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DOI:
10.1016/j.scitotenv.2017.09.010

Science of the Total Environment 612 (2018) 1543–1558

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

A spatio-temporal statistical model of maximum daily river temperatures to inform the management of Scotland's Atlantic salmon rivers under climate change

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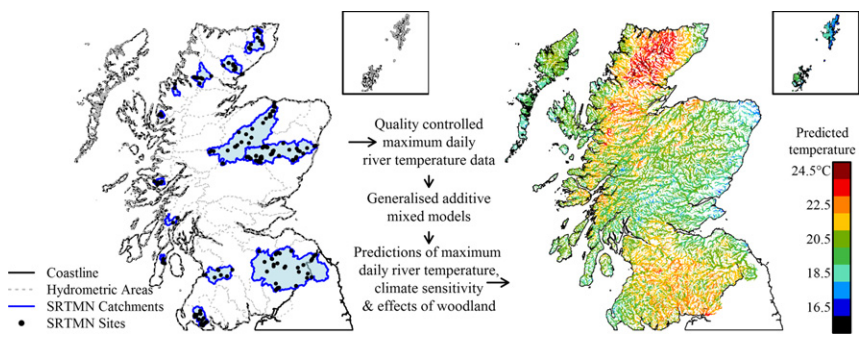
HIGHLIGHTS

- Data collected from strategic river temperature monitoring network
- Novel spatio-temporal model of maximum daily river temperature developed
- Models include air temperature, location, day and landscape characteristics
- Model predictions show spatial temperature variability and climate sensitivity.
- Maps provide tools for fisheries and river managers.

GRAPHICAL ABSTRACT



ARTICLE INFO

Article history:
Received 31 July 2017
Received in revised form 1 September 2017
Accepted 2 September 2017
Available online 15 September 2017

Editor: D. Barcelo

Keywords:
Maximum river temperature
Spatio-temporal model
Generalized additive mixed model
Climate sensitivity
Fisheries management

ABSTRACT

The thermal suitability of riverine habitats for cold water adapted species may be reduced under climate change. Riparian tree planting is a practical climate change mitigation measure, but it is often unclear where to focus effort for maximum benefit. Recent developments in data collection, monitoring and statistical methods have facilitated the development of increasingly sophisticated river temperature models capable of predicting spatial variability at large scales appropriate to management. In parallel, improvements in temporal river temperature models have increased the accuracy of temperature predictions at individual sites. This study developed a novel large scale spatio-temporal model of maximum daily river temperature (Tw_{max}) for Scotland that predicts variability in both river temperature and climate sensitivity. Tw_{max} was modelled as a linear function of maximum daily air temperature (Ta_{max}), with the slope and intercept allowed to vary as a smooth function of day of the year (DoY) and further modified by landscape covariates including elevation, channel orientation and riparian woodland. Spatial correlation in Tw_{max} was modelled at two scales; (1) river network (2) regional. Temporal correlation was addressed through an autoregressive (AR1) error structure for observations within sites. Additional site level variability was modelled with random effects. The resulting model was used to map (1) spatial variability in predicted Tw_{max} under current (but extreme) climate conditions (2) the sensitivity of rivers to climate variability and (3) the effects of riparian tree planting. These visualisations provide innovative tools for informing fisheries and land-use management under current and future climate.

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http://dx.doi.org/10.1016/j.scitotenv.2017.09.010

1. Introduction

River temperature (Tw) has been the focus of much recent research (Caissie, 2006; Webb et al., 2008; Hannah and Garner, 2015), often motivated by a desire to conserve fish populations. River temperature is important for cold water adapted fish species, such as salmonids, affecting their growth, survival and demographic characteristics (McCullough et al., 2001; Gurney et al., 2008; Jonsson and Jonsson, 2009; Elliott and Elliott, 2010). Climate change is expected to increase Tw (Isaak et al., 2012; Hannah and Garner, 2015) potentially altering the thermal suitability of rivers (Isaak et al., 2010, 2012; Comte et al., 2013). Riparian tree planting is a potential tool for reducing maximum temperatures (Malcolm et al., 2008; Hrachowitz et al., 2010; Perry et al., 2015; Ryan and Kelly-Quinn, 2016; Garner et al., 2017; Justice et al., 2017). However, targeted management action requires a detailed understanding of the spatio-temporal variability of river temperatures at large spatial scales (catchment to national); specifically, the locations and times that temperature extremes are likely to occur and the expected effects of climate change and mitigation action. Statistical Tw models are a promising approach for providing this information (e.g. Isaak and Hubert, 2001; Hrachowitz et al., 2010; Moore et al., 2013; Jackson et al., 2017b).

Spatial statistical Tw models have been facilitated by recent technological and statistical developments. These include 1) increased Tw data availability (Isaak et al., 2011; Jackson et al., 2016), 2) improved monitoring design (Dobbie et al., 2008; Som et al., 2014; Jackson et al., 2016; Daigle et al., 2017), 3) greater availability of spatial data e.g. "National Stream Internet" (Nagel et al., 2016), 4) improvements in spatial analysis software across different platforms e.g. ARC (Peterson et al., 2013; Peterson and Ver Hoef, 2014; Jackson et al., 2016) and R (Jackson et al., 2017b) and 5) developments in modelling approaches that account for spatial covariance on river networks (Cressie et al., 2006; Ver Hoef et al., 2006; Jackson et al., 2017b).

Spatial Tw models typically focus on a single annual (static) Tw summary metric, such as mean maximum weekly temperature (Moore et al., 2013) or mean summer temperature (Hill et al., 2014). Tw is then typically modelled as a function of landscape characteristics which are known to affect energy exchange processes (e.g. Isaak and Hubert, 2001; Hrachowitz et al., 2010; Imholt et al., 2011) and often include an air temperature (Ta) metric (Wehrly et al., 2009; Mayer, 2012; Moore et al., 2013; Luce et al., 2014), although other similar metrics of net energy availability e.g. land surface temperature (LST) could also be used (McNyset et al., 2015). These models can be improved by incorporating spatial correlation on river networks (Isaak et al., 2014; Detenbeck et al., 2016; Steel et al., 2016; Jackson et al., 2017a, 2017b) and between catchments or regions (Cressie, 1993; Wehrly et al., 2009), thereby accounting for the effects of advected heat or other uncharacterised controls that vary systematically over space; e.g. changes in hydrogeology and groundwater inputs.

Spatial Tw models can be extended to incorporate within year temporal variability, by including time varying metrics such as Ta or LST that represent changes in energy availability, and discharge that influences the thermal capacity of rivers. The effects of discharge can be incorporated directly (e.g. Sohrabi et al., 2017) or by allowing time varying coefficients for Tw~Ta relationships that reflect seasonality in discharge (Li et al., 2014). However, these models have additional technical challenges as summarised by Letcher et al. (2016): in particular, the need to address 1) apparent non-linearity in relationships between Tw and Ta (Li et al., 2014) 2) seasonal hysteresis in Tw~Ta relationships (Li et al., 2014; Letcher et al., 2016) 3) missing data and 4) temporal correlation (Li et al., 2014; McNyset et al., 2015; Sohrabi et al., 2017).

In principal, spatio-temporal models have some major advantages over static spatial Tw models. Firstly, they provide temporally varying Tw predictions that can be used in studies of biological processes such as fish growth (Bacon et al., 2005; Gurney et al., 2008). Secondly they provide improved spatial coverage and characterisation where Tw data are discontinuous, e.g. when a logger has not operated correctly for part of the year or has moved within year preventing calculation of the Tw summary metric. At their simplest, spatio-temporal models can include a single metric of energy availability (e.g. Ta or LST) and a single relationship between this metric and Tw that extends across sites and time. The underlying assumption of these models is that all of the spatio-temporal variability in Tw can be represented by spatio-temporal variability in the predictor variables.

Spatio-temporal models can be extended to consider spatially and temporally variable relationships between Tw and Ta (or LST), where this relationship is in turn modified by landscape characteristics that influence energy exchange processes (e.g. woodland, geology/groundwater inputs). These models can improve predictions of Tw, identify spatio-temporal variability in climate sensitivity as indicated by the slope of the Tw~Ta relationships (Kelleher et al., 2012; Hilderbrand et al., 2014) and better hindcast or forecast, allowing the analysis of historical biological data, or prediction of climate change impacts. While this model flexibility has not yet been achieved in a single model, a number of studies have employed two stage modelling approaches whereby site-wise models of Tw~Ta are fitted and the parameter estimates subsequently modelled in relation to landscape covariates (Tague et al., 2007; Kelleher et al., 2012; Hilderbrand et al., 2014; Segura et al., 2015; Mauger et al., 2017; Santiago et al., 2017). Although these models incorporate much of the flexibility that would be desired given a process based understanding of river temperature, none of the aforementioned spatio-temporal models also consider network or regional scale covariation, a strength of static Tw models.

This paper develops a model of maximum daily river temperature (Tw_{max}) for Scotland's salmon rivers using data from the strategically designed, quality controlled Scotland River Temperature Monitoring Network (Jackson et al., 2016). As far as the authors are aware, this is the first spatio-temporal model of Tw that allows the Tw~Ta relationships to vary both seasonally and spatially through changes in landscape covariates, that incorporates terms to account for spatial correlations and that addresses all the technical challenges of spatio-temporal modelling identified by Letcher et al. (2016). The model outputs can be used to investigate spatio-temporal variability in climate sensitivity and to support land and fisheries management decisions at local and national levels. The objectives of the study are:

1) Develop a spatio-temporal model of maximum daily river temperature for Scotland's salmon rivers.
2) Assess model performance by cross-validation.
3) Improve understanding of the controls on river temperature.
4) Illustrate spatial variability in river temperature under extreme air temperatures.
5) Understand and predict spatial variability in river sensitivity to climate change.
6) Consider the potential of riparian woodland to reduce temperature extremes.

2. Methodology

2.1. Study area

Scotland occupies an area of ca. 80,000 km^2, with an altitudinal range of 0–1334 m. Rainfall typically varies between <700 mm in eastern Scotland and >4000 mm in the western highlands. Scotland's geology, topography and steep climate gradients have resulted in many rivers with highly variable characteristics (Anon, 2009; Soulsby et al., 2009). There are >16,000 river catchments draining to the sea, of which 255 have an area > 25 km^2 (Fig. 1). Catchments vary from <1 km^2 to 5260 km^2 for the River Tay which has a mean annual discharge of ca. 5.3 km^3 year^{-1} (Soulsby et al., 2009).

Scotland's rivers support a fisheries resource that is valued at >£100 million per year to the Scottish economy (Radford et al., 2004). There are ca. 389 salmon rivers (Anon, 2014), 17 of which are Special Areas

of Conservation (SAC) for Atlantic salmon under the European Union Habitats Directive (Anon, 2009). Scotland's Atlantic salmon populations are of both national and international importance, accounting for ca. 75% and 30% of the estimated UK and European salmon production (pre-fishery abundance) respectively (ICES, 2016).

2.2. Water temperature data

River temperature data came from the Scotland River Temperature Monitoring Network (SRTMN) (Jackson et al., 2016; Fig. 1), a quality controlled network of 223 sites in 13 catchments designed to cover the geographical distribution of Scottish rivers and the environmental range of landscape covariates (e.g. elevation and woodland) expected to influence Tw (Jackson et al., 2016). Tw was recorded at each site every 15 minutes over a 12 month period between 01/07/2015 and 30/06/2016 using Gemini TinyTag Aquatic 2 (TG-4100) dataloggers (reporting resolution 0.01 °C). Field deployed dataloggers were calibrated against an internal reference logger which was in turn calibrated against an external reference at a UKAS (United Kingdom Accreditation Service) certified laboratory. During internal calibration, temperature dataloggers showed good agreement across units, varying by <0.2 °C over the temperature range 0–30 °C. A double calibration correction procedure was then performed to correct observed temperatures to "true" temperatures (±0.02 °C). Field data quality issues (e.g. logger exposure under low flow conditions/channel change, or logger burial) were recorded during download visits and any unreliable data were removed before analysis. After quality control, data remained from 218 of the 223 sites. Maximum daily Tw (Tw_{max}) was calculated from the raw Tw data for each day and site.

2.3. Air temperature data

Maximum daily air temperature (Ta_{max}) was extracted from gridded UKCP09 Ta datasets (available from the UK MET Office) for the years 2003, 2010, 2015, 2016. The UKCP09 Ta datasets are a matrix of maximum, mean or minimum Ta for the UK on each day of the year; see Perry and Hollis (2005a, 2005b) for details. Data were extracted for 2015 and 2016 to correspond to the Tw_{max} data, and for 2003 and 2010 to illustrate model predictions of Tw_{max} in the hottest and coldest years respectively in the last two decades.

2.4. Spatial datasets

River networks were characterised using a corrected version of the Centre for Ecology and Hydrology (2014) Digital River Network (DRN), which consists of line features connected by nodes. Nodes

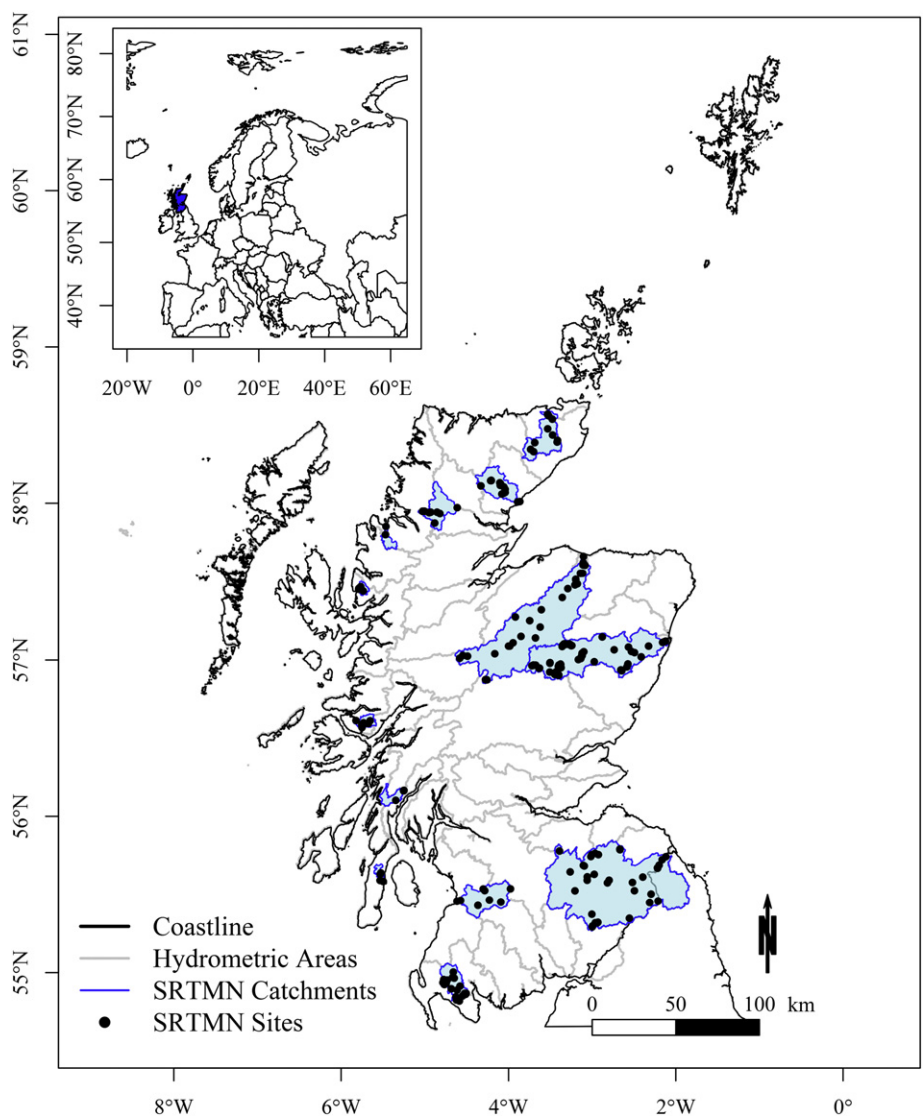

Fig. 1. Scotland River Temperature Monitoring Network site map.

exist at all river sources and confluences, with additional "pseudo nodes" (on river segments that are not sources or confluences) due to the digitisation process. To predict nationally, model covariates were calculated for all nodes in the DRN (ca. 280,000 nodes).

Scotland was divided into 44 regional polygons (Scottish Environment Protection Agency Hydrometric Areas) of approximately similar size (Marsh and Hannaford, 2008), that contained between 1 and 11 river catchments (>25 km^2). These areas were used to characterise large scale spatial variability in temperature (see below). Each catchment in the SRTMN is in a different Hydrometric Area.

Several Ordinance Survey datasets were used to calculate the covariates, including the 10 m digital terrain model, MasterMap land cover and coastline datasets (Jackson et al., 2017b).

2.5. Landscape covariates

A detailed description of the landscape covariates and their calculation can be found in Jackson et al., (2017a, 2017b). In brief, the covariates were: elevation (Elevation), upstream catchment area (UCA), percentage riparian woodland (in a 25 m buffer width extending 1000 m upstream) (%RW), summer and winter hillshading (metrics of the amount of the direct shortwave radiation reaching the channel) (SHS/WHS), channel width (Width), channel gradient (Gradient), channel orientation (Orientation), distance to coast (DC) and distance to the sea along the river (RDS). When necessary, covariates were transformed before model fitting to reduce skewness: Elevation was square root transformed and Gradient, UCA and Width were log transformed. Two extreme low SHS values were replaced by the next smallest value. When pairs of covariates were strongly correlated (>0.8), one of the pair was excluded. This reduced the list of covariates to Elevation, UCA, %RW, SHS, Gradient and Orientation.

2.6. Statistical methods

2.6.1. Modelling motivation and approach

The modelling approach was informed by the objectives of the study, the findings of previous Tw modelling studies, and prior knowledge of the processes controlling Tw variability (e.g. Hannah et al., 2004, 2008; Garner et al., 2014, 2015, 2017). Ta and Tw are both strongly influenced by radiative fluxes, so measures of Ta are frequently used to infer the availability of energy to heat rivers, and to predict spatial (e.g. Chang and Psaris, 2013; Hill et al., 2014; Turschwell et al., 2016) and temporal variability in Tw (e.g. Jeong et al., 2013; Li et al., 2014; Letcher et al., 2016). Previous studies suggest that there will be strong, site-specific relationships between Tw and Ta that can predict much of the temporal variation in Tw (Isaak et al., 2012; Mayer, 2012; Krider et al., 2013; Carlson et al., 2017). Further, these relationships will vary spatially (between sites) depending on the influence of landscape characteristics that affect river energy budgets (Mayer, 2012; Krider et al., 2013; Arismendi et al., 2014; Jackson et al., 2017b) and temporally depending on seasonal changes in river discharge that in turn affect thermal capacity (Sohrabi et al. 2017). It is also increasingly recognised that Tw data can exhibit substantial spatial structure (covariance) within river networks (Isaak et al., 2014), at least partially reflecting advected heat exchange, and can be spatially correlated across catchments, reflecting large scale hydro-climatic controls. Finally, it is well recognised that daily Tw time series are auto-correlated (Caissie, 2006; Li et al., 2014; Letcher et al., 2016). Thus, the models developed in this study aimed to describe spatial and temporal variability in Tw_{max} as a function of Ta_{max}, moderated by process relevant landscape covariates, while also incorporating temporal and spatial correlation at various scales.

2.6.2. Tw ~ Ta relationship and landscape covariates

Many studies have modelled the relationship between Tw and Ta using linear (e.g. Stefan and Preud'homme, 1993; Isaak et al., 2012; Krider et al., 2013; Rice and Jastram, 2015) or non-linear (e.g. Mohseni et al., 1998; Soto, 2016) models or both (e.g. Mayer, 2012; Bal et al., 2014; Segura et al., 2015). Logistic functions are often thought necessary to capture the sigmoidal relationships observed between Tw and Ta when data are aggregated over longer (>6 months) time periods encompassing multiple seasons (Mohseni et al., 1998). However, logistic models do not always improve on linear models and thus simpler linear models are often preferred (Krider et al., 2013). Examination of the daily Tw_{max} data collected in this study (Fig. 2) suggested that a linear relationship between Tw_{max} and Ta_{max} over shorter timescales (e.g. a month) with the slope and intercept of the relationship changing over time would adequately describe the data. We therefore considered models in which Tw_{max} was linearly related to Ta_{max} and the intercept and slope of the relationship was allowed to change smoothly with day of the year (DoY). These models improved short term Tw_{max} predictions (as slopes obtained by fitting to the data for a whole year are inappropriate over shorter time periods e.g. too steep over winter, see Fig. 2), allowed for an apparently non-linear relationship between Tw_{max} and Ta_{max} at low and high temperatures (through lower slopes, particularly in winter) and accounted for hysteresis in the Tw_{max}~Ta_{max} relationship due to seasonality (Li et al., 2014; Letcher et al., 2016). This is illustrated in Fig. 2. More generally, the effect of the landscape covariates on the Tw_{max}~Ta_{max} relationship was incorporated by also allowing the intercept and slope to change smoothly with the landscape covariates. This is important for characterising spatial variability in climate sensitivity (i.e. the slope of the Tw~Ta relationship) and extends previous studies which have generally only included landscape covariates as main effects (Jonkers and Sharkey, 2016) where they do not affect climate sensitivity, or have incorporated their effects in a two stage model (e.g. Mayer, 2012; Chang and Psaris, 2013; Segura et al., 2015).

2.6.3. Spatial and temporal correlation

Spatial correlation was modelled at two scales (1) the river network scale (River Network Smoother: RNS) and (2) regional scale (Hydrometric Area Smoother: HAS). Full details of the RNS can be found in Jackson et al. (2017b). In brief, the RNS is a modified version of the approach developed by O'Donnell et al. (2014) for predicting water quality on river networks, fitted using a set of 'reduced rank' basis functions with the degree of smoothing at a confluence controlled by the proportional influence of upstream tributaries weighted by Strahler river order (Strahler, 1957). None of the RNS bases were highly correlated (>0.8) with any of the covariates, so the RNS should not account for variability that would otherwise be explained by the covariates. River networks are catchment-specific, so a separate RNS was fitted to each catchment. The HAS is a large scale spatial smoother that allows Tw_{max} in neighbouring hydrometric areas to be correlated. The HAS is fitted using a reduced rank Gaussian Markov random field spatial smoother; see Millar et al. (2015, 2016) for details.

Temporal correlation was modelled by assuming an order 1 autoregressive (AR1) error structure for the daily Tw_{max} observations within each site. The AR1 correlation ρ was assumed to be the same for all sites.

2.6.4. Estimating temporal correlation

It was not possible, with the software available, to estimate ρ, fit the spatial smoothers and the covariate-dependent Tw_{max}~Ta_{max} relationships at the same time. To overcome this, ρ was first estimated from a model which explained as much of the spatial and temporal variation as possible using the covariates but which ignored any spatial correlation. The estimate of ρ was then treated as fixed and plugged into models which fitted spatial correlation terms and investigated the relationships with the covariates in more detail.

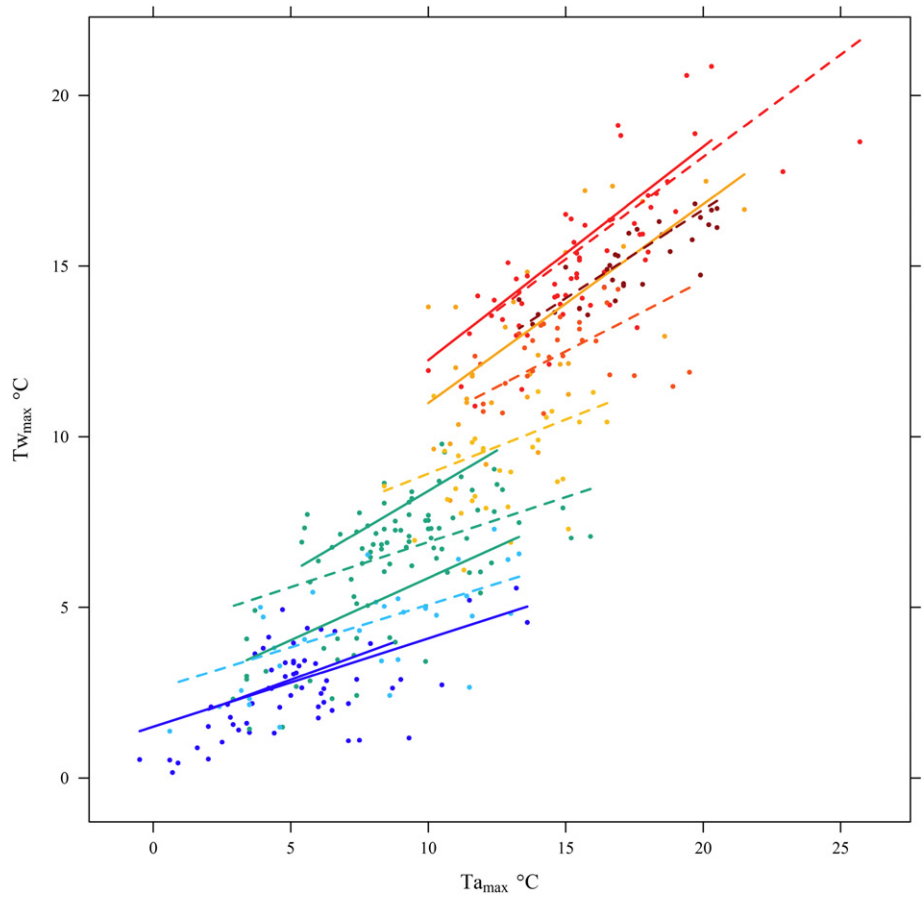

Fig. 2. Relationship between Tw_{max} and Ta_{max} for one site over a twelve month period. Points are pairs of daily temperature observations. Lines illustrate how the intercept and slope of the relationship vary over time. For simplicity, only monthly relationships are shown. Solid lines for the first six months of the year (January–June), dashed lines for the second six months (July–December) illustrate seasonal hysteresis in the relationships. Colours range between blue (cool) and red (warm) and vary according to the maximum observed daily temperature in each month.

Specifically, ρ was estimated from a model of the form

$$\begin{aligned} Tw_{max} \sim\ & Ta_{max} + Catchment + Catchment : Ta_{max} + s(DoY) + s(DoY) \\ & \times Ta_{max} + s(Elevation) + s(Elevation) \times Ta_{max} + s(Gradient) \\ & + s(Gradient) \times Ta_{max} + s(Orientation) + s(Orientation) \times Ta_{max} \\ & + s(UCA) + s(UCA) \times Ta_{max} + s(\%RW) + s(\%RW) \times Ta_{max} \\ & + s(SHS) + s(SHS) \times Ta_{max} + RE(Site) \end{aligned} \quad (1)$$

with Tw_{max} assumed to have Gaussian errors with an AR1 structure. Here, s(.) denotes a smooth term. Residual diagnostics confirmed that the error structure was reasonable. Based on preliminary fits and the likely complexity of responses, the smooths had 2 degrees of freedom (df) for the landscape covariates, giving at most a modal form, and 5 df for DoY. A cyclic smoother was used for DoY. The df were fixed (not estimated from the data) so the model could be fitted as a series of linear terms (see below) and to ensure that the fitted model didn't change if Ta_{max} was either translated (e.g. centred) or scaled. The terms s(DoY) and s(DoY) × Ta_{max} allow the intercept and the slope of the Tw_{max}~-Ta_{max} relationship to vary smoothly with DoY, and similarly for the landscape covariates. The terms Catchment and Catchment:Ta_{max} allow for Catchment-specific intercepts and slopes (with: denoting the interaction between the categorical variable Catchment and Ta_{max}). Finally, RE(Site) denotes a Site random effect allowing the intercept to vary independently with a Gaussian distribution across Sites. Including all these terms should capture most of the temporal and spatial variation in Tw_{max}, giving an unbiased estimate of ρ. The model was fitted as a linear mixed model by restricted maximum likelihood (REML) in package 'nlme' (Pinheiro et al., 2017) having obtained the model matrix from package 'mgcv' (Wood, 2016) using the fixed df for each smooth term. All analysis was done in R version 3.2.3 (R Core Team, 2015).

2.6.5. Model selection

The relationship between Tw_{max} and the covariates was investigated in a forwards and backwards stepwise model selection procedure. The starting model was

$$\begin{aligned} Tw_{max} \sim\ & Ta_{max} + s(DoY) + Elevation + Gradient + Orientation + UCA \\ & + \%RW + SHS + RNS : Catchment + HAS + RE(Site) \\ & + RE(Site) : Ta_{max} \end{aligned} \quad (2)$$

with Tw_{max} assumed to have a Gaussian AR1 structure with $\rho = 0.67$. A cyclic smoother with 5 fixed df was used for DoY. The term RNS:Catchment denotes a separate RNS for each Catchment. Each RNS was allowed up to 7 df based on RNS complexity found in previous studies (Jackson et al., 2017b). The HAS essentially allowed the intercept of the Tw_{max}~Ta_{max} relationship to vary between Catchments in a correlated way. The df for the HAS were unrestricted allowing a wide range of possible relationships, from uncorrelated to identical intercepts. The terms RE(Site) and RE(Site):Ta_{max} allowed random effects for the intercept and the slope of the Tw_{max}~Ta_{max} relationship. The model was fitted by maximum likelihood using a modification of the 'bam' function in package mgcv that called the BFGS optimiser (Nocedal and Wright, 1999). Bam is designed for use with large datasets and allows a fixed AR1 structure to be fitted (Wood, 2016). The landscape and DoY

covariates had a simpler form in the starting model than in Eq. (1) because the inclusion of the spatial correlation terms made model fitting more numerically challenging.

The starting model was then refined using forwards and backward stepwise selection. At each stage, the main effects of the landscape covariates and DoY could switch between absent and linear and between linear and smooth (on 2 fixed df for the landscape covariates and 5 fixed df for DoY) and the RNS:Catchment and HAS terms could switch between present and absent. In addition, the slope of the Tw_{max}~Ta_{max} relationship was allowed to vary with any of the covariates that were present as main effects. If the main effect was linear/smooth, then the covariate was constrained to affect the slope of the Tw_{max}~Ta_{max} relationship linearly/smoothly with the same fixed df. These constraints ensured that fitted models were invariant to translations or scaling of Ta_{max}. Finally, the slope of the Tw_{max}~Ta_{max} relationship was also allowed to vary with Hydrometric Area, giving correlated Catchment-specific slopes (written HAS:Ta_{max}). However, it was not possible to constrain the df of the HAS on the slope to be the same as that on the intercept.

Model selection was based on an adjusted Bayesian Information Criterion:

$$BIC_{adj} = \ln(N)M - 2L \tag{3}$$

where L is the maximised log-likelihood, N is the number of sites ($N = 218$) and M is the number of df in the model. Random effects (RNS, HAS and Site) were given 13, 1 and 1 df respectively, reflecting the number of variance components estimated. The model with the lowest BIC_{adj} was selected as the final model. BIC_{adj} was used rather than the Akaike Information Criterion (AIC) because it penalises additional model terms more heavily and simpler models tend to be more transferable (Millidine et al., 2016; Jackson et al., 2017a); i.e. give better predictions in catchments which have no Tw_{max} data and are not used in the modelling process. To get (approximately) unbiased estimates of the variance components and model standard errors, the final model was refitted by restricted maximum likelihood.

2.6.6. Model performance

Model performance was assessed using two types of cross-validation. The first was 10-fold cross-validation in which the sites were divided at random into 10 approximately equally sized subsets (ca. 22 sites each). Each subset was removed in turn, the model refitted to the remaining data and used to predict Tw_{max} at the missing sites. This approach is similar to that typically used in other studies. The second approach involved leaving out all the sites in each catchment in turn, refitting to the remaining data and predicting Tw_{max} in the missing catchment. This provides a better indication of how well the model predicts to new catchments where there are no Tw data. Model performance was summarised by the root mean square error (RMSE), bias and standard deviation (SD) of the model predictions:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{s,d}\left(\hat{x}_{sd} - x_{sd}\right)^2} \tag{4}$$

$$\mathrm{SD} = \sqrt{\frac{1}{n}\sum_{s,d}\left(\left(\hat{x}_{sd} - \bar{\hat{x}}\right) - \left(x_{sd} - \bar{x}\right)\right)^2} \tag{5}$$

$$\mathrm{Bias} = \bar{\hat{x}} - \bar{x} \tag{6}$$

where x_{sd} and $\hat{x}_{sd}$ are the observed and predicted Tw_{max} at site s on day d, $\bar{x}$ and $\bar{\hat{x}}$ are the mean observed and predicted Tw_{max}, and n is the number of observations (total number of site and day combinations). Standard deviation was used rather than variance so that all three metrics are on the same scale and can be compared. RMSE, bias and SD were calculated for the whole year and for each month in turn to investigate seasonal changes in performance.

2.7. Model illustration

The effects of the covariates on Tw_{max} were illustrated by partial effects plots and by a series of maps of predicted Tw_{max}. The first map was a 'reference' prediction in which all the landscape covariates were held at their median value, the RNS and HAS were centred about zero, DoY was set to 158 (the middle of the hottest week nationwide during the study) and Ta_{max} at each river node was set to the mean observed Ta_{max} at that node during the hottest week. The reference map shows Tw_{max} predictions if the Tw_{max}~Ta_{max} relationship is assumed to be spatially consistent throughout Scotland. The mean Ta_{max} in the hottest week was preferred to the Ta_{max} on the hottest day as the reference map was less susceptible to local variation in Ta_{max}. High Ta_{max} values were chosen because they provided greater spatial contrast in the other covariate effects and because high Tw_{max} is often the focus of management. The subsequent maps showed the difference between the predicted Tw_{max} when one (or more) of the covariates also varied spatially and the reference prediction.

Spatial patterns in predicted Tw_{max} were illustrated for two days during the study, when observed Ta_{max} was on average at its highest (DoY 182) and lowest (DoY 16) across Scotland (identified by summing Ta matrices). The observed values of Ta_{max} on these days were used to make the predictions for each river node. Standard errors were also plotted to visualise spatial variability in prediction error.

Because the 2015–2016 monitoring period was relatively mild in terms of both high and low Ta_{max} the spatial variability of Tw_{max} was illustrated under more extreme climate conditions using the maximum Ta_{max} observed at each node in 2003 (hottest of the last 20 years) and the minimum observed in 2010 (coldest of the last 20 years), combined with the DoY (174 and 16) that gave the highest and lowest effect respectively. The hottest and coldest Ta_{max} did not necessarily occur on DoY 174 and 16, so the predictions represent a potential for extreme temperatures rather than the Tw_{max} that would have occurred on those days.

Climate sensitivity is often defined as the responsiveness of a river to a given Ta increase (Mohseni and Stefan, 1999; Kelleher et al., 2012; Mayer, 2012). Given the linear Tw_{max}~Ta_{max} relationship used in this study, it was possible to illustrate the effect of a 1 °C change in Ta_{max} on Tw_{max} for any given DoY. The DoY values used were 169 and 350, those associated with the steepest (summer) and shallowest (winter) slope in the Tw_{max}~Ta_{max} relationship respectively, and which provided an envelope of potential effect sizes.

The potential of riparian shading to mitigate temperature extremes was explored by repeating the predictions for summer 2003 and winter 2010 with %RW first set at 0 and then at 100% and then plotting the differences in the predictions.

3. Results

3.1. Daily maximum river water temperature model

The final model of Tw_{max} was:

$$\begin{aligned} Tw_{max} \sim\ & Ta_{max} + s(DoY) + s(DoY) \times Ta_{max} + Elevation + Elevation \\ & \times Ta_{max} + \%RW + \%RW \times Ta_{max} + Orientation + HAS \\ & + HAS : Ta_{max} + RNS : Catchment + RE(Site) + RE(Site) : Ta_{max} \end{aligned} \tag{7}$$

The final model explained 91.9% of the variability in Tw_{max} and all the terms in the final model were significant (likelihood ratio test: $p < 0.01$ in all cases). Ten-fold cross validation suggested that bias in the predictions was small (<0.5 °C) and that RMSE varied across months,

from 1.15 °C in October to 2.12 °C in June, with an annual value of 1.57 °C (Table 1). Prediction error was slightly greater when catchments were left out one at a time, with an annual RMSE of 1.60 °C (Table 1).

DoY, Elevation and %RW affected both the intercept and the slope of the Tw_{max}~Ta_{max} relationship whereas Orientation only affected the intercept. The intercept and slope increased between winter and summer and declined in the autumn (Fig. 3a) indicating that, during the summer, Tw_{max} was higher for a given air temperature and more responsive to changes in Ta_{max}. Increasing elevation reduced Tw_{max} at low Ta_{max} (e.g. by ca 1 °C at Ta_{max} of 0 °C over an altitudinal range of 0–625 m) but had a negligible effect at higher Ta_{max} (Fig. 3b). There was a positive relationship between %RW and Tw_{max} at low Ta_{max} and a negative relationship at high Ta_{max} (Fig. 3c). For example, at a Ta_{max} of 25 °C, Tw_{max} under 100%RW was ca. 2 °C lower than under 0%RW. Orientation had a small positive effect on Tw_{max} with higher temperatures predicted for north-south rather than east-west orientations (Fig. 3d).

The spatial effects of the covariates on Tw_{max} are illustrated in Fig. 4 for the hottest week of the study. Fig. 4a shows the spatial effect of Ta_{max} with the other covariates held constant at their median values and essentially shows the predictions that would be obtained if the Tw_{max}~Ta_{max} relationship was assumed to be spatially consistent. Fig. 4b–h are difference plots that illustrate the additional spatial effects of the covariates, both individually (Fig. 4b–f) and combined (Fig. 4g). The Hydrometric Area smoother increased Tw_{max} predictions in the west and north, and reduced temperatures in a small area of the north east relative to other areas. It had an overall effect size of around 2.5 °C (Fig. 4b). The river network smoothers explained spatially structured residual variability for those catchments with data (Fig. 4c) although their effect size was small (ca ±0.5 °C). Elevation decreased Tw_{max} in mountainous areas and increased Tw_{max} in low lying areas, predicting higher Tw_{max} in the low lying urban south-central area of Scotland and coastal areas, relative to the reference predictions (Fig. 4d). The effect of %RW was patchy within catchments, but also showed large scale spatial patterns with increased Tw_{max} in areas of sparse woodland cover at higher altitudes, such as the Cairngorm Mountains in the centre of Scotland, and to the north and west. Across Scotland, %RW altered Tw_{max} by ca. 2 °C, with lower Tw_{max} in areas of higher %RW. Orientation had a small (±0.25 °C) and patchy effect, varying within catchments, but not showing any clear large scale effects. The combination of covariates resulted in differences in Tw_{max} predictions of between −3 and +2 °C (Fig. 4g) relative to the reference predictions (Fig. 4a). Fig. 4g shows that a simple Tw_{max}~Ta_{max} model would tend to over predict Tw_{max} in the south and under predict in the north and west, as well as having some substantial within catchment biases.

3.2. Spatial variability in Tw_{max} in 2015–16

The spatial variability in Tw_{max} predictions for the hottest and coldest days of the study is shown in Fig. 5, with associated standard errors. On the hottest day, Tw_{max} was predicted to vary by ca.10 °C across Scotland and to be warmer at lower elevations in the north and south (Fig. 5a). There was also substantial within catchment variability in Tw_{max} that reflected the combined effects of Ta_{max} and the landscape covariates, producing a patchy mosaic of Tw_{max} predictions superimposed on broader scale catchment wide patterns (Fig. 5e). For example, in the River Dee, Tw_{max} varied by ca. 5 °C, with higher Tw_{max} predicted for upper river tributaries where woodland was absent and the river flowed north-south. On the coldest day, the range of Tw_{max} predictions was smaller across Scotland (ca. 7 °C), with Tw_{max} predicted to be warmer in the south and at the coast (except in the north and west) and cooler in high altitude continental areas, particularly in the north (Fig. 5b). At the scale of the River Dee, winter Tw_{max} generally decreased with distance inland from the coast towards the Cairngorm Mountains reflecting the combined effects of Ta_{max} and Elevation.

The lowest standard errors (<0.5 °C) were in catchments with Tw_{max} data. The highest standard errors were in the islands where there were no data and where nearby Hydrometric Areas also had limited or no data. Standard errors were lower in winter than summer, although the spatial patterns were similar (Figs. 5b, d).

Table 1
Monthly RMSE results from ten-fold and leave one catchment out cross validation.

Month removed	Ten-fold			Leave one catchment out		
	RMSE	Bias	SD	RMSE	Bias	SD
1	1.43	−0.05	1.43	1.49	−0.03	1.49
2	1.22	0.47	1.13	1.24	0.47	1.15
3	1.26	−0.29	1.23	1.25	−0.29	1.22
4	1.34	−0.04	1.34	1.35	−0.03	1.35
5	2.04	0.12	2.04	2.06	0.17	2.06
6	2.12	−0.29	2.1	2.16	−0.23	2.15
7	1.79	0.42	1.74	1.84	0.46	1.78
8	1.62	−0.17	1.62	1.64	−0.1	1.64
9	1.26	−0.36	1.2	1.26	−0.29	1.23
10	1.15	0.21	1.14	1.17	0.26	1.14
11	1.5	0.43	1.43	1.56	0.47	1.49
12	1.71	−0.44	1.65	1.76	−0.39	1.72
Overall	1.57	−0.00	1.57	1.60	0.04	1.60

3.3. Spatial variability in Tw_{max} under extreme climate conditions

When compared to 2015–2016, mean and maximum Tw_{max} predictions were 1.8 and 2.7 °C higher for summer 2003 (Fig. 6a) and 1.05 and 0.53 lower for winter 2010 (Fig. 6b). The warmest rivers in summer 2003 were predicted to be in the north and west, corresponding to low elevation and low %RW (Figs. 3b, c and 4d, e). However, this pattern also reflected the influence of Hydrometric Area (Fig. 4b) which increased Tw_{max} in the north and west at high Ta_{max}. In winter 2010, Tw_{max} was predicted to be warmer in south-central Scotland and at the coast, than in the north and central highlands (Cairngorm Mountains) (Fig. 6b), largely corresponding to differences in elevation (Figs. 3b and 4d).

3.4. Climate sensitivity of rivers

The slope of the Tw_{max}~Ta_{max} relationship measures the sensitivity of rivers to changing Ta with steeper relationships indicating greater sensitivity to climate change. Fig. 7 illustrates the predicted change in Tw_{max} for a 1 °C rise in Ta_{max}. Tw_{max} was predicted to increase by between 0.4 °C and 0.7 °C in summer (Fig. 7a). The increase was smaller in winter, ranging between −0.02 and 0.36 °C (Fig. 7b). The most sensitive rivers were predicted to be in the north and north-west of Scotland and the Cairngorm Mountains (Fig. 7), areas are all characterised by low %RW. The rivers in the north and north west are also influenced by a strong Hydrometric Area effect that increases the slope of the Tw_{max}~Ta_{max} relationship (Fig. 4b). The higher elevation of mountainous areas are also associated with greater Tw_{max}~Ta_{max} slopes.

3.5. Predicted effects of woodland

One of the more feasible climate mitigation options for river systems is the planting of riparian areas with native trees. Fig. 8 illustrates the predicted change in Tw_{max} as %RW increases from 0 to 100% in summer and winter. The effect of %RW is larger at low or high Ta_{max} (Fig. 3c), so the greatest changes in Tw_{max} (up to −2.8 °C) are predicted to occur at nodes with the most extreme Ta_{max}, mainly in low lying areas away from the east coast.

4. Discussion

Evidence based management of rivers and fisheries require a detailed understanding of the spatial and temporal variability of river temperatures if managers are to meet the challenges posed by climate change. Importantly, tools are needed that highlight where rivers are

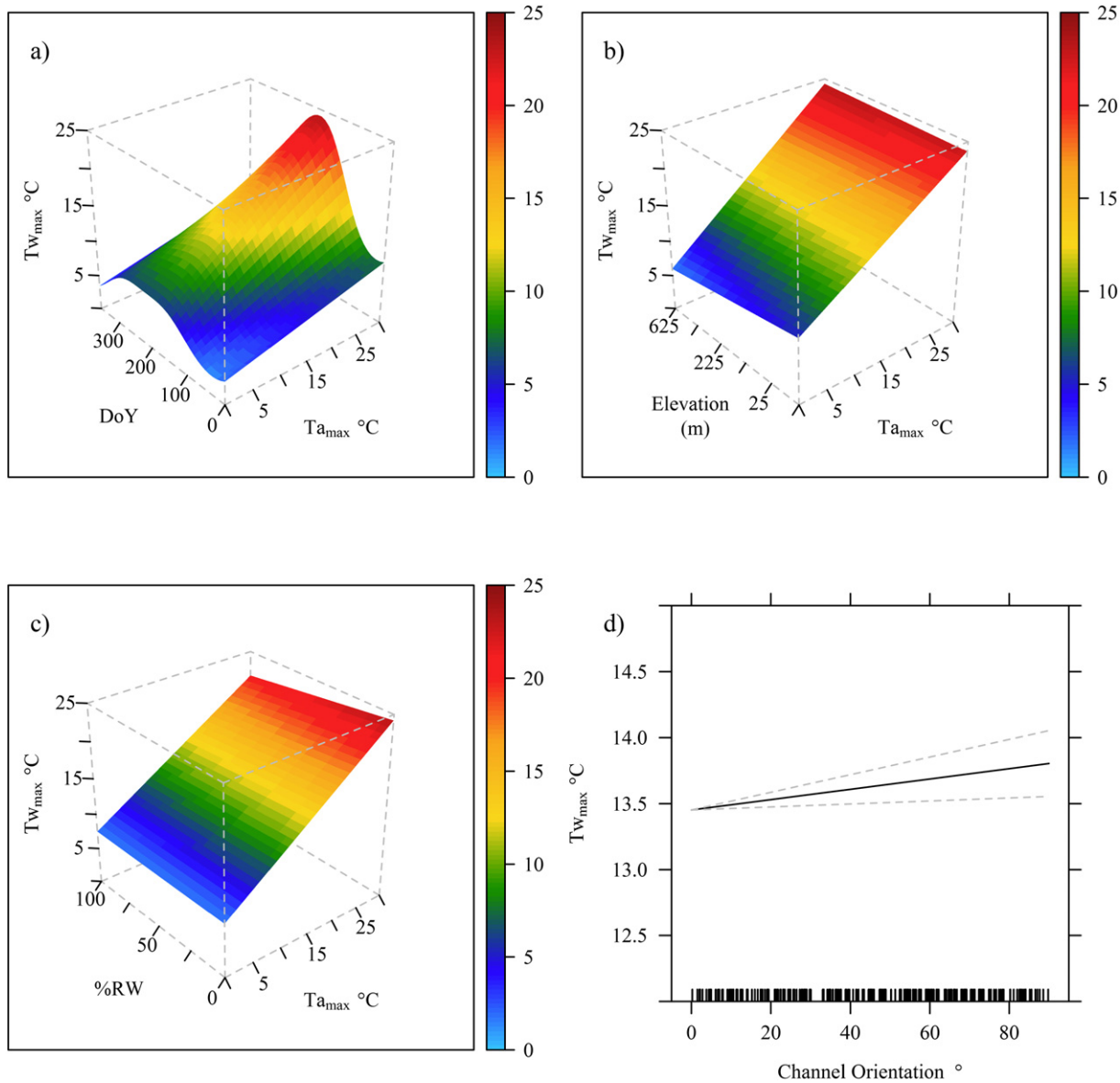

Fig. 3. Joint effects of a) Ta_{max} and DoY, b) Ta_{max} and Elevation, c) Ta_{max} and %RW and the effect of d) Orientation on Tw_{max}. The other covariates are fixed at their median values. Pointwise 95% confidence bands are shown for the Orientation effect. Vertical black lines on the x-axis of the channel orientation plot indicate the presence of data.

likely to become too hot for target species, will be sensitive to climate change, and are susceptible to management action e.g. riparian tree planting.

Although it is simple to describe these information requirements, the modelling needed to underpin this evidence base is challenging and developing rapidly. The models in this study included linear and non-linear terms, seasonally varying coefficients, interaction terms and temporal and spatial correlation at different scales. This complexity was necessary to adequately represent the underlying processes and structure in the data. As far as the authors are aware, this is the first time all of these modelling components have been incorporated in a single model that can predict river temperature and climate sensitivity across time, catchments and regions. The model and its predictions improve understanding of river temperatures, climate sensitivity and the likely effectiveness of riparian planting for Scotland. The Tw_{max} responses to landscape covariates are also potentially generalizable and the modelling approach could be applied to other countries with similar spatial and river temperature datasets. These issues are discussed further below.

4.1. Modelling approach and performance

Statistical models can be used to predict Tw at large spatial scales using landscape covariates that act as proxies for energy exchange processes. Increasingly, spatial models are being developed at catchment (Isaak and Hubert, 2001; Hrachowitz et al., 2010; Imholt et al., 2011; Ruesch et al., 2012; Chang and Psaris, 2013; Detenbeck et al., 2016; Steel et al., 2016; Jackson et al., 2017b) and regional scales (Wehrly et al., 2009; Mayer, 2012; Moore et al., 2013; Luce et al., 2014; Turschwell et al., 2016) to inform management. A few studies have extended these spatial models to include time varying predictors such as Ta or other metrics of energy exchange (McNyset et al., 2015) thereby generating spatio-temporal Tw predictions. However, to date, these models have not included interactions between Ta and time (e.g. DoY) or landscape covariates. As such, Tw sensitivity (to changes in Ta) is constant across the year and the effects of landscape covariates are independent of time and Ta. The modelling approach presented here allowed both the slope and intercept of the Tw~Ta relationships to vary temporally (with DoY) and spatially (with landscape covariates).

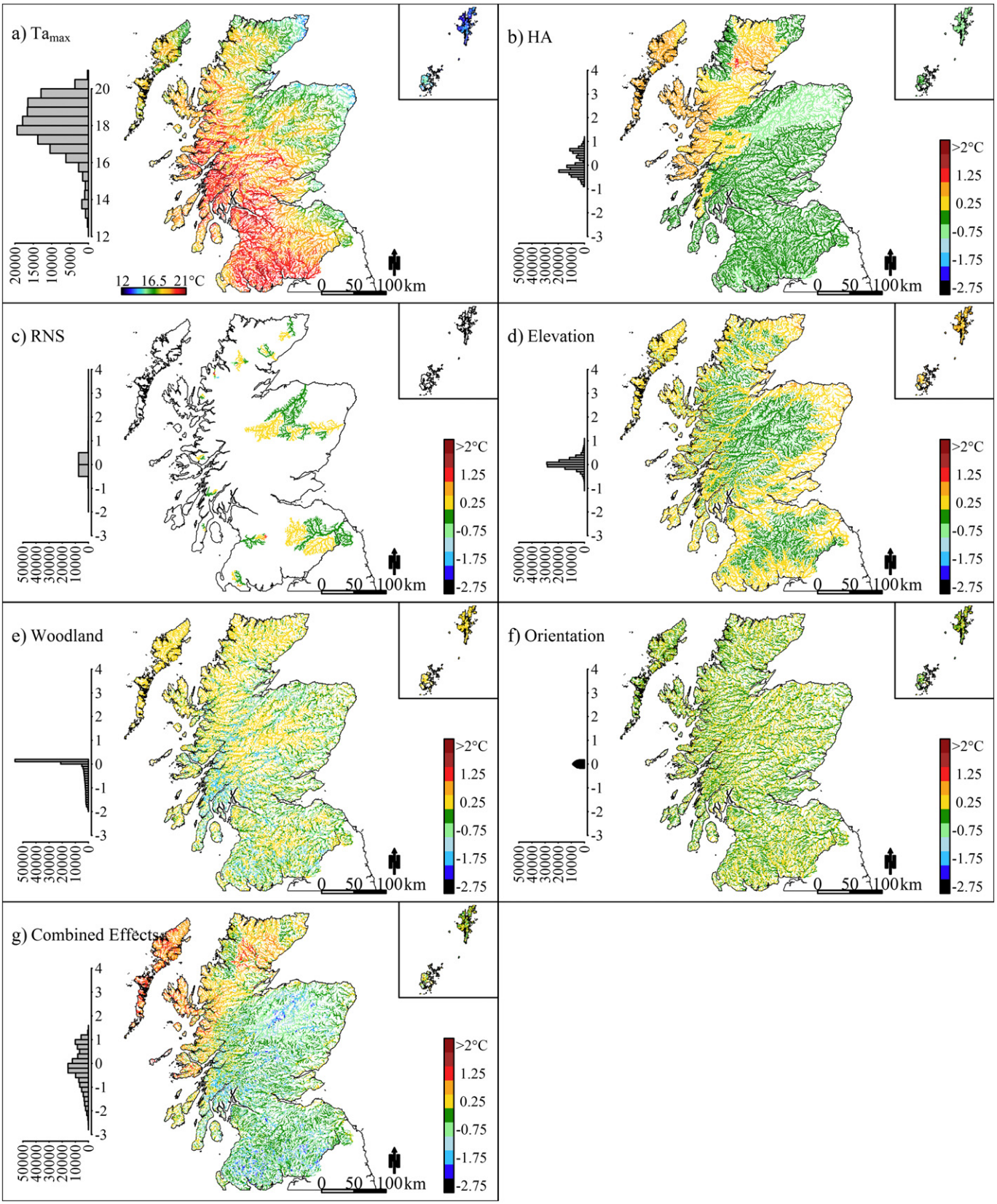

Fig. 4. Effects of Ta_{max}, landscape and spatial covariates on Tw_{max} for the hottest week in the study. Panel a shows the effect of Ta_{max}, conditioned on the median values of the other covariates and DoY 158, consistent with predictions assuming a constant Tw_{max}~Ta_{max} relationship. Panels b-g are difference plots, illustrating the additional effects of covariates, both individually (b–f) and combined (g). Histograms show the distribution of predicted values/differences across all river nodes in Scotland.

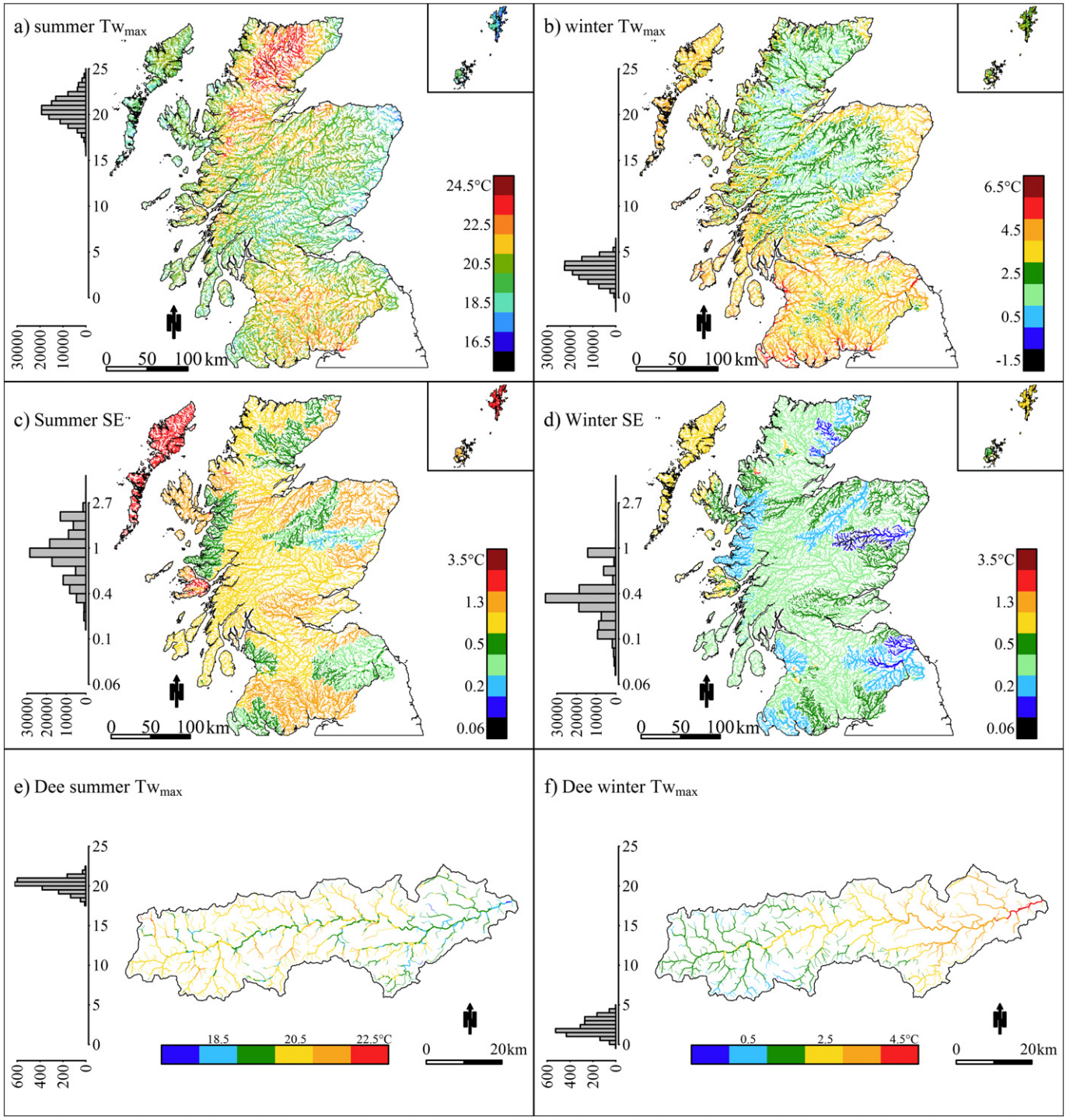

Fig. 5. National Tw_{max} predictions for a) the hottest and b) coldest days of the study (DoY 182 and 16 respectively). Panels c and d show associated standard errors. Panels e and f expand the predictions for the Aberdeenshire Dee.

This allowed Tw_{max} to exhibit a seasonally variable response to Ta (climate sensitivity) and for landscape characteristics to further modify this response.

Although there is increasing awareness of the need to consider spatial correlation in river temperature models, not all studies do so (e.g. Mayer, 2012; McNyset et al., 2015; Jonkers and Sharkey, 2016). In the current study the final model incorporated spatial correlation at two scales (RNS and HAS), representing river network and regional scale spatial covariance, with consequent benefits for model selection (reduced risk of over fitting), more accurate estimates of uncertainty and more precise predictions in catchments and regions where there are data (Isaak et al., 2014).

Where models have incorporated spatial correlation, they are have often been constrained to consider only linear responses between Tw and covariates (Ruesch et al., 2012; Roberts et al., 2013; McNyset et al., 2015; Detenbeck et al., 2016; Steel et al., 2016; Turschwell et al., 2016). While this is reasonable when responses are demonstrably linear, it limits the realistic representation of more complex relationships. The modelling approach in this study used smoothers to represent river network (O'Donnell et al., 2014; Jackson et al., 2017a, 2017b)

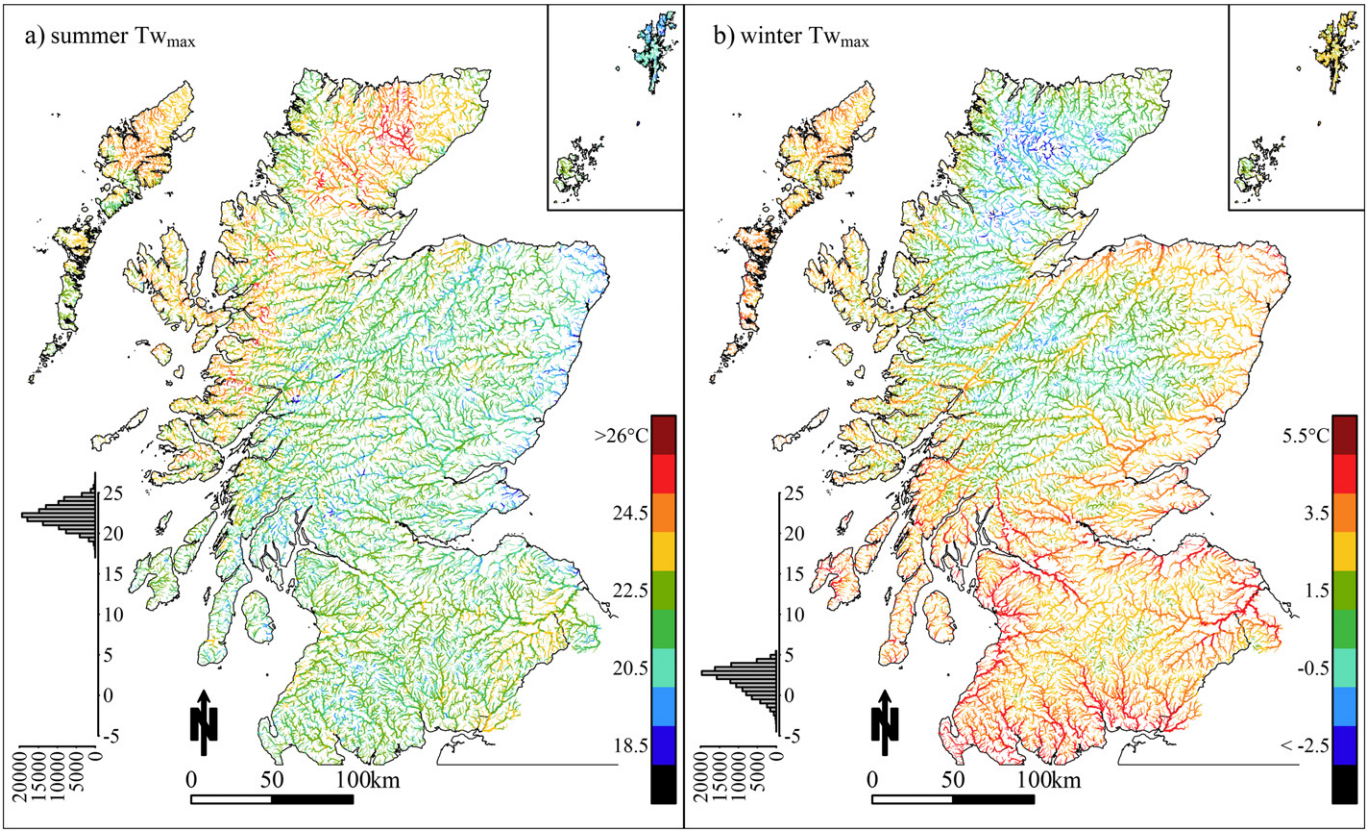

Fig. 6. a) Summer and b) winter Tw_{max} predictions under "extreme" climate conditions. Plots are conditioned on the hottest and coldest Ta_{max} observed at each node in 2003 and 2010 respectively and the DoY that gives the highest and lowest predictions (174 and 16 respectively).

and regional (Millar et al., 2015, 2016) scale spatial covariance thereby allowing the models to be fitted within the 'mgcv' package for R. This made it possible to incorporate more complex responses between Tw_{max} and landscape covariates (Jackson et al., 2017a, 2017b) while also including an auto-regressive temporal correlation structure that has rarely been considered in previous spatio-temporal models (McNyset et al., 2015). Finally, the model included random effects allowing the intercept and slope of the Tw_{max}~Ta_{max} relationship to vary between sites, again improving model selection inference and estimates of uncertainty.

Although associated with greater complexity, spatio-temporal models have a number of potential benefits over simpler spatial models that focus on seasonal or annual summary temperature statistics. By incorporating Ta_{max} as a covariate, and characterising spatial and temporal variability in the Tw_{max}~Ta_{max} relationship, the model can predict Tw_{max} for dates outside the study period, allowing hindcasting and forecasting. This is important where temperature is to be included as a predictor variable in other studies but Tw data are temporally constrained. Furthermore, by modelling daily data, model predictions can be used in detailed biological studies, e.g. fish (Bacon et al., 2005) and invertebrate (Imholt et al., 2010) growth. Spatio-temporal models can also be fitted when there are missing Tw_{max} values in temperature logger time series. This avoids the need for directly comparable time series at all sites, potentially allowing greater spatial coverage and better representation of spatial Tw variability. Finally the spatio-temporal models presented here allow simultaneous assessment of Tw variability and temporally varying climate sensitivity in a single model.

Although many papers have illustrated individual components of the final model presented in this study (see introduction), as far as the authors are aware, this is the first paper to incorporate all these components in a single large scale spatio-temporal model of a Tw metric, thereby addressing the key technical challenges to the development of daily spatio-temporal temperature models summarised by Letcher et al. (2016). Although challenging to specify and fit, the additional model complexity provides more flexible models, reducing bias and giving more appropriate estimates of uncertainty compared to simpler approaches. This is important where management decisions, with associated costs, are dependent on model outputs.

It is not possible to make direct comparisons of model performance between this and other studies because the few examples of spatio-temporal models of daily Tw focus on mean Tw (McNyset et al., 2015; Letcher et al., 2016; Sohrabi et al., 2017) rather than maximum Tw and cover different geographic ranges and numbers of sites. For example, Letcher et al. (2016) monitored four sites in an 11.8 km^2 catchment while McNyset et al. (2015) monitored 510 sites across a 20,000 km^2 catchment. Setting aside these issues, the overall RMSE reported in this paper (1.57 °C) compares reasonably with that in McNyset et al. (2015) (1.29 °C) and Sohrabi et al. (2017) (1.25 °C) but is much higher than that in Letcher et al. (2016) (0.59 °C). However, only McNyset et al. (2015) can be considered broadly comparable to this study, as Sohrabi et al. (2017) and Letcher et al. (2016) also incorporated discharge data in their models, data that were not available in our study (see limitations below).

4.2. Physical process representation

The final model can be reasonably explained by an understanding of physical processes and Tw. The intercept and slope of the Tw_{max}~Ta_{max} relationship varied smoothly with DoY, increasing between winter and summer before declining in the autumn (Li et al., 2014). This likely reflects the influence of lower discharges over the summer and higher discharges in winter, which in turn result in higher and lower sensitivity to climate forcing respectively (Luce et al., 2014; Sohrabi et al., 2017).

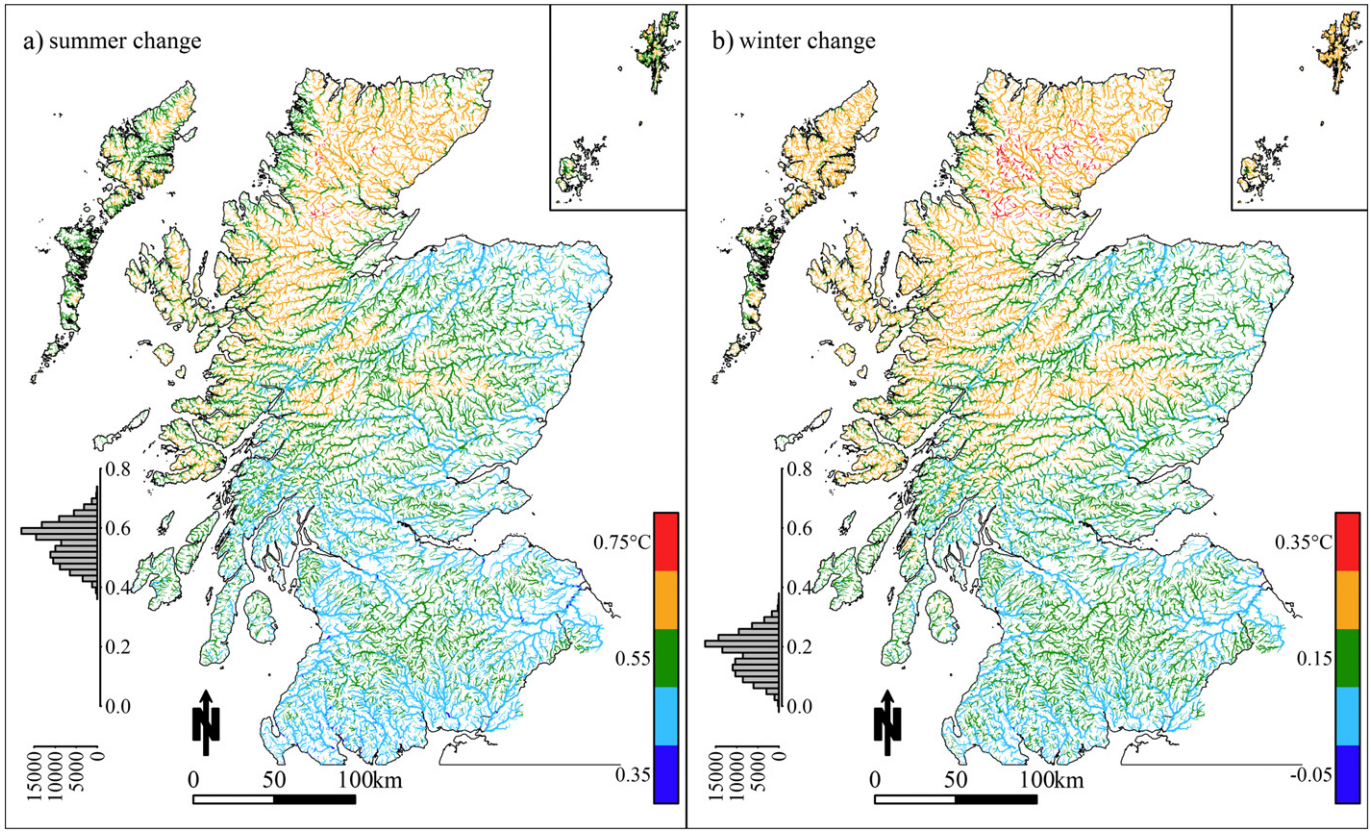

Fig. 7. Sensitivity of rivers to climate change. Maps show the predicted change in Tw_{max} for a 1 °C change in Ta_{max} in a) summer (DoY 169) and b) winter (DoY 350). The DoYs maximise and minimise the slope of the Tw_{max}~Ta_{max} relationship respectively.

Consistent with previous studies, Elevation had a negative effect on Tw_{max} (Isaak and Hubert, 2001; Hrachowitz et al., 2010; Imholt et al., 2011; Ruesch et al., 2012; Chang and Psaris, 2013; Trumbo et al., 2014; Steel et al., 2016; Jackson et al., 2017b). However, in this case Elevation was not simply acting as a proxy for air temperature as this was already included as an explanatory variable. The effect of Elevation was greatest at low Ta_{max} and thus potentially reflected the influence of snow melt on Tw_{max} (Leach and Moore, 2014; Leach et al., 2016) at higher altitudes.

There was a very small positive relationship between %RW and Tw_{max} for low values of Ta_{max} and a stronger negative relationship at high Ta_{max} consistent with previous studies of the effects of riparian woodland (Hannah et al., 2008; Malcolm et al., 2008; Garner et al., 2014, 2015). In summer, woodland reduces the amount of incoming short-wave radiation reaching the channel through shading (Hannah et al., 2008; Garner et al., 2015). In the winter, woodland directs long-wave radiation back to the water surface reducing net energy losses and maintaining higher minimum temperatures than open sites (Hannah et al., 2008; Garner et al., 2015).

The effect of channel orientation was small, but physically plausible and independent of Ta_{max} (i.e. main effect only). Higher temperatures were predicted for north-south rather than east-west orientations (Malcolm et al., 2004; Gomi et al., 2006; Garner et al., 2017) where the effects of shading by channel incision or riparian vegetation would be expected to be smaller.

The HAS characterised large-scale spatially correlated variability in Tw_{max} that was not adequately explained by the landscape covariates. It could include the effects of hydrogeology, hydrology and climate (not explained by Ta_{max}) that were not well characterised in the models. The overall effect of the HAS was to increase Tw_{max} predictions in the west and north of Scotland relative to other areas (Fig. 4b).

The RNS characterised fine scale spatial variability within catchments. The effect was small in all of the catchments (Fig. 4c), suggesting that residual spatial structure in the Tw_{max} data was limited or, more likely, that it varied seasonally and was not adequately described by a temporally constrained RNS.

4.3. Management implications

The outputs of the model in this study provide valuable tools for guiding management decisions and, in particular, riparian tree planting. Depending upon the management objectives, Figs. 6–8 can be used to determine good locations for planting. However, the uncertainty in the predictions should also be considered (Fig. 5b, d), particularly if the primary aim of planting is to manage thermal regime. In locations where uncertainty is high (e.g. Islands) further investigation would be desirable before substantial resource was invested.

Maximum summer temperatures are frequently the focus of management, due to their potentially detrimental impacts on cold water adapted fish (Elliott and Elliott, 2010). Consequently, maps of maximum temperature are often prioritised by managers aiming to reduce temperature extremes. However, many conservation organisations are concerned about the wider ecological impacts of climate change, in which case the illustrations of climate sensitivity (Fig. 7) may be more valuable for focussing management action (Kelleher et al., 2012; Hilderbrand et al., 2014).

Riparian planting is the primary climate change mitigation option being considered by fisheries and river managers in Scotland. Consequently, maps that identify the likely consequences of changing riparian landuse are potentially valuable tools for planning and policy. However, the physical realism of the "planting potential maps" developed in this study was constrained by a) the lack of detail in the available national spatial data sets which, in terms of woodland, essentially only identified

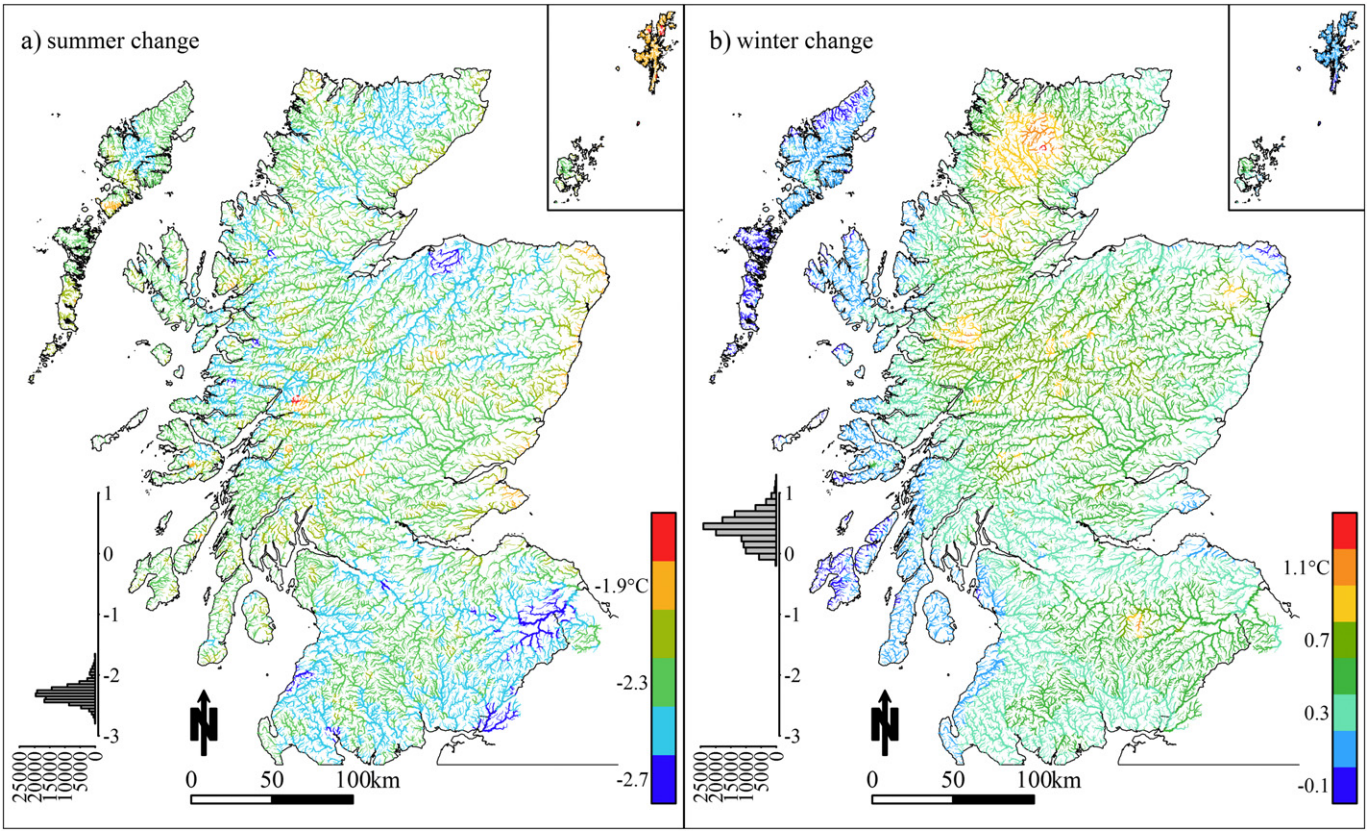

Fig. 8. The predicted change in Tw_{max} when %RW is increased from 0 to 100% in a) summer and b) winter. Plots are conditioned on the hottest and coldest Ta_{max} observed in 2003 and 2010 respectively and the DoY that give the highest and lowest predictions of Tw_{max} (174 and 16 respectively).

the presence of trees rather than their density, height etc.; b) the absence of interaction terms in the model that allow the effects of riparian woodland to vary with other covariates (e.g. DoY, channel orientation, gradient, width). Process based studies have shown that such considerations are important. For example, shading from riparian woodland has a greater effect in narrow low gradient rivers, channel orientation has a substantial impact on shading at intermediate canopy densities (Garner et al., 2017) and canopy density can substantially affect the influence of woodland (Imholt et al., 2013; Leach et al., 2016; Garner et al., 2017). Additionally, deciduous woodland will inevitably have a greater shading effect in summer.

In the short term, the maximum temperature and temperature sensitivity maps might be combined with an understanding of finer scale processes to develop a simple scoring system for prioritising tree planting. Alternatively, it may be possible to develop a single, process derived metric of shading that encompasses topography, riparian vegetation characteristics (i.e. height, density), channel width, channel orientation and velocity, which can then be incorporated into a national spatio-temporal statistical model.

4.4. Limitations and future work

Although the models and data presented in this study represent a significant body of work and advancement in methodology, several limitations remain and these warrant further discussion. First, the model was fitted to a single year of data during which temperatures were generally mild. In colder winters, ice cover prevents surface heat exchange and detaches the Tw_{max}~Ta_{max} relationship (Mohseni and Stefan, 1999). Greater winter snow accumulations may also further moderate spring temperatures (Toffolon and Piccolroaz, 2015; Sohrabi et al., 2017). Under such conditions, the slope of the Tw_{max}~Ta_{max} relationship could be lower in the winter and spring. In contrast, hotter, drier summer conditions may increase the slope of the Tw_{max}~Ta_{max} relationship as high Ta_{max} often coincides with low river flows and lower thermal capacity increases rates of heating (Mohseni and Stefan, 1999). With more years of data, it may be possible to include year random effects, thereby providing predictions for an average condition. Alternatively, discharge and snow cover metrics could be included in the model. Although there is an extensive gauging station network in Scotland (Marsh and Anderson, 2002), there are no models that provide spatially distributed information on discharge (e.g. NOAA, 2016) for Scotland's rivers. 'Prediction in Ungauged Basins' has been a decadal initiative of the International Association of Hydrological Sciences (Sivapalan, 2003) and the development of a model that predicts spatial and temporal variability in discharge in Scotland may benefit Tw modelling.

The characterisation of covariates and choice of underlying spatial data could also be improved. This study necessarily used spatial data that covered the whole of Scotland and that could be processed with available computer resources (Gallice et al., 2015; Millar et al., 2015; Jackson et al., 2016, 2017b). This sometimes required the use of coarser (e.g. DTM), less informative (e.g. woodland) datasets than might have been available or manageable when working at a more local scale. For example, measures of illumination (topographic shading) could be improved using a finer scale DTM. Where working at more local scales, it might be possible to use finer scale DTMs or to draw on remotely sensed lidar data. Similar arguments also apply to the representation of riparian land use where detailed data on tree species, heights or stem density are available for particular areas, but are not available nationally.

The SRTMN sites used to underpin this study were chosen to avoid anthropogenic impacts and the effects of lochs (e.g. Mellina et al., 2002) where possible (Jackson et al., 2016). This means that the models are focussed on understanding spatial variability in near-natural river systems (ignoring issues of historical landuse and vegetation change).

However, thermal discharges (Bae et al., 2015; Xin and Kinouchi, 2013), abstraction (Bae et al., 2015; Xin and Kinouchi, 2013) inter-basin water transfers (Elmore et al., 2016), impoundment and release of water from reservoirs and dams (Dickson et al., 2012; Maheu et al., 2016) and morphological alteration of rivers can all affect river temperature. Where these effects have (unknowingly) been introduced to our dataset they will be reflected in unexplained variability in Tw. Predictions of Tw for rivers affected by these pressures will be less accurate than for other areas, but would instead reflect a prediction of more natural or "reference" conditions. Future work could therefore investigate opportunities for incorporating data on "pressures" into the existing models, while also strategically locating new Tw monitoring to characterise their effects. This application could also inform river management under legislation such as the EU Water Framework Directive, where there is a need to identify and manage pressures to attain good ecological status.

Finally, the models in this study were constrained by the form of the RNS which modelled spatial covariance within catchments. This covariance was fixed across the year (i.e. did not interact with DoY) thereby implicitly assuming that any spatial structure in Tw_{max} that could not be explained by the covariates was constant over time. This is unlikely to be true as spatial variability in Tw is greater at higher temperatures and low flows during the summer (Jackson et al., 2017b) and sites with positive residuals in the summer could well have negative residuals in the winter with effects cancelling out over the year. Consequently, the RNS may be not be adequately explaining the residual spatial structure in the data. Future models could benefit from a temporally varying RNS (that interacts with DoY), but this cannot be implemented with existing software and would require statistical development.

5. Conclusions

This paper reports the results of a novel, large scale Tw modelling study that used the strategically designed and quality controlled Scotland River Temperature Monitoring Network (SRTMN) to understand and predict daily maximum river temperatures across Scotland. The model developed here overcomes some major technical challenges to include time varying Tw~Ta relationships, temporal and spatial correlation (at multiple scales), and non-linear effects of landscape controls. By incorporating Ta_{max} as a covariate, the model can predict Tw_{max} for dates outside the study period, allowing hindcasting and forecasting, and can impute missing Tw_{max} values for discontinuous or incomplete temperature logger time series. By allowing interactions between Ta, DoY and landscape covariates, seasonally variable climate sensitivity across the whole of Scotland could be predicted for the first time. The maps of predicted Tw_{max} under different scenarios are valuable tools for understanding and managing thermal regime with benefits for rivers and fisheries management.

Acknowledgements

This project is part of Marine Scotland Science (MSS) Freshwater Fisheries Laboratories Service Level Agreement FW02G and it is supported by a NERC Open CASE studentship (University of Birmingham and MSS) awarded to Faye Jackson; grant reference NE/K007238/1. Some map features are based on digital spatial data licensed from the Centre of Ecology and Hydrology, NERC © Crown Copyright and database right (2016), all rights reserved, Ordnance Survey License number 100024655. Catchment boundaries were from SEPA (2009). The digitised river network is from the CEH and includes Scottish Environmental Protection Agency (SEPA) coding. Catchment boundaries were from SEPA (2009) and Salmon rivers from Marine Scotland (2008). The gridded Ta dataset was from UKCP09: Daily gridded air temperature datasets UK MET Office. Tw data will be made available as a referenceable dataset, through the Scotland River Temperature Monitoring Network webpages with an associated metadata description. The authors also thank the Scotland River Temperature Monitoring Network collaborators for their contribution to data collection (http://www.gov.scot/Topics/marine/Salmon-Trout-Coarse/Freshwater/Monitoring/temperature/Collaborating).

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