The Drought Dataset

Presenters: Jay Barber and Dan Pagendam

The Drought Dataset

- Exercise developed by Chris Wikle and Dan Pagendam (2019).
- The data for this exercise consists of:
  - monthly grids (2 degree x 2 degree) of sea surface temperature (SST) anomaly.
  - monthly rainfall anomaly in mm for the Murray Darling Basin (MDB).
- The data was obtained from two sources:
  - http://www.bom.gov.au/climate/change/
  - http://iridl.ldeo.columbia.edu/
- We'll attempt to use a Long Short-Term Memory (LSTM) Model to obtain 3 month out forecasts of rainfall anomaly from SST grids.

Required Packages

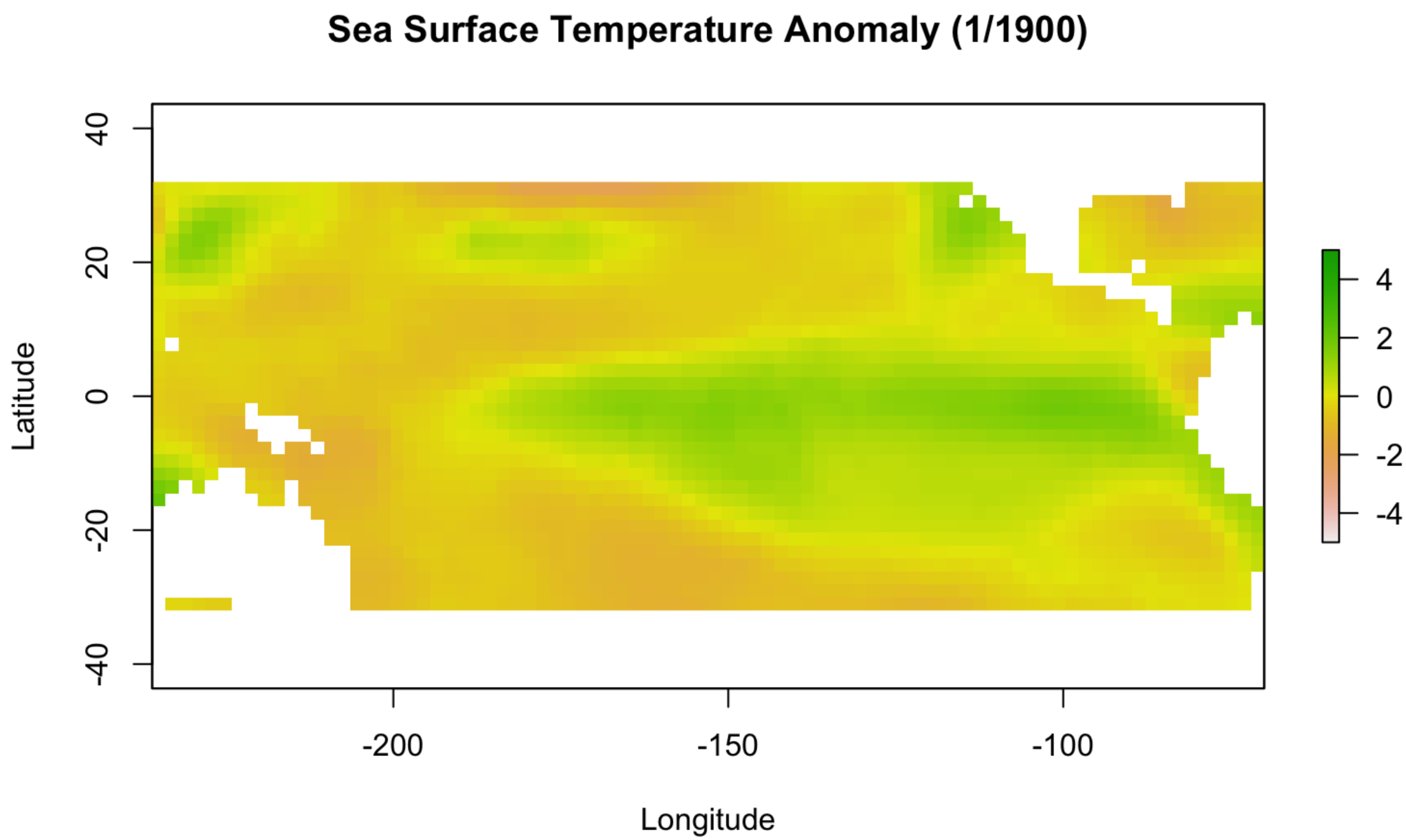
- For this exercise you will require the following packages:
  - raster
- You can install and load these as follows:

```
install.packages("raster", repos = "http://cran.us.r-project.org",
                 quiet = TRUE)
library(raster)
library(deepLearningRshort)
library(keras)
```

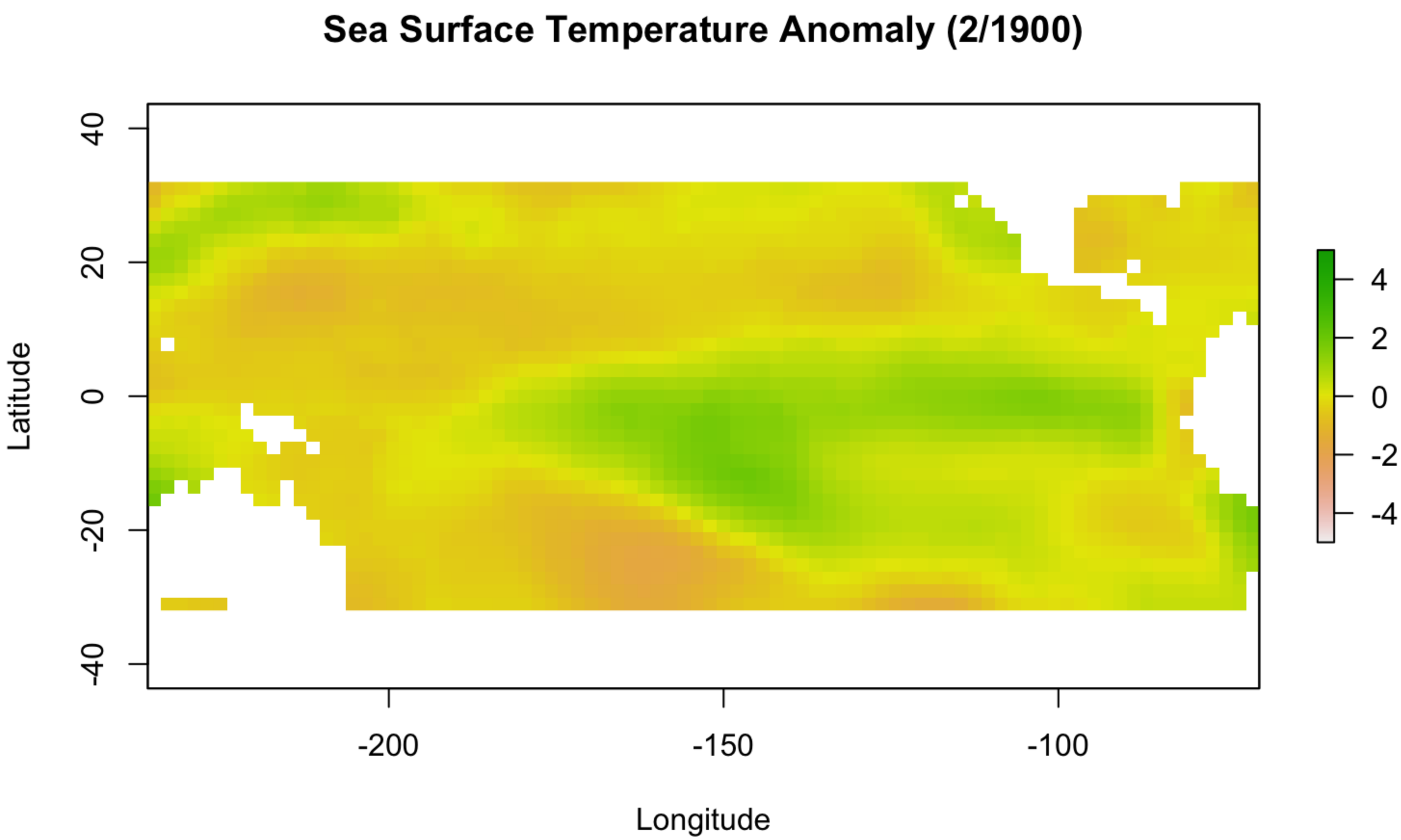
Load the Drought Data

```
data(drought)
```

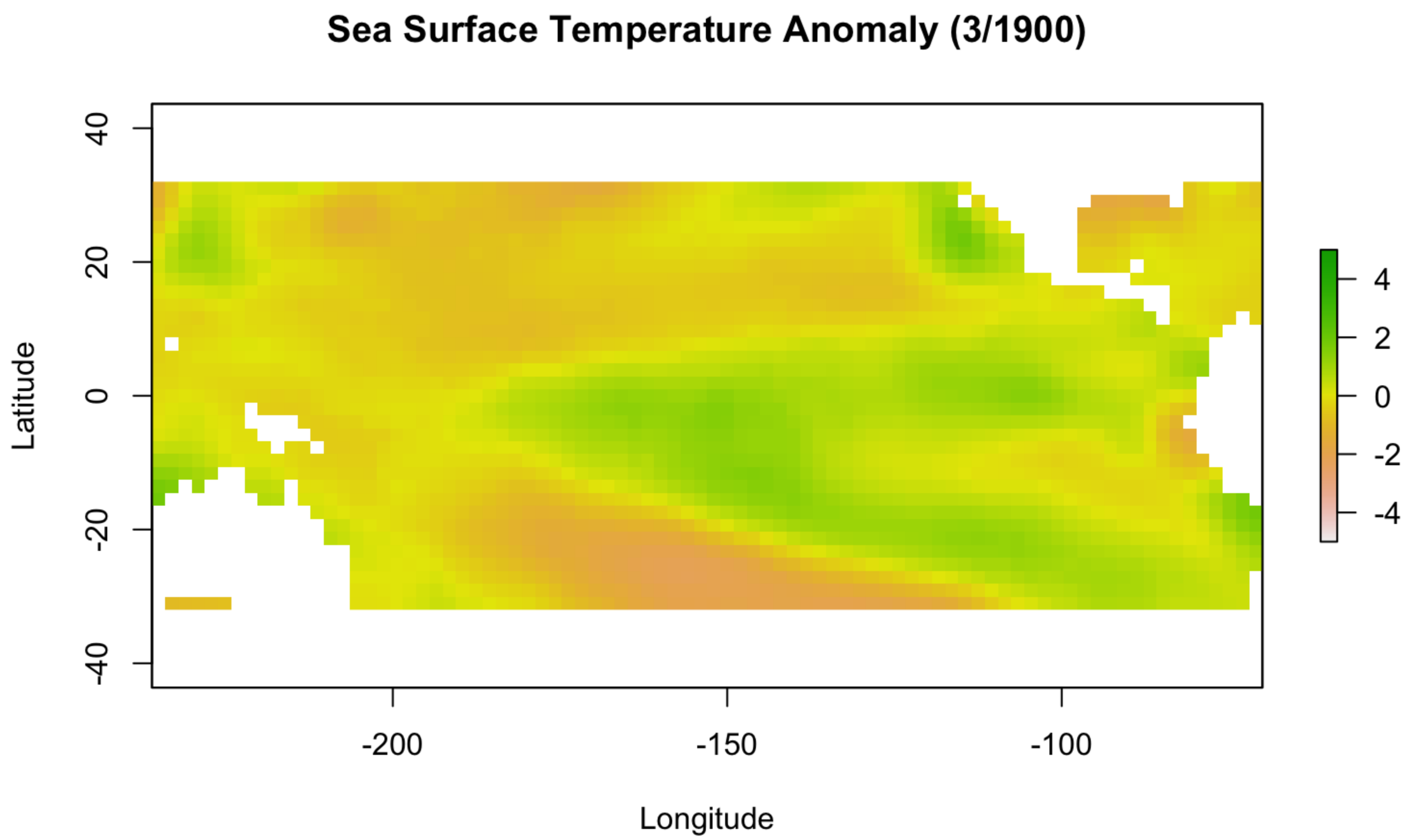
Visualising the SST Anomaly Data



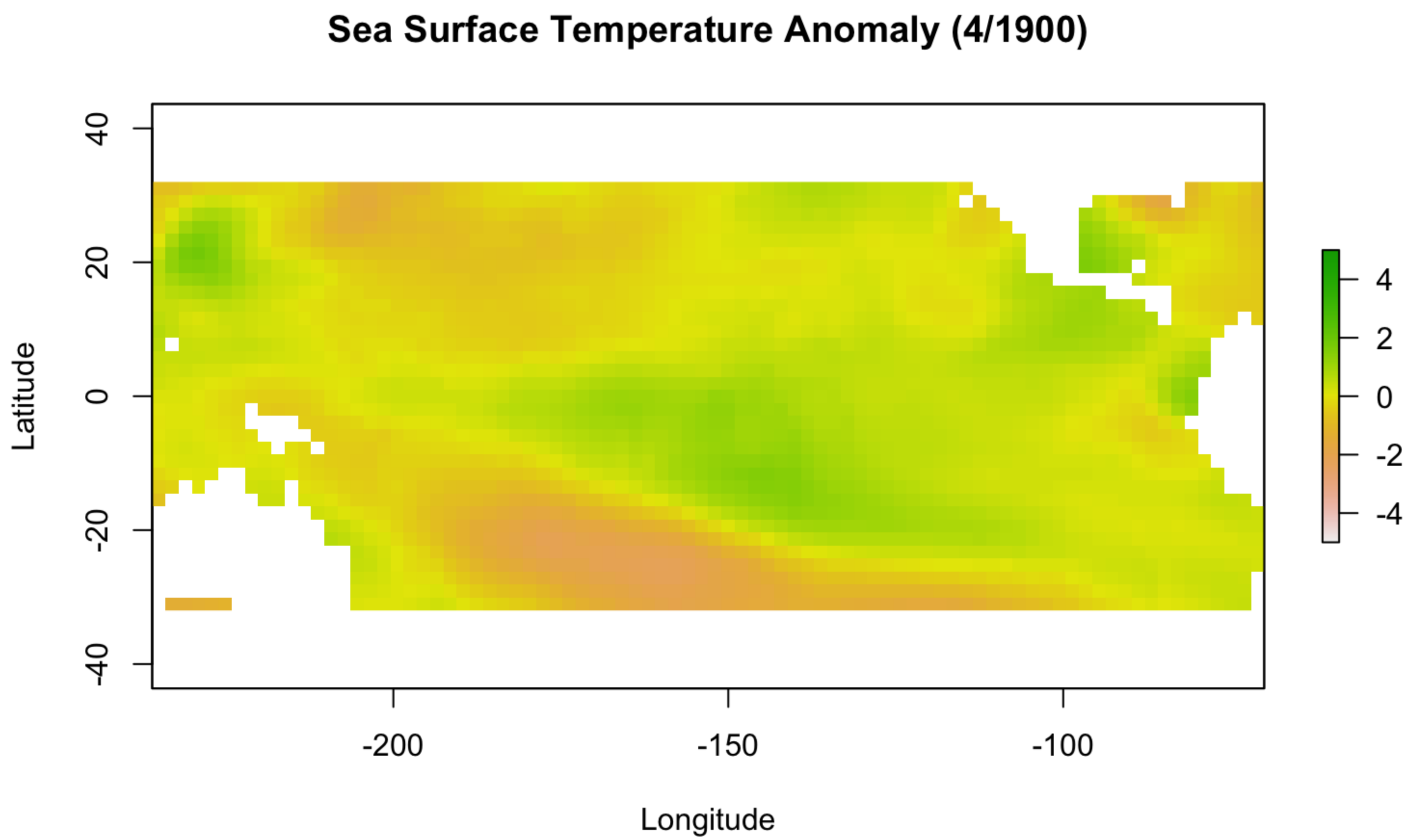
Visualising the SST Anomaly Data



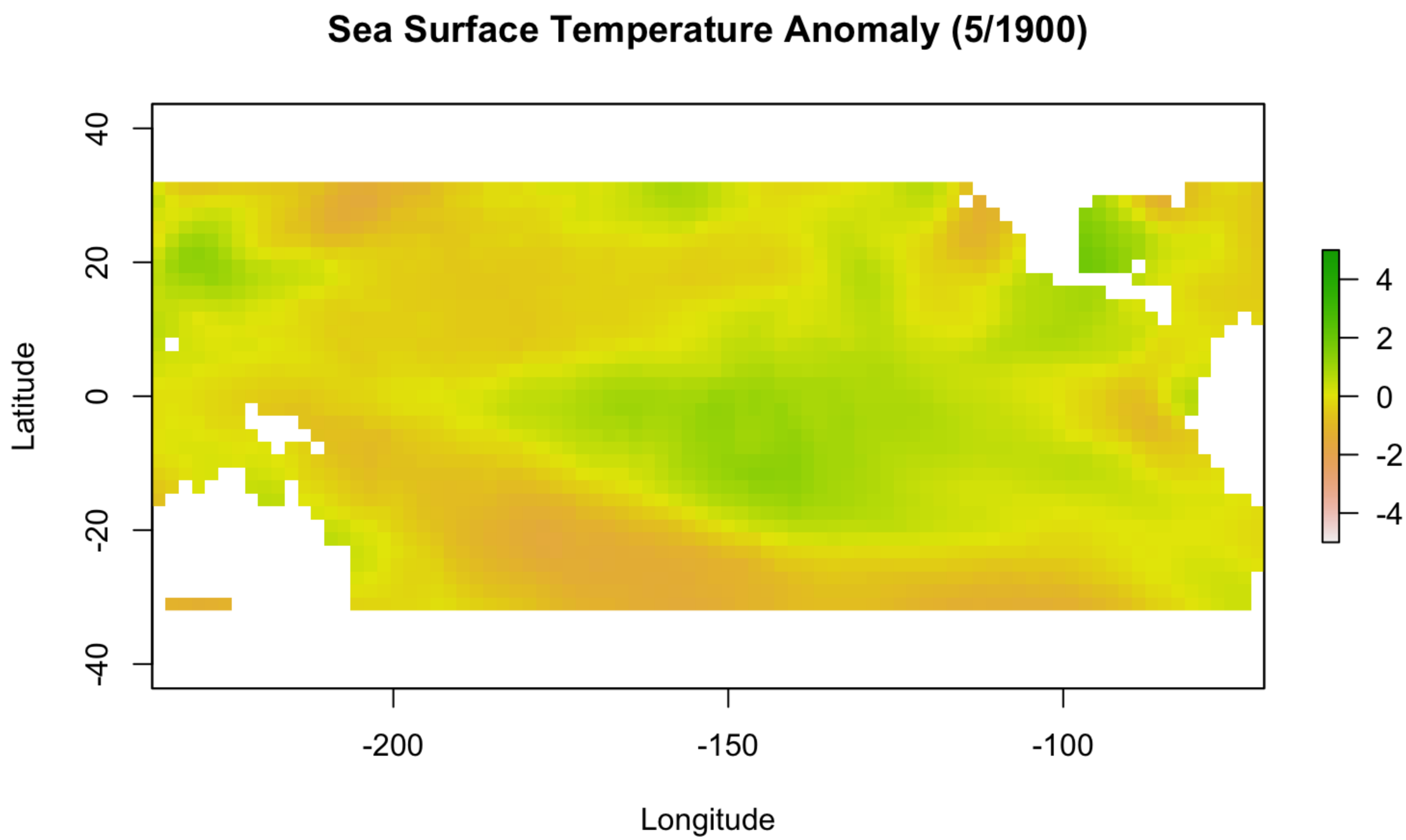
Visualising the SST Anomaly Data



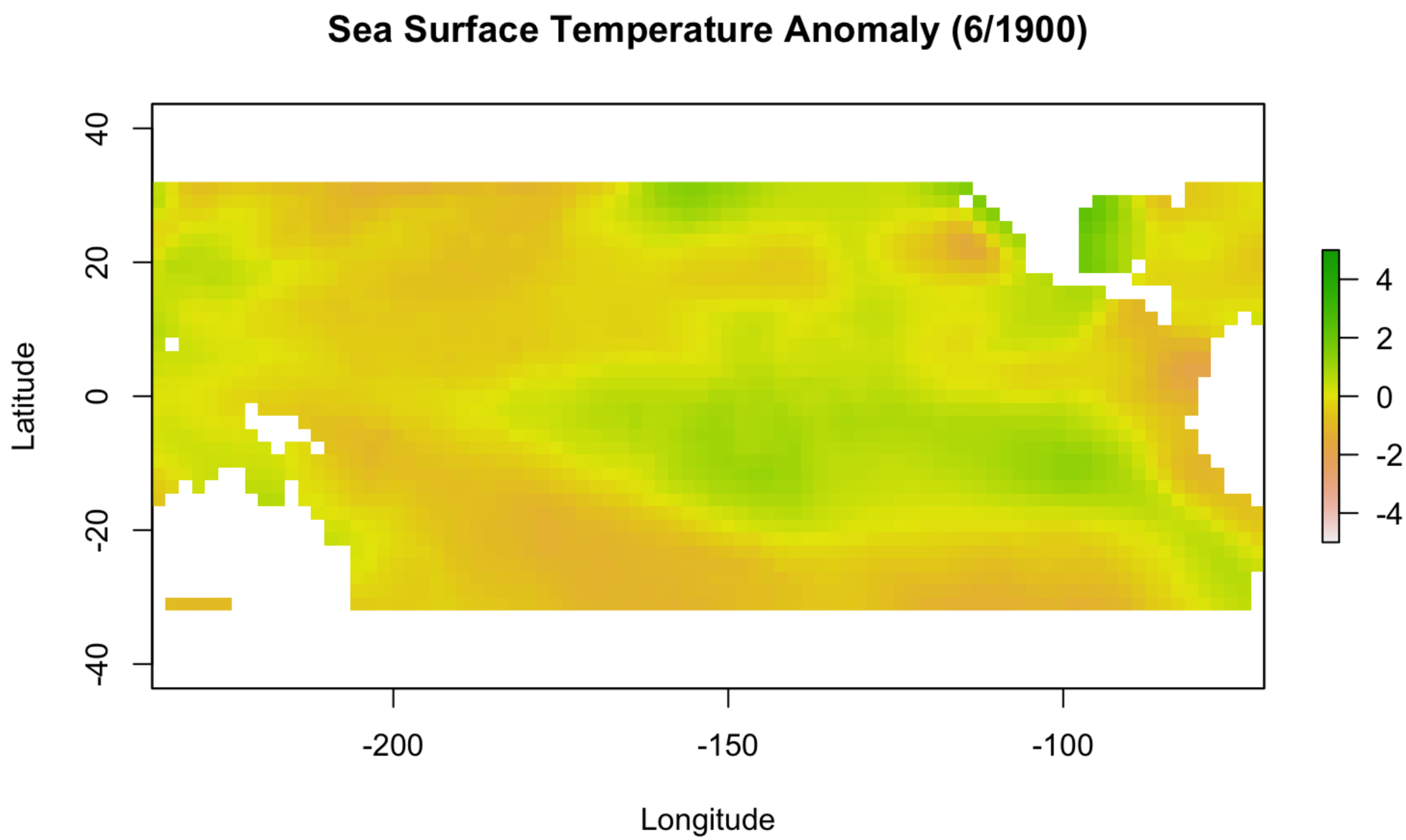
Visualising the SST Anomaly Data



Visualising the SST Anomaly Data



Visualising the SST Anomaly Data



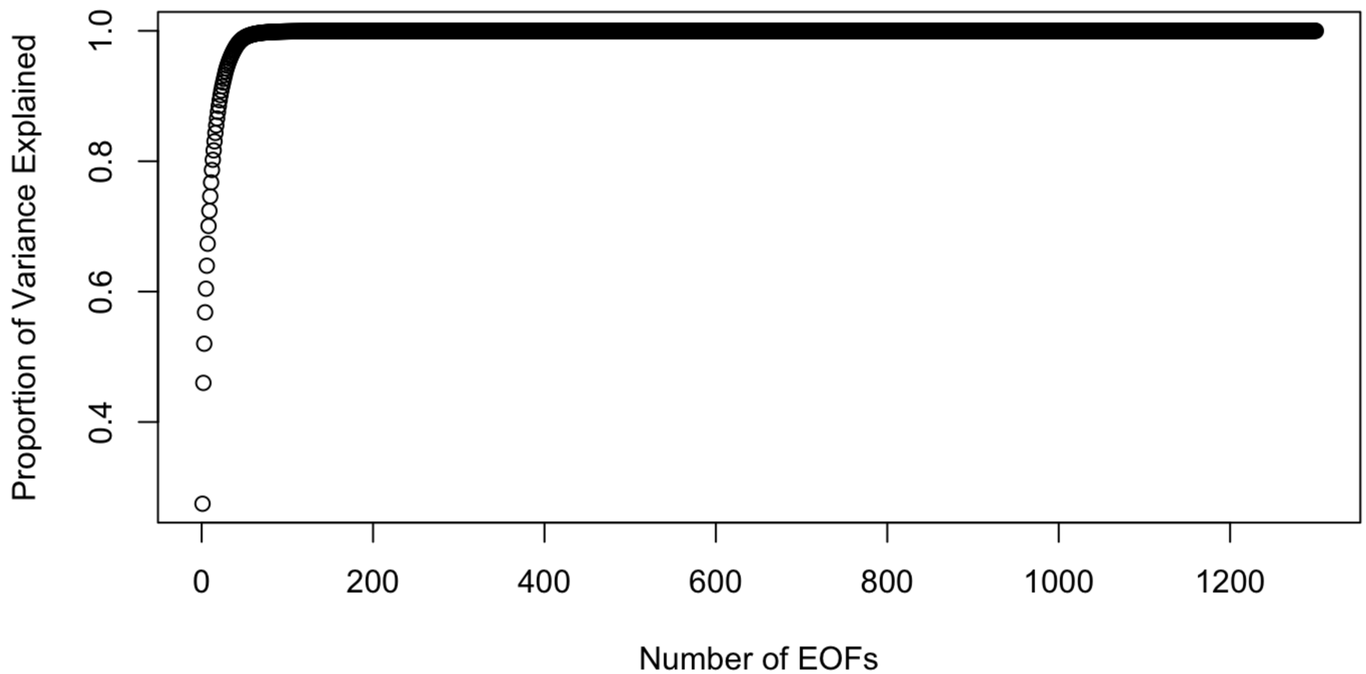
Data Manipulation

```r
batchSize <- 32
forecastMonthsAhead <- 3
timestepsPerSample <- 24
trainingInds <- 1:1300
testInds <- 1301:1434
```

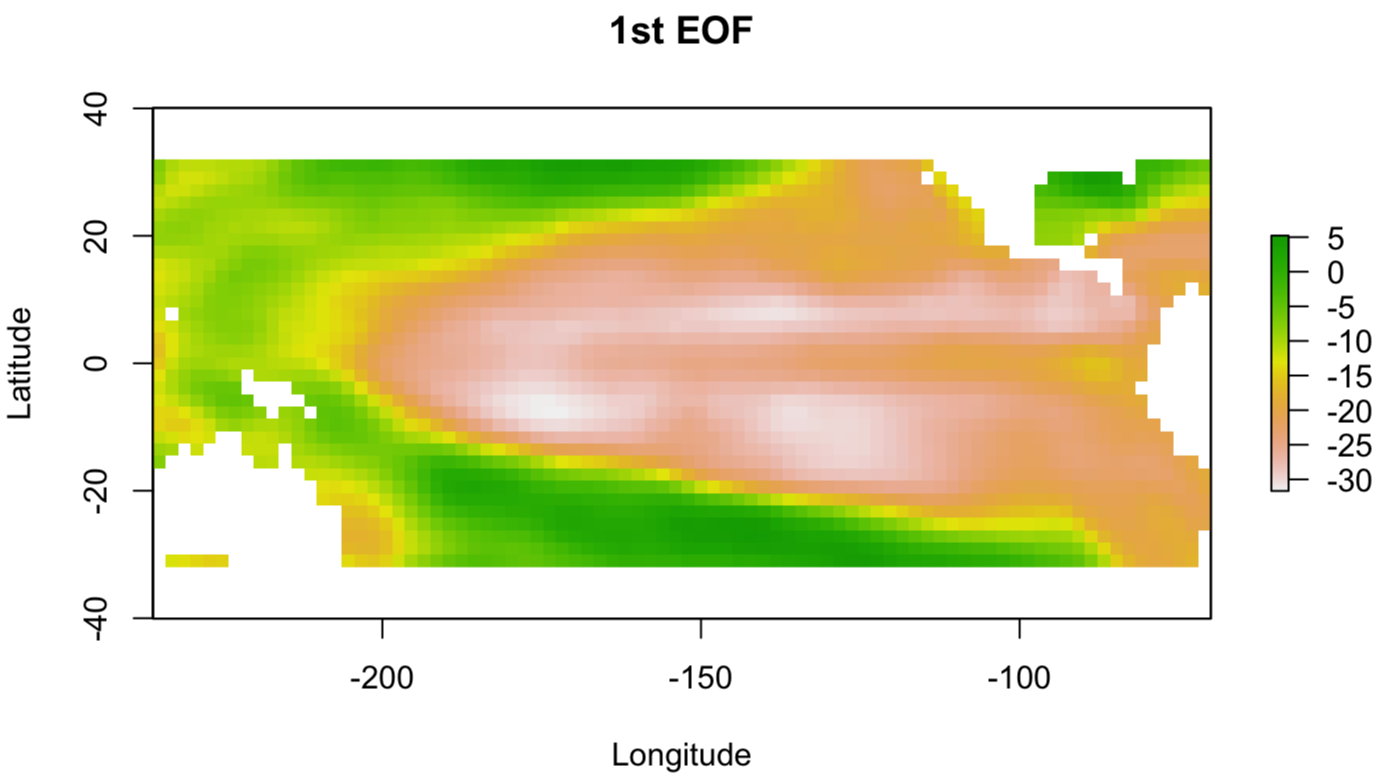
- We will reduce the dimensionality of the rasters using singular value decomposition .
- We will project the 2772 pixels onto 100 Empirical Orthogonal Functions (EOFs).

```r
numComponents <- 100
EOFList <- rasterToEOFs(anomalyRasterList[trainingInds],
            numComponents = numComponents, plot = FALSE)
v.train <- EOFList[["rasterEOFs"]][["v.dim.red"]]
```

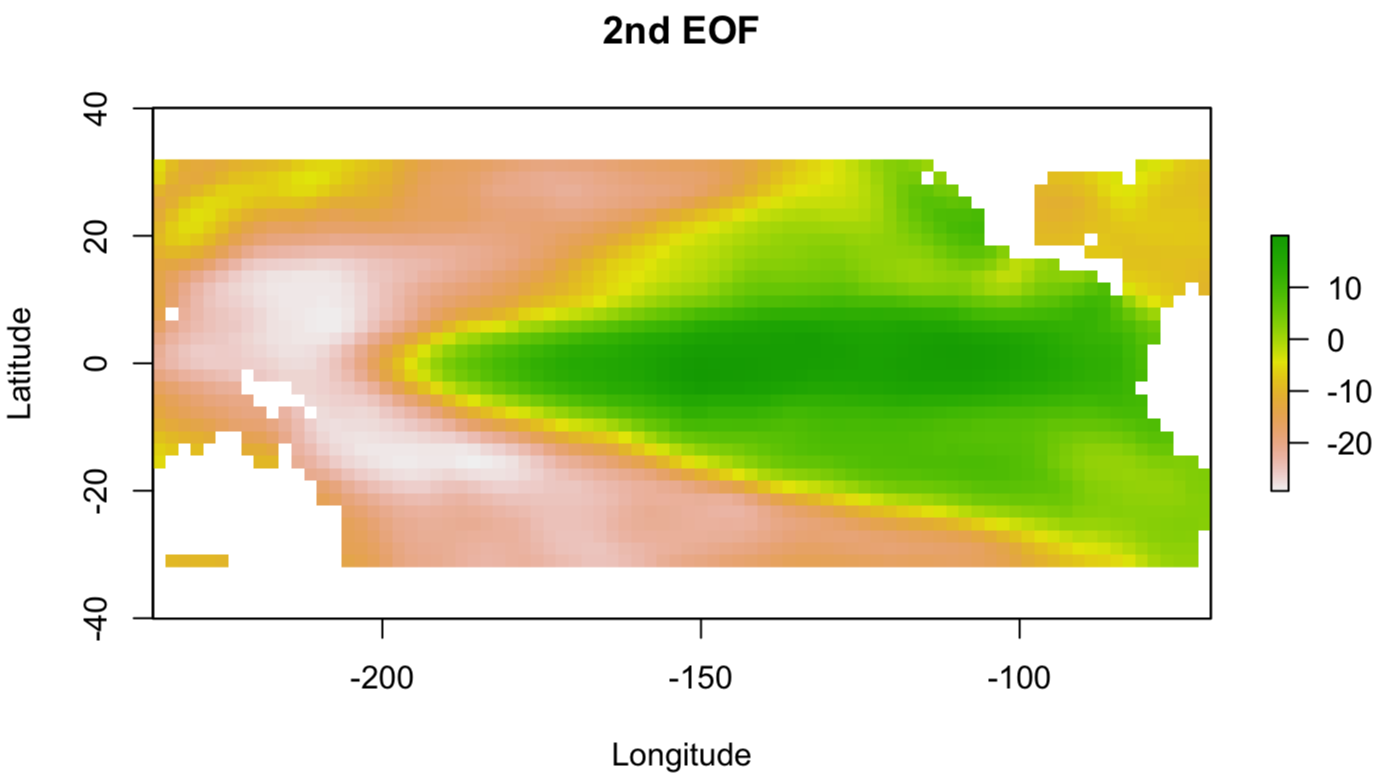
Dimension Reduction



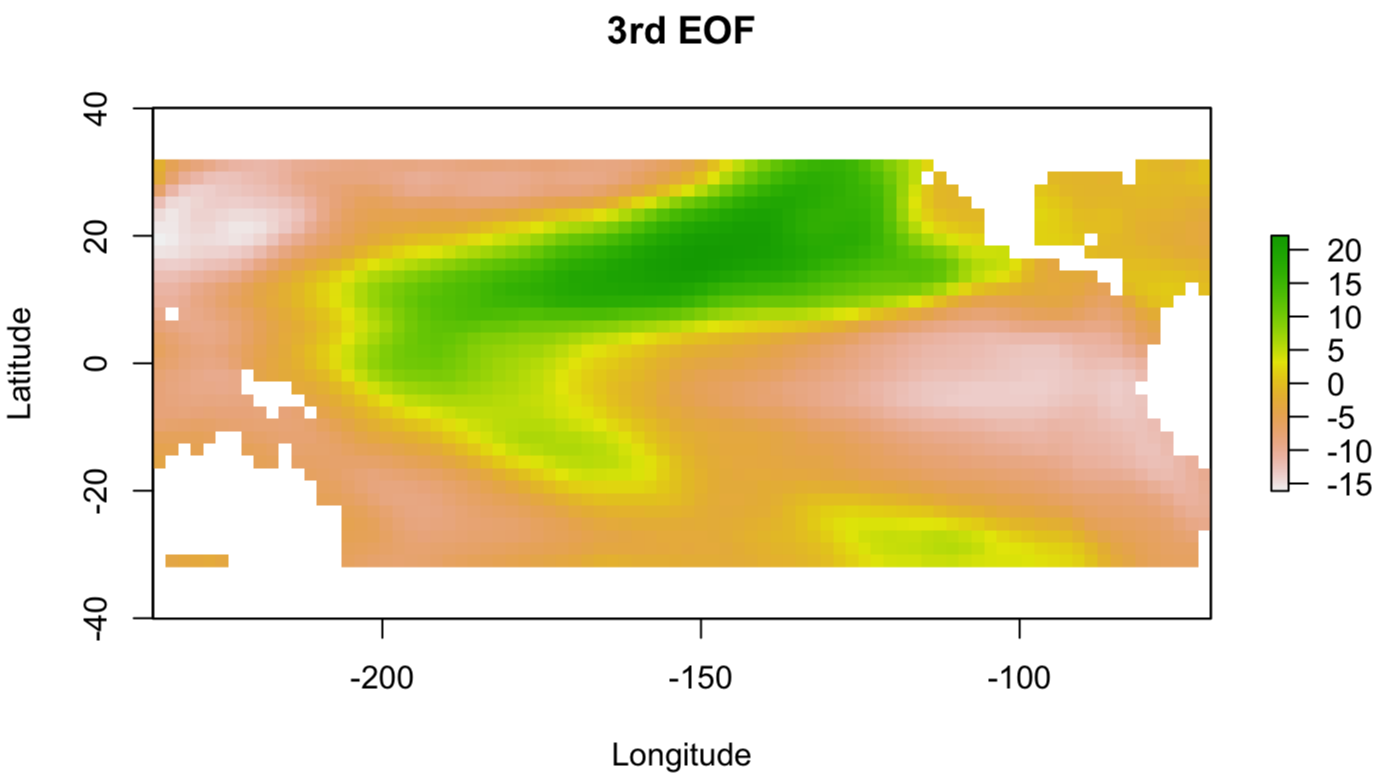
Dimension Reduction



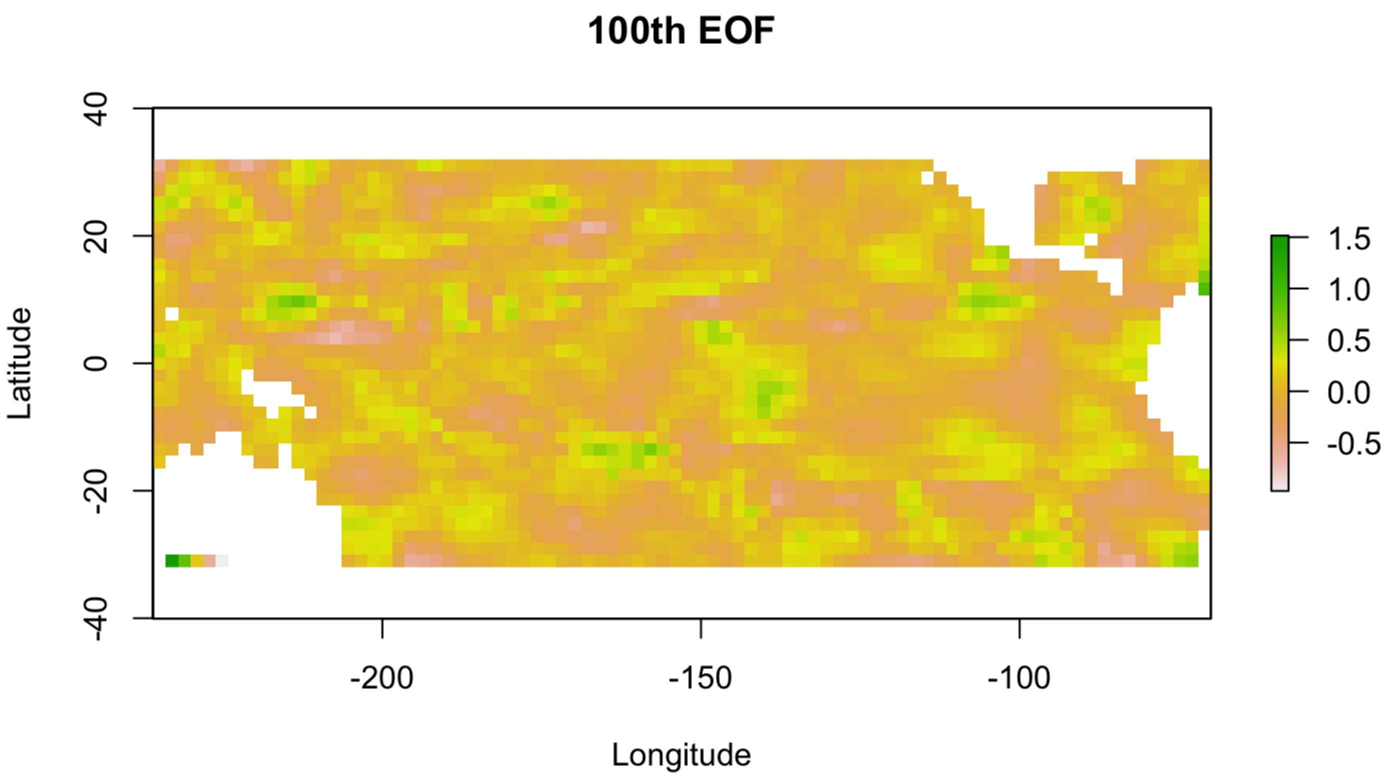
Dimension Reduction



Dimension Reduction



Dimension Reduction



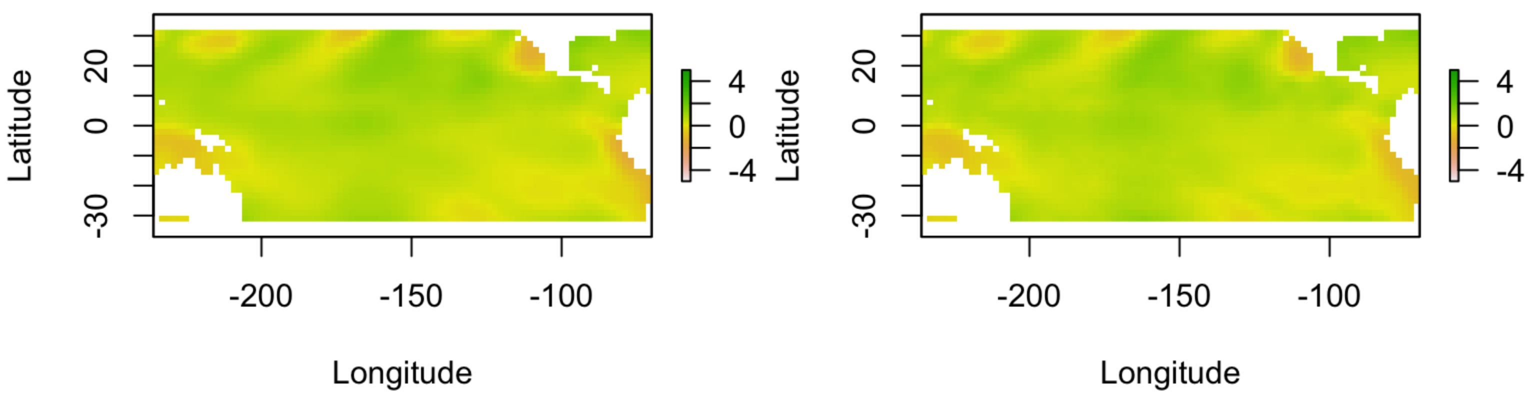
Checking the Dimension Reduction

```
testSample <- 1434
X <- EOFList$rasterEOFs$EOFs
r1 <- anomalyRasterList[[testSample]]
validPixels <- EOFList[["raster.validPixels"]]
Y <- getValues(r1)
Y <- Y[validPixels]
lm1 <- lm(Y~X)
intercept <- coefficients(lm1)[1]
alpha <- coefficients(lm1)[1]
beta <- coefficients(lm1)[2:(numComponents + 1)]
r2 <- alpha + EOFsToRaster(X, matrix(beta, nrow = 1),
      c(33, 84), validPixels)[[1]]
extent(r2) <- extent(r1)
```

Checking the Dimension Reduction

- We can accurately reproduce the SST anomaly grids from the 100 EOFs.

```
par(mfrow = c(1, 2))
plot(r1, xlab = "Longitude", ylab = "Latitude", zlim = c(-5, 5))
plot(r2, xlab = "Longitude", ylab = "Latitude", zlim = c(-5, 5))
```



Dimension Reduction of the Test Data

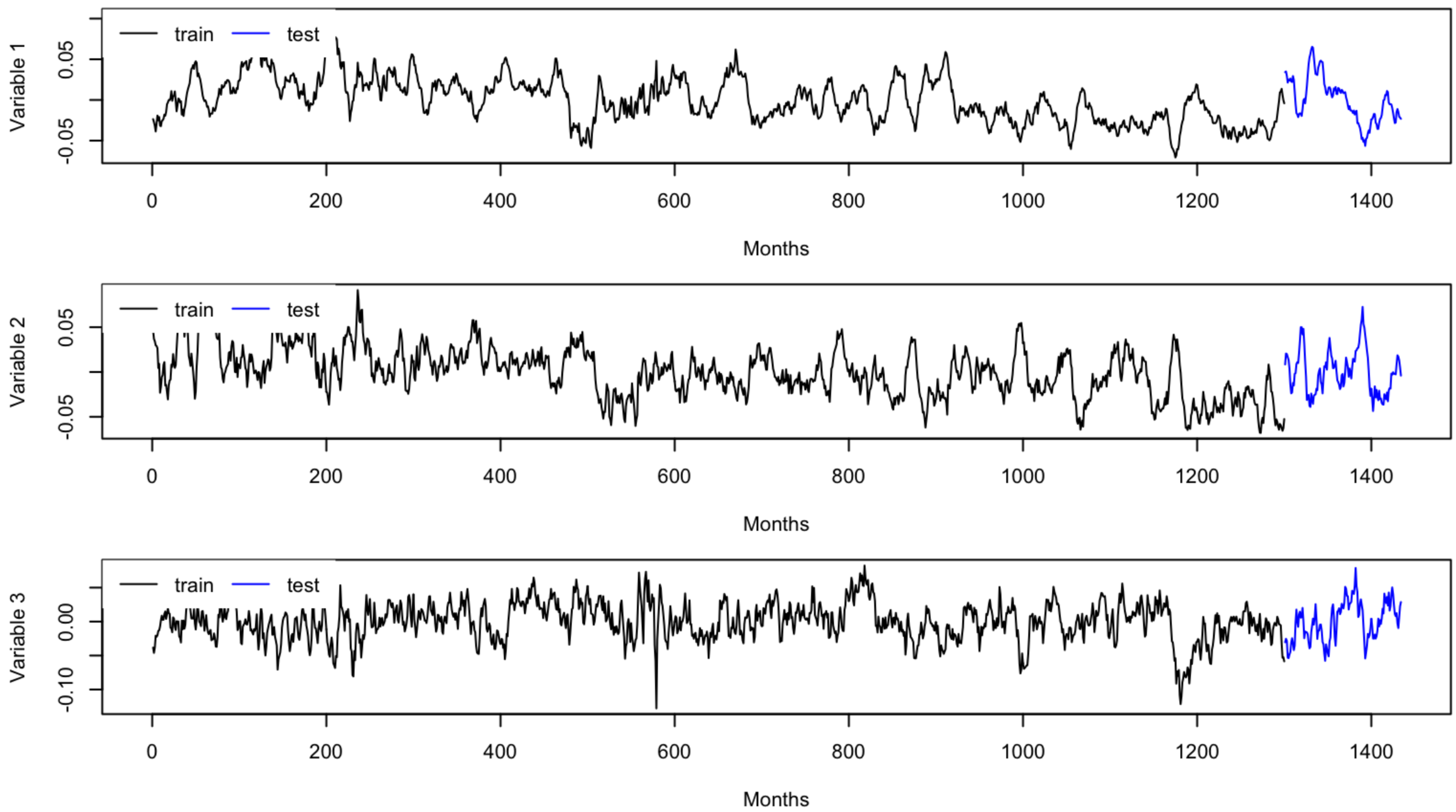
- Here we project the SST anomaly grids in the test set onto the EOFs that we generated from the training data.
- You can think of v.test as a multivariate time series of coefficients that we can use to reconstruct SST anomaly from the EOFs.
- We can think of these as latent features derived from the observed system.

```
v.test <- proj.raster.EOFs(anomalyRasterList[testInds],
         EOFList[["rasterEOFs"]][["EOFs"]],
         EOFList[["raster.validPixels"]])
```

Dimension Reduction of the Test Data

```
par(mfrow = c(3, 1), mar = c(4,4,1,1))
plot(trainingInds, v.train[, 1], ty = "l", xlim = c(0, 1434),
     xlab = "Months", ylab = "Variable 1")
lines(testInds, v.test[, 1], col = "blue")
legend("topleft", legend = c("train", "test"), horiz = TRUE,
       box.lwd = 0, col = c("black", "blue"), lty = 1)
plot(trainingInds, v.train[, 2], ty = "l", xlim = c(0, 1434),
     xlab = "Months", ylab = "Variable 2")
lines(testInds, v.test[, 2], col = "blue")
legend("topleft", legend = c("train", "test"), horiz = TRUE,
       box.lwd = 0, col = c("black", "blue"), lty = 1)
plot(trainingInds, v.train[, 3], ty = "l", xlim = c(0, 1434),
     xlab = "Months", ylab = "Variable 3")
lines(testInds, v.test[, 3], col = "blue")
legend("topleft", legend = c("train", "test"), horiz = TRUE,
       box.lwd = 0, col = c("black", "blue"), lty = 1)
```

Dimension Reduction of the Test Data



Wrangling Data for a RNN in Keras

- The predictors are the coefficients for the EOFs over time.

```
v.combined <- rbind(v.train, v.test)
```

- Scale the predictors to the model.

```
v.scaling.train <- scaleCols.pos(v.combined[trainingInds, ])
v.train.scaled <- v.scaling.train[["X.scaled"]]
v.scaling.test <- scaleCols.pos(v.combined[testInds, ],
                  colMaxsX = v.scaling.train[["colMaxsX"]],
                  colMinsX = v.scaling.train[["colMinsX"]])
v.test.scaled <- v.scaling.test[["X.scaled"]]

v.scaled <- rbind(v.train.scaled, v.test.scaled)
```

Formatting Tensors for a RNN in Keras

```
numDims <- ncol(v.scaled)
tensorData <- tensorfyData.rnn(v.scaled, forecastMonthsAhead,
              timestepsPerSample, indicesX = 1:numDims,
              indicesY = 1:numComponents, indicesTrain = trainingInds,
              indicesTest = testInds)
str(tensorData)
```

```
## List of 8
##  $ X.train.rnn   : num [1:1273, 1:24, 1:100] 0.268 0.248 0.222 0.182 0.237 ...
##  $ Y.train.rnn   : num [1:1273, 1:100] 0.396 0.323 0.363 0.413 0.408 ...
##  $ X.test.rnn    : num [1:107, 1:24, 1:100] 0.597 0.602 0.571 0.524 0.545 ...
##  $ Y.test.rnn    : num [1:107, 1:100] 0.58 0.654 0.7 0.724 0.756 ...
##  $ x.train.tsInds: int [1:1273] 24 25 26 27 28 29 30 31 32 33 ...
##  $ x.test.tsInds : int [1:107] 1324 1325 1326 1327 1328 1329 1330 1331 1332 1333 ...
##  $ y.train.tsInds: int [1:1273] 27 28 29 30 31 32 33 34 35 36 ...
##  $ y.test.tsInds : int [1:107] 1327 1328 1329 1330 1331 1332 1333 1334 1335 1336 ...
```

Scaling Data for a RNN in Keras

- Scale the Outputs of the Model

```
Y.train.inds <- tensorData$y.train.tsInds
Y.test.inds <- tensorData$y.test.tsInds
Y.train.rnn_MDB <- rainfallAnomaly[Y.train.inds, 3]
Y.test.rnn_MDB <- rainfallAnomaly[Y.test.inds, 3]
Y.train.min <- min(Y.train.rnn_MDB)
Y.train.max <- max(Y.train.rnn_MDB)

Y.train.rnn_MDB <- (Y.train.rnn_MDB - Y.train.min)/
                    (Y.train.max - Y.train.min)
Y.test.rnn_MDB <- (Y.test.rnn_MDB - Y.train.min)/
                    (Y.train.max - Y.train.min)
```

Editing the Tensors for the RNN

- By default, tensorfyData.rnn will assume that you are trying to predict the same time series that you are using as inputs.
- In our case, the EOF coefficients are the inputs, but we are attempting to forecast rainfall anomaly.
- So let's replace the output tensors in the list called tensorData.

```
tensorData[["Y.train.rnn"]] <- Y.train.rnn_MDB
tensorData[["Y.test.rnn"]] <- Y.test.rnn_MDB
```

Editing the Tensors for the RNN

- Let's extract the important tensors from the tensor list.

```
X.rnn.train <- tensorData[["X.train.rnn"]]
X.rnn.test <- tensorData[["X.test.rnn"]]

Y.rnn.train <- tensorData[["Y.train.rnn"]]
Y.rnn.test <- tensorData[["Y.test.rnn"]]
```

A Custom Loss Function

- We will use a Gaussian likelihood function and use the negative log-likelihood as our loss function.

```
Gaussian_logLikelihood <- function(y_true, y_pred)
{
  K <- backend()
  muMask <- K$constant(c(1, 0), shape = c(2, 1))
  sigmaMask <- K$constant(c(0, 1), shape = c(2, 1))

  sigma <- K$exp(K$dot(y_pred, sigmaMask))
  mu <- K$dot(y_pred, muMask)

  ll <- -0.5*K$square((mu - y_true)/(sigma)) - K$log(sigma)
  -1*K$sum(ll, axis = 1L)
}
```

Building an LSTM Model

```
library(keras)
model <- keras_model_sequential()
```

```
## Loaded TensorFlow version 2.6.0
```

```
model %>%
  layer_lstm(units = 128,
             input_shape = c(timestepsPerSample, numDims),
             return_sequences = FALSE,
             stateful = FALSE) %>%
  layer_dense(units = 128, activation = "relu") %>%
  layer_dense(units = 2)
```

Compiling the Model

- We compile the model with our custom negative log-likelihood loss.
- We will use the RMSProp optimisation algorithm with default parameters.

```
model %>% compile(loss = Gaussian_logLikelihood,
                  optimizer = optimizer_rmsprop())
```

Training and Early Stopping

```
history <- model %>% fit(x = X.rnn.train, y = Y.rnn.train,
           batch_size = batchSize, epochs = 200, shuffle = TRUE,
           validation_data = list(X.rnn.test, Y.rnn.test),
           callbacks = list(callback_early_stopping(
           monitor = "val_loss", min_delta = 0, patience = 5),
           callback_model_checkpoint(filepath = "MDB_Gaussian.hd5",
           save_best_only = TRUE, save_weights_only = FALSE)))

bestModel <- load_model_hdf5(filepath = "MDB_Gaussian.hd5",
             custom_objects = list(Gaussian_logLikelihood =
             Gaussian_logLikelihood))
```

Assessing the Predictions

- Calculate the mean and standard deviations of the 3 month out (Gaussian) predictive distributions.
- Then create 50% and 95% prediction intervals.

```
lstmPredictions <- bestModel %>% predict(X.rnn.test)

mu <- Y.train.min + lstmPredictions[, 1]*(Y.train.max - Y.train.min)
sigma <- exp(lstmPredictions[, 2])*(Y.train.max - Y.train.min)
n <- length(mu)
upper95 <- mu + 1.96*sigma
lower95 <- mu - 1.96*sigma
upper50 <- mu + 0.674*sigma
lower50 <- mu - 0.674*sigma
```

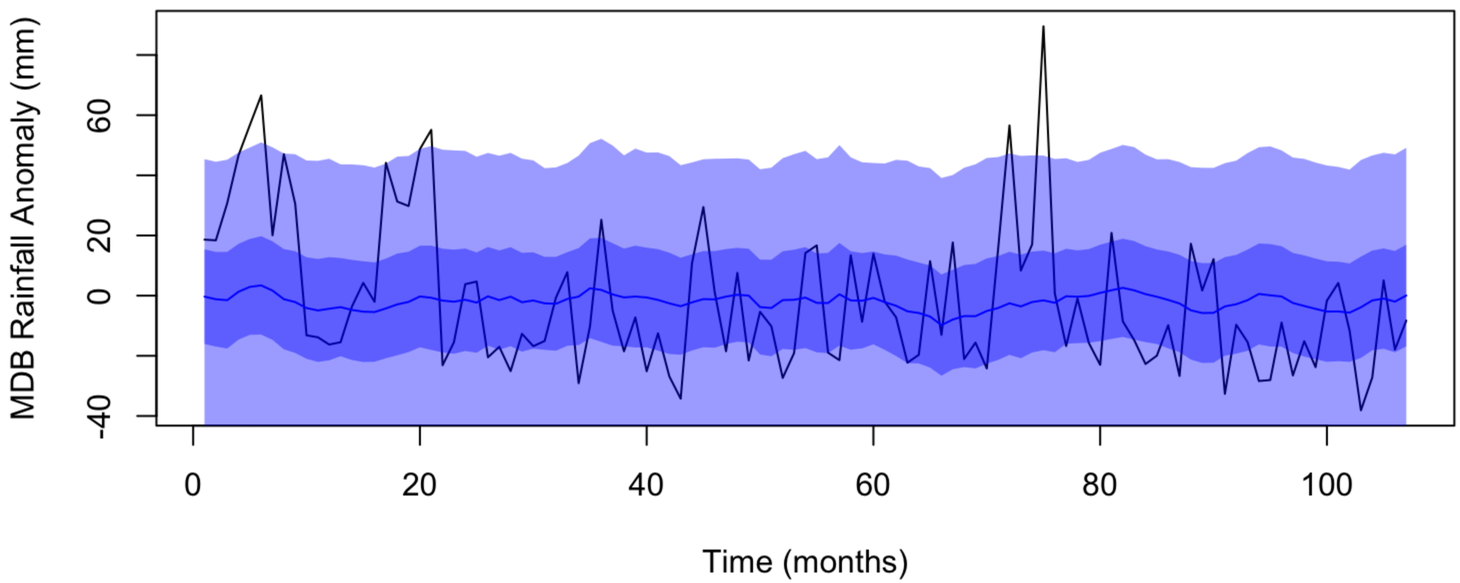
Assessing the Predictions

- Plot the true time series with 3-month-out forecast and 50% and 95% prediction intervals.

```
plot(rainfallAnomaly[Y.test.inds, 3], ty = "l",
     xlab = "Time (months)",
     ylab = "MDB Rainfall Anomaly (mm)")
lines(mu, col = "blue")
polygon(x = c(1:n, rev(1:n), 1),
        y = c(lower95, rev(upper95), lower95[1]),
        col = fade("blue", 100), border = NA)
polygon(x = c(1:n, rev(1:n), 1),
        y = c(lower50, rev(upper50), lower50[1]),
        col = fade("blue", 100), border = NA)
```

Assessing the Predictions

- Plot the true time series with 3-month-out forecast and 50% and 95% prediction intervals.



Assessing the Predictions

- Calculate what percentage of the time the true rainfall anomaly was within the 50% and 95% prediction intervals.

```
n <- (length(Y.test.inds))
coverage50 <- length(which(rainfallAnomaly[Y.test.inds, 3]> lower50
              & rainfallAnomaly[Y.test.inds, 3] < upper50))/n
coverage95 <- length(which(rainfallAnomaly[Y.test.inds, 3] > lower95
              & rainfallAnomaly[Y.test.inds, 3] < upper95))/n
print(coverage50)
```

```
## [1] 0.4953271
```

```
print(coverage95)
```

```
## [1] 0.9439252
```

Some things to try

- How does varying the number of units in the LSTM layer affect the predictions?
- How do the predictions change if you add three dense layers after the LSTM layer (instead of just 1)?
- How are the predictions if much fewer EOFs are used for prediction?
- How does fewer EOFs affect the number of parameters in the model?