Supplementary Material

Climate change and alpine screes: no future for glacial relict *Papaver occidentale* (Papaveraceae) in Western Prealps

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Table S1. Populations of *P. occidentale* and estimated population sizes (number of individuals).

Country	Province	Locality Name	Abbreviation	Longitude	Latitude	Estimated population	Mean elevation
Switzerland	Bern	Hinderi Fromatt	HFR	7.4450013	46.53983	9851	2035
Switzerland	Bern	Gandhore	GAN	7.4212141	46.528269	6760	1852
Switzerland	Bern	Fromatt	FRO	7.4345852	46.541728	3426	1898
Switzerland	Bern	Vorderi Spillgerte	VSP	7.4365279	46.537176	1300	2010
Switzerland	Bern	Holzflue	HOL	7.4301142	46.538193	780	1911
Switzerland	Fribourg	Dent de Ruth	RUT	7.2364394	46.555724	2755	1810
Switzerland	Fribourg	Vanil de l'Ecri	VEC	7.1379997	46.525244	1685	1967
Switzerland	Fribourg	Rocher de Saint-Jacques	STJ	7.1317589	46.518031	331	1859
Switzerland	Fribourg	Combe Vanil de l'Ecri	COM	7.1396163	46.522792	190	2235
Switzerland	Fribourg	Dent de Savigny	SAV	7.2289688	46.552022	145	1883
Switzerland	Fribourg	Pointe de Paray	PAR	7.1363424	46.513986	61	2300
Switzerland	Valais	Le Grammont	GRA	6.8225951	46.357769	141	2118
Switzerland	Vaud	La Pierreuse	PIE	7.1829011	46.442117	604	1653
Switzerland	Vaud	Les Salaires	SAL	7.1740182	46.438463	180	1760
Switzerland	Vaud	Mont Tendre	TEN	6.30482	46.59094	6	1658
Switzerland	Vaud	Grand Cunay	CUN	6.2749005	46.572582	1	1571
France	Haute-Savoie	Morsulaz	MOR	6.4924109	46.022763	2180	1974
France	Haute-Savoie	Creux de Sotty	SOT	6.4576835	46.003484	145	1614
France	Haute-Savoie	Jalouvre	JAL	6.450501	45.99877	110	2127
France	Haute-Savoie	Col Colombière	COL	6.4592451	45.994879	60	2025
France	Haute-Savoie	Pointe Blanche	PTB	6.4600886	45.998943	52	2400

Table S2. Additional information related to SDM.

Generation of occurrences (presence points)

The data collected in the field consists in a list of GPS points with an associated number of individuals (see Table S6). The generation of occurrence (presence points) for the SDM was done as follow :
For each GPS location, random points were generated in a delimited area (a radius of about 10 to 50 m, regarding our knowledge of the field, to represent the best as possible the reality). The number of generated occurrence equals the number of estimated individuals.

Calculation of temperature as a function of elevation

Mean yearly mean temperature (TEMP) (°C) as a function of ELEVATION (m)
TEMP = 11.11 – 0.00424 ELEVATION

VIF Scores

Here are listed the 8 remaining environmental variables, after removal of variables with multicollinearity problems, and their corresponding variance inflation factor (VIF) (function "vif" of the usdm R package).
See Table 1 in the manuscript for the abbreviations of environmental variables.

Variable	VIF
SLOPE	1.947745
NORTHING	2.805017
TEMP	1.235845
PREC_Sum	1.440481
PREC_Win	1.381727
SUNSHINE	1.181926
IRRAD	5.011928
HOURS_SUN	2.271067

Environmental variables selection procedure

See Table 1 in the main manuscript for the abbreviations of environmental variables names.

1) Variables EASTNESS, ELEVATION and SCREES were removed (see main manuscript, chapter 2.2).
2) Some environmental variables have been removed to avoid multicollinearity problems. The eight remaining variables included in the first models were the following: SLOPE, NORTHING, TEMP, PREC_Sum, PREC_Win, SUNSHINE, IRRAD, HOURS_SUN.
3) The eight included variables were significant in GLM and GAM, and were relevant according to AIC and BIC. Only HOURS_SUN was removed from GLM as it increased the AIC.
4) The block cross validation procedure revealed a strong overfitting of the model. Some environmental superfluous variables were removed. Remaining variables : SLOPE, TEMP, NORTHING, PREC_Win.

Final validated GAM Summary (R console)

Formula :	Call: gam(formula = PRESENCE ~ s(SLOPE, 2) + s(NORTHING, 2) + s(TEMP_e, 2) + s(PREC_Win, 2), family = "binomial", data = data)

Deviance Residuals (Dispersion Parameter for binomial family taken to be 1):

Min	1Q	Median	3Q	Max
-2.4529	-0.4500	0.1604	0.5167	3.2360

Null Deviance:	78211.96 on 56417 degrees of freedom
Residual Deviance:	32344.72 on 56409 degrees of freedom
AIC:	32362.72
Number of Local Scoring Iterations:	20

Anova for Parametric Effects					
	Df	Sum Sq	Mean Sq	F value	Pr(>F)
s(SLOPE, 2)	1	58	57.6	100.71	< 2.2e-16 ***
s(NORTHING, 2)	1	5045	5044.9	8820.88	< 2.2e-16 ***
s(TEMP_e, 2)	1	1829	1828.7	3197.53	< 2.2e-16 ***
s(PREC_Win, 2)	1	2186	2185.8	3821.80	< 2.2e-16 ***
Residuals	56409	32262			
--- Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1					

Anova for Nonparametric Effects			
	Df	Chisq	P(Chi)
s(SLOPE, 2)	1	5869.8	< 2.2e-16 ***
s(NORTHING, 2)	1	1985.5	< 2.2e-16 ***
s(TEMP_e, 2)	1	4817.9	< 2.2e-16 ***
s(PREC_Win, 2)	1	2224.3	< 2.2e-16 ***
--- Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1			

Other information
The degree of smoothing (k) of the GAM was 2 for all variables. A GLM with the same environmental variables was very similar to the GAM, but the GAM was slightly more performant during the spatial cross validation, explaining why the GAM was finally selected.

Table S3. Information on climate change scenarios data.

Abbreviation	Variable	Unit	Source	Native resolution	Resolution used in SDM
T85_2.6	Temperature scenario : Mean yearly temperature in 2085, according to the RCP2.6 scenario (Implies strong reduction of greenhouse gas emissions early in the 21st century)	degrees °C	Data from Meteoswiss, see CH2018 (2018)	Approx.. 2.3 x 1.6 km grid	Downscaled to 10 m, same procedure as TEMP
T85_4.5	Temperature scenario : Mean yearly temperature in 2085, according to the RCP4.5 scenario (Emissions decline after 2050, stabilization of radiative forcing)	degrees °C	Data from Meteoswiss, see CH2018 (2018)	Approx.. 2.3 x 1.6 km grid	Downscaled to 10 m, same procedure as TEMP
T85_8.5	Temperature scenario : Mean yearly temperature in 2085, according to the RCP8.5 scenario (Continuously increasing radiative forcing)	degrees °C	Data from Meteoswiss, see CH2018 (2018)	Approx.. 2.3 x 1.6 km grid	Downscaled to 10 m, same procedure as TEMP
PR85_2.6_S	Precipitation scenario : Mean summer precipitation in 2085, according to the RCP2.6 scenario (Implies strong reduction of greenhouse gas emissions early in the 21st century)	Millimeters (mm)	Data from Meteoswiss, see CH2018 (2018)	Approx.. 2.3 x 1.6 km grid	Downscaled to 10m, using bicubic spline interpolation to get a smooth result
PR85_2.6_W	Precipitation scenario : Mean winter precipitation in 2085, according to the RCP2.6 scenario (Implies strong reduction of greenhouse gas emissions early in the 21st century)	Millimeters (mm)	Data from Meteoswiss, see CH2018 (2018)	Approx.. 2.3 x 1.6 km grid	Downscaled to 10m, using bicubic spline interpolation to get a smooth result
PR85_4.5_S	Precipitation scenario : Mean summer precipitation in 2085, according to the RCP4.5scenario (Emissions decline after 2050, stabilization of radiative forcing)	Millimeters (mm)	Data from Meteoswiss, see CH2018 (2018)	Approx.. 2.3 x 1.6 km grid	Downscaled to 10m, using bicubic spline interpolation to get a smooth result
PR85_4.5_W	Precipitation scenario : Mean winter precipitation in 2085, according to the RCP4.5scenario (Emissions decline after 2050, stabilization of radiative forcing)	Millimeters (mm)	Data from Meteoswiss, see CH2018 (2018)	Approx.. 2.3 x 1.6 km grid	Downscaled to 10m, using bicubic spline interpolation to get a smooth result
PR85_8.5_S	Precipitation scenario : Mean summer precipitation in 2085, according to the RCP8.5scenario (Continuously increasing radiative forcing)	Millimeters (mm)	Data from Meteoswiss, see CH2018 (2018)	Approx.. 2.3 x 1.6 km grid	Downscaled to 10m, using bicubic spline interpolation to get a smooth result
PR85_8.5_W	Precipitation scenario : Mean winter precipitation in 2085, according to the RCP8.5scenario (Continuously increasing radiative forcing)	Millimeters (mm)	Data from Meteoswiss, see CH2018 (2018)	Approx.. 2.3 x 1.6 km grid	Downscaled to 10m, using bicubic spline interpolation to get a smooth result

Table S4. R script.

```
setwd("U:/Projets scientifiques/Papaver occidentale/Modelisation/R")
data<-read.csv("data PAPAVER.csv",header=TRUE,sep=",")
attach(data)
summary(data)

# data_PAPAVER is a dataframe of 56418 rows (28209 presences and 28209 pseudo-absences). All pseudo-absences a generated in the areas with screes
# For each point, 12 environnmental variables are extracted (ELEVATION,SLOPE,NORTHING,TEMP,TEMP_Sum,TEMP_Win,PREC,PREC_Sum,PREC_Win,SUNSHINE,IRRAD,HOURS_SUN)
+ env. data for futur climate change scenarios

### 1 step: avoid collinearity problems. Make a selection in environmental variables that are strongly correlated

install.packages("ecospat")
library(ecospat)
install.packages("usdm")
library(usdm)

#extract only backgroud points
data2<-data[PRESENCE==0,]

#select the 12 environmental variables
data3<-subset(data2, select = c(ELEVATION,SLOPE,NORTHING,TEMP,TEMP_Sum,TEMP_Win,PREC,PREC_Sum,PREC_Win,SUNSHINE,IRRAD,HOURS_SUN) )

#Correlation plot with all env. variables and calculation of the variance inflation factor

ecospat.cor.plot(data3)
#vifstep(data3)
vif(data3)

#Suppression of some environmental variables
uncorrdata<-subset(data3, select = -c(ELEVATION,TEMP_Sum,TEMP_Win,PREC) )

vif(uncorrdata)
ecospat.cor.plot(uncorrdata)

# all vif scores  under 5

### 2 step: model construction and calibration

setwd("U:/Projets scientifiques/Papaver occidentale/Modelisation/R")
data<-read.csv("data PAPAVER.csv",header=TRUE,sep=",")
attach(data)
summary(data)

## with GLM, with quadratic term

#glm1<-glm(PRESENCE~poly(SLOPE,2)+poly(NORTHING,2)+poly(TEMP_e,2)+poly(PREC_Sum,2)+poly(PREC_Win,2)+poly(SUNSHINE,2)+poly(IRRAD,2)+poly(HOURS_SUN,2),data=data,
family="binomial")
#summary(glm1)

#Selection of the model with the lowest AIC and BIC

#library(MASS)

#glmstart<-glm(PRESENCE~1, data=data, family="binomial")

#glm.formula<-
formula("PRESENCE~poly(SLOPE,2)+poly(NORTHING,2)+poly(TEMP_e,2)+poly(PREC_Sum,2)+poly(PREC_Win,2)+poly(SUNSHINE,2)+poly(IRRAD,2)+poly(HOURS_SUN,2)")
#glmAIC<-stepAIC(glmstart, glm.formula,data=data, direction = "both", trace = FALSE, k=2)
#summary(glmAIC)
#anova(glmAIC)

#glmBIC<-stepAIC(glmstart, glm.formula,data=data, direction = "both", trace = FALSE, k=log(nrow(data)))
#summary(glmBIC)
#anova(glmBIC)

# Improvement, best model after Cross valisation (see below)

#finalmodel<-glm(PRESENCE~poly(SLOPE,2)+poly(NORTHING,2)+poly(TEMP_e,2)+PREC_Win,data=data, family="binomial")
#summary(finalmodel)
#anova(finalmodel)

## with GAM

install.packages("gam")
library(gam)

gam1<-gam(PRESENCE~s(SLOPE,2)+s(NORTHING,2)+s(TEMP_e,2)+s(PREC_Sum,2)+s(PREC_Win,2)+s(SUNSHINE,2)+s(IRRAD,2)+s(HOURS_SUN,2),data=data, family="binomial")
summary(gam1)

# Improvement, best model after Cross valisation (see below)

finalmodel<-gam(PRESENCE~s(SLOPE,2)+s(NORTHING,2)+s(TEMP_e,2)+s(PREC_Win,2),data=data, family="binomial")
summary(finalmodel)


## Response curves

library(biomod2)
rp<-response.plot2(models=c("finalmodel"), Data=data, show.variables = c("SLOPE","NORTHING","TEMP_e","PREC_Win"))
dev.off()

## Percentage of deviance explained for each variable
```

```
#g1<-gam(PRESENCE~1,data=data, family="binomial")
#gslope<-gam(PRESENCE~s(NORTHING,2)+s(TEMP_e,2)+s(PREC_Win,2),data=data, family="binomial",sp=finalmodel$sp[1])
#gnorthing<-gam(PRESENCE~s(SLOPE,2)+s(TEMP_e,2)+s(PREC_Win,2),data=data, family="binomial",sp=finalmodel$sp[2])
#gtemp<-gam(PRESENCE~s(SLOPE,2)+s(NORTHING,2)+s(PREC_Win,2),data=data, family="binomial",sp=finalmodel$sp[3])
#gprecwin<-gam(PRESENCE~s(SLOPE,2)+s(NORTHING,2)+s(TEMP_e,2),data=data, family="binomial",sp=finalmodel$sp[4])
#dev<-data.frame("devslope"=(deviance(gslope)-deviance(finalmodel))/deviance(g1),"devnorthing"=(deviance(gnorthing)-
deviance(finalmodel))/deviance(g1),"devtemp"=(deviance(gtemp)-deviance(finalmodel))/deviance(g1),"devprecwin"=(deviance(gprecwin)-
deviance(finalmodel))/deviance(g1),"devresid"=deviance(finalmodel)/deviance(g1))




### Step 3 : Model validation

# Draw the roc curve for the model

library(pROC)

rm<-roc(PRESENCE,predict(finalmodel,type="response"), plot=FALSE)
truepositiverate<-rm$sensitivities
falsepositiverate<-1-rm$specificities
plot(truepositiverate~falsepositiverate, xlim=c(0,1),ylim=c(0,1),xlab="False positive rate", ylab="True positive rate", type="n")
lines(truepositiverate~falsepositiverate, col="red", lwd=2)
lines(c(0,0.999999999)~c(0,1),lty=2)

# Mean squared residuals of the model fit, and AUC
auc<-rm$auc
sqresiduals<-(PRESENCE-predict(finalmodel,type="response"))^2
meansqresid<-mean(sqresiduals)

meansqresid
auc




## Monte-carlo cross validation


#Select the number of repetition

repet<-30
msrtot<-rep(0,repet)
auctot<-rep(0,repet)


for(i in 1:repet)


{
  # split data randomly : 90 % training and 10% validation


  randomsample<-sample(1:nrow(data),nrow(data)*0.1)
  trainingdata<-data[-randomsample,]
  validationdata<-data[randomsample,]

  # run model with training data


  testmodel<-gam(PRESENCE~s(SLOPE,2)+s(NORTHING,2)+s(TEMP_e,2)+s(PREC_Win,2),data=trainingdata, family="binomial")


  #plot the roc curves
  actual<-validationdata$PRESENCE
  prediction<-predict(testmodel,newdata=validationdata, type="response")
  rm<-roc(actual,prediction, plot=FALSE)
  truepositiverate<-rm$sensitivities
  falsepositiverate<-1-rm$specificities
  lines(truepositiverate~falsepositiverate, col="grey", lwd=0.5)

  #mean sqared residuals + auc
  msr<-mean((actual-prediction)^2)
  msrtot[i]<-msr
  auc<-rm$auc
  auctot[i]<-auc
}


mean(msrtot)
mean(auctot)
```

```
## k fold cross validation


#adapt the number of fold

k<-10
msrtot<-rep(0,k)
auctot<-rep(0,k)


#create groups (folds)

vectorgroups<-sample(1:k,size=nrow(data),replace=TRUE)

for(i in 1:k)
{

  trainingdata<-data[vectorgroups!=i,]
  validationdata<-data[vectorgroups==i,]

  # run model with training data


  testmodel<-gam(PRESENCE~s(SLOPE,2)+s(NORTHING,2)+s(TEMP_e,2)+s(PREC_Win,2),data=trainingdata, family="binomial")

  actual<-validationdata$PRESENCE
  prediction<-predict(testmodel,newdata=validationdata, type="response")
  rm<-roc(actual,prediction, plot=FALSE)
  truepositiverate<-rm$sensitivities
  falsepositiverate<-1-rm$specificities
  lines(truepositiverate~falsepositiverate, col="grey", lwd=0.5)

  #mean sqared residuals + auc
  msr<-mean((actual-prediction)^2)
  msrtot[i]<-msr
  auc<-rm$auc
  auctot[i]<-auc
}

mean(msrtot)
mean(auctot)






## spatial cross validation

##(spliting the data in 2 blocks N-S and then again 2 blocks E-W)
##equilibrium in each block of presences and pseudo-absences


msrtot<-rep(0,4)
auctot<-rep(0,4)
bestthreshold<-rep(0,4)
xsplit<-582000
ysplit<-153500
splits<-
list(c(0,xsplit,0,1000000),c(xsplit,1000000,0,1000000),c(xsplit,1000000,0,1000000),c(0,xsplit,0,1000000),c(0,1000000,0,ysplit),c(0,1000000,ysplit,1000000),c(0,1000000,ysplit,1000000),c(0,1000000,0,ysplit))



for(i in 1:4)

{

  trainingdata<-data[X>splits[[i*2-1]][1] & X<splits[[i*2-1]][2] & Y>splits[[i*2-1]][3] & Y<splits[[i*2-1]][4],]
  validationdata<-data[X>splits[[i*2]][1] & X<splits[[i*2]][2] & Y>splits[[i*2]][3] & Y<splits[[i*2]][4],]
  l1<-length(trainingdata$PRESENCE[trainingdata$PRESENCE==1])
  l0<-length(trainingdata$PRESENCE[trainingdata$PRESENCE==0])

  maxtraining<-max(c(l1,l0))

  if (maxtraining==l1)
  {
    s1<-sample(l1,l0,replace=FALSE)
    a1<-trainingdata[trainingdata$PRESENCE==1,]
    a0<-trainingdata[trainingdata$PRESENCE==0,]
    a2<-a1[s1,]
    trainingdata<-rbind(a0, a2)
  }

  if (maxtraining==l0)
  {
    s1<-sample(l0,l1,replace=FALSE)
    a1<-trainingdata[trainingdata$PRESENCE==1,]
    a0<-trainingdata[trainingdata$PRESENCE==0,]
```

```
   a2<-a0[s1,]
   trainingdata<-rbind(a1, a2)
  }

  #
  m1<-length(validationdata$PRESENCE[validationdata$PRESENCE==1])
  m0<-length(validationdata$PRESENCE[validationdata$PRESENCE==0])

  maxvalidation<-max(c(m1,m0))

  if (maxvalidation==m1)
  {
   p1<-sample(m1,m0,replace=FALSE)
   b1<-validationdata[validationdata$PRESENCE==1,]
   b0<-validationdata[validationdata$PRESENCE==0,]
   b2<-b1[p1,]
   validationdata<-rbind(b0, b2)
  }

  if (maxvalidation==m0)
  {
   p1<-sample(m0,m1,replace=FALSE)
   b1<-validationdata[validationdata$PRESENCE==1,]
   b0<-validationdata[validationdata$PRESENCE==0,]
   b2<-b0[p1,]
   validationdata<-rbind(b1, b2)
  }



  testmodel<-gam(PRESENCE~s(SLOPE,2)+s(NORTHING,2)+s(TEMP_e,2)+s(PREC_Win,2),data=trainingdata, family="binomial")
  actual<-validationdata$PRESENCE
  prediction<-predict(testmodel,newdata=validationdata, type="response")
  rm<-roc(actual,prediction, plot=FALSE)
  truepositiverate<-rm$sensitivities
  falsepositiverate<-1-rm$specificities
  lines(truepositiverate~falsepositiverate, col="grey", lwd=0.5)

  #mean sqared residuals + auc
  msr<-mean((actual-prediction)^2)
  msrtot[i]<-msr
  auc<-rm$auc
  auctot[i]<-auc

  #best threshold

  distcurve<-sqrt((1-truepositiverate)^2+falsepositiverate^2)
  bestthreshold[i]<-rm$thresholds[distcurve==min(distcurve)]

}


mean(msrtot)
mean(auctot)
mean(bestthreshold)





### step 4 : mapping model and projection in future


#load rasters of environmental variables used in the final model
library(raster)

a<-raster("C:/Users/fragniey/Documents/Projets scientifiques/Papaver occidentale/Modelisation/R/Copie rasters/SLOPE.tif")
b<-raster("C:/Users/fragniey/Documents/Projets scientifiques/Papaver occidentale/Modelisation/R/Copie rasters/NORTHING.tif")
c<-raster("C:/Users/fragniey/Documents/Projets scientifiques/Papaver occidentale/Modelisation/R/Copie rasters/TEMP_e.tif")
d<-raster("C:/Users/fragniey/Documents/Projets scientifiques/Papaver occidentale/Modelisation/R/Copie rasters/PREC_Win.tif")

stackrast<-stack(a,b,c,d)
names(stackrast)
n<-names(stackrast)

#predict and write the raster
pre<-predict(stackrast,finalmodel,type="response")
writeRaster(pre, "C:/Users/fragniey/Documents/Projets scientifiques/Papaver occidentale/Modelisation/SIG/SDM/PAPAVER SDM actual.tif", format="GTiff",overwrite=TRUE)




## Projection with climate change scenarios
#(some rasters are replaced by the corresponding climate change scenario)

# Scenario RCP 2.6


a<-raster("C:/Users/fragniey/Documents/Projets scientifiques/Papaver occidentale/Modelisation/R/Copie rasters/SLOPE.tif")
b<-raster("C:/Users/fragniey/Documents/Projets scientifiques/Papaver occidentale/Modelisation/R/Copie rasters/NORTHING.tif")
c<-raster("C:/Users/fragniey/Documents/Projets scientifiques/Papaver occidentale/Modelisation/R/Copie rasters/T85_2.6.tif")
d<-raster("C:/Users/fragniey/Documents/Projets scientifiques/Papaver occidentale/Modelisation/R/Copie rasters/PR85_2.6_W.tif")
```

```
stackrast<-stack(a,b,c,d)
names(stackrast)
names(stackrast)<-n

#predict and write the raster
pre<-predict(stackrast,finalmodel,type="response")
writeRaster(pre, "C:/Users/fragniey/Documents/Projets scientifiques/Papaver occidentale/Modelisation/SIG/SDM/PAPAVER SDM RCP26.tif", format="GTiff")


# Scenario RCP 4.5


a<-raster("C:/Users/fragniey/Documents/Projets scientifiques/Papaver occidentale/Modelisation/R/Copie rasters/SLOPE.tif")
b<-raster("C:/Users/fragniey/Documents/Projets scientifiques/Papaver occidentale/Modelisation/R/Copie rasters/NORTHING.tif")
c<-raster("C:/Users/fragniey/Documents/Projets scientifiques/Papaver occidentale/Modelisation/R/Copie rasters/T85_4.5.tif")
d<-raster("C:/Users/fragniey/Documents/Projets scientifiques/Papaver occidentale/Modelisation/R/Copie rasters/PR85_4.5_W.tif")


stackrast<-stack(a,b,c,d)
names(stackrast)
names(stackrast)<-n

#predict and write the raster
pre<-predict(stackrast,finalmodel,type="response")
writeRaster(pre, "C:/Users/fragniey/Documents/Projets scientifiques/Papaver occidentale/Modelisation/SIG/SDM/PAPAVER SDM RCP45.tif", format="GTiff")


# Scenario RCP 8.5


a<-raster("C:/Users/fragniey/Documents/Projets scientifiques/Papaver occidentale/Modelisation/R/Copie rasters/SLOPE.tif")
b<-raster("C:/Users/fragniey/Documents/Projets scientifiques/Papaver occidentale/Modelisation/R/Copie rasters/NORTHING.tif")
c<-raster("C:/Users/fragniey/Documents/Projets scientifiques/Papaver occidentale/Modelisation/R/Copie rasters/T85_8.5.tif")
d<-raster("C:/Users/fragniey/Documents/Projets scientifiques/Papaver occidentale/Modelisation/R/Copie rasters/PR85_8.5_W.tif")


stackrast<-stack(a,b,c,d)
names(stackrast)
names(stackrast)<-n

#predict and write the raster
pre<-predict(stackrast,finalmodel,type="response")
writeRaster(pre, "C:/Users/fragniey/Documents/Projets scientifiques/Papaver occidentale/Modelisation/SIG/SDM/PAPAVER SDM RCP85.tif", format="GTiff")
```

Table S5. Cross validation of the final validated GAM: AUC and MSR of the validated model, with different cross validation techniques.

	AUC	**MSR**
Full model	0.95	0.08
10-fold cross validation (mean of the 10 validation datasets)	0.95	0.08
Monte Carlo cross validation (mean of the 30 validation datasets)	0.95	0.08
Spatial cross validation (mean of the 4 blocs used for validation, see methods).	0.90	0.13

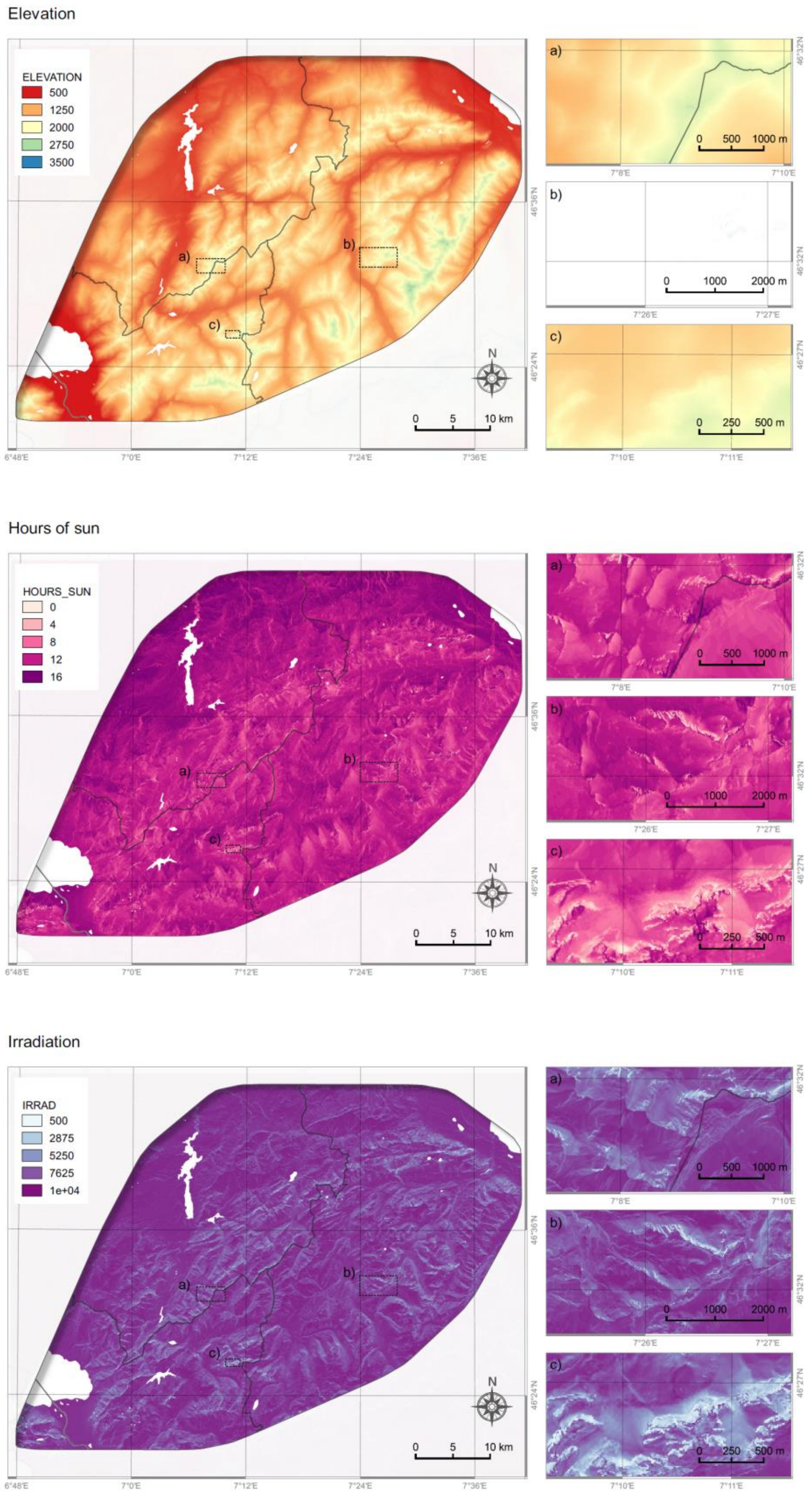
Table S6. Full field counting data.

ID	Region1	Region2	Region3	CoorX	CoorY	NumberIdiv
1	France	Haute-Savoie	Col Colombière	524116	94177	50
2	France	Haute-Savoie	Col Colombière	523694	94429	10
3	France	Haute-Savoie	Jalouvre	523496	94770	10
4	France	Haute-Savoie	Jalouvre	523444	94618	100
5	France	Haute-Savoie	Morsulaz	526723	97245	2000
6	France	Haute-Savoie	Morsulaz	526637	97151	50
7	France	Haute-Savoie	Morsulaz	526463	97059	20
8	France	Haute-Savoie	Morsulaz	526272	96927	50
9	France	Haute-Savoie	Morsulaz	526855	95447	10
10	France	Haute-Savoie	Morsulaz	527554	97427	20
11	France	Haute-Savoie	Morsulaz	526240	96820	30
12	France	Haute-Savoie	Pointe Blanche	524117	94573	2
13	France	Haute-Savoie	Pointe Blanche	524187	94628	50
14	France	Haute-Savoie	Creux de Sotty	523979	95256	5
15	France	Haute-Savoie	Creux de Sotty	524007	95135	100
16	France	Haute-Savoie	Creux de Sotty	523728	95348	40
17	Valais	Port-Valais	Le Grammont	552594	134304	50
18	Valais	Port-Valais	Le Grammont	552585	134230	50
19	Valais	Port-Valais	Le Grammont	552599	134235	10
20	Valais	Port-Valais	Le Grammont	552591	134217	10
21	Valais	Port-Valais	Le Grammont	552588	134215	1
22	Valais	Port-Valais	Le Grammont	552574	134229	10
23	Valais	Port-Valais	Le Grammont	552567	134229	10
24	Vaud	Château-D'Oex	La Pierreuse	580347	143452	400
25	Vaud	Château-D'Oex	La Pierreuse	580034	143270	4
26	Vaud	Château-D'Oex	La Pierreuse	579999	143234	100
27	Vaud	Château-D'Oex	La Pierreuse	579989	143225	100
28	Vaud	Château-D'Oex	Les Salaires	579663	143048	100
29	Vaud	Château-D'Oex	Les Salaires	579610	143000	50
30	Vaud	Château-D'Oex	Les Salaires	579632	143206	30
31	Vaud	Jura	Grand Cunay	510788	158586	1
32	Vaud	Jura	Mont Tendre	513111	160593	3
33	Vaud	Jura	Mont Tendre	513113	160598	3
34	Fribourg	Grandvillars	Combe Vanil de l'Ecri	577026	152436	20
35	Fribourg	Grandvillars	Combe Vanil de l'Ecri	577055	152432	80
36	Fribourg	Grandvillars	Combe Vanil de l'Ecri	577125	152334	10
37	Fribourg	Grandvillars	Combe Vanil de l'Ecri	577165	152350	1
38	Fribourg	Grandvillars	Combe Vanil de l'Ecri	577107	152351	1
39	Fribourg	Grandvillars	Combe Vanil de l'Ecri	577196	152280	3
40	Fribourg	Grandvillars	Combe Vanil de l'Ecri	577191	152270	10
41	Fribourg	Grandvillars	Combe Vanil de l'Ecri	577189	152299	20
42	Fribourg	Grandvillars	Combe Vanil de l'Ecri	577203	152303	5
43	Fribourg	Grandvillars	Combe Vanil de l'Ecri	577140	152353	20
44	Fribourg	Grandvillars	Combe Vanil de l'Ecri	577180	152257	20
45	Fribourg	Grandvillars	Pointe de Paray	576800	151454	30
46	Fribourg	Grandvillars	Pointe de Paray	576820	151445	6
47	Fribourg	Grandvillars	Pointe de Paray	576842	151414	10
48	Fribourg	Grandvillars	Pointe de Paray	576830	151427	10
49	Fribourg	Grandvillars	Pointe de Paray	576849	151413	5
50	Fribourg	Grandvillars	Rocher de Saint-Jacques	576540	151981	6
51	Fribourg	Grandvillars	Rocher de Saint-Jacques	576499	151907	1
52	Fribourg	Grandvillars	Rocher de Saint-Jacques	576436	151924	20
53	Fribourg	Grandvillars	Rocher de Saint-Jacques	576445	151909	25
54	Fribourg	Grandvillars	Rocher de Saint-Jacques	576450	151905	150
55	Fribourg	Grandvillars	Rocher de Saint-Jacques	576440	151928	20

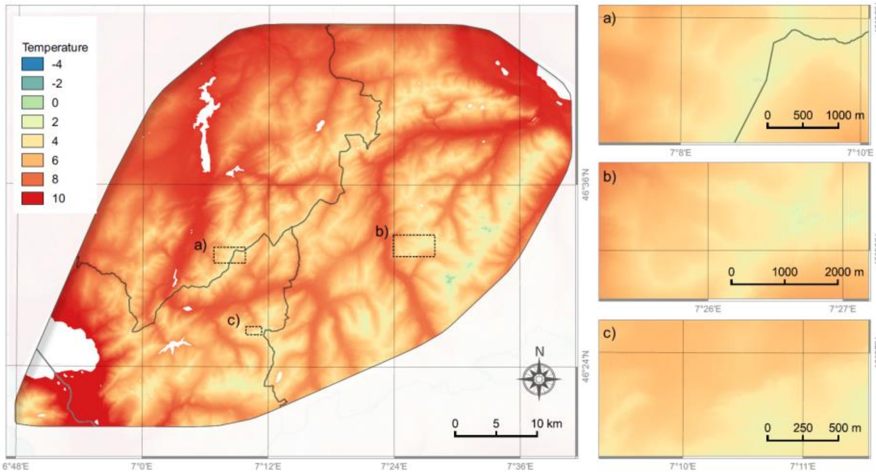
56	Fribourg	Grandvillars	Rocher de Saint-Jacques	576472	151926	40
57	Fribourg	Grandvillars	Rocher de Saint-Jacques	576483	151950	4
58	Fribourg	Grandvillars	Rocher de Saint-Jacques	576554	151770	15
59	Fribourg	Grandvillars	Rocher de Saint-Jacques	576687	151826	30
60	Fribourg	Grandvillars	Rocher de Saint-Jacques	576696	151817	10
61	Fribourg	Grandvillars	Rocher de Saint-Jacques	576883	152100	10
62	Fribourg	Grandvillars	Vanil de l'Ecri	577001	152789	3
63	Fribourg	Grandvillars	Vanil de l'Ecri	577021	152648	20
64	Fribourg	Grandvillars	Vanil de l'Ecri	577004	152665	100
65	Fribourg	Grandvillars	Vanil de l'Ecri	576970	152744	500
66	Fribourg	Grandvillars	Vanil de l'Ecri	576932	152705	1000
67	Fribourg	Grandvillars	Vanil de l'Ecri	576877	152665	10
68	Fribourg	Grandvillars	Vanil de l'Ecri	576854	152626	20
69	Fribourg	Grandvillars	Vanil de l'Ecri	576799	152663	25
70	Fribourg	Grandvillars	Vanil de l'Ecri	576783	152658	5
71	Fribourg	Grandvillars	Vanil de l'Ecri	576833	152762	2
72	Fribourg	Val-de-Charmey	Dent de Ruth	584494	156069	2000
73	Fribourg	Val-de-Charmey	Dent de Ruth	584554	156073	10
74	Fribourg	Val-de-Charmey	Dent de Ruth	584606	156028	100
75	Fribourg	Val-de-Charmey	Dent de Ruth	584623	156126	50
76	Fribourg	Val-de-Charmey	Dent de Ruth	584726	156032	500
77	Fribourg	Val-de-Charmey	Dent de Ruth	584807	156035	25
78	Fribourg	Val-de-Charmey	Dent de Ruth	584914	156060	50
79	Fribourg	Val-de-Charmey	Dent de Ruth	584925	156124	20
80	Fribourg	Val-de-Charmey	Dent de Savigny	583809	155591	20
81	Fribourg	Val-de-Charmey	Dent de Savigny	583832	155598	20
82	Fribourg	Val-de-Charmey	Dent de Savigny	583920	155659	50
83	Fribourg	Val-de-Charmey	Dent de Savigny	583871	155673	5
84	Fribourg	Val-de-Charmey	Dent de Savigny	583901	155679	20
85	Fribourg	Val-de-Charmey	Dent de Savigny	583972	155641	30
86	Bern	Zweisimmen	Fromatt	599739	154462	500
87	Bern	Zweisimmen	Fromatt	599689	154493	1000
88	Bern	Zweisimmen	Fromatt	599648	154523	50
89	Bern	Zweisimmen	Fromatt	599554	154550	200
90	Bern	Zweisimmen	Fromatt	599533	154555	100
91	Bern	Zweisimmen	Fromatt	599448	154555	100
92	Bern	Zweisimmen	Fromatt	599356	154609	300
93	Bern	Zweisimmen	Fromatt	599318	154588	1
94	Bern	Zweisimmen	Fromatt	599305	154558	50
95	Bern	Zweisimmen	Fromatt	599318	154558	20
96	Bern	Zweisimmen	Fromatt	599230	154542	500
97	Bern	Zweisimmen	Fromatt	599256	154501	500
98	Bern	Zweisimmen	Fromatt	599180	154567	30
99	Bern	Zweisimmen	Fromatt	599125	154509	5
100	Bern	Zweisimmen	Fromatt	599115	154511	20
101	Bern	Zweisimmen	Fromatt	599140	154460	50
102	Bern	Zweisimmen	Gandhore	598883	152964	10
103	Bern	Zweisimmen	Gandhore	598875	152925	500
104	Bern	Zweisimmen	Gandhore	598856	153069	250
105	Bern	Zweisimmen	Gandhore	598858	152946	250
106	Bern	Zweisimmen	Gandhore	598878	152976	100
107	Bern	Zweisimmen	Gandhore	598802	153036	150
108	Bern	Zweisimmen	Gandhore	598763	152991	500
109	Bern	Zweisimmen	Gandhore	598663	152997	5000
110	Bern	Zweisimmen	Hinderi Fromatt	600360	154423	1
111	Bern	Zweisimmen	Hinderi Fromatt	600367	154424	800
112	Bern	Zweisimmen	Hinderi Fromatt	600488	154282	3000
113	Bern	Zweisimmen	Hinderi Fromatt	600517	154290	500
114	Bern	Zweisimmen	Hinderi Fromatt	600432	154194	1000

115	Bern	Zweisimmen	Hinderi Fromatt	600479	154357	100
116	Bern	Zweisimmen	Hinderi Fromatt	600486	154339	50
117	Bern	Zweisimmen	Hinderi Fromatt	600455	154236	50
119	Bern	Zweisimmen	Hinderi Fromatt	600417	154258	1000
120	Bern	Zweisimmen	Hinderi Fromatt	600271	154210	100
121	Bern	Zweisimmen	Hinderi Fromatt	600286	154226	300
122	Bern	Zweisimmen	Hinderi Fromatt	600307	154160	100
123	Bern	Zweisimmen	Hinderi Fromatt	600167	154186	2500
124	Bern	Zweisimmen	Hinderi Fromatt	600248	154209	50
125	Bern	Zweisimmen	Hinderi Fromatt	599952	154419	300
126	Bern	Zweisimmen	Holzflue	599346	154100	500
127	Bern	Zweisimmen	Holzflue	599325	154128	20
128	Bern	Zweisimmen	Holzflue	599503	154137	50
129	Bern	Zweisimmen	Holzflue	599516	154116	20
130	Bern	Zweisimmen	Holzflue	599524	154097	20
131	Bern	Zweisimmen	Holzflue	599632	154052	50
132	Bern	Zweisimmen	Holzflue	599732	154105	100
133	Bern	Zweisimmen	Holzflue	599722	154025	20
134	Bern	Zweisimmen	Vorderi Spillgerte	599784	153988	100
135	Bern	Zweisimmen	Vorderi Spillgerte	599838	153987	250
136	Bern	Zweisimmen	Vorderi Spillgerte	599843	153989	200
137	Bern	Zweisimmen	Vorderi Spillgerte	599879	153989	200
138	Bern	Zweisimmen	Vorderi Spillgerte	599902	153995	50
139	Bern	Zweisimmen	Vorderi Spillgerte	600008	153939	100
140	Bern	Zweisimmen	Vorderi Spillgerte	600070	153910	100
141	Bern	Zweisimmen	Vorderi Spillgerte	600167	153897	250
142	Bern	Zweisimmen	Vorderi Spillgerte	600183	153904	50
143	Lucern	Flühli	Blattenegg	644462	182601	10
144	Lucern	Flühli	Blattenegg	644466	182597	8
145	Lucern	Flühli	Blattenegg	644472	182535	2
146	Lucern	Flühli	Blattenegg	644440	182711	2
147	Lucern	Flühli	Blattenegg	644439	182705	1
148	Lucern	Flühli	Blattenegg	644650	182748	3
149	Lucern	Flühli	Blattenegg	644674	182775	1
150	Lucern	Flühli	Blattenegg	644664	182785	1
151	Lucern	Flühli	Blattenegg	644685	182816	1
152	Lucern	Flühli	Blattenegg	644730	182954	2
153	Lucern	Flühli	Blattenegg	644691	182742	1

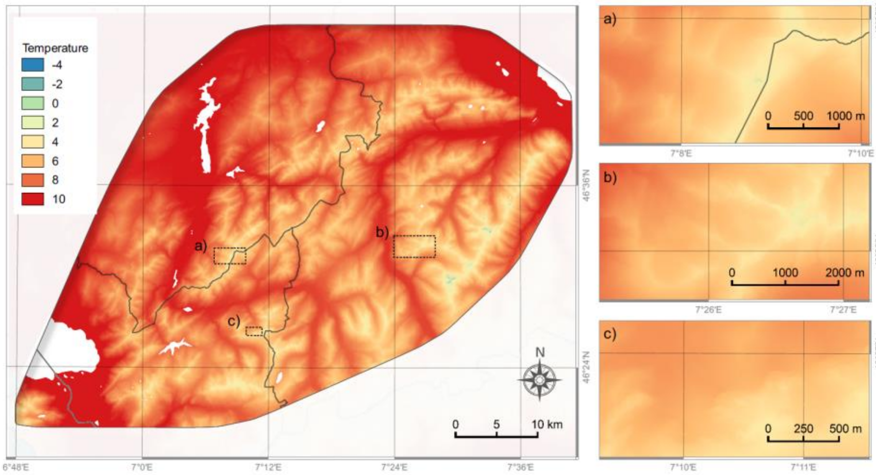
Figure S1. Series of maps representing environmental variables on the studied area. The right panels show 3 zoomed areas where *P. occidentale* occurs (see Figure 4 in the main manuscript).



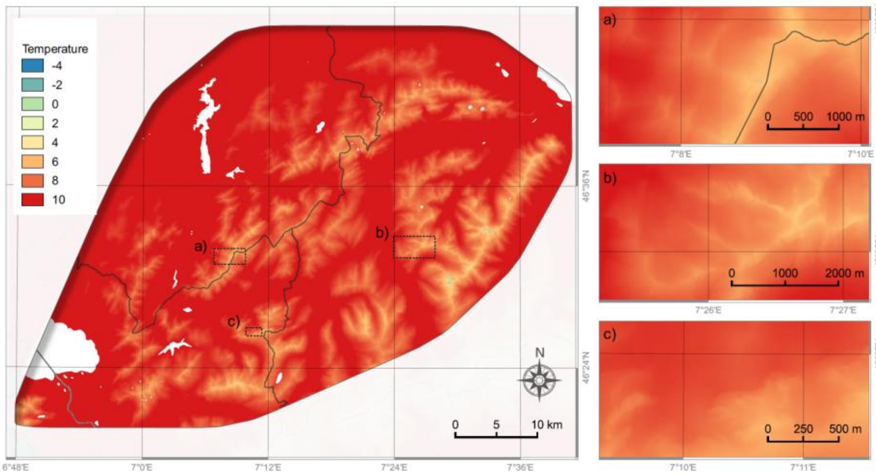
Mean annual temperature 2085 (RCP 2.6)



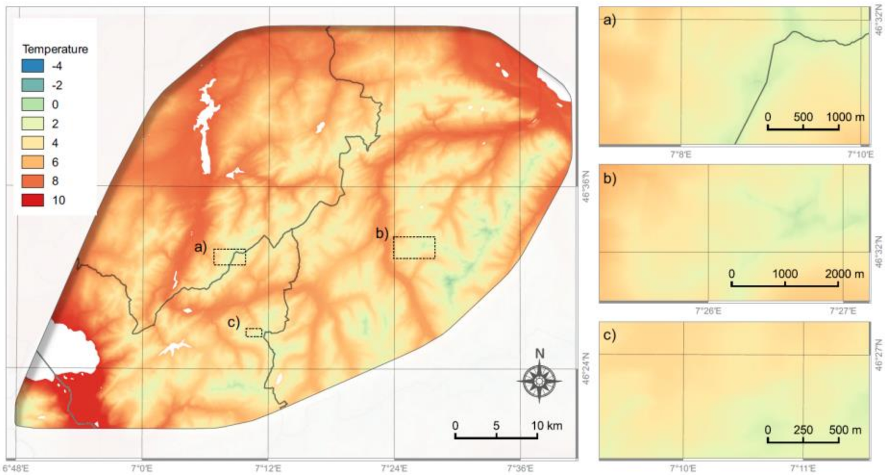
Mean annual temperature 2085 (RCP 4.5)



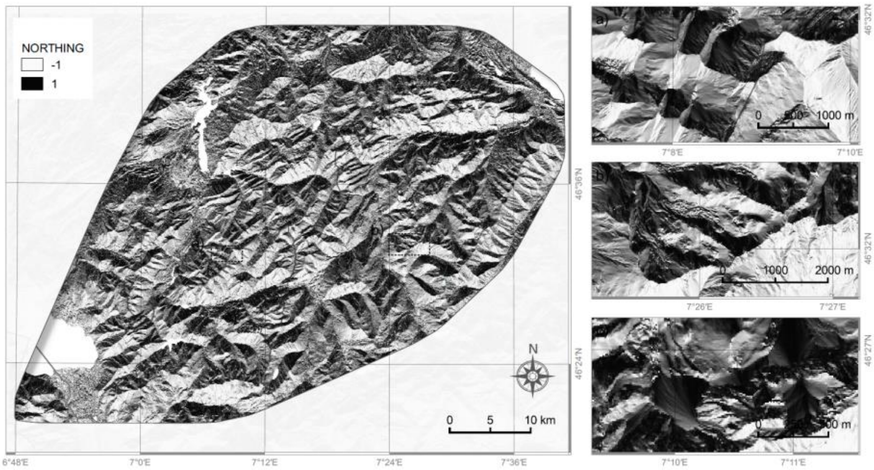
Mean annual temperature 2085 (RCP 8.5)



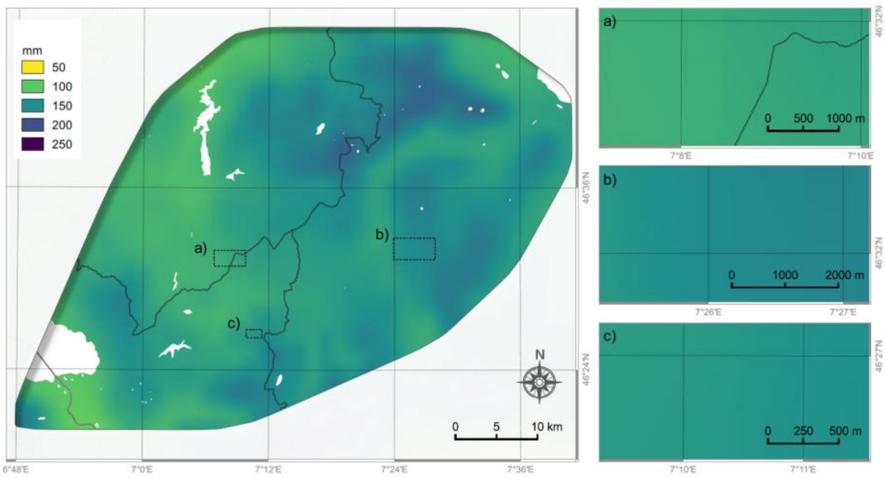
Mean annual temperature



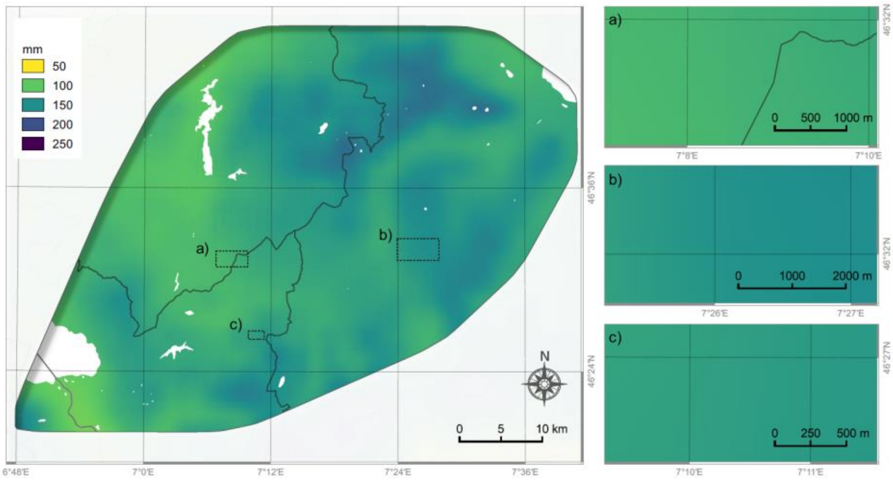
Northing



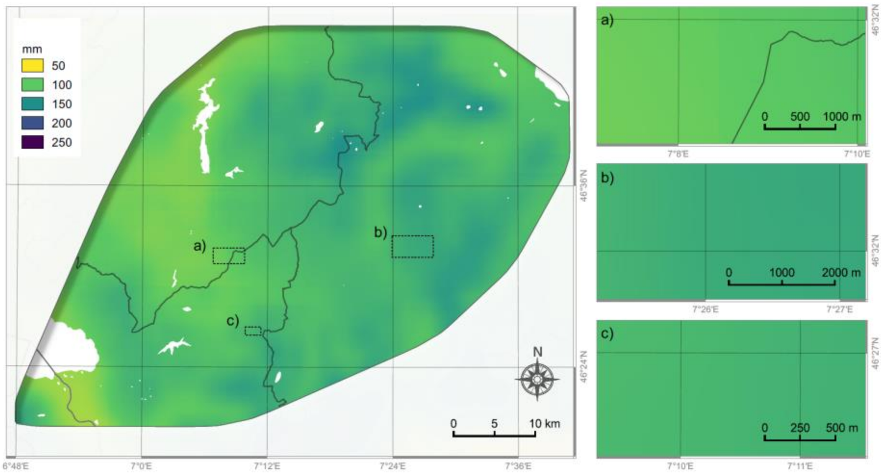
Precipitation summer 2085 (RCP 2.6)



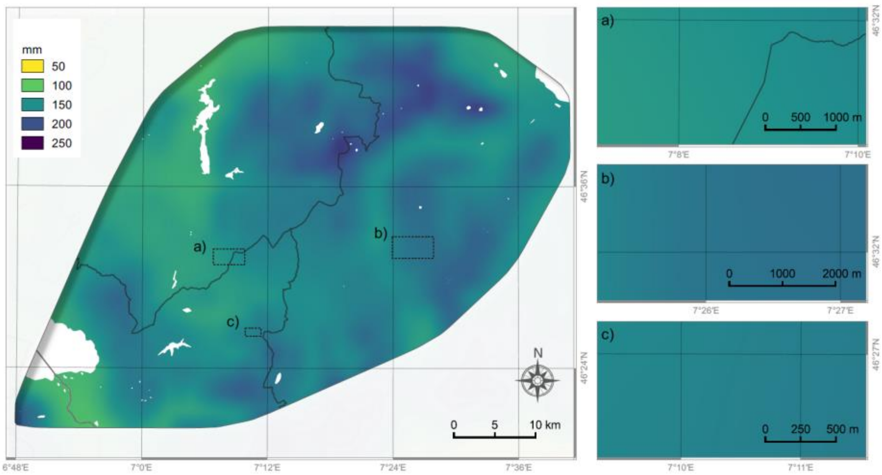
Precipitation summer 2085 (RCP 4.5)



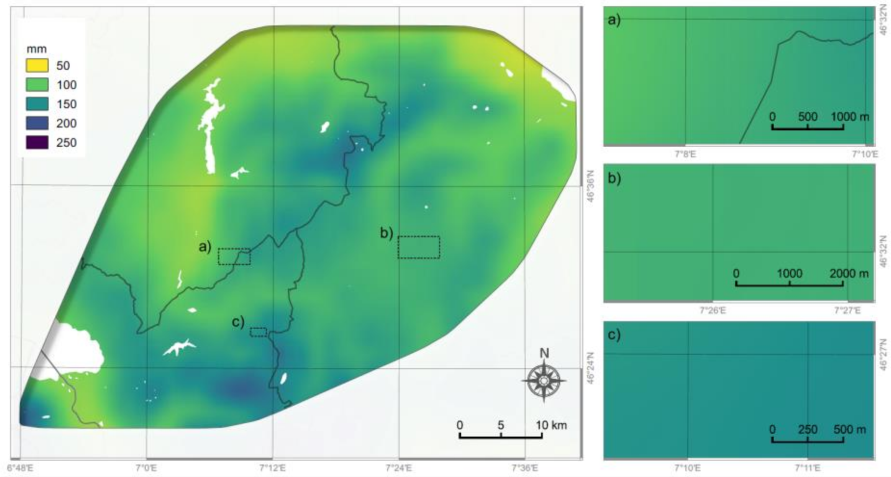
Precipitation summer 2085 (RCP 8.5)



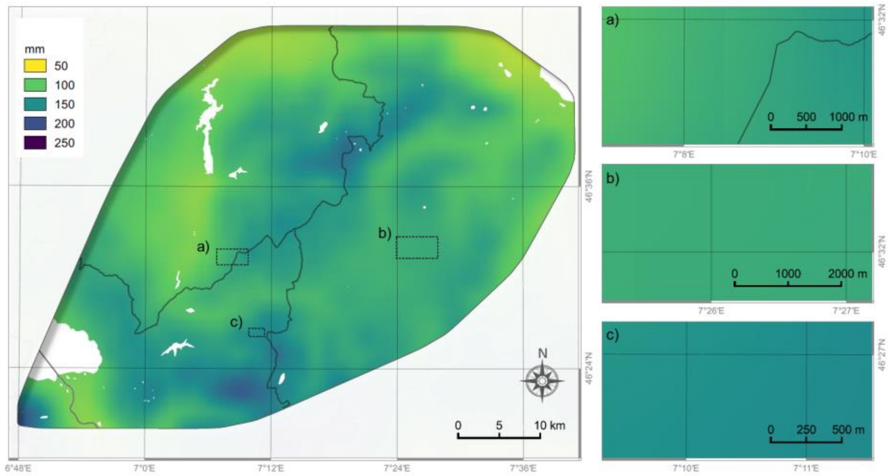
Precipitation summer



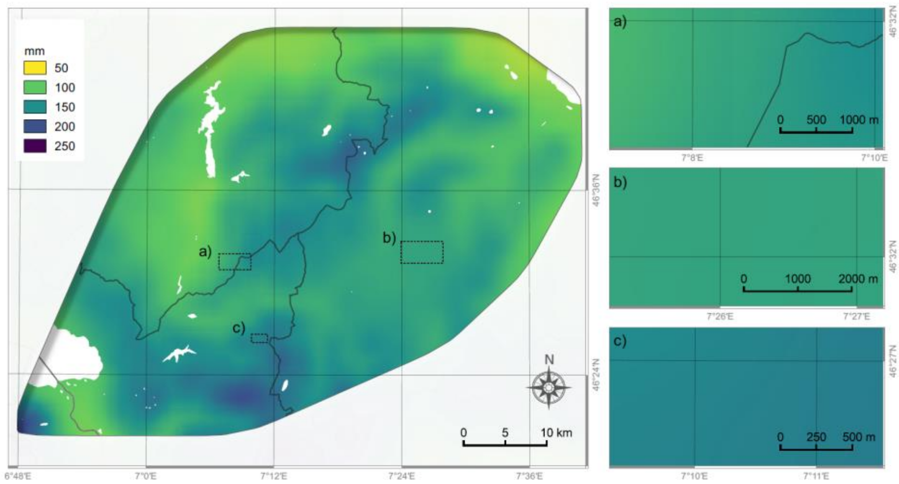
Precipitation winter 2085 (RCP 2.6)



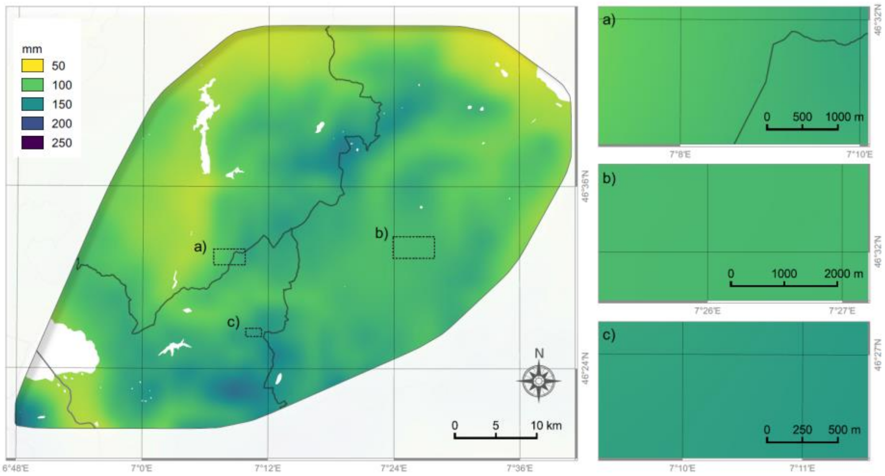
Precipitation winter 2085 (RCP 4.5)



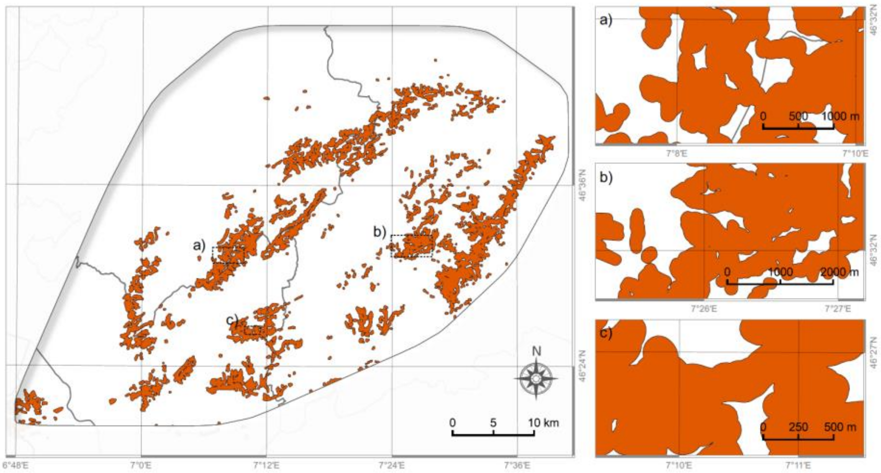
Precipitation winter 2085 (RCP 8.5)



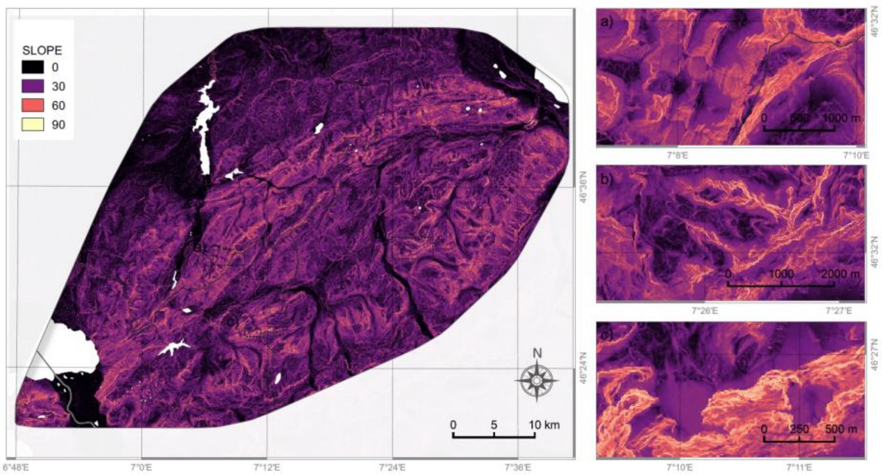
Precipitation winter



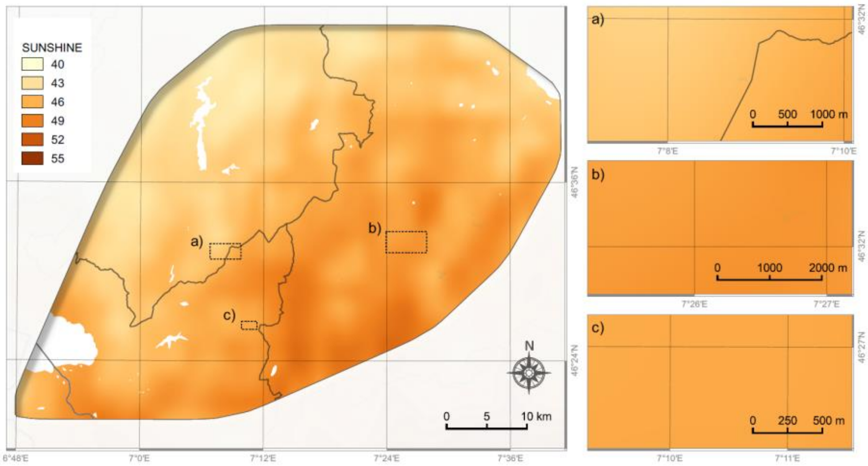
Area with screes



Slope



Sunshine



SUNSHINE
40
43
46
49
52
55
a)
b)
c)
N
0 5 10 km
6°48'E
7°0'E
7°12'E
7°24'E
7°36'E
46°36'N
46°24'N
0 500 1000 m
7°8'E
7°10'E
46°32'N
0 1000 2000 m
7°26'E
7°27'E
0 250 500 m
7°10'E
7°11'E
46°27'N

Figure S2. Paired correlation plot with all environmental variables. For the meaning of abbreviations, see table 1 in the main manuscript.

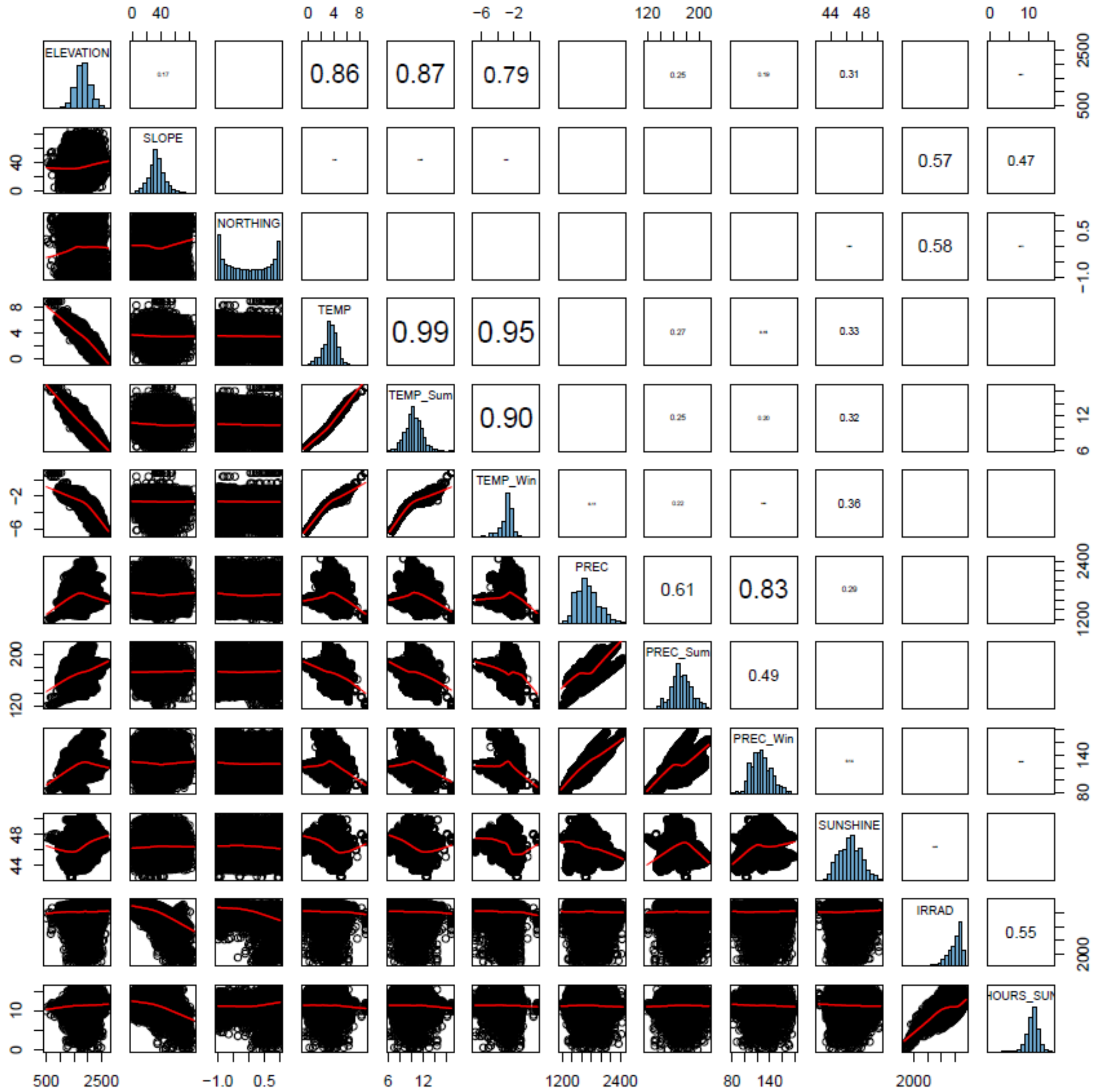


Figure S3. Paired correlation plot with the 8 selected (uncorrelated) environmental variables. For the meaning of abbreviations, see table 1 in the main manuscript.

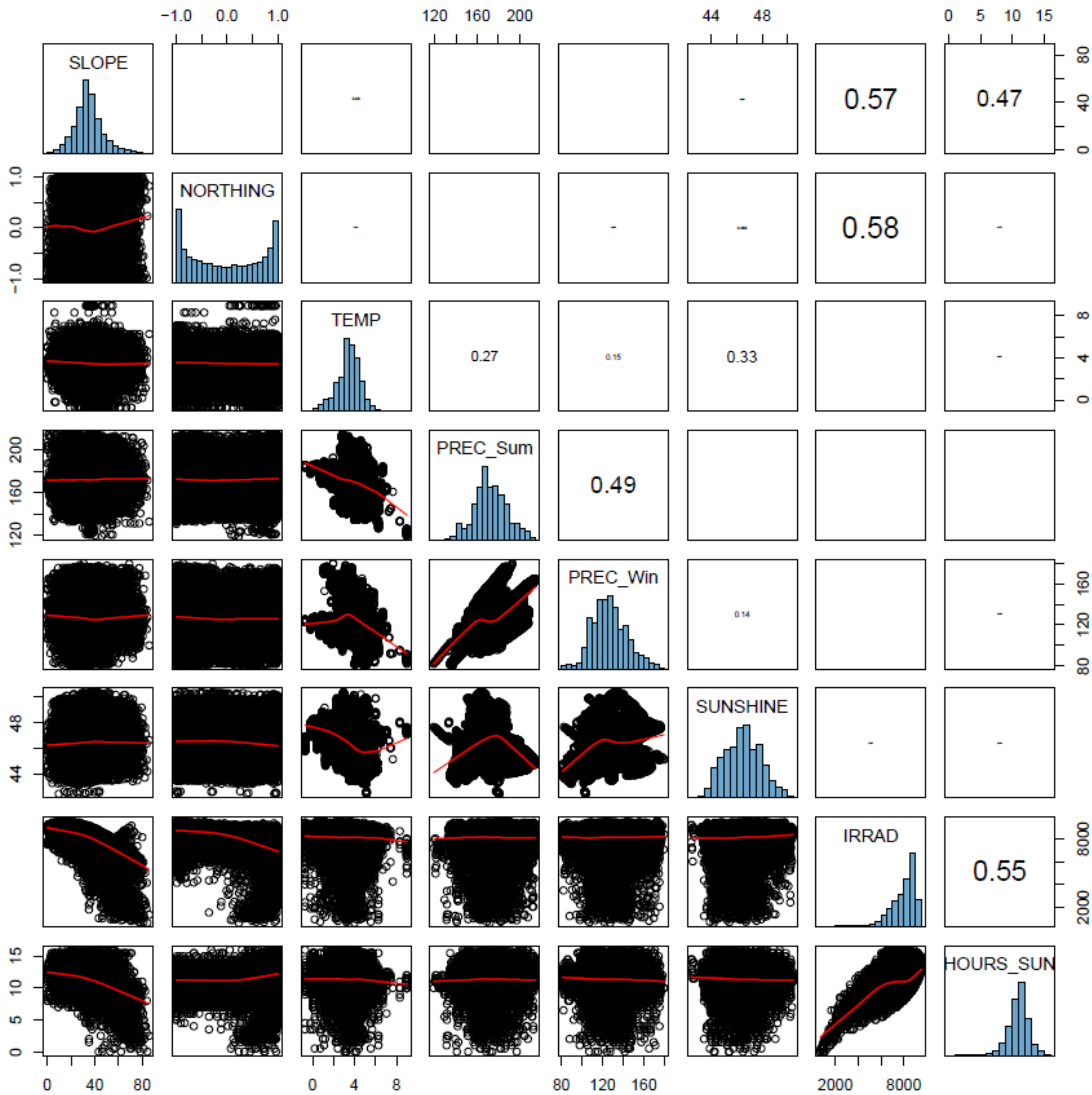
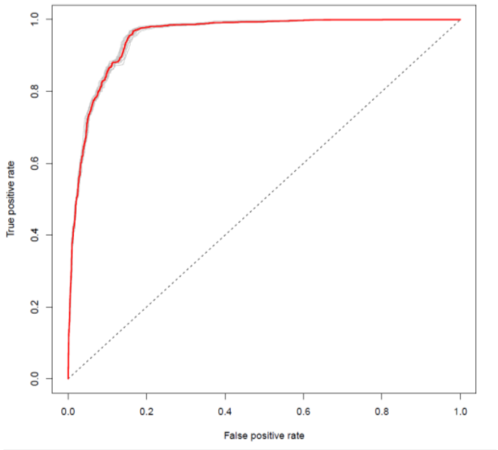
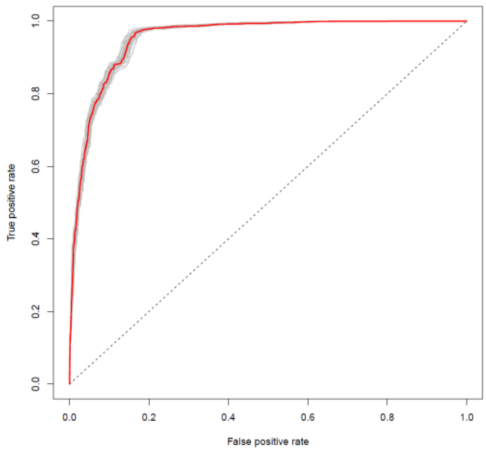


Figure S4. Receiver operating characteristic (ROC) curves for different cross validation techniques (red line, full model ROC curve with all the data, grey lines, ROC curves of validation datasets).

a) 10 fold cross validation



b) Monte-carlo cross validation (randomly 10% of the data for validation, 30 repetition)



c) Spatial cross validation

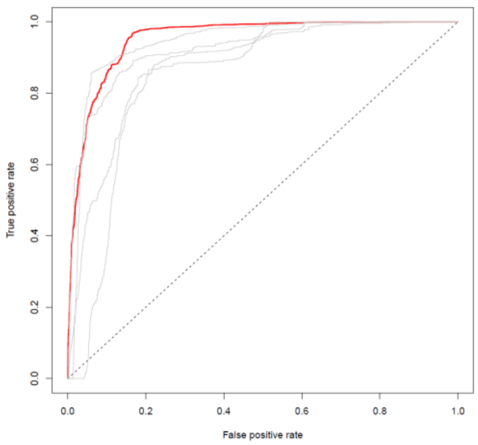


Figure S5. Response curves for the final validated General Additive Model (GAM).