
DRN_MEAN_ALT + DRN_DIST2MTH + DRN_STRAHLER + geo_calc_us + USUrbSub +
USFarmland + USWoodland + USWildgrass + Easting + (Random effects)
```

'Random effects' were applied sequentially as follows (1) Absent, (2) the intercept could vary between sites `(1 | Sites)`, (3) the intercept could vary between catchments `(1 | catchments)`, or (4) the slope and intercept of the *Ta* / *Tw* relationship could vary between sites `(Tair | Sites)`. The different 'random effects' outcomes were compared using Bayesian Information Criterion (BIC) and the best performing 'full' model reduced to its simplest, statistically significant form to give the following optimised 'global' model for monthly mean water temperature:

```
MdTw = Tair: Season + geo_calc_us + USUrbSub + (Tair | Sites)
```

Ideally, predicted *Tw* values generated by a model would be identical to observed *Tw* values in a training dataset so that all points would fall on the $x = y$ identity line when plotting observed against predicted *Tw* values. Such an outcome would have an R^2 value of 1 and a Root Mean Squared error (RMSE) of 0. The optimised 'global' model developed here generated good estimates of *MdTw* in the training data ($R^2 = 0.94$, RMSE = 0.97°C; Table 2 and Figure 5 (right panel)) and performed well with the validation dataset ($R^2 = 0.85$, RMSE = 1.47°C; Figure 6 (right panel)). These R^2 and RMSE values compared well with those generated by the more complex 'full' model (left panels of Figures 5 and 6), indicating that all significant factors had been retained in the optimised 'global' model and that it had strong predictive performance for the generation of *MdTw* estimates for chalk stream sites from limited environmental and air temperature information.

Table 2: Structure and summary statistics of the optimised 'global' model for chalk stream monthly mean daytime water temperatures. σ^2 = random effect variance, τ_{00} = random intercept variance, τ_{11} = random slope variance, ρ01 = random slope-intercept correlation, ICC = intraclass correlation coefficient. Marginal R^2 conditional R^2

	Tw_mean_mo		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	2.00	0.91 – 3.10	**<0.001**
geo calc us	0.02	0.01 – 0.03	**0.003**
USUrbSub	0.03	0.02 – 0.04	**<0.001**
Season [Aut] * Ta mean	0.72	0.69 – 0.76	**<0.001**
Season [Spr] * Ta mean	0.74	0.71 – 0.78	**<0.001**
Season [Sum] * Ta mean	0.77	0.74 – 0.80	**<0.001**
Season [Win] * Ta mean	0.61	0.58 – 0.64	**<0.001**
Random Effects			
σ^2	0.96		
τ_{00} Sites	1.94		
τ_{11} Sites.Ta_mean	0.02		
ρ_{01} Sites	-0.89		
ICC	0.67		
N_{Sites}	81		
Observations	9521		
Marginal R^2 / Conditional R^2	0.833 / 0.945		

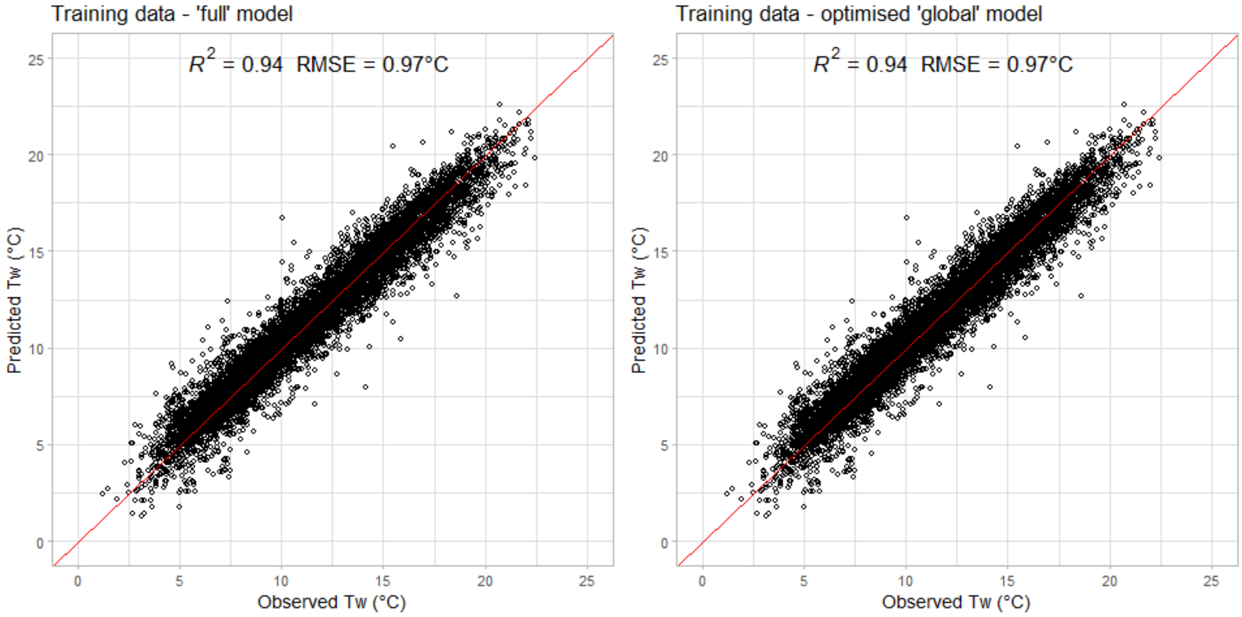

Figure 5: Performance of the 'full' (left) and optimised 'global' model (right) for chalk stream water temperature prediction against the training dataset (3+ value monthly mean *Tw* values from sites with over 5 years of data; $n = 9521$). The red line indicates the $x = y$ identity line.

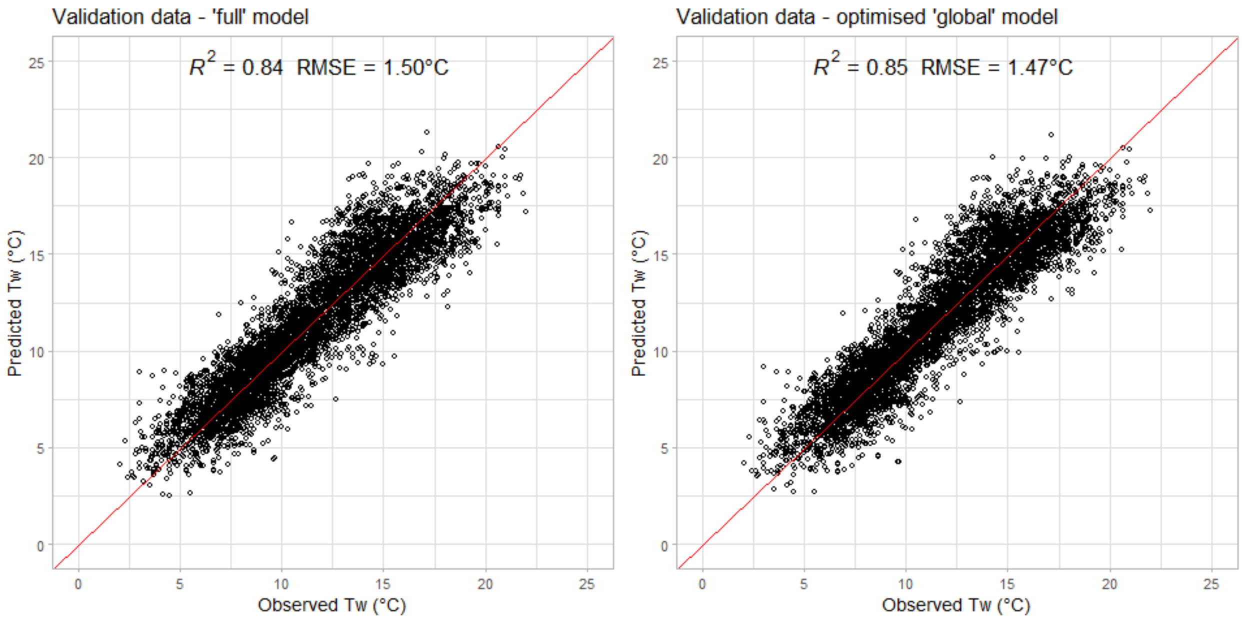

Figure 6: Performance of the 'full' (left) and optimised 'global' model (right) for chalk stream water temperature prediction against the validation dataset (3+ value monthly mean Tw values from sites with less than 5 years of data; $n = 6080$). The red line indicates the $x = y$ identity line.

Future projections of chalk stream water temperatures

Bias-corrected UKCP18 monthly air temperature values and sample site covariate information (percentage chalk geology and percentage urban and suburban land use upstream of the sample site) were used in the optimised 'global' model to generate predictions of monthly mean river water temperature at each of the 893 sites having some historical 3+ value monthly mean water temperature data. Water temperature predictions were generated for each of the twelve UKCP18 potential outcomes and the median value taken for each month between 1981 and 2080 for each site as a summary statistic.

These median values of projected water temperature were used to investigate potential temperature changes that could impact on the life cycles of two important salmonid fish species, brown trout (*Salmo trutta*) and Atlantic salmon (*Salmo salar*). Two temperature thresholds were analysed: Firstly, the upper critical range over which fish survival is compromised, and secondly, the maximum temperatures experienced during the spawning season (October/November – February/March) which impact on egg survival. The percentage of sites predicted to exceed these temperature thresholds was recorded for each decade across the UKCP18 climate change projection range 1981-2080.

Catchment-specific models

Catchment specific *MdTw* models were created for four catchments with more than 5 monitoring sites each with more than five years of *MdTw* data: the rivers Avon (Hampshire), Hull, Test and Wensum. The ‘full’ model with all selected covariates but without any ‘random effects’ elements was applied in turn to each catchment’s qualifying data and the resultant model optimised to find the simplest solution. The performance of each catchment model at predicting *MdTw* for other sites in the same catchment, other chalk river sites in the same river basin district and other chalk river sites in England was assessed by generating predictions of *MdTw* and comparing these predictions to observed *MdTw* values (see Appendix for details and main observations).

Results

‘Global’ model temperature projections

Of the median projected monthly mean daytime water temperatures (*MdTw*) values derived from the 12 RCP85 UKCP18 potential outcomes, Figure 7 presents the maximum projected *MdTw* value seen at each of the 893 qualifying sites in each of 4 decades up to 2080 (2010 to 2019, 2030 to 2039, 2050 to 2059 and 2070 to 2079). These values relate to summer monthly mean daytime maximum water temperatures and give an indication of the change in water temperature across these decades as well as the spatial distribution of these changes across chalk catchments. Regional differences are seen with sites in the north-east of England (Lincolnshire and Yorkshire Wolds) projected to experience the lowest increases in maximum water temperatures whereas those in the vicinity of London (rivers Colne, Lee, Hogsmill, Mole and Wandle) are projected to experience the highest. Some ‘hotspots’ as well as ‘cold spots’ can also be identified amongst the sites.

While the median value of the 12 potential outcomes derived from the UKCP18 climate change projections provides a suitable summary statistic, the range of responses encompassed by these 12 outcomes is also of interest. Figure 8 presents the range of minimum (blue points), mean (black points) and maximum (red points) values predicted for each of the twelve UKCP18 potential outcomes across all sites for the UKCP18 projection period 1981 to 2080. Though all ranges indicate an increasing Tw trend, the rate of change is highest for the maximum values (21.50±1.06°C in the 1981-2005 reference period to 26.12±1.12°C in decade 2070-2079; a change of +4.62°C) and lowest for the minimum values (3.68±1.09°C in the 1981-2005 reference period to 6.07±0.82°C in decade 2070-2079; a change of +2.37°C).

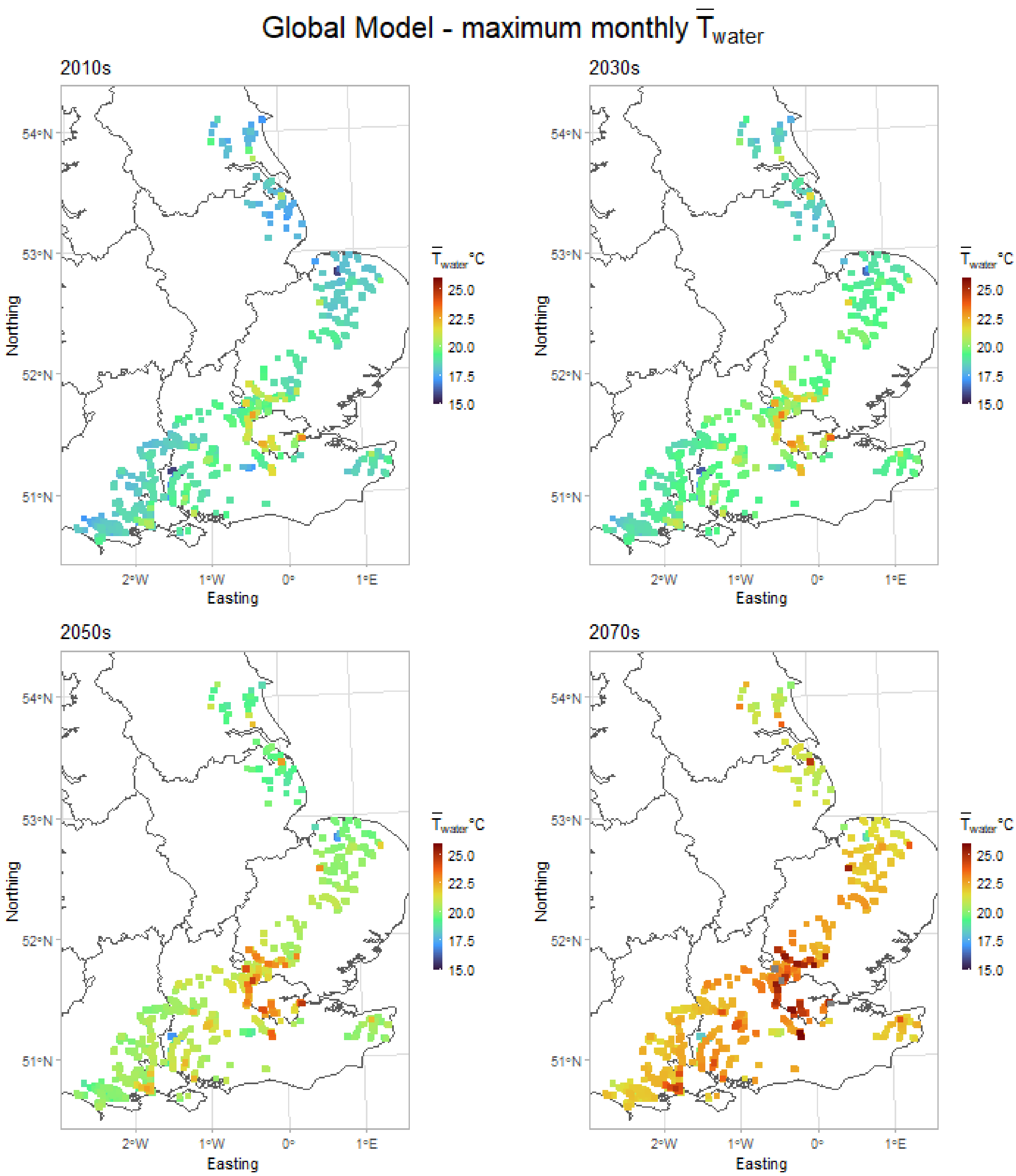

Figure 7: Predicted maximum monthly mean daytime water temperatures at English chalk stream sample sites for the decades 2010-2019, 2030-2039, 2050-2059 and 2070-2079, based on bias corrected UKCP18 RCP8.5 air temperature projections and the global model for monthly mean water temperatures. Values represent the maximum median Tw across all UKCP18 ensemble members for each site in each decade. Larger figures are available in the Appendix.

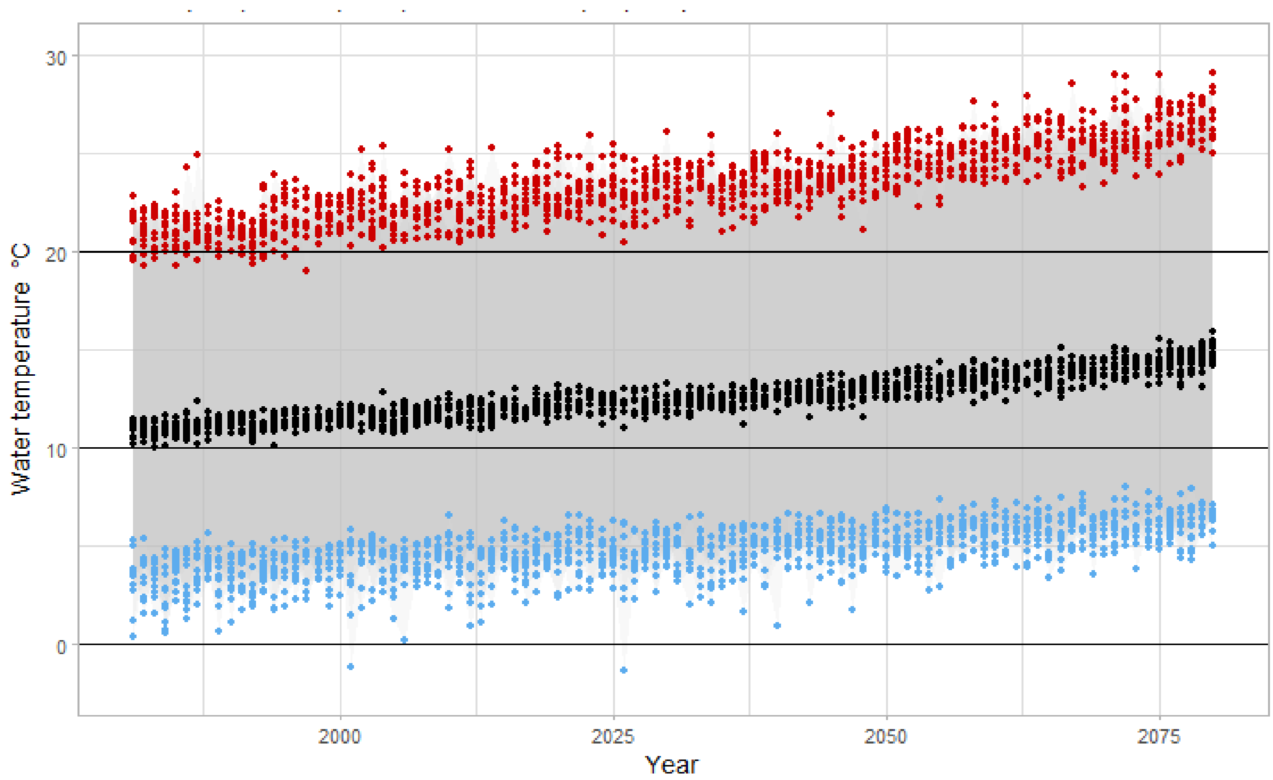

Figure 8: Predicted change in monthly mean daytime water temperature in chalk streams over the UKCP18 projection period 1981 to 2080. Each series of coloured points represent the values predicted for each of the 12 ensemble members: blue points = minimum values, black points = mean values, and red points = maximum values.

Critical temperature thresholds for brown trout and Atlantic salmon

Brown trout (*Salmo trutta*) and Atlantic salmon (*Salmo salar*) are two important salmonid fish species found in English chalk streams, both adapted to the cool, stable water conditions usually found there (Elliott and Elliott, 2010). The critical temperature range for brown trout is between 3.5 and 19.5°C and that for Atlantic salmon is between 6 and 22.5°C (Solomon and Lightfoot, 2008). The percentage of sites predicted to exceed the upper values of these ranges is presented in Figure 9. Maximum monthly mean daily water temperatures are projected to exceed the upper boundary for brown trout at all sites by 2070. The higher Salmon threshold is projected to start being exceeded in the 2050's increasing to 30% of sites affected by 2080.

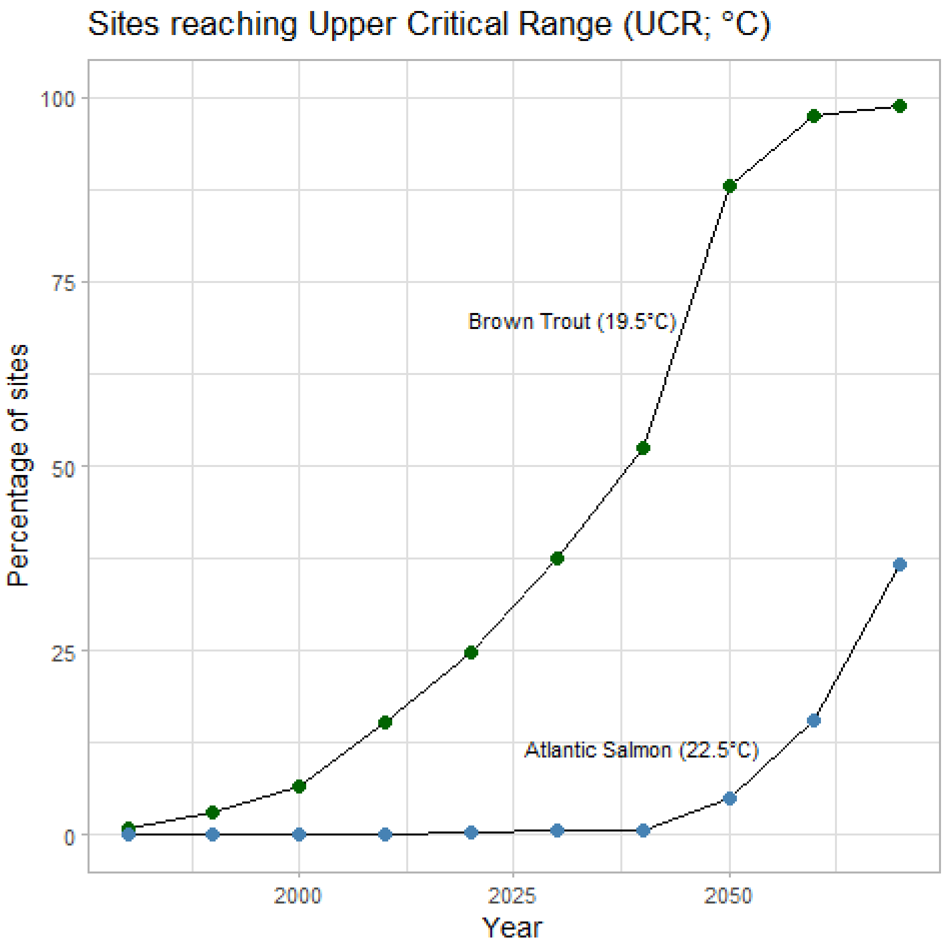

Figure 9: Percentage of sites projected to reach critical temperature thresholds for two salmonid fish species found in English chalk streams

The spawning season for both Atlantic salmon and brown trout is during the late autumn and winter months (October/November to February/March). Egg survival is temperature dependent with critical ranges of 0 to 13°C for trout and 0 to 16°C for salmon. An additional important threshold of 12°C relates to an increased rate of egg mortality and deformity for both species. Sites predicted to exceed this 12°C threshold during the spawning season in different decades up to 2080 are shown in Figure 10. While the initial sites affected appear few and spread across chalk catchments (Figure 10, 2010 panel), an increasing number of catchments have multiple impacted sites as the decades progress with 85% of sites projected to be impacted by 2080. Figure 11 shows the percentage of sites projected to experience temperatures at or above these three important spawning threshold temperatures of 12°C, 13°C and 16°C to 2080 and indicates a significant number of sites reaching 12°C and 13°C across this period, particularly after 2040.

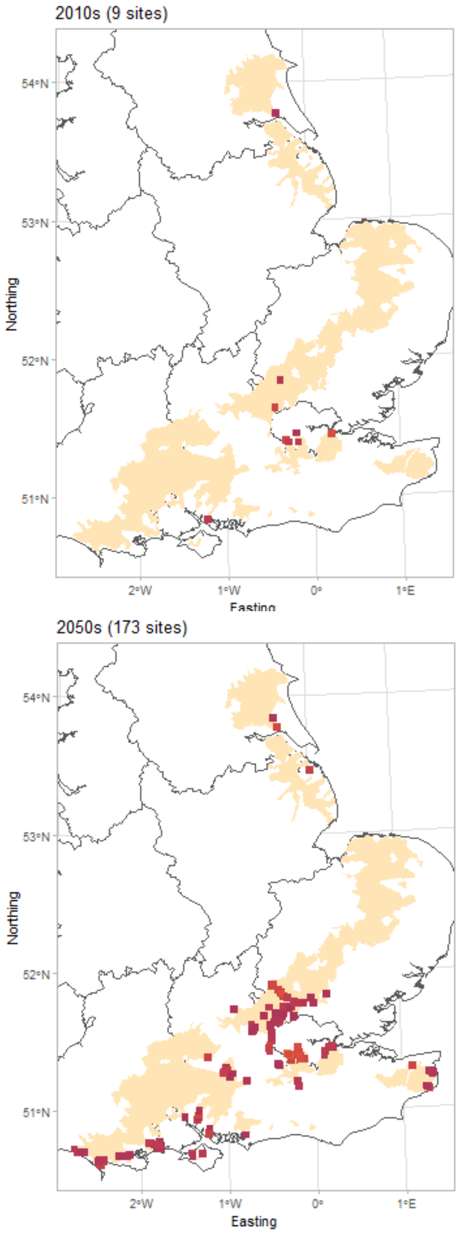

Figure 10: Sample sites in chalk catchments projected to exceed a monthly mean daily water temperature of 12°C in the November to February fish spawning period in the decades 2010-2019, 2030-2039, 2050-2059 and 2070-2079. Chalk catchment extent marked in yellow, sites exceeding threshold marked in red/orange (total number of sites modelled: 893)

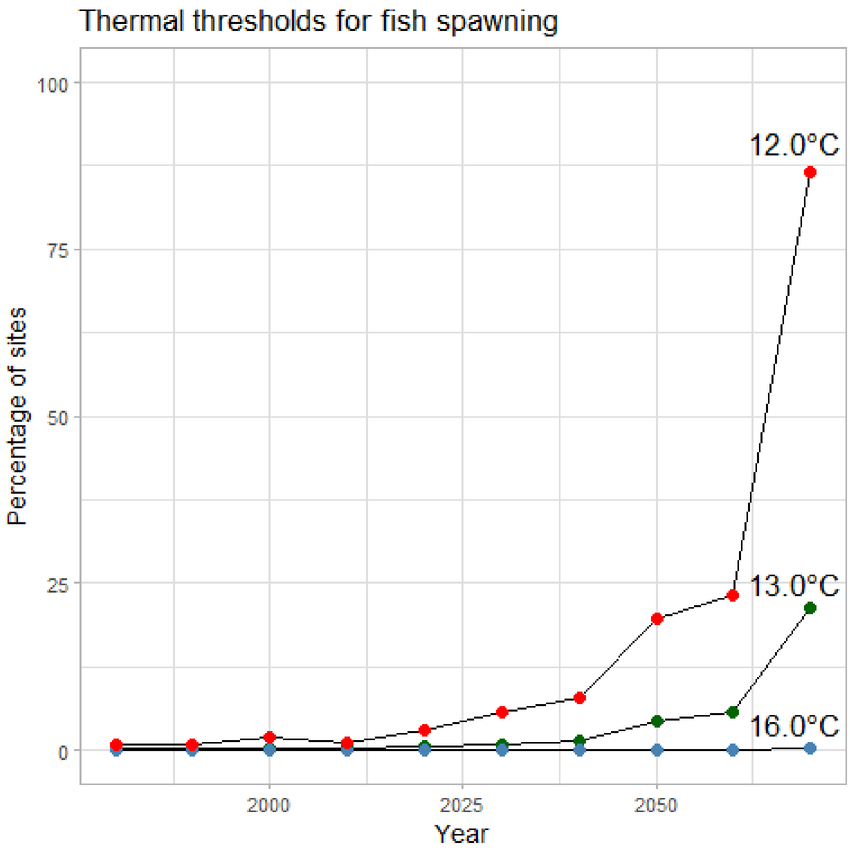

Figure 11: Projected changes in thermal thresholds important for fish egg survival during spawning season (Nov – Feb) from 1981 to 2080. The 13°C threshold is the upper limit for brown trout egg survival, the 16°C threshold relates to Atlantic salmon egg survival, and the 12°C threshold is associated with increased egg mortality and increased deformity rates.

Catchment specific models

Catchment-specific models were generated to help understand which predictor variables influenced water temperature in different catchments. Models were created for four catchments containing multiple sites with more than five years of 3+ value monthly mean *Tw* data (see Appendix for details). While each model started with the same default set of covariates as the 'full' model, stepwise optimisation selected a different group of covariates in each case. The ranges of some of these covariates were very small and, while sufficient for modelling within that group of catchment sites, could not support the development of *Tw* predictions for wider groups of sites.

Example results relating to the River Avon in Hampshire are presented in Figure 12. The yellow map markers indicate sites included in model development and the right group of graphs indicate the performance of that model with different groups of chalk stream data. The top-left graph shows the model performance with the data from the sites marked on the map in yellow and indicates a robust model solution but applying that model to data from other sites in the same catchment (top-right), the wider river basin district (bottom-left) or to all chalk sites (bottom-right) shows a deterioration of performance and a breakdown of the model's ability to generate good estimates of water temperature from the available data.

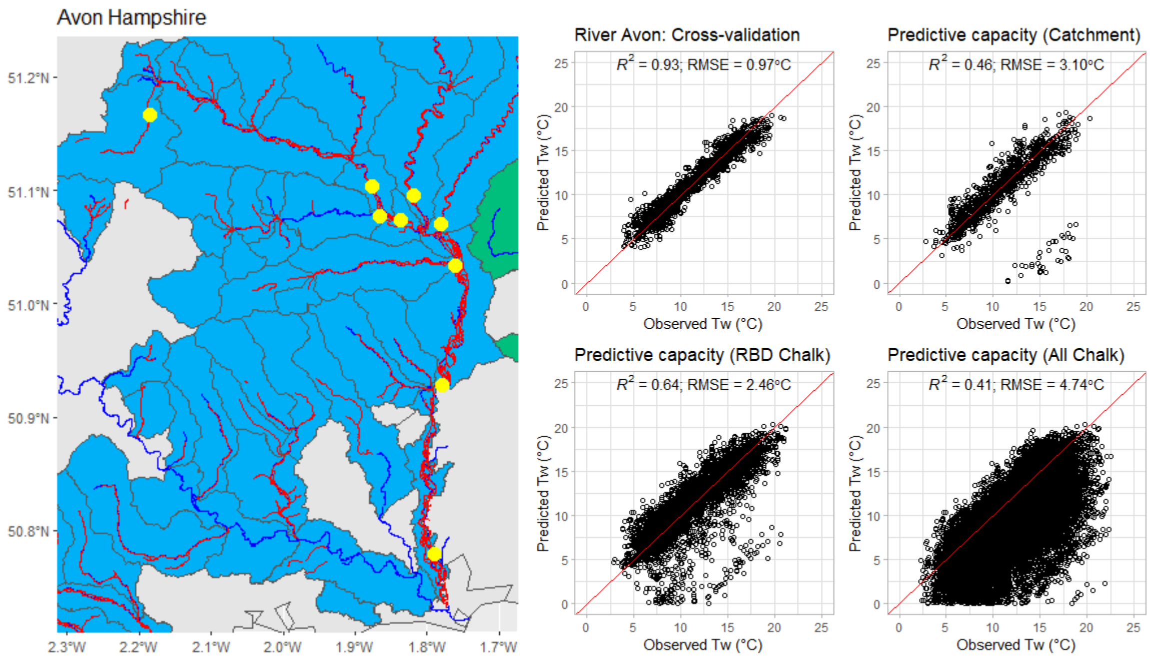

Figure 12: Catchment-based model developed for the River Avon in Hampshire. *MdTw* data from the sites marked in yellow (left) were used to develop a linear model which was then applied sequentially to wider groups of chalk stream sites (right). See main text for more information and Appendix for additional details.

In this case, six covariates were retained by the modelling optimisation process as being significant for water temperature estimation: upstream catchment size, distance to the river mouth, mean altitude, river width, percentage upstream calcareous geology and the percentage upstream land use given over to wild/natural grassland. The ranges of some of these covariates within the participating sites (yellow markers, Figure 12) were small (percentage upstream calcareous geology: 88.2-100 out of a potential range 0-100; percentage upstream wild grassland: 1-14 out of a potential range 0-100) and the model failed to generate acceptable estimates of water temperature when encountering values outside these limited ranges. This highlights the need for models to be developed based on sites that encompass the full environmental range of each significant covariate or equivalent data from a catchment with comparable characteristics.

Discussion

Data availability

Effective modelling of water temperature in complex fluvial systems requires a baseline of water temperature records at a sufficient sampling frequency and over a sufficient period to reflect the temporal dynamics of in-channel temperature variability (Environment Agency, 2021). Much of the water temperature data collected under the Environment Agency's long-running environmental monitoring programme has been to inform an understanding of water chemistry rather than river water temperature dynamics and the data available to this study supported the development of a water temperature model for chalk streams based around monthly daytime mean water temperature only. Using a monthly mean value as an indicator of a temporally and spatially dynamic variable such as water temperature presents obvious limitations but is not without value, particularly when projecting long-term trends and relative changes. Averaging water temperature over a monthly period could miss the impacts of highly dynamic events (e.g., precipitation, short-term heatwaves) and modelling at this temporal scale will also limit a model's sensitivity to environmental and landscape characteristics known to influence river water temperature (Jackson et al., 2018). It is unsurprising that the broad environmental covariates of 'underlying geology' and 'percentage urbanisation' were the only ones found to exert some influence on the water temperature modelling outcomes across all chalk catchments when modelling at this 'monthly' scale.

The spot-sample water temperature readings in the combined *Tw* dataset provide a 'snapshot' temperature value for water from various sources (e.g., upstream flow, precipitation, surface water runoff, groundwater supply) all of which will have different temperature profiles and volume contributions to the water in the river. These values will also contain a reflection of the physical environment surrounding the river channel and the dynamics of water exchange between different compartments within the channel. These contributions will vary throughout the year and across climatic cycles and model development requires a strong baseline of measurements which encompass a significant amount of this variation. The qualifying threshold of sites to have a minimum of five years monthly mean water temperature data before inclusion in the model development process was a pragmatic choice given the data available but was regarded as an absolute minimum to reflect meaningful interannual *Tw* variation.

Modelling process

Given the limitations of the data available, the model development process previously described by the Environment Agency (2021) was successfully implemented to develop a model for chalk stream water temperature based around monthly mean daytime values. The selection of suitable covariates known to influence in-channel water temperatures was guided by previous studies (Jackson et al., 2016, 2018) and the pragmatic choice to limit these to values that could be derived from GIS sources was taken with practical management application in mind. Establishing values for all selected covariates using this method was not entirely successful as sample site locations did not always coincide with river sections where such values could be derived. Covariate values for river width could not be calculated where channel modification (culverts, pipes, underground sections) had taken place and 'distance' metrics (Distance to mouth of river, Strahler river order) were not available where sites where there were multiple river channels (Coley et al., 2018). This reduced the number of sites that could be included in model development and could be mitigated by closer inspection of site/GIS alignments and/or the development of automated processing to establish suitable values from nearby sites.

The developed models displayed a strong reliance on the air temperature / water temperature relationship. The seasonal nature of this relationship (Mohseni and Stefan, 1999; Webb et al., 2008) was reflected in the monthly mean water temperature measurements derived from the combined *Tw* dataset and a series of seasonal linear relationships were included to approximate the 'S' shaped curve usually used to describe this relationship in river and open water systems. The 'summer' *Ta* / *Tw* relationship is of particular significance when modelling maximum water temperatures as too steep a gradient in this section of the relationship will over-estimate water temperatures from the corresponding air temperature values. Including this seasonal aspect of the *Ta* / *Tw* relationship was judged essential in model development and was therefore present in all model solutions.

The 'global' model for monthly mean daytime water temperatures for English chalk streams presented here is a relatively simple one. Apart from the seasonal *Ta* / *Tw* relationship, the model is only dependent on two covariate values, the percentage upstream calcareous hard geology and the percentage urban and suburban land use upstream, and a 'random effects' component allowing the seasonal *Ta* / *Tw* relationship to vary between sites. This concise group of dependencies is seen as a function of the coarse monthly timestep employed and the large spatial scale of the modelled sites. The influence of landscape and river channel covariates would be expected to increase as the modelling timestep, or spatial scale were able to be reduced. Catchment-specific models developed for river systems where sufficient *Tw* data existed did generally select larger groups of covariates than the 'global' model (Appendix, Case Study) but the limited ranges of some of these covariates restricted the ability to use these models to predict water temperature values in other catchments or at sites where covariates extended beyond these limited ranges. However, in locations where sufficient historic observations of Tw exist catchment specific models are worth considering.

The 'global' model outputs presented here are based on the high emissions RCP85 scenarios of the UKCP18 climate change projections. While these are seen as a suitable basis for contingency planning there is some debate whether they present a realistic projection given their reliance on continued rises in CO_2 levels due to fossil fuel burning well into the 21st century. The 'global' model is not dependent on this particular projection of future *Ta* and could take input from different scenarios as they are developed and refined.

Model outputs

Validation of the developed 'global' model for chalk stream water temperatures showed strong predictive performance (R^2=0.85). Application of this model to predict monthly mean water temperature values at sites under the influence of climate change showed significant water temperature increases of ecological significance. Regional variation in the level of *Tw* rise is seen with sites around London showing the highest increases.

It should be noted that the projections are based on a simple future scenario where only air temperature is changing. More complex future scenarios incorporating changes in rainfall frequency and intensity, surface water/groundwater balance, evapotranspiration, as well as changes in water-temperature-influencing environmental and landscape characteristics would help increase confidence in water temperature projections. There is also the balance of demands placed on chalk aquifers due to human activity and climate change that can influence flow levels in chalk streams and exacerbate water temperature rises especially during low summer flows.

Changes in a monthly mean value will disguise potentially significant fluctuations in water temperature that may occur throughout that monthly period. An increased frequency of summer heat waves may only influence the monthly mean temperature by a small amount, yet may cause significant stress on ecological habitats, including aquatic systems. Model sensitivity to such fluctuations would require a move to higher frequency *Tw* data collection in the sub-daily range.

The ecological significance of these potential increases in chalk river water temperatures is demonstrated by the effect on important temperature thresholds for salmonid fish. Thermal boundaries are known to affect salmonid fish migration and the increasing number of sites projected to experience water temperatures above the upper critical range for brown trout (19.5°C) is of particular concern. The challenge to salmonid egg survival during the winter spawning period is also projected to increase throughout the UKCP18 projection period, with the important 12°C threshold, over which increased deformity rates and decreased egg survival are experienced, being breached extensively by 2080.

Recommendations

Targeted placement of temperature dataloggers with 15-minute monitoring resolution across catchments and regions at sites representative of different temperature-influencing landscape and environmental features is driving water quality management decisions in Scotland (Jackson et al., 2016; 2018; 2020) and offers an alternative to highly monitored, staff-intensive approaches (Webb et al., 2008). High frequency water temperature data from the WISKI network could provide a useful source of information but this has not been routinely captured and archived within the Environment Agency and has only recently been identified as a priority. The WISKI flow monitoring sites located in chalk catchments (n =56) could potentially provide useful high-frequency water temperature data once collated and quality-assured. Groundwater level and flow data is being combined into a national resource which could also provide important modelling inputs once available. Maps identifying riparian tree cover and GIS Relative Riparian Shade maps are under development (LIDAR | Environment Agency Geomatics Hub - arcgis.com). These sources could provide valuable information on riparian shading along the river channel; a factor known to influence water temperature and identified as a future management technique to mitigate adverse river temperatures (Garner et al., 2017).

The significant consideration of sampling site-selection remains. Utilising pre-defined sampling sites from existing datasets can only capture a limited range of the covariates known to influence river water temperature (reviewed in Jackson et al., 2016) and reduces the potential to apply any generated water temperature models to unmonitored sites. Monitoring site selection must maximise the environmental range of covariates and have an established relationship to hydrological processes within the catchment. Only then can management intervention be considered at a reach or catchment scale for river water temperature mitigation based on model outputs. This can only be addressed through careful sample site selection and the development of a dedicated temperature monitoring network for England's rivers.

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List of abbreviations

AIC	Akaike Information Criterion
AICc	Akaike Information Criterion with correction for small sample sizes
BIC	Bayesian Information Criterion
CEH	Centre for Ecology and Hydrology
DRN	Digital River Network
GAM	Generalized Additive Model
GAMM	Generalized Additive Mixed effect Model
GIS	Geographical Information Systems
LCM	Land Cover Map
LIDAR	Light detection and ranging
LM	Linear Model
LMM	Linear Mixed effect Model
MdTw	Monthly mean daytime water temperature
RMSE	Root Mean Squared Error
RNS	River Network Smoother
SSN	Spatial Statistical Model
SWTA	Surface Water Temperature Archive (Environment Agency)
Ta	Temperature of the air at the land surface
Tw	Temperature of the water
UCR	Upper Critical Range
WIMS	Water quality data archive (Environment Agency)

Appendix

Detailed methodology

All data analysis presented herein was conducted using R (R Core Team, 2021). In addition to the base functions in R the following packages were used: the ‘tidyverse’ ecosystem (Wickham et al., 2019), ‘readxl’ (Wickham and Bryan, 2019), ‘lubridate’ (Grolemund and Wickham, 2011), ‘data.table’ (Dowle and Srinivasan, 2021) and ‘skimr’ (Waring et al., 2021) for data import, manipulation, generating summaries and plotting data; ‘car’ (Fox and Weisberg, 2019) for correlation analysis; ‘sp’ (Pebesma and Bivand, 2005, Bivand et al., 2013) and ‘sf’ (Pebesma, 2018) for spatial data analysis; ‘lme4’ (Bates et al., 2015), ‘lmerTest’ (Kuznetsova et al., 2017), ‘MuMIn’ (Barton, 2020), ‘caret’ (Kuhn, 2021), ‘effects’ (Fox and Weisberg, 2019) and ‘sjstats’ (Lüdecke, 2021) for developing mixed effects models and aiding model selection.

Data preparation

Observed water temperature data were acquired from 2 sources: the Environment Agency’s Surface Water Temperature Archive up to 2007 (Orr et al., 2015) and Water Quality Data (WIMS). Details regarding the creation of the former can be found in Orr et al., 2015 (and on data.gov.uk). It consists of 7 Microsoft Access databases, one containing data for each of the previous 7 Environment Agency regions in England. All water temperature data were filtered to select only those samples collected from “RIVER / RUNNING SURFACE WATER”. These were then extracted and saved as CSV files for each region. Data on OpenWIMS is available from 2000. All samples between the years 2000 and 2021 were downloaded for the determinand “0076” (Temperature of Water) and filtered for those where the sampled Material Type was “RIVER / RUNNING SURFACE WATER” and saved as an additional CSV file.

Gridded air temperature values were downloaded from the Centre for Environmental Data Analysis (CEDA) website https://archive.ceda.ac.uk. Historical air temperature values were obtained from the HADUK 1km gridded datasets to cover the same date range as seen in the *Tw* samples (1952 to present day). Monthly mean air temperature (*tas*) and monthly mean of the daily maximum air temperature (*tasmax*) datasets were downloaded in NetCDF format (one file per year). *‘tas’* and ‘tasmax’ datasets of monthly data were also obtained for the UKCP18 regional projections at 12km resolution for 1980-2080 for all RCP85 scenarios from the same site (NetCDF format).

R code data folder structure

```
<DataRoot folder> ─ External_data ─ CEDA ─ Air_temp ─ monthly ─ Ta_max_1km (HADUK tasmax)
          │                  │           │                  └──── Ta_mean_1km (HADUK tas)
          │                  │           └── ukcp18 ─ Ta_max (UKCP18 tasmax)
          │                  │                   └──── Ta_mean (UKCP18 tas)
          │                  ├────── CEH_LCM_DRN ─ EA_GIS (Site DRN data)
          │                  ├────── EA ─ Water_temp (SWTA and WQA data)
          │                  └────── shapefiles ─ EA_ChalkRivers_SHP_Full (Chalk_Rivers)
          │                                 ├──── EA_Operational_Catchments (Eng. Regions)
          │                                 ├──── EA_River_Water_Bodies (WFD catchments)
          │                                 └──── England_Rivers (EA Main river map)
          ├────── Generated_data (R code generated output)
          │                  └────── Chalk_Combined_shapefile (Chalk catchments)
          └────── R_Code (task-based R scripts)
```

Observed water temperature readings: sampling frequency analysis

Analysis of record extent and sampling frequency of Tw readings was carried out for each site/cluster in the combined *Tw* dataset at hourly, daily, weekly, two-weekly and 30-day (≈monthly) levels. Some tolerance was allowed between consecutive readings to account for sample timing variability and sequences of consecutive readings were allowed to continue if a reading was missed but the next reading occurred within a defined timeframe (Table A1). Isolated readings and short time sequences were discarded before calculating summary statistics of the sampling time sequences observed (Table A2). The distribution of sites with significant run lengths of weekly, 2-weekly and monthly values across England is shown in figure A3. Only runs of monthly values had sufficient length to summarise the interannual variation required for water temperature modelling.

Table A1: Tolerances allowed within time series sequence analysis of *Tw* sampling data at each sampling site.

Frequency of Tw reading	Time tolerance	Allow missed reading if subsequent reading taken within:	Sequences ignored if reading count is less than:
Hourly	+30 minutes	2 hours	24 (= 1 day)
Daily	+12 hours	2 days	7 (= 1 week)
Weekly	+12 hours	2 weeks	26 (= 6 months)
Two-weekly	+12 hours	3 weeks	26 (= 1 year)
30-day / monthly	+12 hours	6 weeks	24 (= 2 years)

Table A2: Breakdown of sampling frequency in the combined *Tw* dataset for England and chalk stream catchments.

Monitoring frequency	England (28214 sites*)					
	Number of sites**	Median sequence with IQR **	Sequence equivalent to:	Number of 2+ value means	Number of 3+ value means	Number of 5+ value means
Hourly	186 (0.7%)	48.5 ± 11 hours	~ 2 days	5330	1292	155
Daily	1206 (4.3%)	12 ± 7.1 days	~ 1 – 3 weeks	21665	5126	2215
Weekly	1747 (6.2%)	44 ± 16.0 weeks	~ 6 – 14 months	68792	13225	4140
2-weekly	3034 (10.7%)	50 ± 27.0 fortnights	~ 1 – 3 years	166791	31237	5766
Monthly (30 days)	11716 (41.5%)	51 ± 37.5 months	~ 1 – 7.5 years	483037	124780	29656
	Chalk catchments (1727 sites*)					
Hourly	6 (0.3%)	48.0 ± 6.2 hours	~ 2 days	77	18	10
Daily	133 (7.2%)	13.5 ± 8.0 days	~ 1 – 3 weeks	2228	297	160
Weekly	218 (11.7%)	37.0 ± 8.5 weeks	~ 7 – 11 months	8359	1624	732
2-weekly	393 (21.2%)	55.0 ± 43.0 fortnights	~ 0.5 - 4 years	24846	4163	769
Monthly (30 days)	1108 (59.7%)	54.0 ± 54.5 months	~ 0 – 9 years	55415	17687	4911

* Sampling sites in proximity of 20 meters grouped and sampling data combined
** Minimum threshold applied; 1 day for hourly data, 1 week for daily data, 6 months for weekly data, 1 year for 2-weekly data, and 2 years for monthly data. IQR = Interquartile range

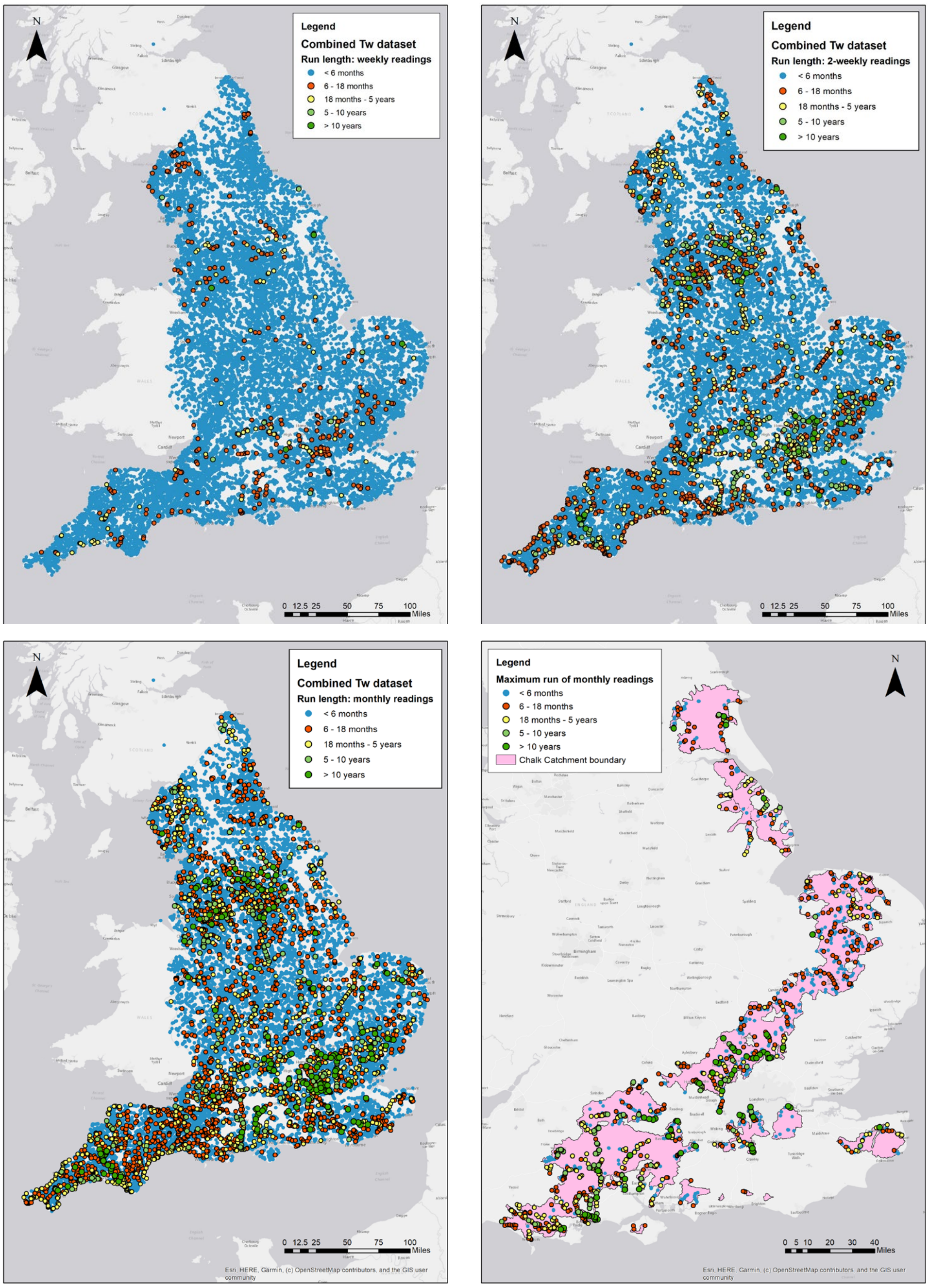


Figure A3: Length of runs of consecutive readings; weekly (top-left), 2-weekly (top-right) and four-weekly (bottom-left) and the consecutive four-weekly run lengths available at sites within the chalk catchment boundary (bottom-right)

Selection of water temperature model

The river water temperature modelling process was guided by the previously established framework developed by Environment Agency (2021) and summarised in Figures A4 and A5. The first stage involved identification of the most suitable modelling approaches given the data sets available. An initial assessment highlighted that adequate data was not available to build a 'process-based' or 'hybrid' model to predict water temperature. A regression-based approach was favoured over a machine-learning model or black-box model as the ability to assess the physical plausibility of coefficients was deemed essential. The schematic in Figure A4 was adopted to identify the most suitable regression approach. A temporally dynamic model was required and given the data available at multiple sites, a mixed model was identified as the most suitable approach.

REGRESSION APPROACHES

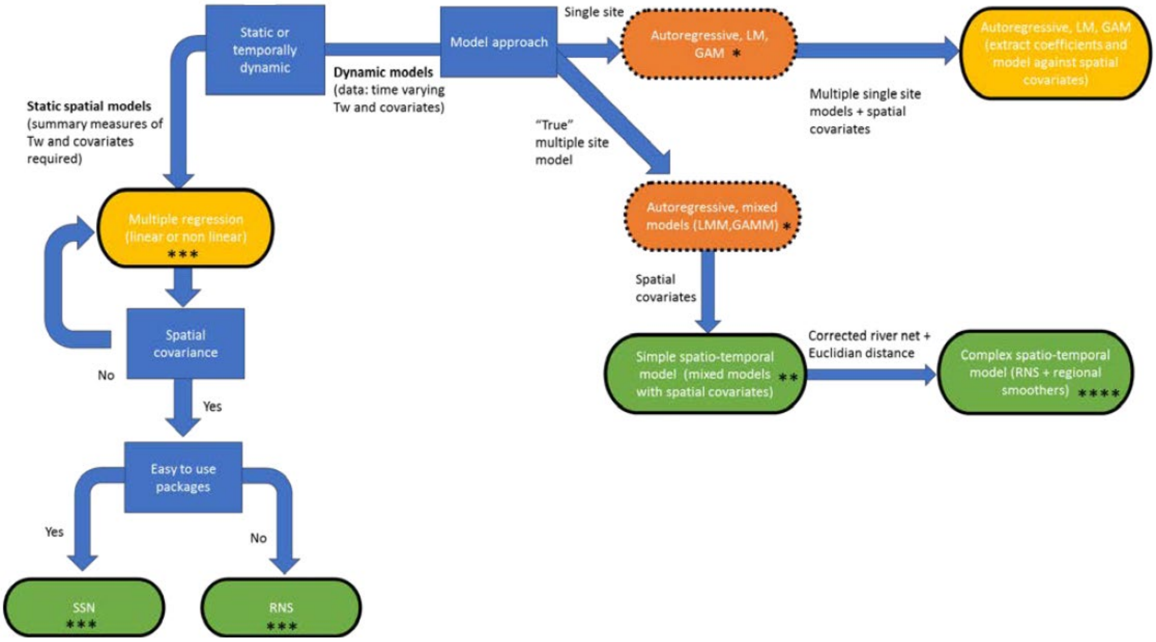


Figure A4: Decision tree for selecting the appropriate regression-based method for water temperature modelling. Taken from Environment Agency (2021)

REGRESSION BASED MODELLING FLOWCHART

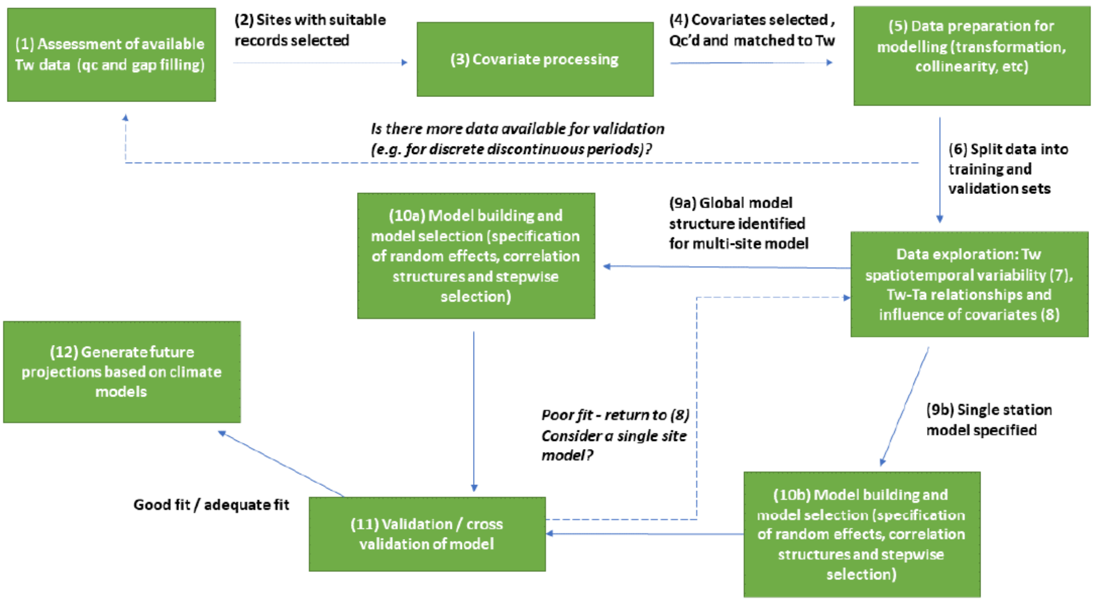


Figure A5: High-level schematic representation of the steps required when developing regression-based models for site specific water temperature predictions. Taken from Environment Agency (2021).

Model development and validation: Air temperature – water temperature relationship

With the inherent daytime sampling bias within the combined Tw dataset, consideration was given to whether monthly mean *Ta* or monthly mean of the daily maximum *Ta* would be the most appropriate air temperature metric to use in model development. Comparison of the linear trends in these relationships showed very similar correlation coefficients ($r^2 = 0.86$) and the monthly mean *Ta* was selected as a modelling input based on a more compressed distribution (trendline slope = 0.79 vs 0.68 for the mean of the daily maximum *Ta* values: Figure A6)

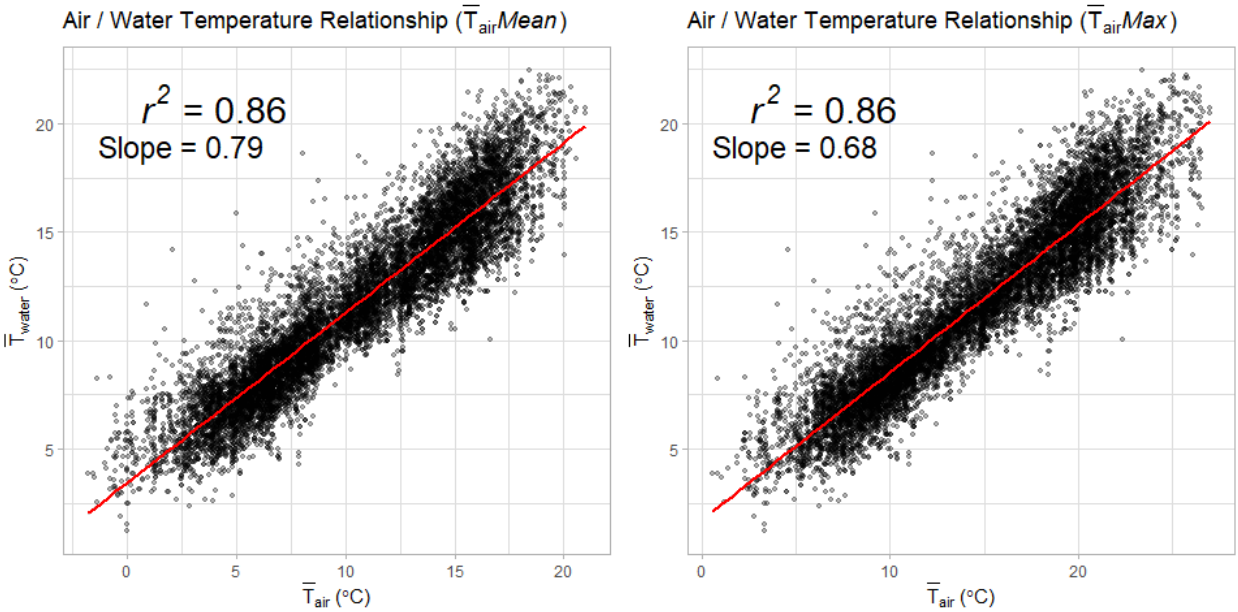


Figure A6: Comparison between air temperature / water temperature relationships using monthly mean air temperature (left) and monthly means of daily maximum air temperatures (right). The red trendline was fitted using ordinary least squares (OLS) regression. n=10,927; 3+ value monthly mean Tw data for chalk sites with at least 5 years of qualifying data.

Model development and validation: Covariate correlation analysis

Relationships between covariates were assessed and those displaying strong correlations (Pearson correlation coefficient; r > 0.8) were rationalised (Figure A7). The ‘Altitude’ covariates (Altitude_m, Av_Alt_US_m and DRN_MEAN_ALT) aligned closely with each other and the hard geology variables were strongly negatively correlated. ‘DRN_MEAN_ALT’ was carried forward as the altitude indicator due to greatest data availability and ‘geo_calc_us’ used for hard geology indicator. Rationalisation of correlations within the upstream land cover variables, particularly farmland and urban development, were considered but discounted due to their potential to impact on different hydrological processes.

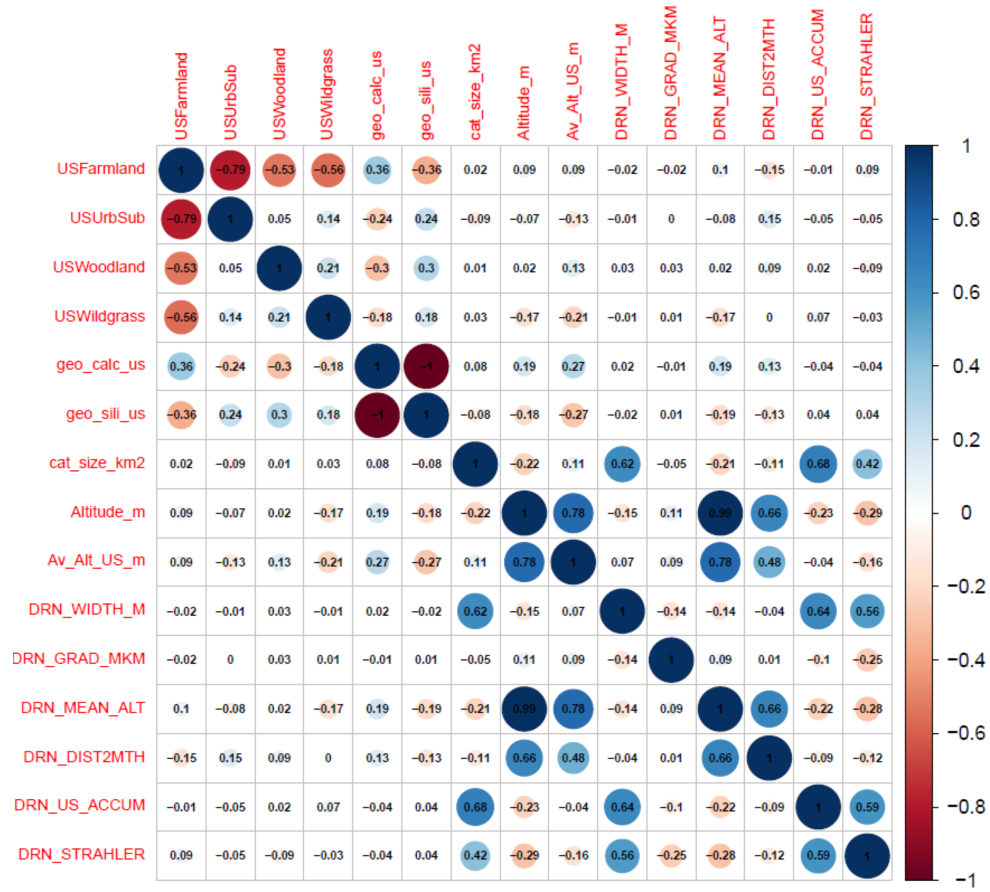
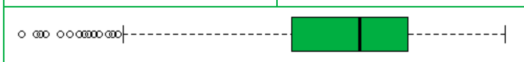
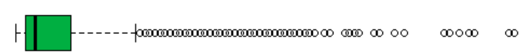
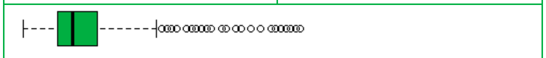
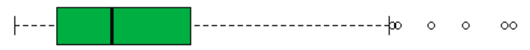
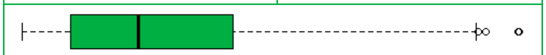
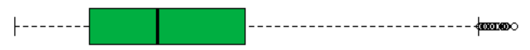


Figure A7: Correlation matrix of covariates including Pearson correlation coefficients. Blue circles indicate positive correlations and red circles indicate negative correlations. Circle size is proportional to the Pearson correlation coefficient.

Covariate selection was guided by previous studies which had demonstrated the benefit of representation across the full environmental range of each covariate to maximise model performance (Jackson et al., 2016, 2018). Site selection in this study was dependent on the number of *Tw* readings available rather than a site's representation of a particular environmental characteristic and the ranges of each selected covariate available for modelling of chalk stream water temperatures is presented in table A8.

Table A8: Covariates selected for water temperature model generation. Boxplots indicate the median, interquartile range, and distribution of the variables within the chalk catchment monitoring sites

Identifier	Description	Minimum value	Maximum Value
USFarmland	Upstream land dedicated to farming (Arable and improved grassland; %)	0 	100
USUrbSub	Upstream land dedicated to urban and suburban development (%)	0 	100

USWoodland	Upstream land covered in broadleaf and conifer woodland (%)	0	56	
USWildgrass	Upstream land covered in undisturbed natural grassland (+ set-aside; %)	0	100	
Geo_calc_us	Upstream calcareous hard geology (%)	0	100	
Geo_sili_us	Upstream siliceous hard geology (%)	0	100	
Cat_size_km2	Size of upstream catchment (km^2)	0	1800	
Altitude_m	Altitude of sampling point (m)	0	190	
Av_Alt_US_m	Average altitude of upstream catchment (m)	0	215	
DRN_WIDTH_M	River channel width (m)	0	59	
DRN_GRAD_MKM	Gradient of river section (m/km)	0	318	
DRN_MEAN_ALT	Mean altitude of river section (m)	-0.85	158.45	
DRN_DIST2MTH	Distance downstream to the end of the DRN (m)	1570.8	280393.9	
DRN_US_ACCUM	Total length of the river upstream of section (m)	3.8	3517782.3	
DRN_STRAHLER	Strahler river order at site	1	7	

Global model temperature predictions

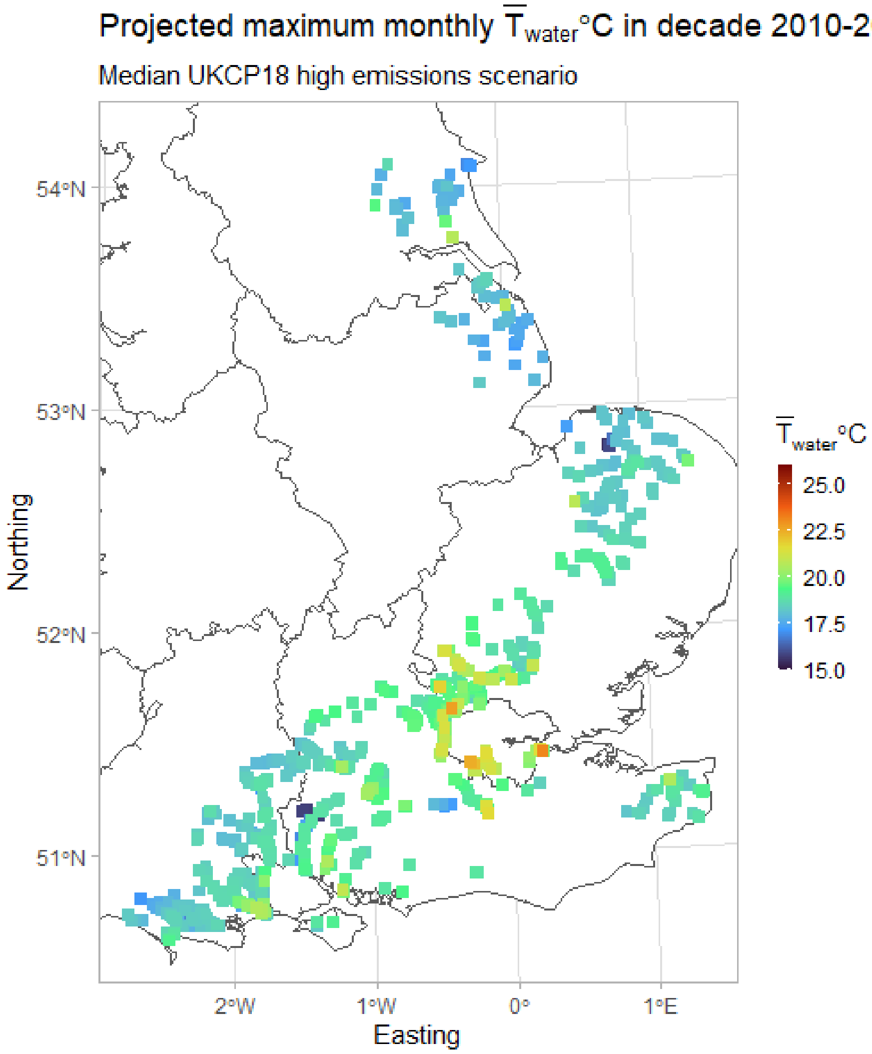


Figure A9(i): Enlarged version of Figure 7, top-left panel showing the maximum *MdTw* projected at each qualifying site in the decade 2010 to 2019

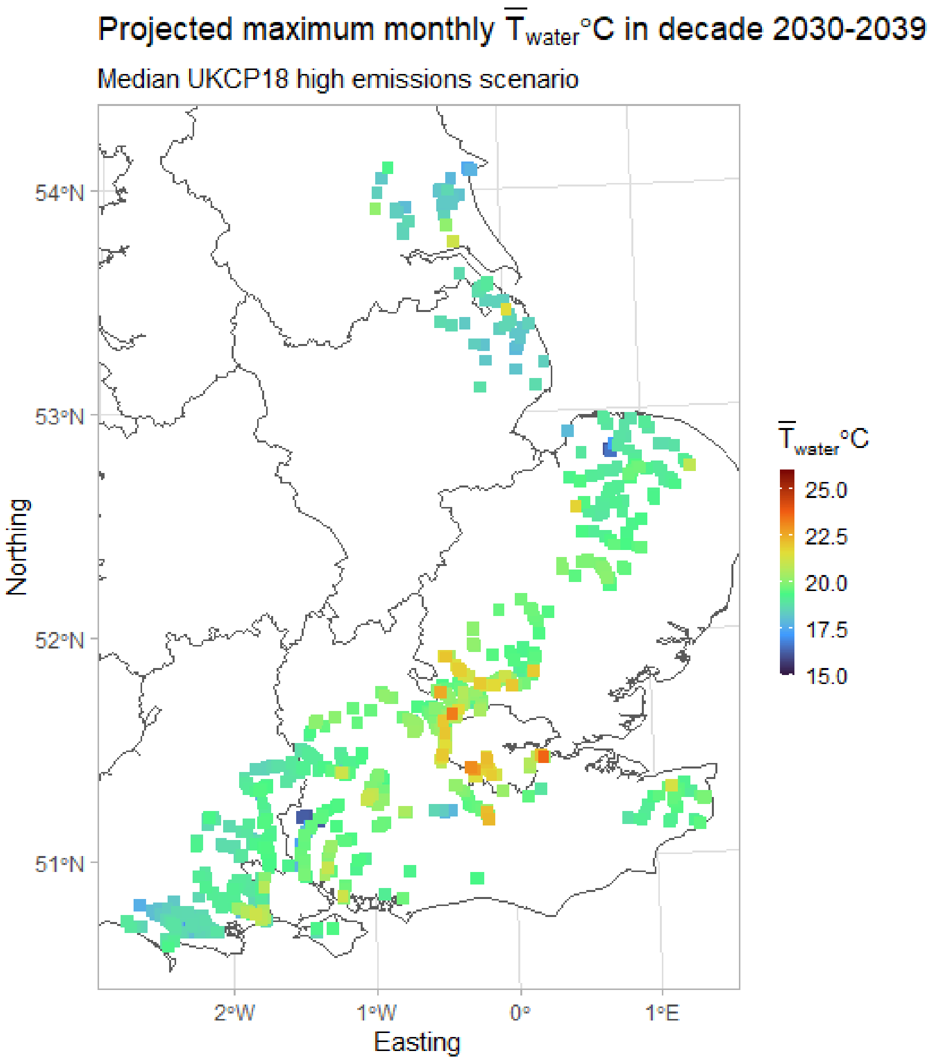


Figure A9(ii): Enlarged version of Figure 7, top-right panel showing the maximum *MdTw* projected at each qualifying site in the decade 2030 to 2039

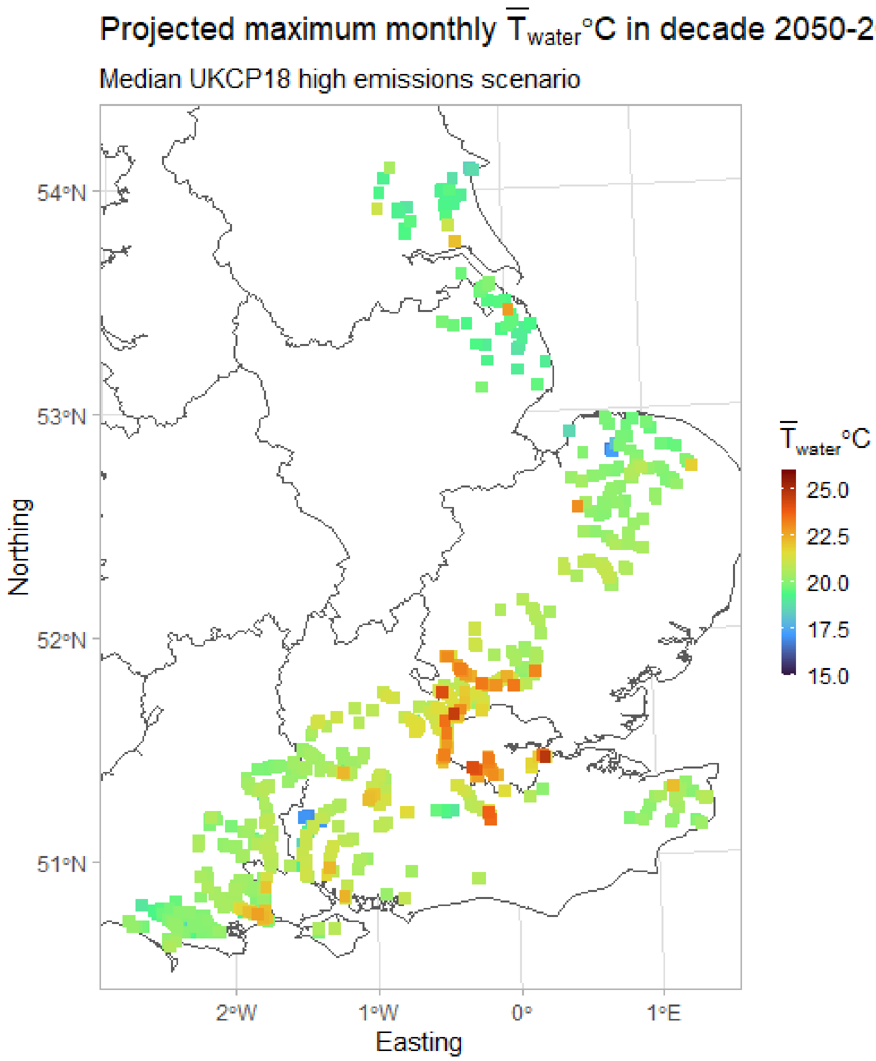


Figure A9(iii): Enlarged version of Figure 7, bottom-left panel showing the maximum *MdTw* projected at each qualifying site in the decade 2050 to 2059

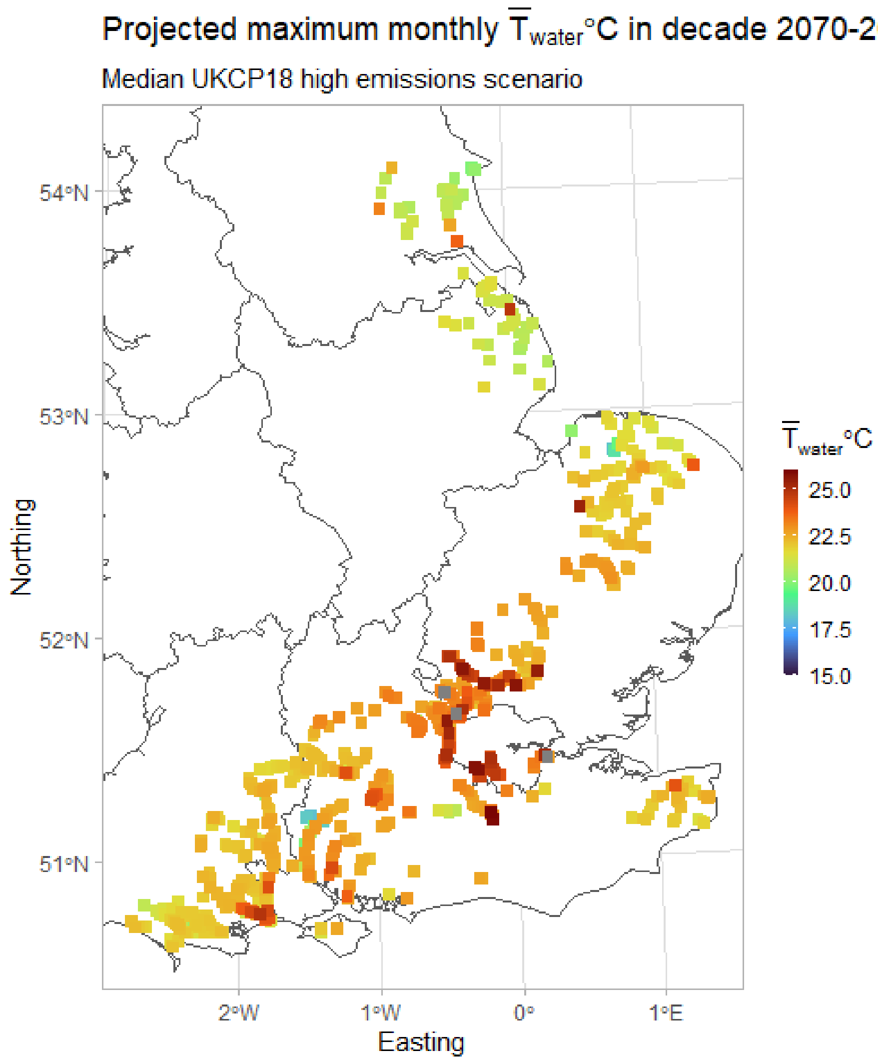


Figure A9(iv): Enlarged version of Figure 7, bottom-right panel showing the maximum *MdTw* projected at each qualifying site in the decade 2070 to 2079

Case Study – Catchment specific models

During the appraisal of available modelling methods (Task 2), four river catchments were identified having multiple (more than 5) monitoring sites with more than five years of monthly mean data and the potential for the development of catchment-specific water temperature models.

Table A10: Catchment model candidate sites

Catchment / Basin	River Basin District	Sample Sites with >60 months data
River Test	South-East	SO-G0003890, SO-G0003918, SO-G0003926, SO-G0003929, SO-G0004067, SO-G0004076, SO-G0004084, SO-G0004095, SO-G0006183, SO-G0006184

Hampshire Avon	South-West	SW-50210209, SW-50220110, SW-50220136, SW-50230145, SW-50240116, SW-50250102, SW-50250634, SW-50280344, SW-50280585
River Wensum	Anglian	AN-TUD070, AN-WEN010, AN-WEN020, AN-WEN040, AN-WEN160, AN-WEN175, AN-WEN180
River Hull	Humber	NE-49200141, NE-49200137, NE-49200090, NE-49200071, NE-49200035, NE-49200025

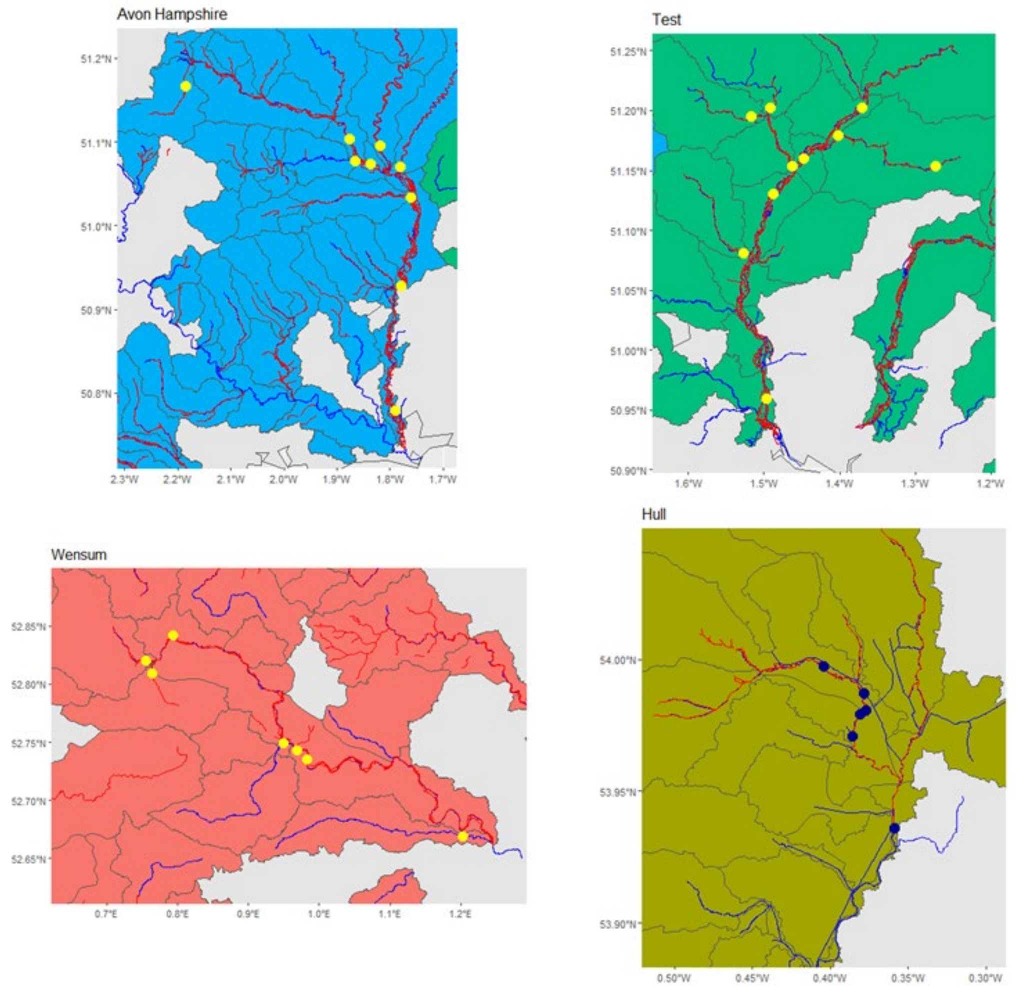


Figure A11: Location of sampling points in catchments proposed for catchment-based model development

Model development started with a similar ‘full’ model to that used in development of the ‘global’ model except that it lacked the spatial component (Easting) and any random effects elements:

Tw_{mean} = T_{air}: Season + cat_size_km2 + DRN_WIDTH_M + DRN_GRAD_MKM + DRN_MEAN_ALT +
DRN_DIST2MTH + DRN_STRAHLER + geo_calc_us +
USUrbSub + USFarmland + USWoodland + USWildgrass

These linear models (lm) were optimised for each catchment (dredge function, MuMin R library) and the model with the minimum AICc value selected as the best model candidate.

The covariates remaining in each catchment's model are set out in Table A12. Each model was then applied to increasing sets of chalk sites to assess model transferability and robustness. The models were first applied to those sites in the same catchment which had not participated in model development, then sites in the same river basin district and finally to all chalk sites used in this study (Figures 16 to 19).

Table A12: Covariates remaining in optimised catchment models

Catchment model	Covariates in optimised model
River Test	DRN_MEAN_ALT, DRN_STRAHLER, DRN_WIDTH_M, USUrbSub
Hampshire Avon	Cat_size_km2, DRN_DIST2MTH, DRN_MEAN_ALT, DRN_WIDTH_M, geo_calc_us, USWildgrass
River Wensum	DRN_MEAN_ALT, DRN_WIDTH_M
River Hull	DRN_MEAN_ALT

River Test

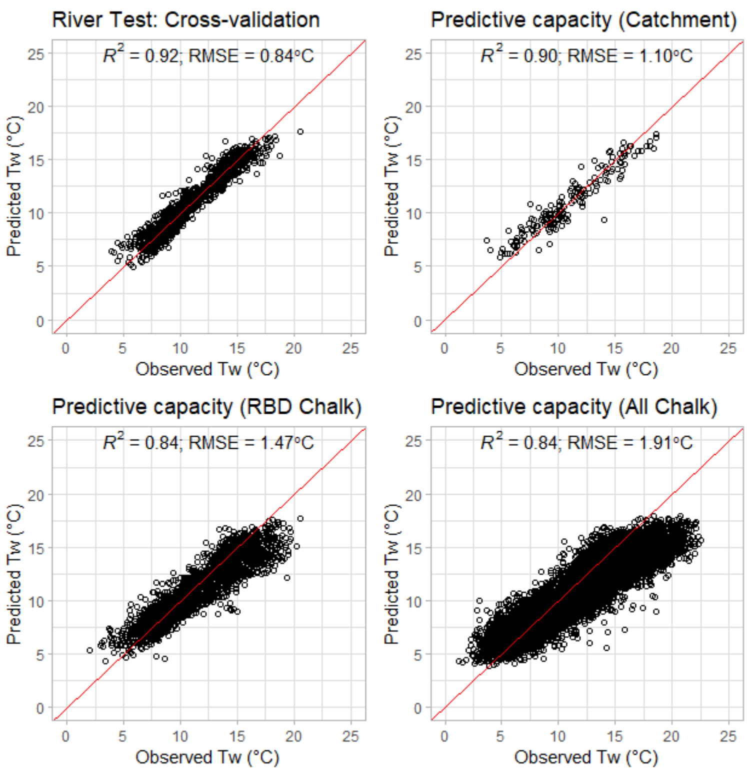


Figure A13: Performance of the River Test model at different landscape scales: training data sites in the Test catchment (top left), additional sites in the Test catchment (top right), chalk sites in the same River Basin District (bottom left), all chalk sites (bottom right). Red lines show *x* = *y* identity lines.

Hampshire Avon

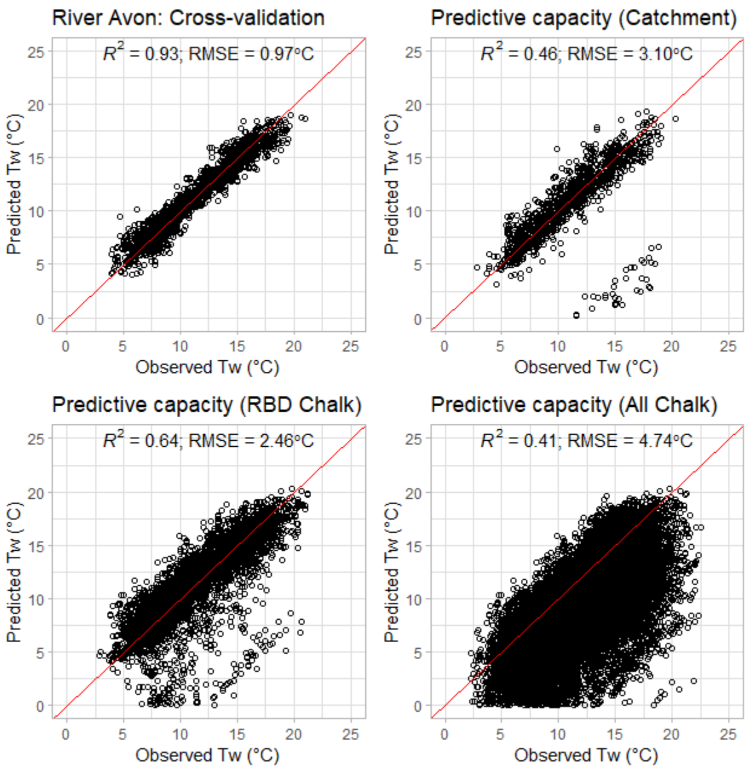


Figure A14: Performance of the River Avon model at different landscape scales: training data sites in the Avon catchment (top left), additional sites in the Avon catchment (top right), chalk sites in the same River Basin District (bottom left), all chalk sites (bottom right).

River Wensum

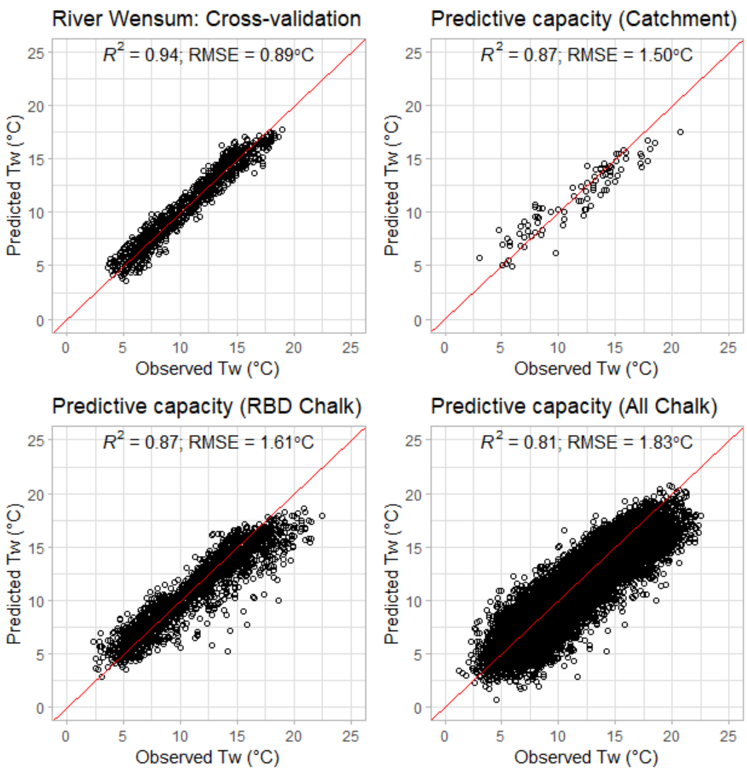


Figure A15: Performance of the River Wensum model at different landscape scales: training data sites in the Wensum catchment (top left), additional sites in the Wensum catchment (top right), chalk sites in the same River Basin District (bottom left), all chalk sites (bottom right).

River Hull

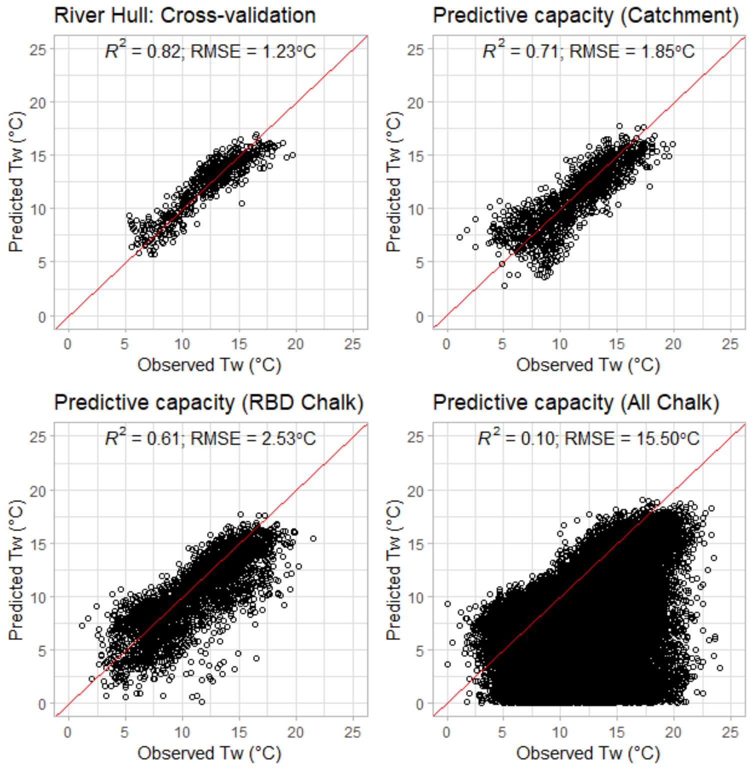


Figure A16: Performance of the River Hull model at different landscape scales: training data sites in the Hull catchment (top left), additional sites in the Hull catchment (top right), chalk sites in the same River Basin District (bottom left), all chalk sites (bottom right).

The reducing R^2 values in the plot groups above (the four panels in each of figures A13 to A16) indicate that the overall performance of these catchment models degrades as the model is applied to increasing number of sites, some by a large degree. The ‘Avon’ and ‘Hull’ models show particularly poor performance when applied to all chalk sites with the ‘Avon’ model displaying divergence even at the catchment scale. Analysis of the covariates selected during the model development stage show that some covariates have very compressed numerical ranges which do not represent the overall range seen across chalk catchments (Table A17). Stepwise removal of these ‘compressed range’ covariates did show improvement in the model fit at larger scales but created a manual assessment stage to apply judgement to the validity of each model (data not shown).

Table A17: Covariate ranges in catchment-based models. Shaded cells highlight small ranges of values when compared to the overall covariate range seen across all chalk water temperature sampling sites.

Covariate	Overall		Test		Avon		Wensum		Hull	
	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max
Altitude (m)	-0.85	158	2.6	69.1	2	114.4	8.7	41.8	3.4	7.5
River width (m)	0	59	6.1	27.7	5.4	28	2.5	11.9		
Strahler order	1	7	3	6						
Catchment size upstream (km^2)	0	1800			0	1707				
Distance to river mouth (m)	1.5k	280k			6.3k	111k	75.7k	81.8k		
Calcareous geology (%)	0	100			88.2	100				
Upstream urbanisation (%)	0	100	3	57			2	4		
Upstream wild grassland (%)	0	100			1	14				

Table A18: Chalk stream water body groupings into main catchments.

Chalk Catchment	Water bodies
Adur	Adur, Woodsmill Stream
Ancholme	Ancholme, Rase, Kingerby Beck, North Willingham
Arun	Arun
Asker	Asker
Avon Hampshire	Allen, Ashford Water, Bourne, Chalke Valley Stream, Chitterne Brook, Ebble, Etchilhampton Water, Fonthill Stream, Fovant Brook, Hampshire Avon, Nadder, Nine Mile River, Sweatfords Water, Teffont, The Clockhouse Stream, Till, Wylye, The Were or Swan
Babingley River	Babingley River
Bride	Bride
Bure	Bure, Marys Beck
Cam	Bottisham Lode, Bulbeck Lode, Cam, Cherry Hinton Brook, Debden Water, Hobson’s Brook, New River, Slade, Soham Lode, Swaffham, Wendon Brook, Wicken Water
Colne	Alderbourne, Bulbourne, Chess, Colne, Ellen Brook, Gade, Misbourne, Ver
Cray	Cray
Darent	Darent
Derwent Yorks	Barlam Beck, Bielby Beck, Derwent, Langton Beck, Menethorpe Beck, Pocklington Beck, Scampston Beck, Settrington Beck, Skirpen Beck
Dour	Dour
Eaus / Steeping	Burwell Beck, Great Eau, Long Eau, Lymn, Steeping, Wainsfleet Haven, Willoughby High Drain

Foulness	Foulness
Frome	Cerne, Frome, Hooke, South Winterbourne, Sydling Water, Tadnoll Brook, Win
Glaven	Glaven, Gunthorpe Stream
Granta	Granta
Great Stour	Great Stour, Little Stour, Nailbourne, North and South Streams, Wingham
Gypsey Race	Gypsey Race
Heacham	Heacham
Hull	Beverley and Barmston Drain, Bryan Mills Beck, Driffield Trout Stream, Ella Dyke, Eastburn Beck, Frodingham Beck, Garton Wold / Water Forlorns, Hull, Lowthorpe / Kelk / Foston Brooks, Nafferton Beck, Scorborough Beck, Scurf Dyke, Skerne Beck, Watton Beck, Wellsprings Drain, West Beck
Humber (Becks Northern)	Barrow Beck, Laceby Beck, Louth Canal, Lud, North Beck Drain, Skitter Beck / East Halton Beck, Thoresway Beck, Waithe Beck
Ingol	Ingol
Isle of Wight Rivers	Caul Bourne, Lukely Brook
Itchen	Arle, Candover Brook, Candover Stream, Cheriton Stream, Itchen
Ivel	Cat Ditch, Hiz, Ivel, Pix Brook, Purwell
Jordan	Jordan
Kennet	Aldbourne, Dun, Froxfield Stream, Kennet, Lambourn, Og, Shalbourne, Winterbourne
Kennett	Lee Brook, Kennett

Lark	Cavenham Stream, Culford Stream, Hawstead Tributary, Lark, Linnet, Tuddenham Stream
Lee	Ash, Beane, Bourne Brook, Lee, Mimram, Quin, Rib, Stort
Little Ouse	Little Ouse, Pakenham Stream, Sapiston, Stowlangtoft Stream
Loddon	Blackwater, Loddon, Lyde, Whitewater
Meon	Meon
Nar	Nar
North Norfolk Rivers	River Burn, Binham Tributary, Stiffkey
Piddle	Bere Stream, Cheselbourne Stream, Devils Brook, Piddle
Rhee / Cam	Mel, Mill River, Rhee, Shep, Whaddon Brook
Rother	Costers Brook, Elsted Stream, Harting Stream
Stour Dorset	Allen, Bourne Stream, Crane, Crichel Stream, Fontmell Brook, Gussage Stream, Iwerne, North Winterbourne, Shreen Water, Stour, Tarrant
Test	Anton, Blackwater, Bourne Rivulet, Dever, Dun, Pilhill Brook, Sombourne Stream, Test, Wallop Brook
Thame	Chalgrove Brook, Kingsey Cuttle Brook, Lewknor Brook
Thames	Ewelme Stream, Ginge Brook, Hamble Brook, Hogsmill, Letcombe Brook, Mill Brook, Mole, Ock, Pang
Thet	Buckenham Stream, Larling Brook, Stow Bedon Stream, Thet, Whittle
Upper Hamble	Upper Hamble
Wandle	Wandle

Wensum	Blackwater, Blackwater Drain, Little Ryburgh, Tat, Tud, Wendling Beck, Wensum
Western Streams	Bosham Stream, Ems, Fishbourne Stream, Lavant
Wey	Caker Stream, North Wey, Tillingbourne
Wey (Dorset)	Wey (Dorset)
Wissey	Gadder, Gladder, Thompson Stream, Watton Brook, West Tofts Stream, Wissey
Witham	Bain, Stainfield Beck
Wye (Chilterns)	Hughenden Stream, Wye
Yare	Tas, Tiffey

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