

Supplementary Material

Climate change and alpine scree: 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	HFR	7.4450013	46.53983	9851	2035
		Fromatt					
Switzerland	Bern	Gandhore	GAN	7.4212141	46.528269	6760	1852
Switzerland	Bern	Fromatt	FRO	7.4345852	46.541728	3426	1898
Switzerland	Bern	Vorderi	VSP	7.4365279	46.537176	1300	2010
		Spillgerte					
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 analyses related to SDM.

VIF Scores	Variables VIF 1 SLOPE 1.947745 2 NORTHING 2.805017 3 TEMP 1.235845 4 PREC_Sum 1.440481 5 PREC_Win 1.381727 6 SUNSHINE 1.181926 7 IRRAD 5.011928 8 HOURS_SUN 2.271067
Final validated GAM Summary	Call: gam(formula = PRESENCE ~ s(SLOPE, 2) + s(NORTHING, 2) + s(TEMP_e, 2) + s(PREC_Win, 2), family = "binomial", data = data) Deviance Residuals: Min 1Q Median 3Q Max -2.4529 -0.4500 0.1604 0.5167 3.2360 (Dispersion Parameter for binomial family taken to be 1) 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 0.6 --- Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 Anova for Nonparametric Effects Npar Df Npar Chisq P(Chi) (Intercept) 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
Calculation of temperature as a function of elevation	Mean yearly mean temperature (TEMP) (°C) as a function of DEM (ELEVATION) (m) TEMP = 11.11 – 0.00424 ELEVATION

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 are generated in the areas with screens
# For each point, 12 environmental 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 background 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
uncorrddata<-subset(data3, select = -c(ELEVATION,TEMP_Sum,TEMP_Win,PREC) )

vif(uncorrddata)
ecospat.cor.plot(uncorrddata)

# 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$sp[1])
#g1northing<-gam(PRESENCE~s(SLOPE,2)+s(TEMP_e,2)+s(PREC_Win,2),data=data, family="binomial",sp=finalmodel$sp[2])
#g1temp<-gam(PRESENCE~s(SLOPE,2)+s(NORTHING,2)+s(PREC_Win,2),data=data, family="binomial",sp=finalmodel$sp[3])
#g1precwin<-gam(PRESENCE~s(SLOPE,2)+s(NORTHING,2)+s(TEMP_e,2),data=data, family="binomial",sp=finalmodel$sp[4])
#dev<-data.frame("devslope"=(deviance(gslope)-deviance(finalmodel))/deviance(g1),"devnorthing"=(deviance(g1northing)-
deviance(finalmodel))/deviance(g1),"devtemp"=(deviance(g1temp)-deviance(finalmodel))/deviance(g1),"devprecwin"=(deviance(g1precwin)-
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 squared 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 squared residuals + auc
  msr<-mean((actual-prediction)^2)
  msrtot[i]<-msr
  auc<-rm$auc
  auctot[i]<-auc
}

mean(msrtot)
mean(auctot)


## spatial cross validation

##(splitting 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)
xsplrit<-582000
ysplrit<-153500
splrits<-
list(c(0,xsplrit,0,1000000),c(xsplrit,1000000,0,1000000),c(xsplrit,1000000,0,1000000),c(0,xsplrit,0,1000000),c(0,1000000,0,ysplrit),c(0,1000000,ysplrit,1000000),c(0,1000000,ysplrit,1000000),c(0,1000000,0,ysplrit))

for(i in 1:4)
{

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

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

  if (maxtraining==1)
  {
    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 squared 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/PAPAVR 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/PAPAVR 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/PAPAVR SDM RCP85.tif", format="GTiff")

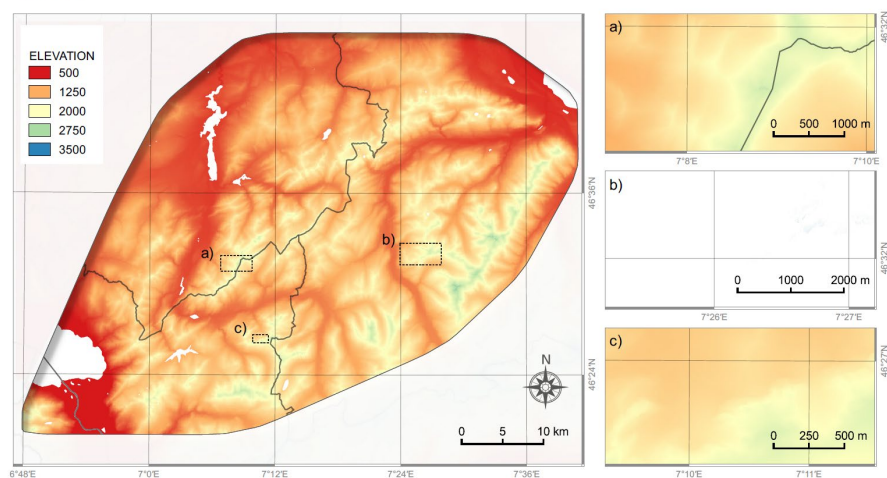
```

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

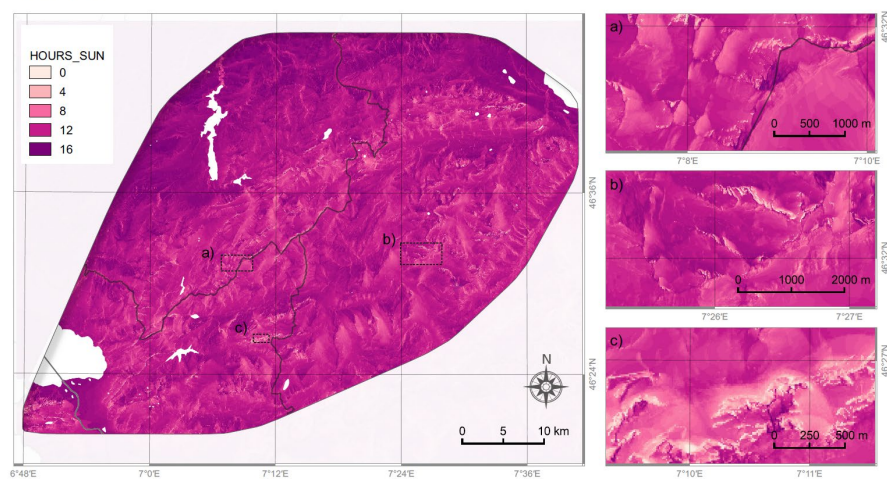
	AUC	MSR
Full model	0.95	0.08
10-fold cross validation (mean of the 10 validation datasets)	0.95	0.08
Monte Carlo cross validation (mean of the 30 validation datasets)	0.95	0.08
Spatial cross validation (mean of the 4 blocs used for validation, see methods).	0.90	0.13

Figure S1. Series of maps representing environmental variables on the studied area.

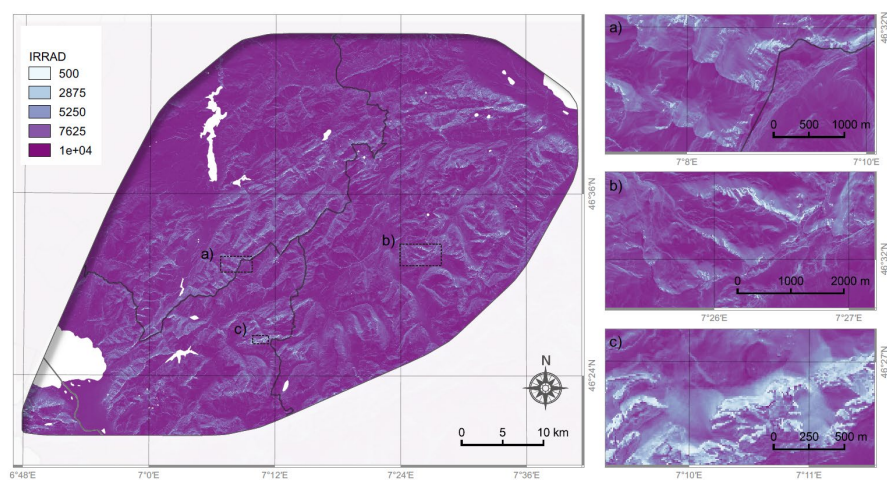
Elevation



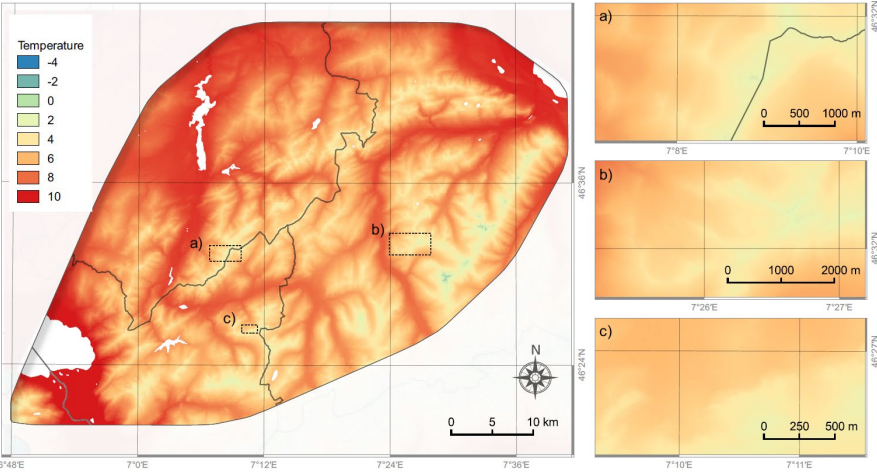
Hours of sun



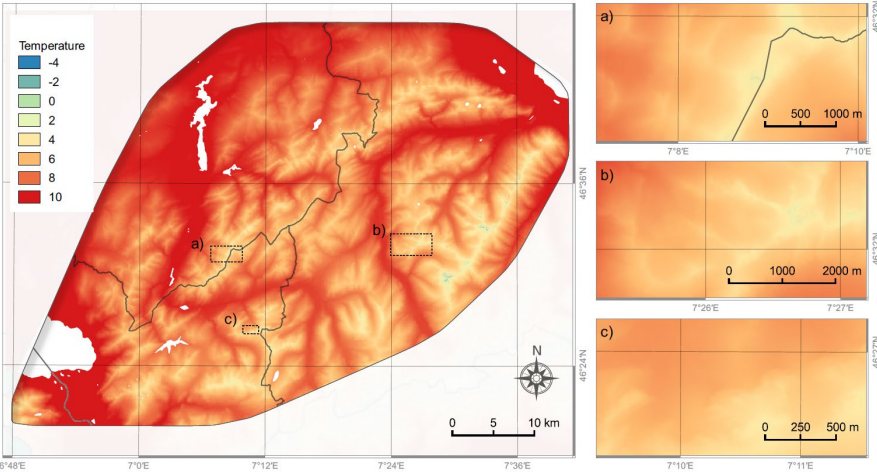
Irradiation



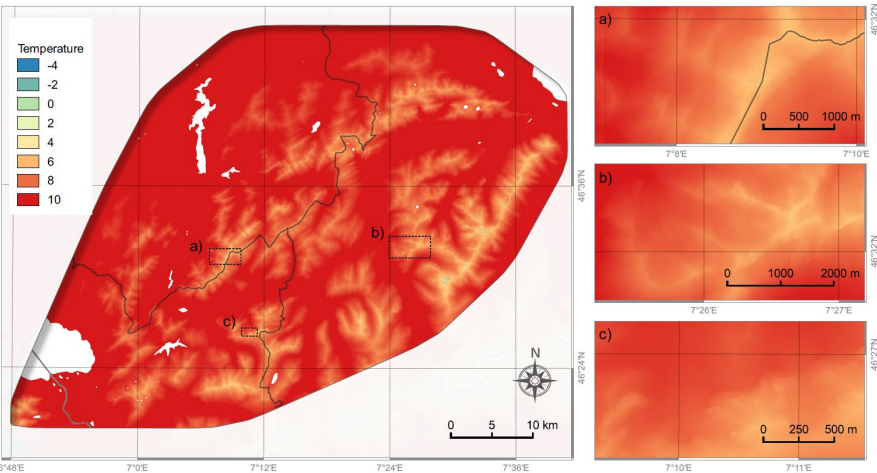
Mean annual temperature 2085 (RCP 2.6)



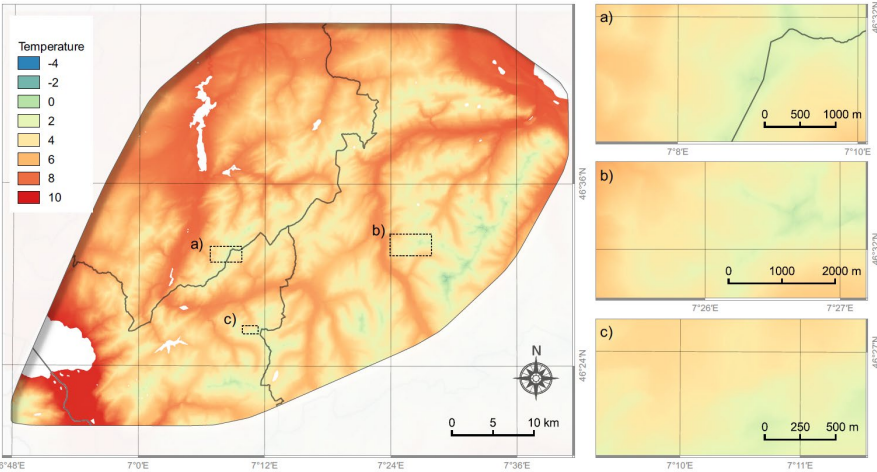
Mean annual temperature 2085 (RCP 4.5)



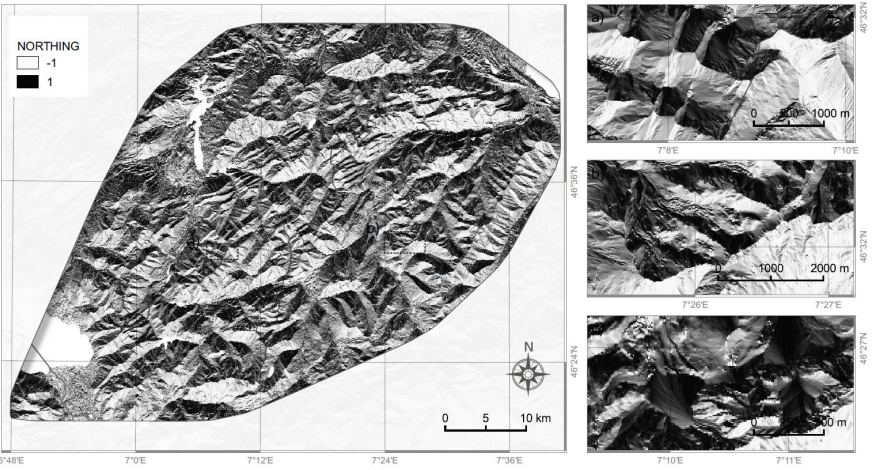
Mean annual temperature 2085 (RCP 8.5)



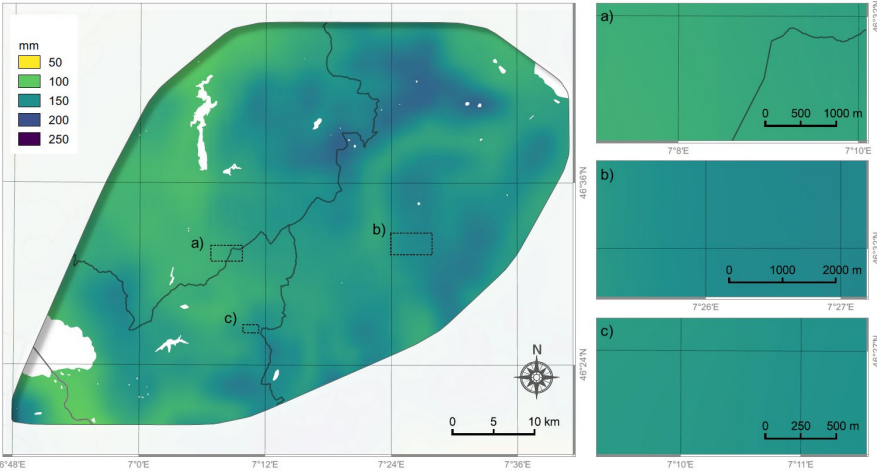
Mean annual temperature



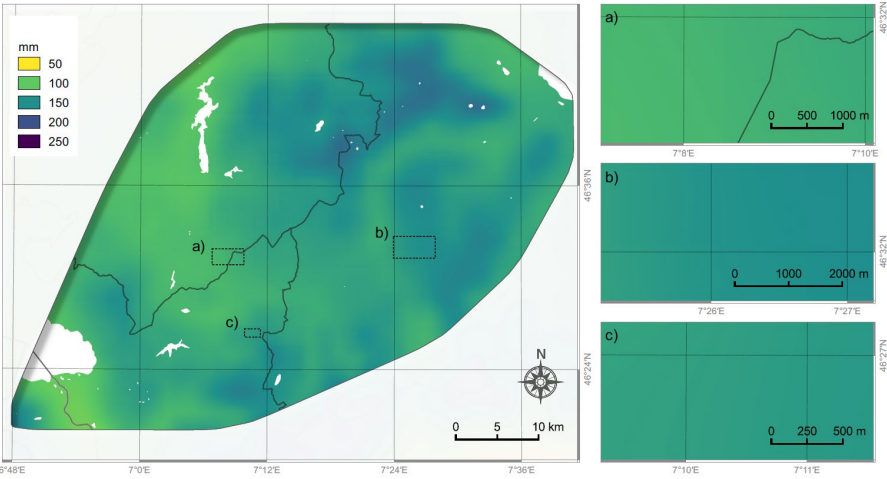
Northing



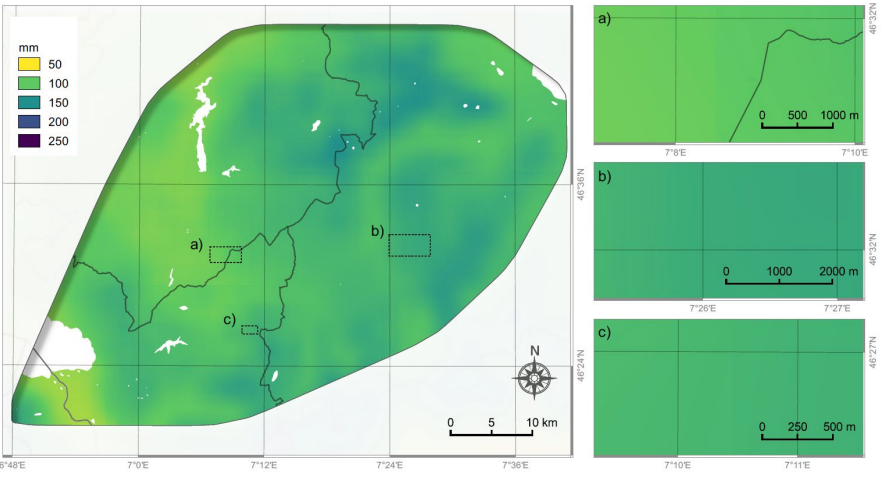
Precipitation summer 2085 (RCP 2.6)



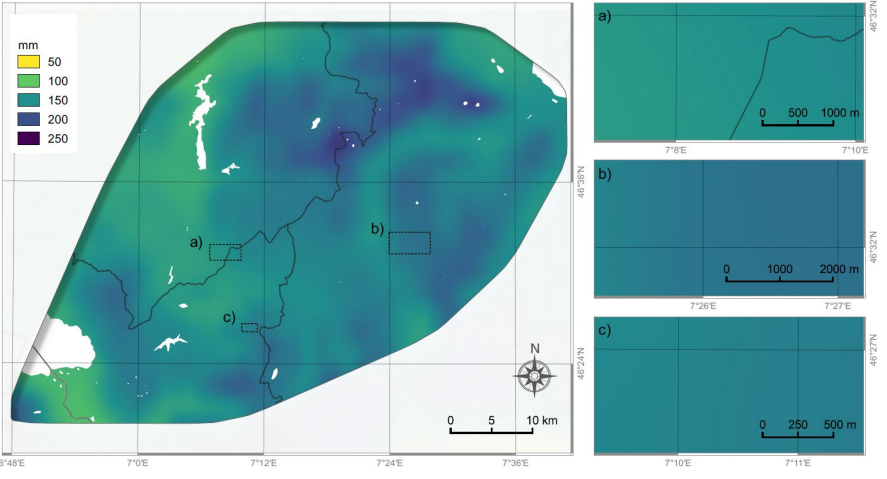
Precipitation summer 2085 (RCP 4.5)



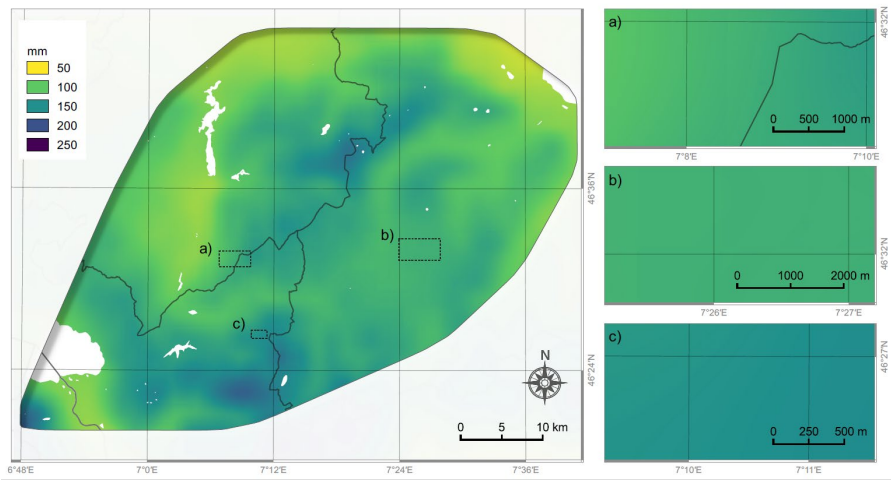
Precipitation summer 2085 (RCP 8.5)



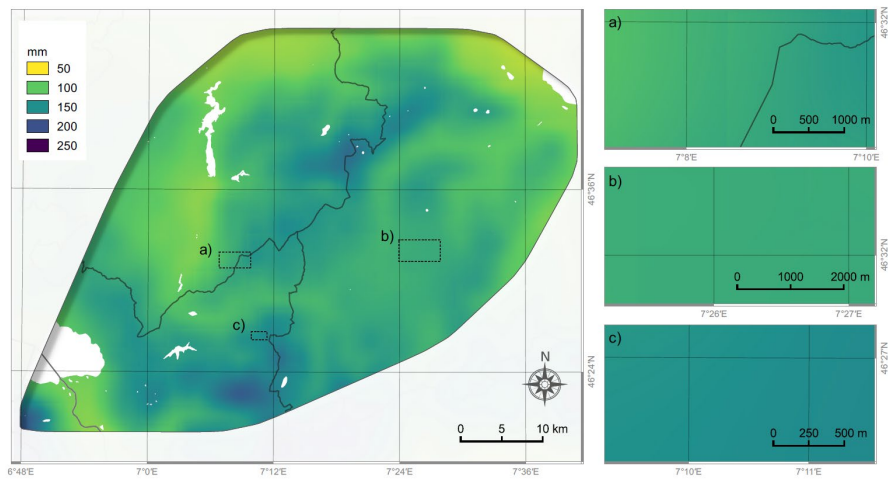
Precipitation summer



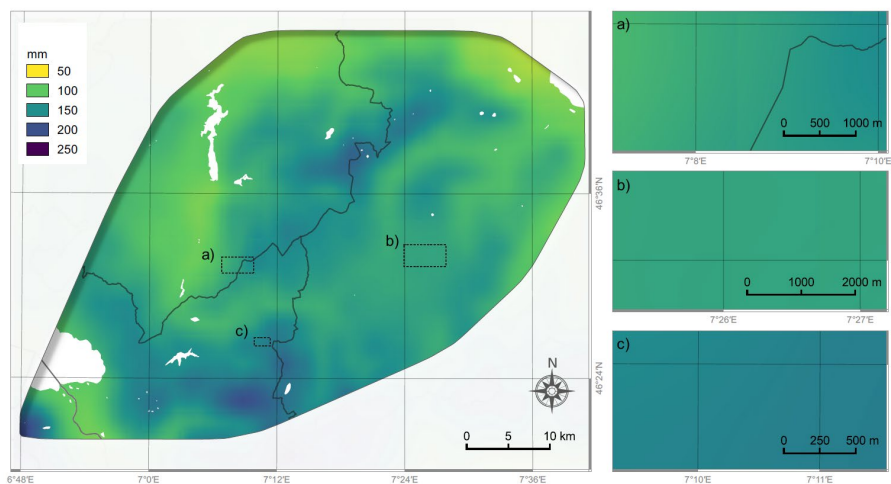
Precipitation winter 2085 (RCP 2.6)



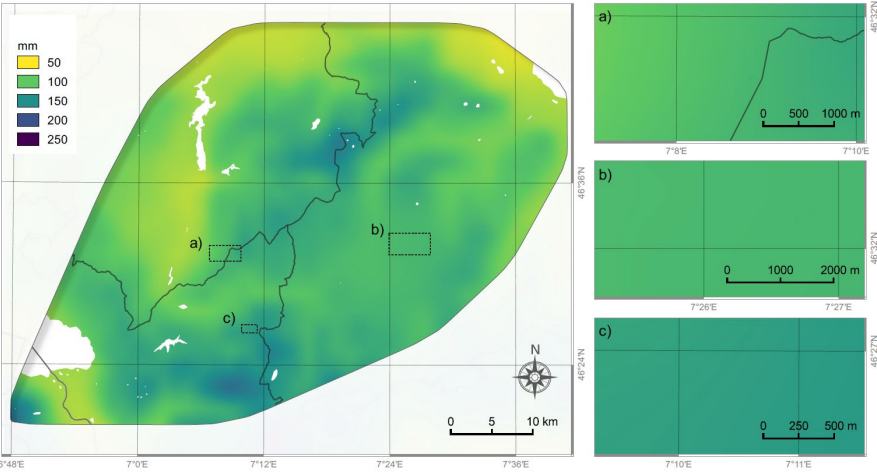
Precipitation winter 2085 (RCP 4.5)



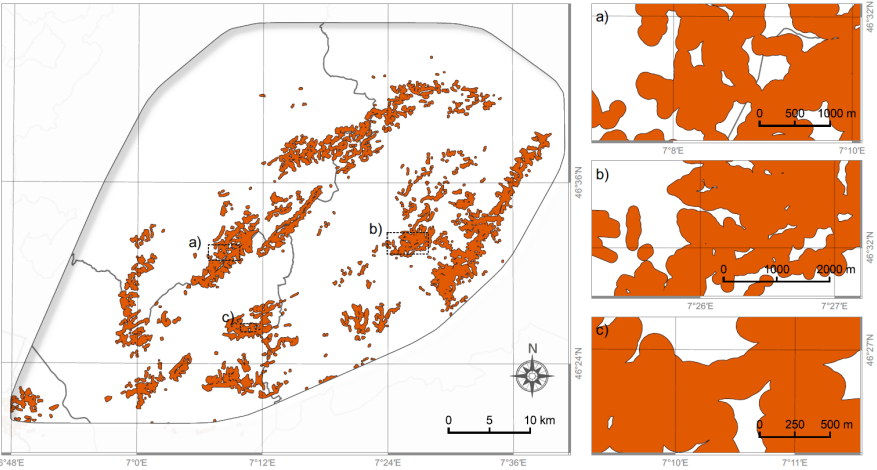
Precipitation winter 2085 (RCP 8.5)



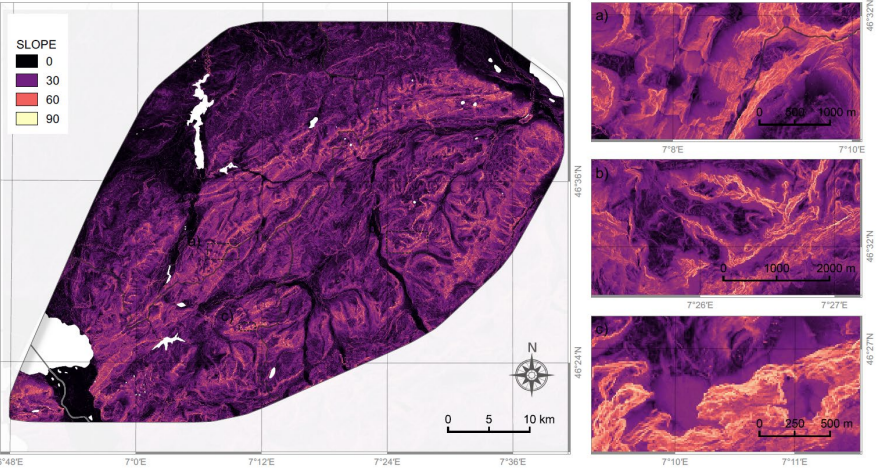
Precipitation winter



Area with screes



Slope



Sunshine

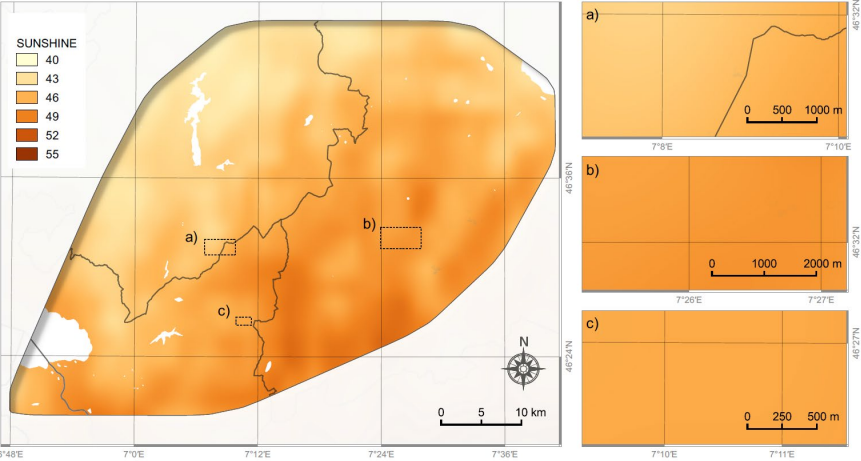


Figure S2. Paired correlation plot with all environmental variables.

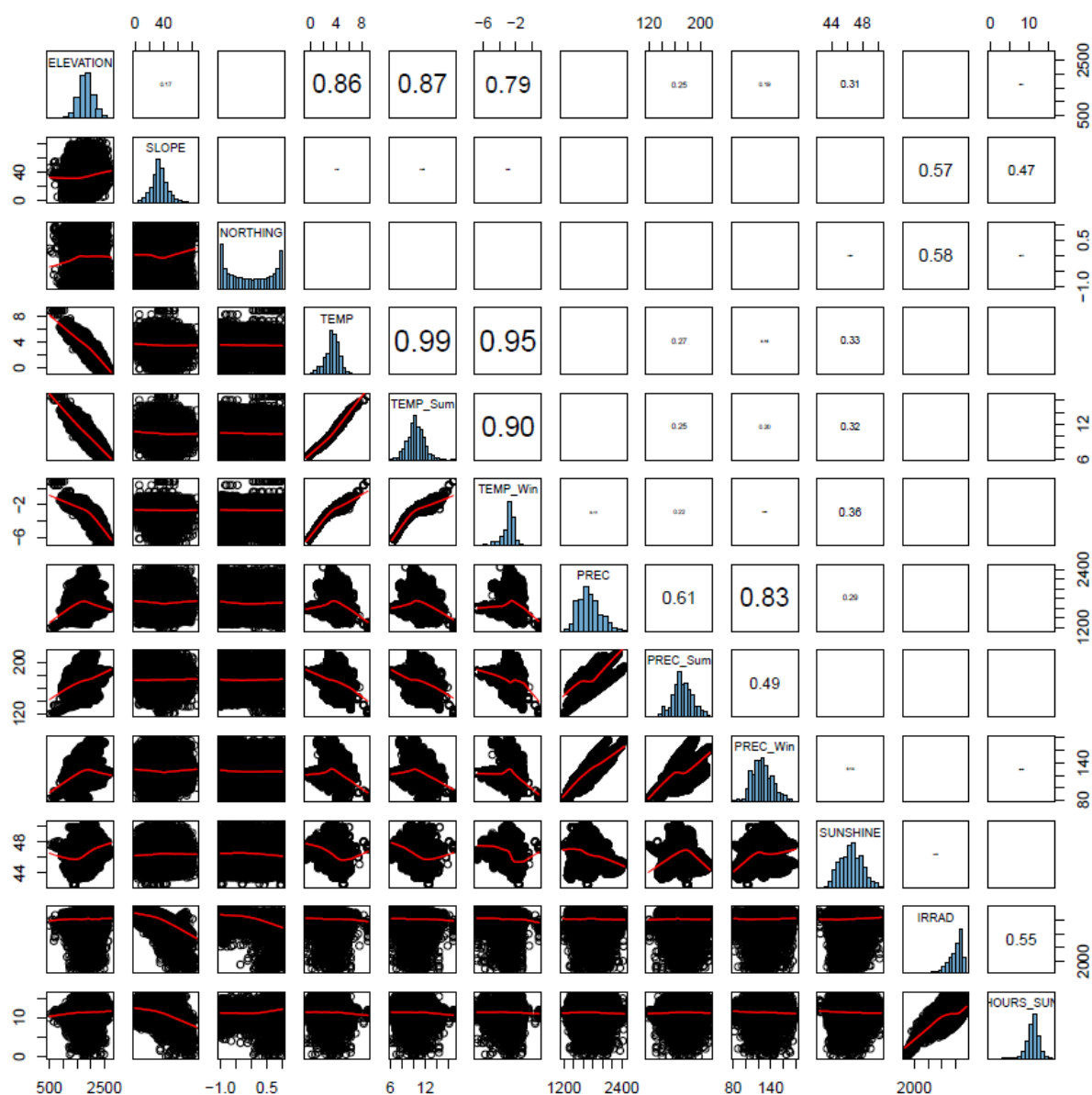


Figure S3. Paired correlation plot with the 8 selected (uncorrelated) environmental variables.

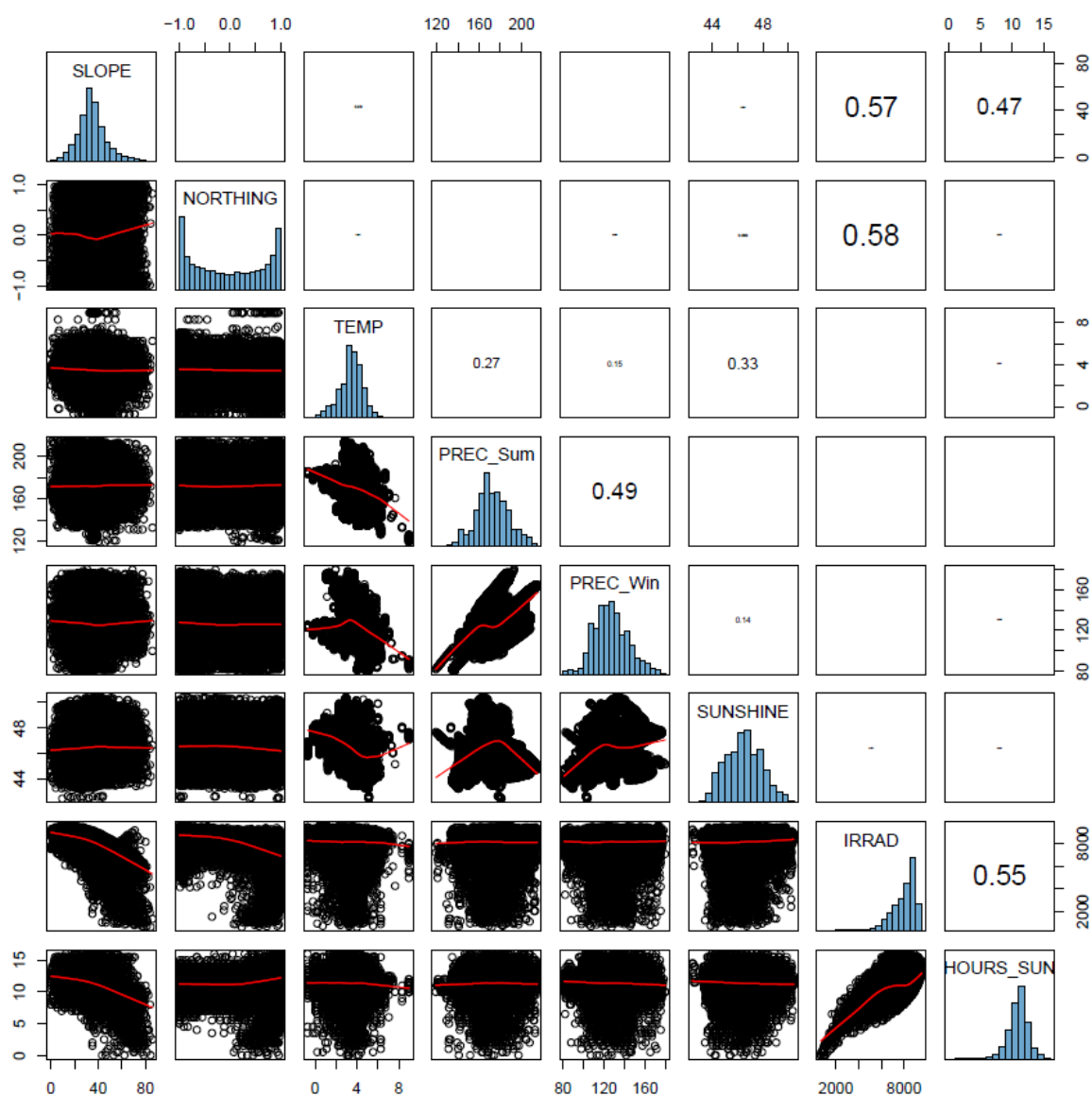
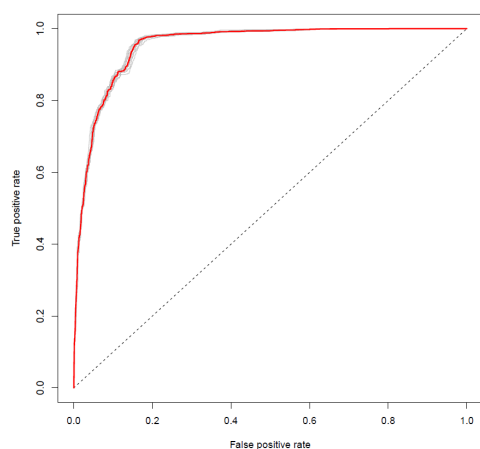
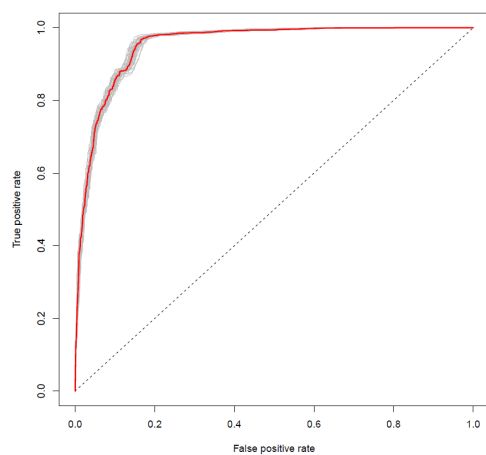


Figure S4. Roc curves for different cross validation techniques (red line, full model ROC curve with all the data, grey lines, ROC curves of validation datasets).

a) 10 fold cross validation



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



c) Spatial cross validation

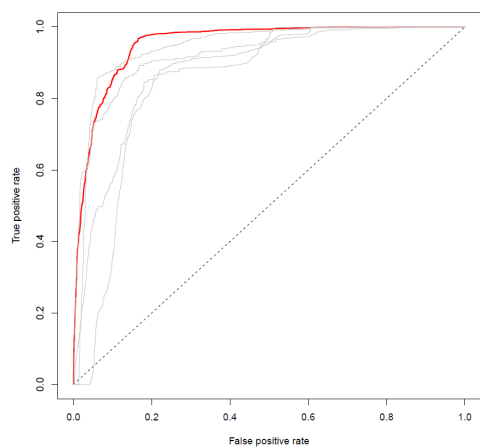


Figure S5. Response curves for the final validated GAM.

