

1 **Empirical validation of the InVEST water yield ecosystem service**
2 **model at a national scale**

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21 **Abstract**

22 A variety of tools have emerged with the goal of mapping the current delivery of ecosystem services
23 and quantifying the impact of environmental changes. An important and often overlooked question
24 is how accurate the outputs of these models are in relation to empirical observations. In this paper
25 we validate a hydrological ecosystem service model (InVEST Water Yield Model) using widely
26 available data. We modelled annual water yield in 22 UK catchments with widely varying land cover,
27 population and geology, and compared model outputs with gauged river flow data from the UK
28 National River Flow Archive. Values for input parameters were selected from existing literature to
29 reflect conditions in the UK and were subjected to sensitivity analyses. We also compared model
30 performance between precipitation and potential evapotranspiration data sourced from global- and
31 UK-scale datasets. We then tested the transferability of the results within the UK by additional
32 validation in a further 20 catchments.

33 Whilst the model performed only moderately with global-scale data (linear regression of modelled
34 total water yield against empirical data; slope = 0.763, intercept = 54.45, $R^2 = 0.963$) with wide
35 variation in performance between catchments, the model performed much better when using UK-
36 scale input data, with closer fit to the observed data (slope = 1.07, intercept = 3.07, $R^2 = 0.990$). With
37 UK data the majority of catchments showed less than 10% difference between measured and
38 modelled water yield but there was a minor but consistent overestimate per hectare (86
39 $\text{m}^3/\text{ha}/\text{year}$). Additional validation on a further 20 UK catchments was similarly robust, indicating
40 that these results are transferable within the UK. These results suggest that relatively simple
41 models can give accurate measures of ecosystem services. However, the choice of input data is
42 critical and there is a need for further validation in other parts of the world.

43 **Keywords**

44 UK, mapping, rainfall, evapotranspiration, river flow, land cover

45

46 **1. Introduction**

47 Ecosystem services are increasingly used to assess likely impacts of environmental change in societal
48 and economic terms and to provide a rationale for conservation or environmental management
49 (Tallis *et al.* 2008; Braat & de Groot 2012). However, to incorporate the ecosystem services concept
50 into assessments and decision making, there is a requirement for accurate mapping and
51 measurement of ecosystem services (Malinga *et al.* 2015). In some cases, this requirement has
52 itself been incorporated into policy (European Commission 2011).

53 To meet this rising demand there has been a proliferation of methods and tools to map, quantify
54 and value the provision of ecosystem services (Fisher, Turner & Morling 2009; Seppelt *et al.* 2011;
55 Malinga *et al.* 2015). These vary in complexity from simple approaches based on maps and land use
56 or habitat-based proxies to complex, process-based models (Seppelt *et al.* 2011). Ecosystem service
57 tools have been designed and applied at widely varying geographic locations and both spatial and
58 temporal scales. Potential users must thus choose which tools are most appropriate for their
59 particular situation, and be aware of the limitations of these tools (Willcock *et al.* 2016). Recent
60 reviews have identified that one of the key obstacles to successful ecosystem service mapping and
61 implementation into decision making processes is the comparative scarcity of validation or
62 measurements of uncertainty in many applications of ecosystem service models (Seppelt *et al.* 2011;
63 Maes *et al.* 2012; Schulp *et al.* 2014; Malinga *et al.* 2015). Whilst it is frequently acknowledged that
64 ecosystem service models function at best as reliable proxies, and at worst as crude estimates, the
65 validation of the results of ecosystem service models against empirical measurements is
66 comparatively rare (Seppelt *et al.* 2011; Vigerstol & Aukema 2011; Schulp *et al.* 2014; Hamel &
67 Guswa 2015). Of those studies which do employ validation, many do so at a limited number of
68 locations to check the performance of a model within their study region (e.g. Bai *et al.* 2013; Boithias
69 *et al.* 2014; Terrado *et al.* 2014; Xiao *et al.* 2015). Whilst this is entirely sensible, the results of such
70 local-scale validation are less likely to be transferrable to new locations and the regional or national
71 scales at which ecosystem service models are most widely used (Martínez-Harms & Balvanera 2012)
72 and most water resource planning takes place (Watts *et al.* 2015). Several studies have compared
73 different ecosystem service models (e.g. Vigerstol & Aukema 2011; Cheaib *et al.* 2012; Rosenzweig
74 *et al.* 2014; Dennedy-Frank *et al.* 2016), which gives some insight into the *uncertainty* surrounding
75 the modelling of the service in question (see Hou, Burkhard and Müller (2013) concerning
76 uncertainty in ecosystem service modelling) and the utility of the different models, but does not
77 provide insight into the *accuracy* of each model in estimating ecosystem service delivery or
78 representing the biophysical process underpinning the service.

79 This relative scarcity of large-scale validation means that, for many models, there is comparatively
80 little information on either the accuracy of model outputs (Seppelt *et al.* 2011), or on the
81 performance of models in different circumstances and locations, especially where the latter are in
82 poorly-studied regions. There is also a lack of information on the requirements of the input data. In
83 many cases, the availability and spatial coverage of data is inversely correlated with its resolution
84 (Hijmans *et al.* 2005) and, potentially, its accuracy. Thus it is uncertain whether the most widely
85 available data, even when used in a model which performs well under ideal circumstances, will
86 produce sufficiently accurate results. Potential users are thus missing vital information on the

87 performance of models, which they need if they are to make informed decisions on which tools to
88 use and how best to employ them to provide accurate assessments for decision makers (Willcock *et*
89 *al.* 2016). Validation also provides valuable feedback to ecosystem service model developers who
90 are seeking to improve the accuracy, utility and efficiency of their models.

91 Hydrological services are particularly well suited to empirical validation, as the ecosystem processes
92 which underpin them (e.g. runoff of water, nutrients and sediment) have physical expressions which
93 can be directly measured at appropriate spatial and temporal resolutions (river flow, nutrient
94 concentration and sediment load, respectively). In the UK, these measurements are undertaken by
95 government bodies and are readily available for academic purposes (e.g. The National River Flow
96 Archive, NRFA).

97 This study aims to validate a hydrological ecosystem service tool at the national scale, using widely
98 available spatial data (of the sort available to most potential users and decision makers) for both
99 model inputs and validation. We used a tool from a widely used, open-source ecosystem service
100 modelling suite, InVEST (Integrated Valuation of Ecosystem Services and Tradeoffs, Sharp *et al.*
101 2015). Whilst InVEST tools have been widely used for a variety of research and planning applications
102 (e.g. British Hydropower Association 2010; Bai *et al.* 2013; Bangash *et al.* 2013; Leh *et al.* 2013;
103 Boithias *et al.* 2014; Terrado *et al.* 2014; Pessacg *et al.* 2015; Xiao *et al.* 2015), as with other
104 ecosystem service models, comparatively few applications have employed an empirical validation of
105 results at anything other than a local scale. Therefore our objectives are 1) to examine the
106 sensitivity of the model to variation in the values of input parameters in a UK context; 2) to compare
107 the performance of the model using two points on the spectrum of data availability and spatial
108 coverage (global climatic data and UK specific climate data) by validation against empirical
109 measurements; 3) to examine whether our results are transferable within the UK.

110 2. Methods

111 2.1. THE INVEST WATER YIELD MODEL

112 The InVEST suite of tools has been developed to enable decision makers to assess trade-offs among
113 ecosystem services and to compare scenarios of change, for example in land use or climate (Sharp *et*
114 *al.* 2015). To this end, InVEST comprises a set of models covering a wide variety of ecosystem
115 services. The models are based on comparatively simple production functions, being intended to
116 run quickly on a standard desktop computer and to take advantage of readily available data (Sharp
117 *et al.* 2015). Although InVEST models are not designed to reproduce empirical observations, the
118 water yield model is intended to quantify the relative yields of different catchments or sub-
119 catchments, and be sensitive to modelled changes in drivers such as land use change or climate

120 change. We would also suggest that, because the model produces figures of water yield which
121 appear to have a high degree of numerical precision, and is freely available, it is important to test
122 whether the results are accurate, as users may not always familiarise themselves with the intended
123 use and limitations of the model before incorporating the results into the decision making process
124 (see Willcock *et al.* 2016).

125 The InVEST water yield model (Hydropower/Water Yield, InVEST v3.2.0, Sharp *et al.* 2015) calculates
126 annual water yield from a catchment, with the intended end use of reservoir hydropower
127 production (Sharp *et al.* 2015). Although hydropower forms a relatively small contribution to the UK
128 energy sector (DECC 2015), total annual water yield can be considered in the light of many potential
129 services, including agricultural irrigation, provision of drinking water, hydropower and industrial
130 abstraction. The UK is densely populated and has a large proportion of its land area under
131 anthropogenic land uses. This leads to competition between demands for water, which is likely to
132 intensify in the future due to population growth and climate change (Weatherhead & Knox 2000;
133 Knox *et al.* 2009). Validated models of current and predicted future water yield, with clear estimates
134 of their accuracy and uncertainty, are thus of great importance in strategic water resource planning
135 (Watts *et al.* 2015). Therefore, in this study we focused on the biophysical output of water yield. As
136 the InVEST model is compartmentalised into water yield, water consumption and hydropower
137 valuation, we used the first two components only.

138 The model estimates the total annual water yield (Y) for each grid square (x) of the study catchment
139 as total catchment annual rainfall (P) minus total catchment annual actual evapotranspiration (AET)
140 (equation 1). The model assumes that, on an annual time step, all water falling as rainfall over a
141 catchment, minus that which is evapotranspired, leaves the catchment. No distinction is made
142 between surface and sub-surface water flow.

Eqn. 1
$$Y(x) = \left(1 - \frac{AET(x)}{P(x)}\right) \cdot P(x)$$

143 In practice, the measurement of annual actual evapotranspiration at the catchment scale is
144 extremely difficult. Even plot scale evaluation requires highly specialised equipment, and plot and
145 field scale methods to determine actual evapotranspiration are problematic to apply at the
146 landscape scale (Evans *et al.* 2012). The InVEST approach relates AET to potential evapotranspiration
147 (PET), which is easier to model, using the methodology developed by Budyko (1974) and later
148 adapted by Fu (1981) and Zhang *et al.* (2004) (equation 2) where ω is an empirical parameter which

149 defines the shape of the curve relating potential to actual evapotranspiration.

$$\text{Eqn. 2} \quad \frac{AET(x)}{P(x)} = 1 + \frac{PET(x)}{P(x)} - \left[1 + \left(\frac{PET(x)}{P(x)} \right)^\omega \right]^{1/\omega}$$

150 PET is estimated as the product of the reference evapotranspiration and the crop coefficient for
151 each grid square. ω is related to the plant available water content (AWC), precipitation and the
152 constant Z which captures the local precipitation pattern and additional hydrogeological
153 characteristics (equation 3) (Sharp *et al.* 2015).

$$\text{Eqn. 3} \quad \omega = Z \frac{AWC(x)}{P(x)} + 1.25$$

154 For a more detailed description of the water yield model see Sánchez-Canales *et al.* (2012); Bangash
155 *et al.* (2013); Hamel and Guswa (2015); Pessacg *et al.* (2015); and Sharp *et al.* (2015).

156 2.2. MODEL INPUT PARAMETERS

157 The InVEST model requires five biophysical parameters as georeferenced rasters. These are root
158 restricting layer depth (mm), plant available water content (AWC, as a proportion), average annual
159 precipitation (mm), average annual potential evapotranspiration (PET, mm) and land use/land cover
160 (LULC). We obtained these data from a variety of sources, with the aim of ensuring that the data
161 were easily obtainable and free to license for at least academic use. These are the kind of data
162 which are likely to be most widely used in a freely available tool such as InVEST, in terms of
163 precision, spatial resolution and spatial coverage.

164 Root restricting layer depth and AWC were obtained from the European Soil Database (ESDB)
165 version 2.0 (Panagos 2006; Panagos *et al.* 2012). Annual precipitation and reference
166 evapotranspiration were obtained from several alternative sources. We used two pairings of these
167 two variables, to compare model performance with data from two points on the spectrum of data
168 availability and spatial coverage. First, we used global scale precipitation data from WorldClim
169 (Hijmans *et al.* 2005) and PET from the CGIAR-CSI Global-Aridity and Global-PET Database (Zomer *et al.*
170 *et al.* 2007; Zomer *et al.* 2008). These are both freely available and have global coverage, at
171 approximately 1km resolution. Secondly, we used UK Met Office UKCP09 precipitation data at 5km
172 resolution (Perry & Hollis 2005; Jenkins, Perry & Prior 2008) and Met Office Rainfall and Evaporation
173 Calculation System (MORECS) evapotranspiration data. These datasets are UK-specific and available
174 to a wide variety of users under the UK's open government license. Where necessary, data were
175 geoprocesed to meet the data formatting requirements of the InVEST model in ArcMap (v10.1,
176 ESRI, Redlands, CA).

177 Where possible, all input data were limited to the same date range as the validation data (2000-
178 2010, see below) and averaged across years, giving average annual precipitation and average annual
179 PET. LULC data were obtained from the 25 m raster version of the UK Land Cover Map 2007
180 (LCM2007, Morton *et al.* 2011).

181 The InVEST model also requires several tabular values for each LULC class. These include whether
182 the land cover class is vegetated or not, rooting depth and a plant evapotranspiration coefficient
183 (K_c). This last is used to obtain potential evapotranspiration by modifying the reference
184 evapotranspiration, which is based on a 15cm tall surface of actively growing, well-watered grass.
185 We estimated these coefficients for LCM2007 broad habitat classes by matching class descriptions
186 with those in Canadell *et al.* (1996), Allen *et al.* (1998) and Sharp *et al.* (2015). Further amendments
187 were made to these values, to reflect the damp climate of the UK (Smethurst, Clarke & Powrie
188 2012). This generally resulted in raised crop coefficients and shallower rooting depths. The
189 coefficients for urban and suburban areas were amended to reflect the approximate proportion of
190 green space they typically contain (20% and 60% respectively). Coefficients for K_c and rooting depth
191 for each LCM2007 broad habitat are given in Supplementary Material, Table S1. For arable land uses,
192 actual evapotranspiration varies over the course of a year as crops are sown, grow and are harvested
193 before the land is then re-cultivated. Evapotranspiration of growing crops also varies between crop
194 plant species, crop condition and many other factors (Allen *et al.* 1998; Hulme, Rushton & Fletcher
195 2001). For UK crops and soil conditions, preliminary investigation and previous studies (Allen *et al.*
196 1998; Hulme, Rushton & Fletcher 2001) suggested a value of K_c close to one to best represent
197 annual evapotranspiration from arable land.

198 The seasonality constant (Z) was estimated as $0.2 \cdot N$, where N is the average number of rain days ($>$
199 1mm) per year over the study period (Donohue, Roderick & McVicar 2012; Hamel & Guswa 2015). N
200 was estimated at approximately 150 from UK Met Office data
201 (<http://www.metoffice.gov.uk/climate/uk/datasets/>), giving a value of 30 for Z .

202 Because the validation data (i.e. gauged annual yield, see below) are affected by any consumptive
203 water use, it was important to account for this. The InVEST model uses a comparatively crude
204 method of estimating consumptive water use, by assigning a value of annual consumption per
205 hectare to each land cover class (Sharp *et al.* 2015). Because abstraction varies widely across the UK
206 (DEFRA 2015), we split the LULC raster based on administrative regions, such that each LULC class-
207 region combination had a unique value, allowing us to assign a suitable abstraction value from
208 regional abstraction statistics (DEFRA 2015). We used only the values for abstraction for agricultural
209 purposes (assigned to the arable LULC class) and public and industrial water supply (assigned to the
210 urban/suburban LULC class), as most other uses (e.g. hydropower) do not consume water but return

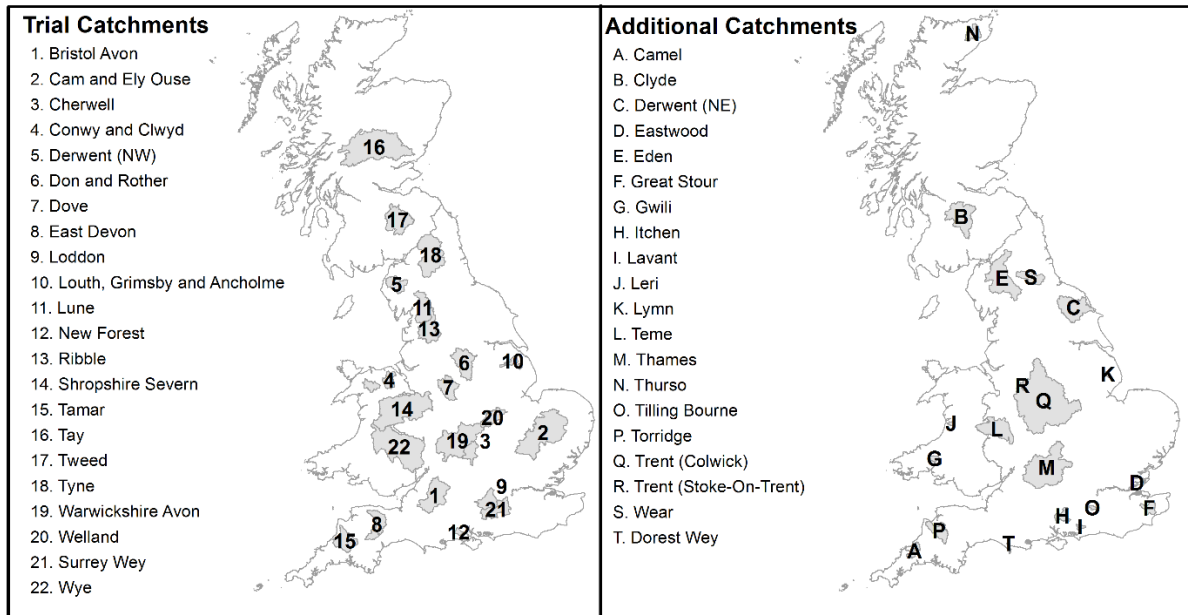
211 it to the catchment after use (Terrado *et al.* 2014). Public and industrial water supply may also
212 return water after use, but in many cases it may be returned further downstream from the point at
213 which it was abstracted, or to a different catchment.

214 2.3. SENSITIVITY ANALYSIS

215 We investigated the sensitivity of the model to variations in precipitation, PET, rooting depth, AWC,
216 K_c and Z following Sánchez-Canales *et al.* (2012) and Hamel and Guswa (2015). The biophysical
217 parameters, which are input as rasters, were varied by $\pm 10\%$ and $\pm 20\%$ applied uniformly across the
218 raster. Sensitivity to K_c was examined by varying its value for the two dominant LULC classes across
219 all catchments (arable and improved grassland), by the same proportions as the biophysical
220 parameters. Sensitivity to Z was tested using values of zero, one, two, five and further increments of
221 five up to 50. The model was run independently for each of these variations.

222 2.4. VALIDATION DATA

223 For initial validation of the model and comparison of the two sets of climate datasets we selected 22
224 catchments in England, Scotland and Wales with widely varying land cover, rainfall, elevation, and
225 geology (Fig. 1 and Supplementary Material, Table S2). All of these factors are likely to affect actual
226 water yield and, potentially, the performance of the InVEST water yield model. Empirical
227 measurements of gauged daily water flow were obtained from the National River Flow Archive
228 (NRFA), which collates, quality controls, archives and disseminates hydrometric data from gauging
229 station networks operated by government environmental bodies across the UK (Fry & Swain 2010).
230 The catchments for each NRFA gauging station have been defined using the Centre for Ecology &
231 Hydrology's Integrated Hydrological Digital Terrain Model (Morris & Flavin 1990). We calculated
232 total gauged annual water yield for each catchment by summing gauged daily mean flow for each
233 year from 2000 – 2010 and took the mean value across years. We analysed how well the modelled
234 data predicted the empirical data using linear regression. This was done using total annual yield, but
235 also the per hectare yield, i.e. the total yield divided by the catchment area, to remove trivial
236 correlation caused by the large variation in area among the catchments. These calculations (and all
237 subsequent data manipulation and statistics) were performed in R (v3.1.0, R Core Team 2014).



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239 Fig. 1 Coastline of Great Britain overlain with the 22 trial catchments selected for testing the InVEST
 240 water yield model and the 20 additional catchments used for additional validation (grey shaded
 241 areas). See Supplementary Material, Table S2 for catchment characteristics.

242 2.5. ADDITIONAL VALIDATION OF THE MODEL

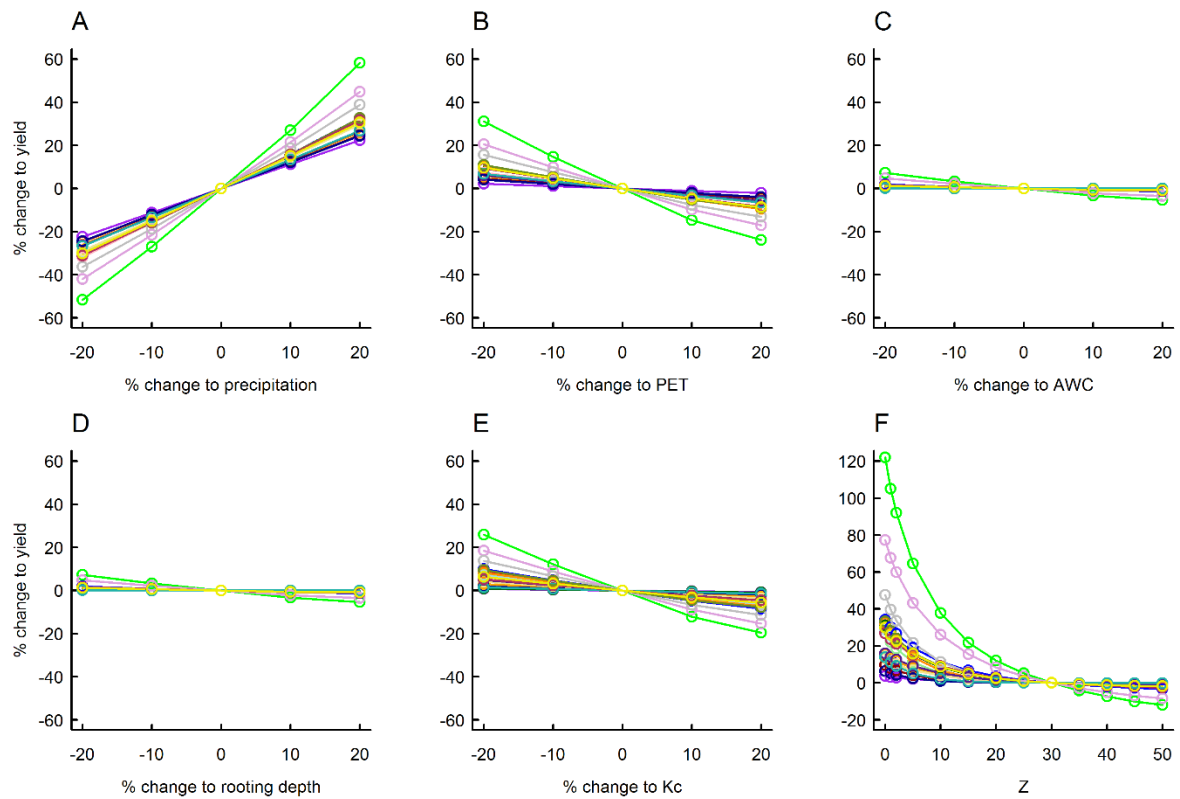
243 To ensure that our selected values of K_c , Z and input datasets for precipitation and PET did not
 244 simply ‘calibrate’ the model to the 22 trial catchments, (i.e. to check that the model performance
 245 obtained from the trial catchments was representative of UK catchments in general and thus that
 246 our results are transferable between UK catchments) we selected the climatic datasets and
 247 parameter values which resulted in the best fit to validation data for the original 22 catchments, and
 248 used these to run the model for a further 20 catchments (Fig. 1). Catchments were again defined
 249 from NRFA gauging station locations and were chosen to show wide variation in area, land cover and
 250 geology (Supplementary Material, Table S2).

251 **3. Results**

252 3.1. SENSITIVITY ANALYSIS

253 Modelled water yield was highly sensitive to changes in precipitation (Fig. 2A), with a 10% increase
 254 in precipitation resulting in an 11% -27% increase in water yield, and was somewhat less sensitive to
 255 variation in PET (Fig. 2B). Sensitivity to both precipitation and PET was highly catchment specific.
 256 With PET, in some catchments a 10% increase in PET resulted in a 14% decrease in water yield, while
 257 the mean decrease was only 5%. The model was relatively insensitive to rooting depth and AWC,
 258 with a 10% increase in either of these datasets resulting in a yield decrease of 0% - 3%. Sensitivity to

259 Kc was roughly similar to that for PET, which is unsurprising since the effect of the former in the
 260 model is to modify the latter, and was likewise catchment specific. In general, catchments were
 261 either 'highly sensitive', responding to variation in values of all input parameters with variation in
 262 water yield, or 'less sensitive', showing comparatively little variation in water yield with any variation
 263 in the values of model input parameters, although the latter still responded to percentage changes
 264 in precipitation with at least a corresponding percentage change in modelled yield.



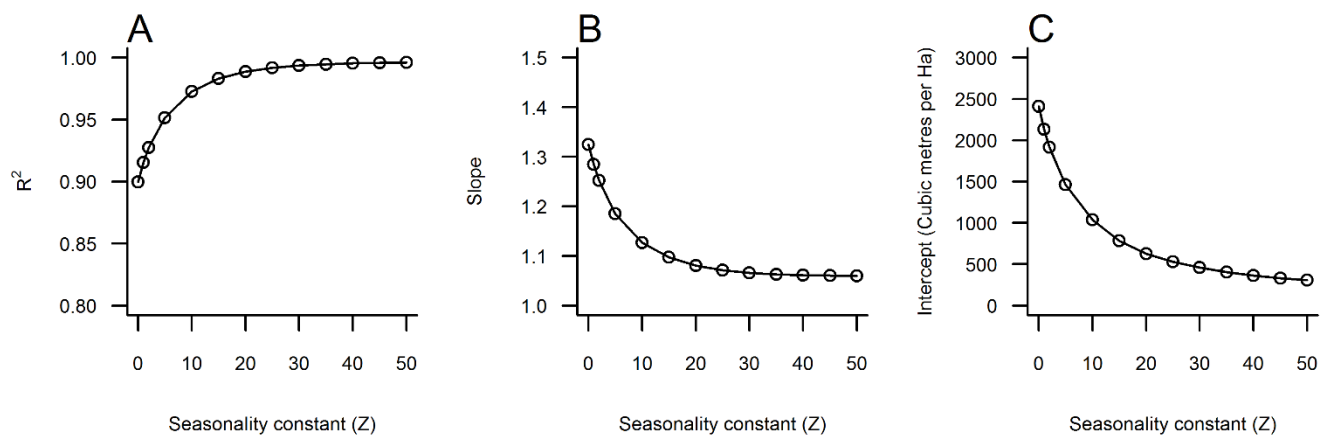
265
 266 Fig. 2 Sensitivity of the InVEST water yield model to variation in the values of input parameters for 22
 267 test catchments. Variation shown as percentage change relative to a 'baseline' run with $Z = 30$ using
 268 UKCP09/MORECS data. A coloured set of points with connecting line are shown for each catchment.

269 Catchment sensitivity to variation in precipitation (and thus in other model parameter values) was
 270 significantly positively correlated with mean PET (Pearson's $r = 0.555$, $p = 0.011$) and area of arable
 271 land (Pearson's $r = 0.759$, $p < 0.001$), and significantly negatively correlated with altitude (Pearson's r
 272 $= -0.676$, $p = 0.001$) and area of semi-natural habitat (Pearson's $r = -0.577$, $p < 0.008$). All of these
 273 catchment characteristics are significantly inter-correlated, such that catchments with higher mean
 274 altitude have a lower cover of arable land and a correspondingly higher cover of semi-natural habitat
 275 and a lower mean PET.

276 The sensitivity of the model to changes in the value of Z was also strongly catchment specific (Fig.
 277 2F), as expected given the spatial variation in the biophysical variables which modulate the effect of

278 Z on water yield (Hamel & Guswa 2015). Because it is difficult to translate the sensitivity of the
 279 model to Z into an appropriate value of Z to use, the outputs from models with varying values of Z
 280 were compared to the validation data to identify which value of Z resulted in the best fit to the
 281 validation data. The results of this analysis (Fig. 3) showed that model fit (R^2) levelled off at $Z \approx 30$
 282 (Fig. 3A), as did slope (Fig. 3B), whilst overestimation of per hectare water yield was also much
 283 reduced at values above 30 (Fig. 3C). This supports the value of $Z = 30$ for the model runs detailed
 284 below and hence the estimation of Z from mean annual rain days.

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287 Fig. 3 Effects of varying the value of the seasonality constant (Z) on the relationship between
 288 modelled and gauged water yield for 22 test catchments, using the UKCP09/MORECS data. A) R^2 of
 289 linear regression between modelled and gauged catchment yield; B) Slope of linear regression
 290 between modelled and gauged catchment yield; C) Intercept of linear regression between modelled
 291 and gauged yield per hectare.

292 3.2. MODEL VALIDATION AND COMPARISON OF CLIMATIC DATASETS

293 Both global- and UK-scale climate datasets resulted in estimated water yields which were strongly
 294 correlated with empirical yields obtained from NRFA gauged river flow (Fig 4, Table 1). The
 295 WordClim and CGIAR-CSI data performed less well than the UKCP09/MORECS datasets. Although R^2
 296 values for models using the global input data were only slightly lower (e.g. 0.96 compared with 0.99;
 297 Table 1), the slope values for per hectare yield (including confidence intervals) were less than one
 298 (Table 1). Hence the global data led to considerable under-estimates (up to 45%) of water yield for
 299 catchments where the yield per hectare was high and to overestimates of water yield for those
 300 where it was low (Fig. 4B), leading to the intercept of 1443.63 m^3 per hectare per year. By contrast,
 301 the UKCP09/MORECS data led to more consistent and accurate estimates for total water yield when
 302 adjusted for consumptive abstraction (Table 1). When per hectare yield was considered, the

303 UKCP09/MORECS data gave good fits to the NRFA data ($R^2 = 0.949$), with a slope not significantly
 304 different from one and the intercept indicating a consistent but minor overestimate of 86.3 m³ per
 305 hectare per year when adjusted for consumptive abstraction (Fig 4D).

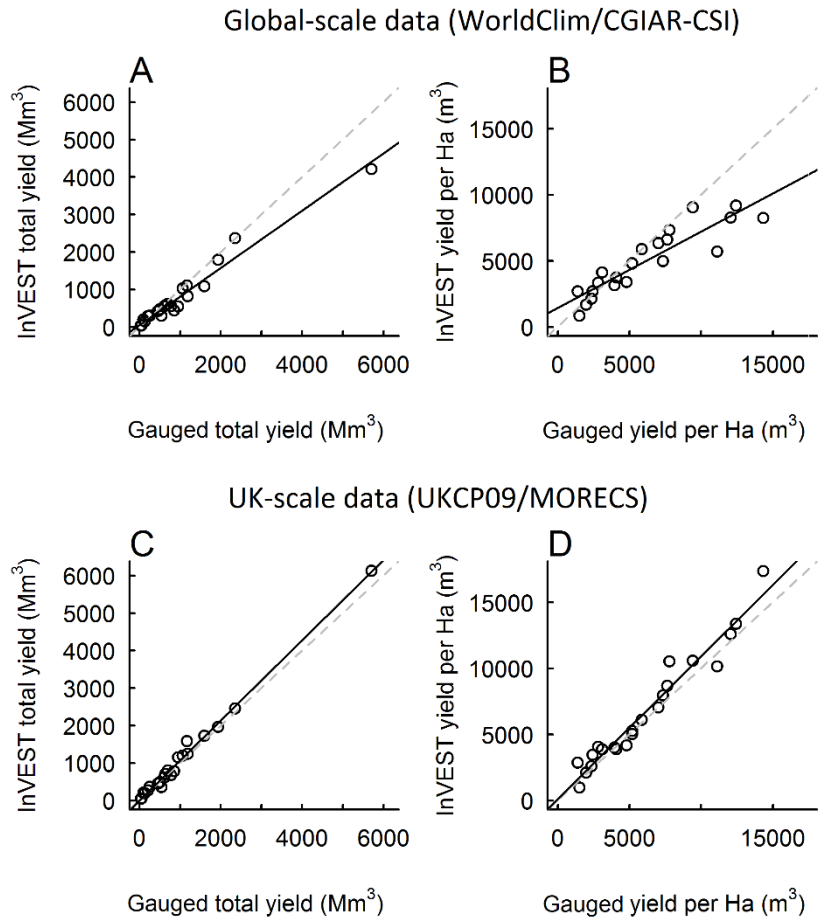
306 Table 1. Results of linear regressions between InVEST modelled and empirical water yield for the 22
 307 original catchments, using two input datasets for the precipitation and reference evapotranspiration
 308 parameters. Intercept, slope \pm 95% confidence interval and R^2 are given for total catchment yield in
 309 millions of cubic metres and yield per hectare in cubic metres, for both raw water yield (R) and yield
 310 adjusted for consumptive abstraction (A)

Input data	Abstraction	<u>Total estimated yield</u>			<u>Estimated yield per hectare</u>		
		Intercept	Slope	R^2	Intercept	Slope	R^2
WordClim/ CGIAR-CSI	R	86.52	0.759 \pm 0.072	0.958	1814.68	0.549 \pm 0.131	0.781
	A	54.45	0.763 \pm 0.068	0.963	1443.63	0.577 \pm 0.127	0.810
UKCP09/ MORECS	R	35.13	1.066 \pm 0.041	0.993	457.38	1.053 \pm 0.115*	0.946
	A	3.07	1.069 \pm 0.044	0.992	86.32	1.081 \pm 0.114*	0.949

* Confidence intervals of slope include one

311 The mean percentage differences between gauged and modelled water yield were \pm 23.36% (SE \pm
 312 4.40) for the WordClim/CGIAR-CSI data and \pm 18.55% (SE \pm 4.94) for the UKCP09/MORECS data.
 313 However, in both cases one catchment (Welland, labelled 20 on Fig.1) showed a percentage
 314 difference of over 100%. Although the difference between the mean percentage
 315 under/overestimates of the two datasets does not appear great, it is important to note that the
 316 mean is somewhat skewed by the few catchments for which the model performs particularly poorly,
 317 especially for the UKCP09/MORECS data. Median values show that for the UKCP09/MORECS data
 318 the majority of catchments had percentage differences between gauged and modelled water yield of
 319 less than 10% (median = 9.74%) whilst for the WordClim/CGIAR-CSI data more catchments vary by
 320 up to 20% (median = 17.19%).

321 Despite the significant correlations between catchment sensitivity to variation in the input
 322 parameter values and catchment characteristics, percentage under/overestimates of total water
 323 yield using the UKCP09/MORECS data did not show any significant correlations with catchment area,
 324 altitude, mean precipitation, mean PET, geology (i.e. base flow index) or land cover.



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Fig. 4 InVEST modelled water yield (corrected for estimated consumptive abstraction) vs gauged water yield, using two input datasets for the precipitation and reference evapotranspiration parameters. A) Estimated total catchment yield in millions of cubic metres, using WordClim/CGIAR-CSI data; B) Estimated yield per hectare in cubic metres, using WordClim/CGIAR-CSI data; C) Estimated total catchment yield using UKCP09/MORECS data; D) Estimated yield per hectare using UKCP09/MORECS data. Grey, dashed line indicates a relationship with intercept = zero and slope = one.

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3.3. ADDITIONAL VALIDATION

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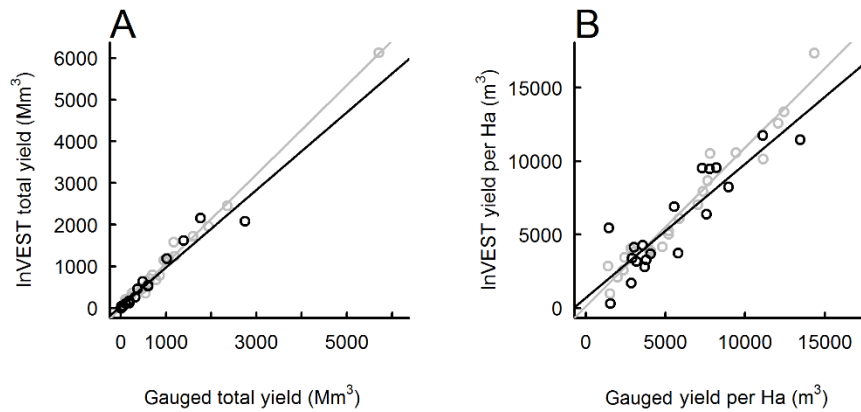
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Comparing modelled and gauged data for a further 20 catchments (using the UKCP09/MORECS dataset because this gave the best results for the original 22 catchments) showed very similar results to the original 22 catchments (Figure 5). Confidence intervals for the linear regression slopes again overlapped with one, and R^2 values were high for both total yield (intercept = 41.48, slope = 0.93 ± 0.13 , $R^2 = 0.92$) and yield per hectare (intercept = 684.75, slope = 0.91 ± 0.23 , $R^2 = 0.87$), suggesting that the data and parameters used to obtain the best results on the original catchments are likely to be applicable across a wide range of catchments within the UK.



341

342 Fig. 5 InVEST modelled total water yield (millions of m^3) (A) and per hectare water yield (m^3/Ha) (B)
 343 against gauged water yield for the 22 original test catchments (grey symbols and line) and the 20
 344 additional catchments (black symbols and line). Model run using UKCP09/MORECS dataset for
 345 precipitation and PET and corrected for estimated consumptive abstraction.

346 **4. Discussion**

347 Our results show that the InVEST water yield model can produce accurate estimates of water yield in
 348 UK river catchments. However, this accuracy is dependent upon careful selection of appropriate
 349 model parameters and input data, especially precipitation and PET to which the model is most
 350 sensitive. The input values used in this study are transferrable to other UK catchments (as seen by
 351 our additional validation using extra catchments). However, when the model is to be used
 352 elsewhere, we strongly advocate the trialling of different values for input parameters representing
 353 different environmental contexts and empirical validation wherever possible.

354 The InVEST model was initially designed to assess water availability for hydropower production.
 355 Hydropower forms a relatively small contribution to the UK energy sector (DECC 2015) and the
 356 spatial distribution of hydropower generation is very uneven, with most large hydropower schemes
 357 in large, upland catchments with abundant space for reservoirs. Of course, accurate assessments of
 358 water yield are also important for examining the current delivery of, and impact of future
 359 environmental change on, other ecosystem services including, water quality in terms of nutrients
 360 and sediment, drinking water and crop production. The demand for, and conflicts between, the
 361 latter two services are likely to increase with the effects of climate change both at a UK
 362 (Weatherhead & Knox 2000; Knox *et al.* 2009) and global scale (Döll 2002). As such, the InVEST water
 363 supply model has more general uses than for estimating hydropower. Although there is also the
 364 potential for ecosystem disservices from, for example, erosion and flooding, these are dependent on
 365 a wide range of additional factors (Brown & Damery 2002; CEH 2008).

367 Several studies have sought to address the issue of validating ecosystem service models. However,
368 many of these have been limited by the availability of suitable validation data. For example, Schulp
369 *et al.* (2014) sought to undertake model validation for a variety of ecosystem services at a European
370 scale, and whilst their results give an indication of the ability of different modelling approaches to
371 predict spatial patterns of ecosystem service delivery, their need to use proxies in the absence of
372 empirical ecosystem service measures prevented a quantitative assessment of model accuracy.
373 Where data have been available, some studies at global or continental scales have compared results
374 from the InVEST water yield model (Mendoza *et al.* 2011), or the Budyko modelling framework upon
375 which it is based (Zhang *et al.* 2004; Zhou *et al.* 2012), to empirical observations. Such studies are
376 useful in comparing models in terms of their ability to respond to global patterns of precipitation but
377 do not provide the information necessary for users to assess whether the model is accurate at a
378 national or regional scale, despite these being the scales at which the majority of ecosystem service
379 mapping exercises are performed (Martínez-Harms & Balvanera 2012) and at which most strategic
380 water resource planning takes place (Watts *et al.* 2015).

381 Other recent studies have used empirical validation data to assess the performance of the InVEST
382 Water Yield model, but covering only single catchments or sub-catchments within a single river
383 basin. In contrast to the present study, several of these studies have had the primary aim of
384 quantifying spatial variation and predicted changes in water yield, with validation at a small number
385 of points to check the reliability of their results, rather than a more general validation of the model
386 across catchments (e.g. Bai *et al.* 2013; Boithias *et al.* 2014; Terrado *et al.* 2014; Xiao *et al.* 2015).
387 Whilst this is entirely sensible, and such studies have found the InVEST model to be a good predictor
388 of measured water yield, the results of such studies are not necessarily transferable to other
389 locations or scales, especially where model inputs have been 'calibrated' to match the empirical
390 data.

391 Comparatively few studies have had the explicit aim of investigating the model performance,
392 uncertainty and sensitivity of the InVEST water yield model. These have largely been conducted in
393 sub-catchments within single river basins which vary widely in area, climate and land cover (e.g.
394 4950 Km² Llobregat River basin, Catalonia, Spain (Sánchez-Canales *et al.* 2012); 23 600 Km² Cape Fear
395 basin, North Carolina, USA (Hamel & Guswa 2015); 57 400 Km² Chubut River basin, Patagonia,
396 Argentina (Pessacg *et al.* 2015)). However, their results are generally corroborated by our national
397 scale analysis (UK land area = 241 930 km²). These include high sensitivity to precipitation and, to a
398 slightly lesser extent, to evapotranspiration data, as well as empirical support for setting Z from
399 numbers of rain events per year (Hamel & Guswa 2015). Our results also corroborate those of these

400 previous studies in demonstrating the substantial improvements in model performance which can
401 be obtained by comparing alternative data sources, especially for those parameters which sensitivity
402 analysis identifies as being major drivers of the model (Sánchez-Canales *et al.* 2012; Hamel & Guswa
403 2015; Pessacg *et al.* 2015). For example, Boithias *et al.* (2014) paid particular attention to obtaining
404 precipitation and evapotranspiration data, because of the sensitivity analysis undertaken by
405 Sánchez-Canales *et al.* (2012) in a similar catchment. As a result, they were able to obtain a good fit
406 to their gauged data by relatively minor ($\pm 10\%$) calibration of Z , K_c and water demand values
407 (Boithias *et al.* 2014).

408 All of these studies using some form of validation, and the differences between them, support our
409 suggestion that formal sensitivity analysis and, where empirical data are available, validation should
410 be employed whenever the InVEST model is being used in new regions. Even a relatively small
411 number of validation points from a range of locations can provide valuable insights into the accuracy
412 of the model and the relative performance of different input datasets. If there are no validation
413 data, our results suggest that datasets of the appropriate spatial scale (e.g. national rather than
414 global) may perform better. The observed differences between our two pairs of input precipitation
415 and PET datasets are probably due to several causes. The WorldClim and CGIAR-CSI data are annual
416 averages calculated over the approximate period 1950-2010. The fact that they do not span the
417 same date range as the validation data may explain some of their poor performance, although
418 annual mean precipitation over England and Wales has not changed significantly over the date range
419 (Jenkins, Perry & Prior 2008). Furthermore, WorldClim and CGIAR-CSI data are interpolated from
420 data which are not spatially uniform in distribution, and thus vary spatially in the uncertainty around
421 the given value of precipitation (Hijmans *et al.* 2005; Hamel & Guswa 2015; Pessacg *et al.* 2015). The
422 UKCP09 data are also interpolated from a network of UK rain gauges, but at a much higher density of
423 sampling points (Perry & Hollis 2005). Errors in the WorldClim precipitation data also tend to be
424 highest in regions with high rainfall (Hijmans *et al.* 2005), such as the UK. Global-scale datasets like
425 WorldClim are both widely used and readily available, so their relatively inconsistent performance
426 across catchments, and the much better performance of the UKCP09 and MORECS data highlights
427 the need for validation to select the most appropriate input data, or at least to assess model
428 performance and the resultant confidence in the results if no other data are available. As might be
429 expected, it appears that large improvements in model performance can be achieved simply by
430 ensuring the input data are matched to the study region in terms of spatial and temporal scales.

431 The apparent trend for catchments to be consistently 'sensitive' or 'insensitive' to variation in the
432 values of all model input parameters suggests that catchment characteristics (e.g. soil and bedrock
433 characteristics) can strongly influence the degree to which errors in the input parameter values will

434 affect the model outputs. Our results suggested that, in the UK, 'upland' type catchments, with low
435 PET and high cover of semi-natural habitats are less sensitive than 'lowland' catchments with high
436 PET and a higher cover of arable land (which has a high K_c). Pessacg *et al.* (2015) found that
437 catchments with a higher cover of LULC classes with a high value of K_c were most sensitive,
438 potentially giving a +150% change in modelled water yield in response to a +30% error in
439 precipitation data, a response very similar to the most sensitive catchments in our results (see Fig.
440 2A). However, the good overall fit between modelled and measured data across catchments and the
441 lack of significant correlation between model accuracy and catchment descriptors suggest that,
442 when using UKCP09 and MORECS data, errors in the input datasets are comparatively minor, at least
443 to the extent where they are not the major driver of differences between modelled and gauged
444 water yield. The remaining model error is therefore likely to be due to limitations of the model or
445 the validation data (see section 4.2) or more complex interplay between catchment characteristics.
446 A productive area for further research could be more detailed investigation into the drivers of
447 varying sensitivity between catchments, with the aim of using catchment descriptors as predictive
448 variables in determining the impact of driving data on change in water yield.

449 4.2. LIMITATIONS OF THE MODEL AND VALIDATION DATA

450 Despite the good performance of the InVEST model when refined to account for water abstractions
451 and using national input datasets, the accuracy of the modelled water yield values still varied to
452 some extent between catchments (see Fig. 4C and 4D) and there was a slight but consistent
453 overestimate of per hectare water yield. The InVEST water yield model contains several
454 acknowledged limitations and simplifications (Sharp *et al.* 2015). These include the limited ability of
455 the model to account for inter- or intra- annual variation in water supply. Many ecosystem services
456 (irrigation, hydropower) and disservices (flooding) linked to water yield will be affected by the timing
457 of water availability and peak flows, not just total annual yield. A further simplification is the lack of
458 consideration of lateral and groundwater flows, such that effects of complex land use patterns or
459 underlying geology remain unaccounted for (Sharp *et al.* 2015). Finally, the model handles
460 consumptive water use in a very simplistic fashion, by allocating a per hectare value to each LULC.
461 Although including per hectare estimates of consumptive abstraction did reduce overestimation of
462 water yield and slightly improved model performance (Table 1), consumptive use is likely to vary
463 widely between catchments and between different areas of the same LULC. In the UK (and in many
464 other parts of the world), many large contributors to consumptive use are single point intakes. The
465 use of reservoirs and water transfer schemes to regulate river flows for abstraction or flood
466 prevention is common (Gibbins *et al.* 2001), can involve very large volumes of water (Davies, Thoms
467 & Meador 1992; Boithias *et al.* 2014) and is indicated (but not quantified) in the NRFA catchment

468 description metadata for several of the gauging stations used in this study (Fry & Swain 2010).
469 Although the InVEST model structure does not directly account for point abstractions, where the
470 locations of these are known, these can be represented as separate LULC classes, with
471 corresponding consumptive water use values. Alternatively, the model outputs can be adjusted on a
472 per catchment basis to account for known point source abstractions. However, such data can be
473 hard to obtain due to regulatory restrictions in the UK water industry.

474 It is also worth noting that the empirical validation data themselves are also affected by issues of
475 accuracy, many of which are not captured by the model (e.g. the InVEST water yield model does not
476 distinguish between surface and sub-surface water flow). Measured river flows may be reduced by
477 bypassing of the gauging station via flooding, canals or groundwater flow and either reduced or
478 increased by catchment transfer, which may occur either consistently or only at times of particularly
479 high or low flow. These factors are likely to result in measurements which accurately record the
480 flow of water in the gauged channel, but not the true total water yield from the catchment of the
481 gauging station. Catchments where a significant proportion of total water yield leaves via sub
482 surface flow (or other routes) will show a considerable overestimate of total yield as gauged from
483 stream flow. These issues are likely to affect many individual stations. For example, the severe
484 model overestimation in the Welland catchment might be explained by the fact that it is
485 comparatively small (707 km²) and subject to high levels of abstraction to a reservoir. More
486 seriously, gauging stations may be unable to record accurate readings of water flow over or under
487 certain flow thresholds. Whilst at least one of these factors was present in the majority of
488 catchments in this study (Fry & Swain 2010), these issues are unlikely to cause systematic bias
489 because they are not consistent across catchments. For example, over half of the 42 catchments
490 studied had factors affecting runoff documented by the NRFA which potentially offset one another
491 (i.e. some factors likely to divert water flow from the river channel and others likely to increase it).
492 The prevalence of these issues, along with the presence of outliers, does serve to illustrate the
493 importance of incorporating local knowledge into decision making, alongside ecosystem service
494 models and empirical validation, as stakeholders may often be able to provide information on
495 processes not captured by the model which can help to explain or mitigate against poor model
496 performance. Users of InVEST are strongly encouraged to involve stakeholders in scenario
497 development and interpretation of model outputs (Sharp *et al.* 2015).

498 4.3. CONCLUSIONS

499 Ecosystem service models such as InVEST have the potential to provide a crucial underpinning to
500 decision and policy making. However lack of robust testing limits their credibility. The work

501 presented here demonstrates that the relatively InVEST simple water yield modelling framework can
502 perform well as long as input data and parameters are representative of the spatial and temporal
503 scale concerned. Care should be taken with application of these tools using indicative datasets at the
504 global scale, and in the absence of more local scale data, empirical validation of model outputs
505 becomes even more important. However, the need for ecosystem service models is driven by the
506 fact that many parts of the world lack relevant empirical data (Crossman *et al.* 2013). Therefore, we
507 firstly recommend that, where empirical data are available, models should be validated for locations
508 in the region of interest and the effect of alternative parameter values or input data should be
509 explored. Secondly, we recommend the application of sensitivity analyses to understand how model
510 outputs vary across the region of interest, either in tandem with validation or, if validation data are
511 not available, to understand uncertainty in model predictions. Finally, if no validation data are
512 available, we advise exercising caution when interpreting model output values. For example, our
513 results suggest that the InVEST water yield model could still be used to assess the rank order of
514 catchments in terms of water yield or the direction of change in relation to scenarios of
515 environmental change (e.g. Willcock *et al.* 2016) even where absolute values are less reliable.

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