Contents

1 Loading Data **1**

2 Downscaling **5**
2.1 Generalized Linear Models (GLM) 5
2.2 Downscaling - Deep Neural Networks 5

3 Validation of the Results **8**
3.1 Intercomparison of Methods 8
3.2 Spatial Maps 11

4 Technical Aspects **12**

1 Loading Data

All the working steps rely on the climate4R packages (loadeR, transformeR, downscaleR, visualizeR and climate4R.value), which is a set of libraries especifically developed to handle climate data. In particular to this study, climate4R functions are through the loading, post-processing, downscaling, validation and visualization of the data. Especific notebooks have been developed to illustrate the working of climate4R functions and we refer the reader to the github repository that allocates these notebooks for more explanation on the particularities of every package and function.

Therefore, we load the core libraries of climate4R: loadeR, transformeR, downscaleR and visualizeR. We also load climate4R.value of climate4R which would permit us to compute the validation indices as well as other auxiliary libraries mainly for plotting concerns.

```
library(loadeR)
library(transformeR)
library(downscaleR)
library(visualizeR)
library(climate4R.value)
library(magrittr)
library(gridExtra)
library(RColorBrewer)
library(sp)
```

To load the data we rely on the loadeR package who permits an easy access to the datasets listed in the User Data Getaway (UDG) which is maintained by the Santander Meteorology Group. To access the datasets we first have to log in to our UDG account. If you do not have an account follow the instructions in the UDG description page

```
loginUDG(username = "", password = "")
```

In order to avoid possible errors while running the notebook, you have to set the path to your desired working directory and create two files named "Data" and "models", that will contain the downscaled predictions and the trained deep models, respectively. Moreover, as we perform 2 distinct studies, one for precipitation and other for temperature, you should create 2 new directories named "precip" and "temperature" within the previous created directories (i.e., "Data" and "models"). An example of the latter would be "personalpath/Data/temperature". The predictions and models infered will be automatically saved in these folders and therefore the not creating them will end into saving errors across the notebook.

```
path = ""
setwd(path)
dir.create("Data")
```

```r
dir.create("Data/temperature/")
dir.create("models")
dir.create("models/temperature/")
```

We find the label associated to ERA-Interim via the UDG.datasets() function of loadeR: "ECMWF_ERA-Interim-ESD". Then we load the predictors by calling loadGridData of loadeR.

```r
variables <- c("z@500","z@700","z@850","z@1000",
               "hus@500","hus@700","hus@850","hus@1000",
               "ta@500","ta@700","ta@850","ta@1000",
               "ua@500","ua@700","ua@850","ua@1000",
               "va@500","va@700","va@850","va@1000")
x <- lapply(variables, function(x) {
  loadGridData(dataset = "ECMWF_ERA-Interim-ESD",
               var = x,
               lonLim = c(-10,32), # 22 puntos en total
               latLim = c(36,72),  # 19 puntos en total
               years = 1979:2008)
}) %>% makeMultiGrid()
```

The E-OBS dataset is also accesible in the UDG datasets. Thus, we load the predictand dataset by calling again loadGridData.

```r
y <- loadGridData(dataset = "E-OBS_v14_0.50regular",
                   var = "tas",lonLim = c(-10,32),
                   latLim = c(36,72),
                   years = 1979:2008)
```

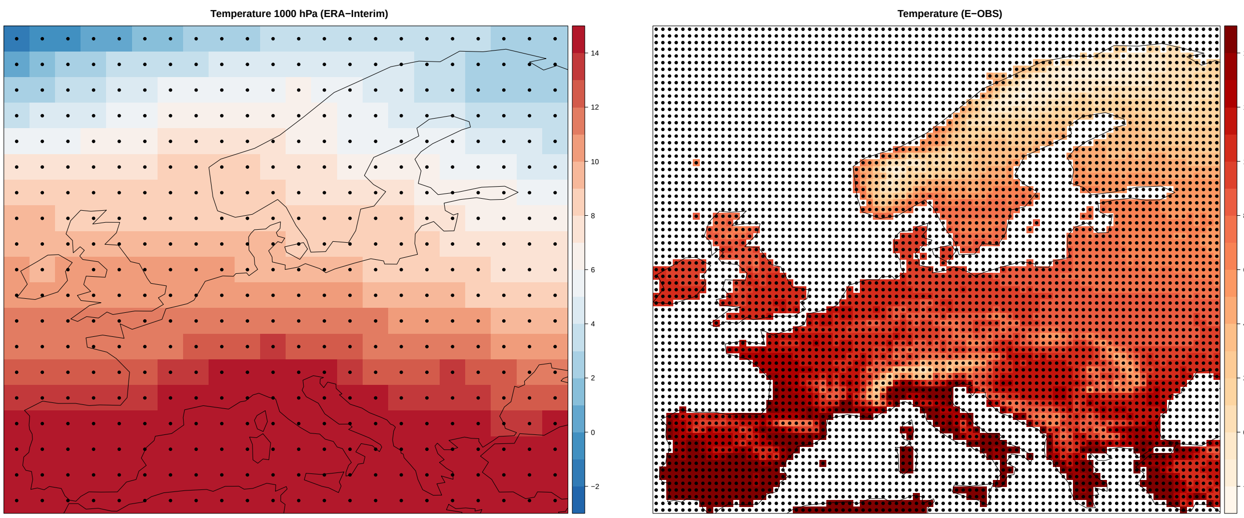
We split into train (i.e., 1979-2002) and test (i.e., 2003-2008).

```r
# Train
xT <- subsetGrid(x,years = 1979:2002)
yT <- subsetGrid(y,years = 1979:2002)
# Test
xt <- subsetGrid(x,years = 2003:2008)
yt <- subsetGrid(y,years = 2003:2008)

save(xT,file = "./Data/temperature/xT.rda")
save(xt,file = "./Data/temperature/xt.rda")
save(yT,file = "./Data/temperature/yT.rda")
save(yt,file = "./Data/temperature/yt.rda")
rm(x,y)
```

We can take a look at the grid resolutions of ERA-Interim and E-OBS in order to better visualize the gap we try to bridge with the downscaling.

```r
cb <- colorRampPalette(brewer.pal(9, "OrRd"))(80)
coords_x <- expand.grid(xt$xyCoords$x,xt$xyCoords$y) ; names(coords_x) <- c("x","y")
coords_y <- expand.grid(yt$xyCoords$x,yt$xyCoords$y) ; names(coords_y) <- c("x","y")
colsindex <- rev(brewer.pal(n = 9, "RdBu"))
cb2 <- colorRampPalette(colsindex)

pplot <- list()
pplot[[1]] <- spatialPlot(climatology(subsetGrid(xt,var = "ta@1000")), backdrop.theme = "coastline",
                          main = "Temperature 1000 hPa (ERA-Interim)",
                          col.regions = cb2,
```

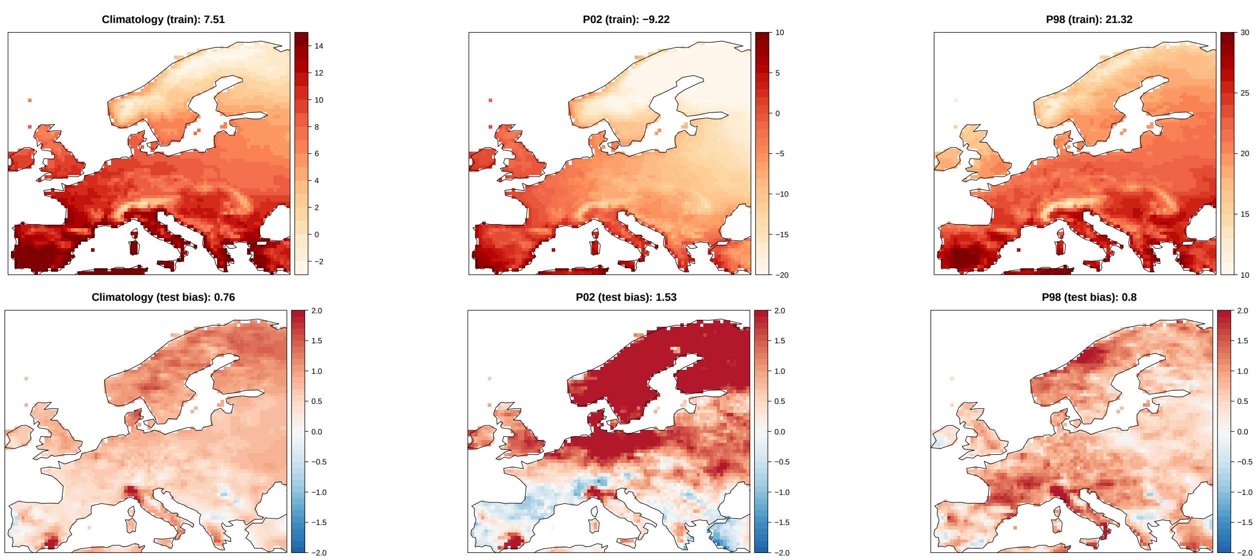
```
                              at = seq(-3, 15, 1),
                              set.min = -3, set.max = 15, colorkey = TRUE,
                              sp.layout = list(list(SpatialPoints(coords_x),
                                                    first = FALSE, col = "black",
                                                    pch = 20, cex = 1)))
pplot[[2]] <- spatialPlot(climatology(yt), backdrop.theme = "coastline",
                              main = "Temperature (E-OBS)",
                              col.regions = cb,
                              at = seq(-3, 15, 1),
                              set.min = -3, set.max = 15, colorkey = TRUE,
                              sp.layout = list(list(SpatialPoints(coords_y),
                                                    first = FALSE, col = "black",
                                                    pch = 20, cex = 1)))

lay = rbind(c(1,2))
grid.arrange(grobs = pplot, layout_matrix = lay)
```



We can visualize some statistics of the train and test distributions, such as the climatology, the frequency of rainy days and the percentile 98th in order to gain knowledge about the observed data. To compute the statistics we use the library climate4R.value of climate4R.

```
cb <- colorRampPalette(brewer.pal(9, "OrRd"))(80)
colsindex <- rev(brewer.pal(n = 9, "RdBu"))
cb2 <- colorRampPalette(colsindex)

pplot <- at <- list()
n1 <- 0; n2 <- 3
indexNames <- c("Climatology", "P02", "P98")
for (indexName in indexNames) {
  if (indexName == "Climatology") {
    indexTrain <- valueIndex(yT,index.code = "Mean")$Index %>% redim()
    indexTest <- valueIndex(yt,index.code = "Mean")$Index %>% redim()
    at[[1]] <- seq(-3, 15, 1); at[[2]] <- seq(-2, 2, 0.1)
  }
  if (indexName == "P02") {
    indexTrain <- valueIndex(yT,index.code = "P02")$Index %>% redim()
    indexTest <- valueIndex(yt,index.code = "P02")$Index %>% redim()
    at[[1]] <- seq(-20, 10, 1); at[[2]] <- seq(-2, 2, 0.1)
```

```
  }
  if (indexName == "P98") {
    indexTrain <- valueIndex(yT,index.code = "P98")$Index %>% redim()
    indexTest <- valueIndex(yt,index.code = "P98")$Index %>% redim()
    at[[1]] <- seq(10, 30, 1); at[[2]] <- seq(-2, 2, 0.1)
  }

  for (i in 1:2) {
    if (i == 1) {
      dataset <- "(train)"; index <- indexTrain; n1 <- n1 + 1; n <- n1
      value <- index$Data; colorbar <- cb
    }
    if (i == 2) {
      indexTest <- gridArithmetics(indexTest,indexTrain,operator = "-")
      dataset <- "(test bias)"; index <- indexTest; n2 <- n2 + 1; n <- n2
      value <- abs(index$Data); colorbar <- cb2
    }
    pplot[[n]] <- spatialPlot(climatology(index), backdrop.theme = "coastline",
                              main = paste(indexName,paste0(dataset,":"),
                                           round(mean(value, na.rm = TRUE),digits = 2)),
                              col.regions = colorbar,
                              at = at[[i]],
                              set.min = at[[i]][1], set.max = at[[i]][length(at[[i]])],
                              colorkey = TRUE)
  }
}

lay = rbind(c(1,2,3),
            c(4,5,6))
grid.arrange(grobs = pplot, layout_matrix = lay)
```



Once the data is loaded we standardize the predictors by calling scaleGrid function of transformeR.

```
xt <- scaleGrid(xt,xT, type = "standardize", spatial.frame = "gridbox") %>% redim(drop = TRUE)
xT <- scaleGrid(xT, type = "standardize", spatial.frame = "gridbox") %>% redim(drop = TRUE)
```

2 Downscaling

2.1 Generalized Linear Models (GLM)

To downscale via generalized linear models (GLM) we rely on the downscaleR package of climate4R. In particular, we use the downscaleChunk function of downscaleR to downscale the precipitation. Below we define a new function, called trainPredictGLM, which encapsulates downscaleChunk and outputs the predictions for the temperature for the train and test sets. In the case of temperature, the generalized linear model has a gaussian family with link identity which is, in fact, an ordinary least squares regression. Therefore, we input to the function the predictor (x), the number of local predictors to be used (neighbours), the predictand (y) and the test set where to apply the infered relationship. Moreover, the predictions are saved in a especific path indicated by the user through the function parameter 'filename'.

Note that downscaleChunk temporarily creates .rda files in your working directory, containing the predictions per chunk. The final binded predictions are saved in your previously created "Data/temperature/" directory.

```
trainPredictGLM <- function(x,y,newdata,neighbours=1,filename) {
  pred <- downscaleChunk(x = x, y = y, newdata = newdata,
                 method = "GLM", family = "gaussian", simulate = "no",
                 local.predictors = list(n=neighbours, vars = getVarNames(x))
  )
  pred_train <- pred[[1]] %>% redim(drop = TRUE)
  pred_test <- pred[[2]] %>% redim(drop = TRUE)

  pred <- pred_train
  save(pred,file = paste0("./Data/temperature/predictions_train_",filename,".rda"))
  pred <- pred_test
  save(pred,file = paste0("./Data/temperature/predictions_test_",filename,".rda"))
}
```

Now, we downscale by calling the function defined above.

```
# glm1
trainPredictGLM(x = xT,y = yT,newdata = list(xt),
                        filename = "glm1",neighbours = 1)
# glm4
trainPredictGLM(x = xT,y = yT,newdata = list(xt),
                        filename = "glm4",neighbours = 4)
```

2.2 Downscaling - Deep Neural Networks

2.2.1 Training

To infer deep learning models we rely on Keras.

```
library(keras)
```

In the following we provide the code related to the deep learning architectures.

```
architectures <- function(architecture,input_shape,output_shape) {
  if (architecture == "CNN-LM") {
    inputs <- layer_input(shape = input_shape)
    x = inputs
    l1 = layer_conv_2d(x ,filters = 50, kernel_size = c(3,3), activation = 'linear', padding = "same")
    l2 = layer_conv_2d(l1,filters = 25, kernel_size = c(3,3), activation = 'linear', padding = "same")
```

```
    l3 = layer_conv_2d(l2,filters = 1, kernel_size = c(3,3), activation = 'linear', padding = "same")
    l4 = layer_flatten(l3)
    outputs = layer_dense(l4,units = output_shape)
    model <- keras_model(inputs = inputs, outputs = outputs)
  }

  if (architecture == "CNN1") {
    inputs <- layer_input(shape = input_shape)
    x = inputs
    l1 = layer_conv_2d(x ,filters = 50, kernel_size = c(3,3), activation = 'relu', padding = "same")
    l2 = layer_conv_2d(l1,filters = 25, kernel_size = c(3,3), activation = 'relu', padding = "same")
    l3 = layer_conv_2d(l2,filters = 1, kernel_size = c(3,3), activation = 'relu', padding = "same")
    l4 = layer_flatten(l3)
    outputs = layer_dense(l4,units = output_shape)
    model <- keras_model(inputs = inputs, outputs = outputs)
  }

  if (architecture == "CNN10") {
    inputs <- layer_input(shape = input_shape)
    x = inputs
    l1 = layer_conv_2d(x ,filters = 50, kernel_size = c(3,3), activation = 'relu', padding = "valid")
    l2 = layer_conv_2d(l1,filters = 25, kernel_size = c(3,3), activation = 'relu', padding = "valid")
    l3 = layer_conv_2d(l2,filters = 10, kernel_size = c(3,3), activation = 'relu', padding = "valid")
    l4 = layer_flatten(l3)
    outputs = layer_dense(l4,units = output_shape)
    model <- keras_model(inputs = inputs, outputs = outputs)
  }

  if (architecture == "CNN-PR") {
    inputs <- layer_input(shape = input_shape)
    x = inputs
    l1 = layer_conv_2d(x ,filters = 10, kernel_size = c(3,3), activation = 'relu', padding = "valid")
    l2 = layer_conv_2d(l1,filters = 25, kernel_size = c(3,3), activation = 'relu', padding = "valid")
    l3 = layer_conv_2d(l2,filters = 50, kernel_size = c(3,3), activation = 'relu', padding = "valid")
    l4 = layer_flatten(l3)
    outputs = layer_dense(l4,units = output_shape)
    model <- keras_model(inputs = inputs, outputs = outputs)
  }

  if (architecture == "CNNdense") {
    inputs <- layer_input(shape = input_shape)
    x = inputs
    l1 = layer_conv_2d(x ,filters = 50, kernel_size = c(3,3), activation = 'relu', padding = "valid")
    l2 = layer_conv_2d(l1,filters = 25, kernel_size = c(3,3), activation = 'relu', padding = "valid")
    l3 = layer_conv_2d(l2,filters = 10, kernel_size = c(3,3), activation = 'relu', padding = "valid")
    l4 = layer_flatten(l3)
    l5 = layer_dense(l4,units = 50, activation = "relu")
    l6 = layer_dense(l5,units = 50, activation = "relu")
    outputs = layer_dense(l6,units = output_shape)
    model <- keras_model(inputs = inputs, outputs = outputs)
  }

  return(model)
```

```
}
```

To train the latter architectures we have encapsulated them into a more general funcion called trainDEEP.

```
trainDEEP <- function(x,y,architecture, epochs=10000,patience=30,
                      learning_rate = 0.0001){

  x <- x$Data
  x <- x %>% aperm(c(2,3,4,1))
  y <- y$Data
  dim(y) <- c(dim(y)[1],dim(y)[2]*dim(y)[3])
  indLand <- (!apply(y,MARGIN = 2,anyNA)) %>% which()
  y <- y[,indLand]

  callbacks <- list(callback_early_stopping(patience = patience),
                    callback_model_checkpoint(filepath=paste0('./models/temperature/',
                                                              architecture,'.h5'),
                                              monitor='val_loss', save_best_only=TRUE)
  )

  model <- architectures(architecture,input_shape = dim(x)[-1],output_shape = ncol(y))
  model %>% compile(optimizer = optimizer_adam(lr = learning_rate), loss = "mse")
  model %>% fit(x, y, epochs = epochs, batch_size = 100,
                validation_split = 0.1, callbacks = callbacks, verbose = 0)
  k_clear_session()
}
```

Finally, we train the models and save the model in the path specified in the trainDEEP function, according to the early-stopping criteria.

```
trainDEEP(xT,yT,architecture = "CNN-LM")
trainDEEP(xT,yT,architecture = "CNN1")
trainDEEP(xT,yT,architecture = "CNN10")
trainDEEP(xT,yT,architecture = "CNN-PR")
trainDEEP(xT,yT,architecture = "CNNdense")
```

2.2.2 Prediction

Once the models are trained and saved, we predict onto the train and test datasets. To do so, we first define a function called predictDEEP that encapsulates the deterministic and stochastic predictions. Recall that, accpording to the loss function, the net estimates the parameters p, α and β of a Bernouilli-Gamma distribution. In the deterministic way, the prediction for a given day is the expectance of the conditional Bernouilli-Gamma distribution infered. In the stochastic way, we sample from the conditional Bernouilli-Gamma distribution. This sampling is coded in the functions simulateOcu and simulateReg.

```
predictDEEP <- function(x,template,architecture,dataset) {
  model <- load_model_hdf5(filepath = paste0("./models/temperature/",architecture,".h5"))
  x <- x$Data %>% aperm(c(2,3,4,1))
  pred <- model$predict(x)
  ntime <- dim(template$Data)[1]
  nlat <- dim(template$Data)[2]
  nlon <- dim(template$Data)[3]

  # Converting to 2D-map (including sea)
  yT1D <- yT$Data
```

```r
  dim(yT1D) <- c(dim(yT1D)[1],nlat*nlon)
  indLand <- (!apply(yT1D,MARGIN = 2,anyNA)) %>% which()
  indSea <- (apply(yT1D,MARGIN = 2,anyNA)) %>% which()
  convert2map2D <- function(grid,template) {
    dim(template$Data) <- c(ntime,nlat*nlon)
    out <- template
    out$Data[,indLand] <- grid
    out$Data[,indSea] <- NaN
    dim(out$Data) <- c(ntime,nlat,nlon)
    return(out)
  }
  pred <- convert2map2D(pred,template)

  save(pred,
       file = paste0("./Data/temperature/predictions_",dataset,"_",architecture,".rda"))
  k_clear_session()
}
```

Then we predict and save the predictions.

```r
# Train
predictDEEP(xT,architecture = "CNN-LM",template = yT,dataset = "train")
predictDEEP(xT,architecture = "CNN1",template = yT,dataset = "train")
predictDEEP(xT,architecture = "CNN10",template = yT,dataset = "train")
predictDEEP(xT,architecture = "CNN-PR",template = yT,dataset = "train")
predictDEEP(xT,architecture = "CNNdense",template = yT,dataset = "train")

# Test
predictDEEP(xt,architecture = "CNN-LM",template = yt,dataset = "test")
predictDEEP(xt,architecture = "CNN1",template = yt,dataset = "test")
predictDEEP(xt,architecture = "CNN10",template = yt,dataset = "test")
predictDEEP(xt,architecture = "CNN-PR",template = yt,dataset = "test")
predictDEEP(xt,architecture = "CNNdense",template = yt,dataset = "test")
```

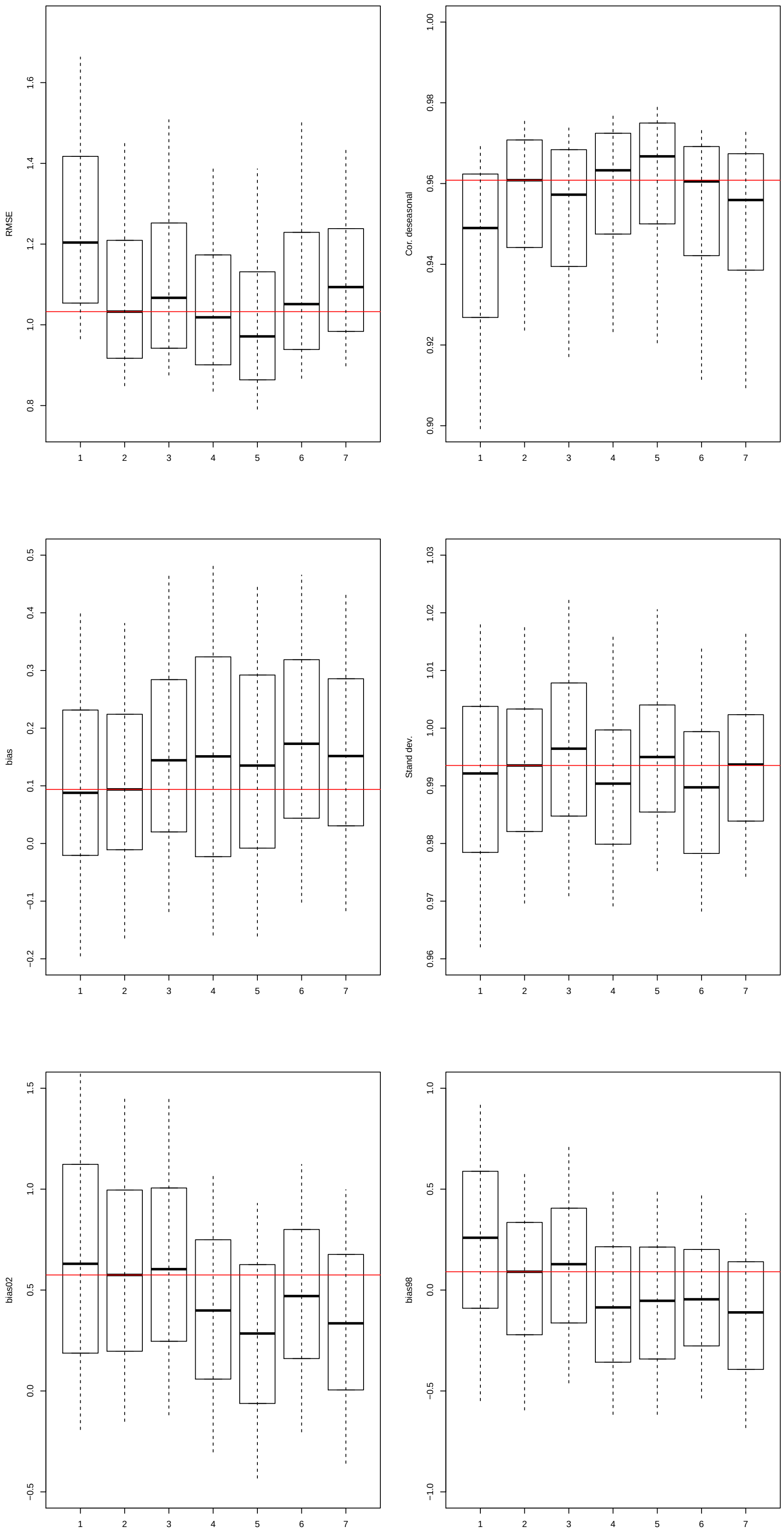
3 Validation of the Results

3.1 Intercomparison of Methods

In this figure, we calculate the validation indices by using the library climate4R.value of climate4R. In particular the indices used are: the Roc Skill Score (ROCSS), the Root Mean Squared Error (RMSE), the spearman correlation and the relative biases of the climatology and of the percentile 98 of the rainy days distribution (both deterministic and stochastic predictions). The indices are plotted with the function violinPlot of climate4R's package visualizeR.

```r
# file_name <- paste0("./figures/fig06_temperature.pdf")
# pdf(file = file_name,width = 5,height = 10)
par(mfrow = c(3,2))

yt2 <- scaleGrid(yt,time.frame = "daily",window.width = 31) %>% redim(drop=TRUE)
filepreds=list("glm1","glm4",
               "CNN-LM","CNN1","CNN10",
               "CNN-PR","CNNdense")
datasetspred <- length(filepreds)
```

```r
indexNames <- c("RMSE","Cor. deseasonal",
                "bias","Stand dev.","bias02","bias98")
pplot <- list(); n <- 0
for (indexName in indexNames) {
  index <- array(dim = c(datasetspred,dim(yT$Data)[2:3]))
  for (i in 1:datasetspred) {
    load(paste0("./Data/temperature/predictions_test_",filepreds[[i]],".rda"))

    if (indexName == "RMSE") {
      index[i,,] <- valueMeasure(yt,pred,measure.code="ts.RMSE")$Measure$Data
      ylim <- c(0.75,1.75)
    }

    if (indexName == "Cor. deseasonal") {
      pred2 <- scaleGrid(pred,time.frame = "daily",window.width = 31) %>% redim(drop=TRUE)
      index[i,,] <- valueMeasure(yt2,pred2,measure.code="ts.rp")$Measure$Data
      ylim <- c(0.9,1)
    }

    if (indexName == "Stand dev.") {
      index[i,,] <- valueMeasure(yt,pred,measure.code="ratio",index.code="Var")$Measure$Data
      index[i,,] <- index[i,,] ** (1/2)
      ylim <- c(0.96,1.03)
    }
    if (indexName == "bias") {
      index[i,,] <- valueMeasure(yt,pred,measure.code="bias",index.code="Mean")$Measure$Data
      ylim <- c(-0.2,0.5)
    }
    if (indexName == "bias02") {
      index[i,,] <- valueMeasure(yt,pred,measure.code="bias",index.code="P02")$Measure$Data
      ylim <- c(-0.5,1.5)
    }
    if (indexName == "bias98") {
      index[i,,] <- valueMeasure(yt,pred,measure.code="bias",index.code="P98")$Measure$Data
      ylim <- c(-1,1)
    }
  }
  n <- n + 1
  dim(index) <- c(datasetspred,prod(dim(yT$Data)[2:3]))
  indLand <- (!apply(index,MARGIN = 2,anyNA)) %>% which()
  index <- index[,indLand] %>% t()
  mglm4 <- median(index[,2],na.rm = TRUE)
  perc <- apply(index,MARGIN = 2,FUN = function(z) quantile(z,probs = c(0.1,0.9)))
  boxplot(index, outline = FALSE, asp = 1, ylim = ylim, range = 0.0001, ylab = indexName)
  lines(c(0,8),c(mglm4,mglm4), col = "red")
  for (i in 1:datasetspred) lines(c(i,i),perc[,i], lty = 2)
}
```


RMSE
Cor. deseasonal
bias
Stand dev.
bias02
bias98
1 2 3 4 5 6 7

```r
# dev.off()
```

3.2 Spatial Maps

The above indices can be visualized spatially, this is, observing the results per gridbox. To do so, we define a function called experiment1 that encapsulates the code needed for plotting. The spatial map is plotted with the function spatialPlot of visualizeR, which we remind is a package of climate4R.

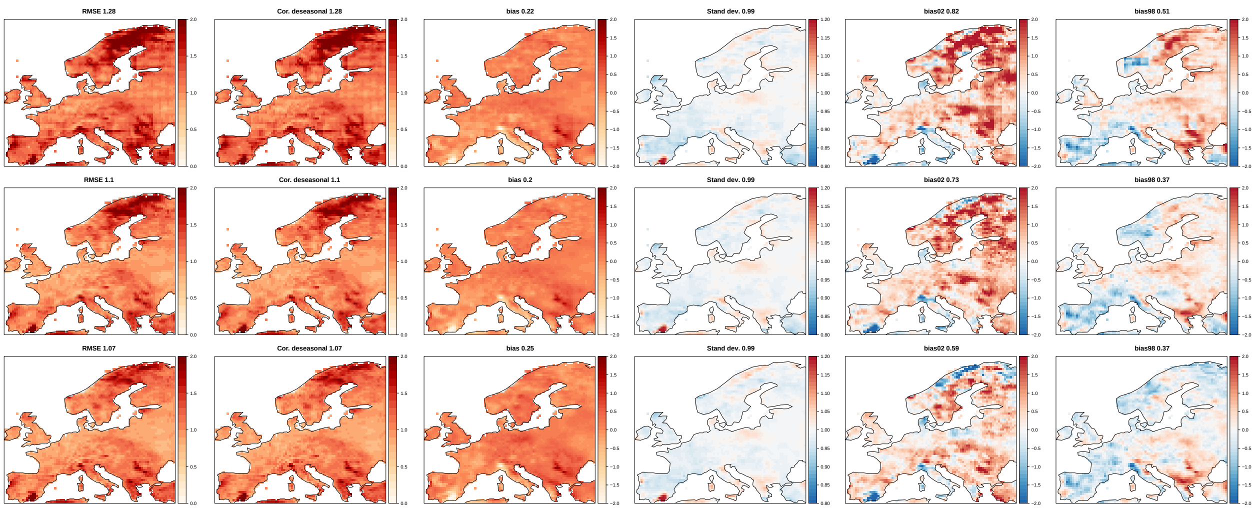
```r
experiment1 <- function(model) {
  cb <- colorRampPalette(brewer.pal(9, "OrRd"))(80)
  colsindex <- rev(brewer.pal(n = 9, "RdBu"))
  cb2 <- colorRampPalette(colsindex)

  yt2 <- scaleGrid(yt,time.frame = "daily",window.width = 31) %>% redim(drop=TRUE)
  load(paste0("./Data/temperature/predictions_test_",model,".rda"))
  indexNames <- c("RMSE","Cor. deseasonal",
                  "bias","Stand dev.","bias02","bias98")
  pplot <- list(); n <- 0
  for (indexName in indexNames) {
    if (indexName == "RMSE") {
      index <- valueMeasure(yt,pred,measure.code="ts.RMSE")$Measure %>% redim()
      at <- seq(0, 2, 0.1); colorbar <- cb
    }
    if (indexName == "Cor.deseasonal") {
      pred2 <- scaleGrid(pred,time.frame = "daily",window.width = 31) %>% redim(drop=TRUE)
      index <- valueMeasure(yt2,pred2,measure.code="ts.rp")$Measure %>% redim()
      at <- seq(0.85, 1, 0.005); colorbar <- cb
    }
    if (indexName == "bias") {
      index <- valueMeasure(yt,pred,measure.code="bias",index.code="Mean")$Measure %>% redim()
      at <- seq(-2, 2, 0.1); colorbar <- cb2
    }
    if (indexName == "Stand dev.") {
      index <- valueMeasure(yt,pred,measure.code="ratio",index.code="Var")$Measure %>% redim()
      index$Data <- index$Data ** (1/2)
      at <- seq(0.8, 1.2, 0.01); colorbar <- cb2
    }
    if (indexName == "bias02") {
      index <- valueMeasure(yt,pred,measure.code="bias",index.code="P02")$Measure %>% redim()
      at <- seq(-2, 2, 0.1); colorbar <- cb2
    }

    if (indexName == "bias98") {
      index <- valueMeasure(yt,pred,measure.code="bias",index.code="P98")$Measure %>% redim()
      at <- seq(-2, 2, 0.1); colorbar <- cb2
    }

    n <- n + 1
    pplot[[n]] <- spatialPlot(climatology(index), backdrop.theme = "coastline",
                              main = paste(indexName,round(mean(abs(index$Data), na.rm = TRUE),
                                                           digits = 2)),
                              col.regions = colorbar,
                              at = at,
```

```
                              set.min = at[1], set.max = at[length(at)], colorkey = TRUE)
  }

  lay = rbind(c(1,2,3,4,5,6,7,8))
  grid.arrange(grobs = pplot, layout_matrix = lay)
}
```

Now we call the experiment1 to obtain the figures for the following methods: glm1, glm4 and CNN1.

```
figure <- list()
figure[[1]] <- experiment1(model = "glm1")
figure[[2]] <- experiment1(model = "glm4")
figure[[3]] <- experiment1(model = "CNN1")
```

```
lay = rbind(1,2,3)
grid.arrange(grobs = figure,layout_matrix = lay)
```



4 Technical Aspects

To perform all the stages involved in this study we relied on the local machine described below. Therefore, the latter was used to load, process, downscale, validate and visualize the results. The times needed for training both linear models and deep neural networks were similar, and took approximately 2-4 hours per model.

1. Local Machine (HP-ProDesk-600-G2-MT)
    - Operating system: ubuntu 16.04 LTS
    - Memory: 15.6 GiB
    - Processor: Intel® Core™ i7-6700 CPU @ 3.40GHz × 8
    - SO: 64 bits
    - Disc: 235.1 GiB