

Figure S1: Comparison between the downscaled SM and in situ SM of Babao Network.

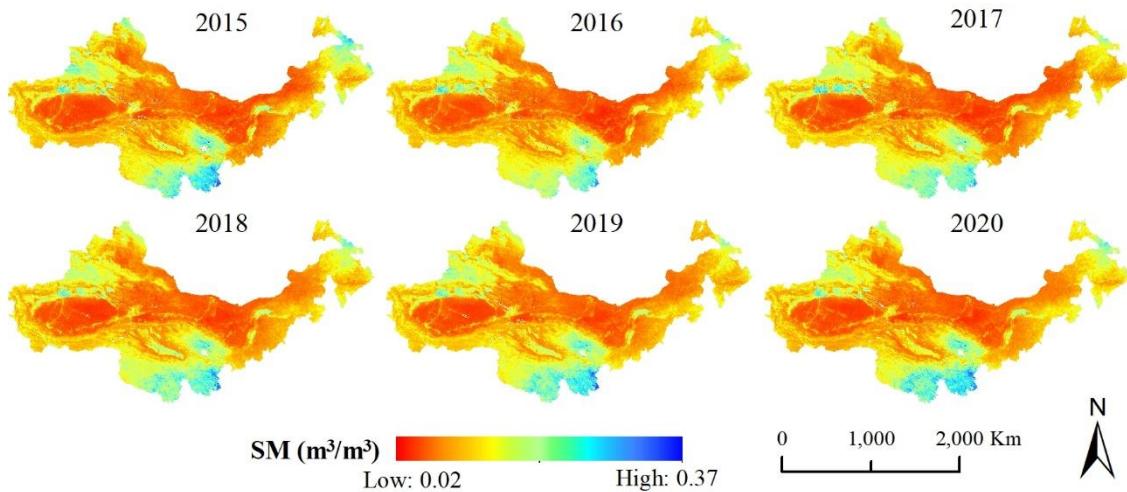


Figure S2: Annual average SM in the study area. Note: The SM data for 2015 are only from 2015/3/22.

CODES: The codes were written using RStudio based on the R language.

(1) The codes for sample selection, PATH present the path of the file.

##Selection of valid samples for the study area

```

rm(list = ls())
library(xlsx)
library(randomForest)
library(varSelRF)
library(pROC)
library(raster)
library(rgdal)
library(fpp2)
library(tcltk)
library(forecast)
library(ggplot2)
library(tweedie)
library(e1071)
library(RSNNS)
library(rpart)
# input terrain parameters
DEMFILE <-
  raster('PATH/DEM/DEM36000.tif')
SLOPEFILE <-
  raster('PATH/DEM/Slope36000.tif')
ASPECTFILE <-
  raster('PATH/DEM/Aspect36000.tif')
#input longitude and latitude, The results show that latitude and longitude have little effect
LONGFILE <-
  raster('PATH/Location/long36000.tif')

```

```

LATFILE <-
  raster('PATH/Location/lat36000.tif')
# input soil parameters
SANDFILE <-
  raster('PATH/soil/SA36000.tif')
SILTFIELD <-
  raster('PATH/soil/SI36000.tif')
CLAYFILE <-
  raster('PATH/soil/CL36000.tif')

path <- 'PATH/MODIS/MOD13A2/tif36000/'
docs <- dir(path, '*EVI.tif')
n <- length(docs)
num <- matrix(nrow = n, ncol = 1)
Factors <-
c(
  'LST',
  'EVI',
  'NDVI',
  'DEM',
  'SLOPE',
  'ASPECT',
  'SAND',
  'SILT',
  'CLAY',
  'LONG',
  'LAT',
  'LAI',
  'FAPAR',
  'NDWI',
  'LSWI',
  'NSDSI',
  'ALBEDO',
  'SM'
)
for (k in 1:n) {
  iris <- matrix(nrow = 1, ncol = 18)
  iris2 <- matrix(nrow = 1, ncol = 18)
  colnames(iris) <- Factors
  colnames(iris2) <- Factors
  print(docs[k])
}

```

```

date <- substr(docs[k], 1, 7)
date <- as.numeric(date) #numeric

# var explained
# read MOD13A2
EVIFILE <- raster(paste0(path, docs[k]))
NDVIFILE <- raster(paste0(path, date, '.1_km_16_days_NDVI.tif'))

#Samples for 16 days
for (i in 1:16) {
  date1 <- date + i - 1
  date2 <- as.Date(as.character(date1), '%Y%j')
  date2 <- gsub("-", "", date2)
  filename1 <-
    paste0('PATH/MODIS/MOD11A1/tif36000/',
           date1,
           '.LST_Day_1km.tif')
  filename2 <-
    paste0('PATH/SMAP/xibei36000/',
           'SMAP_L3_SM_P_',
           date2,
           '_R17000_001.h5.tif')
  filename22 <-
    paste0('PATH/SMAP/xibei36000/',
           'SMAP_L3_SM_P_',
           date2,
           '_R17000_002.h5.tif')
  filename3 <-
    paste0('PATH/MODIS/MCD43D58/tif36000/',
           'MCD43D58.A',
           date1,
           '.tif')

  if (i < 9) {
    LAIFILE <-
      raster(paste0('PATH/MODIS/MOD15A2/tif36000/',
                    date,
                    '.Lai_500m.tif'))
    FAPARFILE <-
      raster(paste0('PATH/MODIS/MOD15A2/tif36000/',
                    date,
                    '.Fpar_500m.tif'))
  }
}

```

```

NDWIFILE <-
  raster(paste0('PATH/MODIS/MOD09A1/tif36000/',
                date,
                '_NDWI.tif))

LSWIFILE <-
  raster(paste0('PATH/MODIS/MOD09A1/tif36000/',
                date,
                '_LSWI.tif'))

NSDSIFILE <-
  raster(paste0('PATH/MODIS/MOD09A1/tif36000/',
                date,
                '_NSDSI.tif'))

} else{

  LAIFILE <-
    raster(paste0(
      'PATH/MODIS/MOD15A2/tif36000/',
      date + 8,
      '.Lai_500m.tif
    ))

  FAPARFILE <-
    raster(paste0(
      'PATH/MODIS/MOD15A2/tif36000/',
      date + 8,
      '.Fpar_500m.tif
    ))

  NDWIFILE <-
    raster(paste0('PATH/MODIS/MOD09A1/tif36000/',
                  date + 8,
                  '_NDWI.tif'))

  LSWIFILE <-
    raster(paste0('PATH/MODIS/MOD09A1/tif36000/',
                  date + 8,
                  '_LSWI.tif'))

  NSDSIFILE <-
    raster(paste0('PATH/MODIS/MOD09A1/tif36000/',
                  date + 8,
                  '_NSDSI.tif'))

}

if (file.exists(filename2)) {
  SMFILE <- raster(filename2)
} else if (file.exists(filename22))

```

```

{
  SMFILE <- raster(filename22)
} else{
  next
}

if (file.exists(filename1) & file.exists(filename3)) {
  LSTFILE <- raster(filename1)
  ALBEDO <- raster(filename3)
  LAIFILE[LAIFILE > 100] <- 0
  FAPARFILE[FAPARFILE > 100] <- 0

## Selection of valid samples
iriss <-
  cbind(
    matrix(LSTFILE),
    matrix(EVIFILE),
    matrix(NDVIFILE),
    matrix(DEMFILE),
    matrix(SLOPEFILE),
    matrix(ASPECTFILE),
    matrix(SANDFILE),
    matrix(SILTFILE),
    matrix(CLAYFILE),
    matrix(LONGFILE),
    matrix(LATFILE),
    matrix(LAIFILE),
    matrix(FAPARFILE),
    matrix(NDWIFILE),
    matrix(LSWIFILE),
    matrix(NSDSIFILE),
    matrix(ALBEDO),
    matrix(SMFILE)
  )
xuhao1 <-
  which(iriss[, 1] > 0 &
        iriss[, 9] > 0 &
        iriss[, 18] >= 0 &
        rowSums(is.na(iriss)) == 0)
iris <- rbind(iris, iriss[xuhao1,])
}
}

```

```

num[k, 1] = length(iris[, 1]) - 1
# Write valid sample in 'PATH/smaples/'
write.csv(iris[-1,],
          file = paste0('PATH/smaples/',
                        date,
                        '.csv'))
}

```

(2) The codes for the optimal regression model building and the result prediction, PATH present the path of the file.

```

##1.Regression for daily SM data at 1 km resolution
rm(list = ls())
library(xlsx)
library(randomForest)
library(varSelRF)
library(pROC)
library(raster)
library(rgdal)
library(fpp2)
library(tcltk)
library(forecast)
library(ggplot2)
library(tweedie)
library(e1071)
library(RSNNS)
library(rpart)
# library(keras)
library(caret)
library(xgboost)
pb <- tkProgressBar("Progress", "Doing %", 0, 100)

##Prediction
#Input parameters
DEMFILE2 <-
raster('PATH/DEM/DEM1000.tif')

```

```

SLOPEFILE2 <-
  raster('PATH/DEM/Slope1000.tif')
ASPECTFILE2 <-
  raster('PATH/DEM/Aspect1000.tif')
#input longitude and latitude
LONGFILE2 <-
  raster('PATH/Location/long1000.tif')
LATFILE2 <-
  raster('PATH/Location/lat1000.tif')
# input soil parameters
SANDFILE2 <-
  raster('PATH/soil/SA1000.tif')
SILTFILE2 <-
  raster('PATH/soil/SI1000.tif')
CLAYFILE2 <-
  raster('PATH/soil/CL1000.tif')

#Path of the samples
path1 <- 'PATH/smaples/'
docs <- dir(path1, '*.csv')
n <- length(docs)
Factors <-
c(
'LST',
'EVI',
'NDVI',
'DEM',
'SLOPE',
'ASPECT',
'SAND',
'SILT',
'CLAY',
'LAI',
'NDWI',
'LSWI',
'NSDSI',
'ALBEDO'
)
AC <- matrix(0, nrow = n, ncol = 20)    #Accuracy
Imorptance1 <-
  matrix(0, nrow = 14, ncol = n)    #RF variable importance

```

```

Imorptance2 <-
  matrix(0, nrow = 14, ncol = n)    #xgb variable importance

for (k in 1:n) {
  date <- substr(docs[k], 1, 7)
  date <- as.numeric(date)  #numeric format
  iris <-
    read.csv(paste0(path1, date, '.csv'))
  if (nrow(iris) > 60) {
    ### Divide training samples and test samples
    xuhao1 <-
      createDataPartition(y = iris$SM, p = 0.5, list = FALSE)
    #Training set
    ir <- iris[xuhao1, ]
    #Test set
    ir2 <- iris[-xuhao1, ]

    #Random Forest (RF)
    set.seed(1000)
    gx.rf <-
      randomForest(
        SM ~ LST + EVI + NDVI + DEM + SLOPE + ASPECT + SAND + SILT + CLAY + LAI + NDWI +
        LSWI + NSDSI + ALBEDO,
        data = ir,
        important = TRUE,
        ntree = 1000,
        proximity = TRUE,
        mtry = 10
      )
    # print(gx.rf)

    # Training accuracy
    pre_rf <- predict(gx.rf, newdata = ir)
    frecoff <-
      cor.test(pre_rf, ir[, 19], method = "pearson", na.action = na.omit)
    AC[k, 1] <- frecoff$estimate  #The correlation coefficient
    AC[k, 2] <- accuracy(pre_rf, ir[, 19])[1, 2]  #RMSE
    ##validation accuracy
    pre_rf2 <- predict(gx.rf, newdata = ir2)
    frecoff2 <-
      cor.test(pre_rf2, ir2[, 19], method = "pearson", na.action = na.omit)
    AC[k, 3] <- frecoff2$estimate  #The correlation coefficient
  }
}

```

```

AC[k, 4] <- accuracy(pre_rf2, ir2[, 19])[1, 2] #RMSE
Imorptance1[, k] <- gx.rf$importance

#Multivariable Linear Regression (MLR)
gx.mlr <-
  lm(
    SM ~ LST + EVI + NDVI + DEM + SLOPE + ASPECT + SAND + SILT + CLAY + LAI + NDWI +
    LSWI + NSDSI + ALBEDO,
    data = ir
  )
# training accuracy
pre_lm <- predict(gx.mlr, newdata = ir)
frecoff <-
  cor.test(pre_lm, ir[, 19], method = "pearson", na.action = na.omit)
AC[k, 5] <- frecoff$estimate #The correlation coefficient
AC[k, 6] <- accuracy(pre_lm, ir[, 19])[1, 2] #RMSE
# validation accuracy
pre_lm2 <- predict(gx.mlr, newdata = ir2)
frecoff2 <-
  cor.test(pre_lm2, ir2[, 19], method = "pearson", na.action = na.omit)
AC[k, 7] <- frecoff2$estimate #The correlation coefficient
AC[k, 8] <- accuracy(pre_lm2, ir2[, 19])[1, 2] #RMSE

### Artificial neural network (ANN)
ir_mlp <- as.matrix(ir[, c(-1,-11,-12,-14)])
df <-
  splitForTrainingAndTest(ir_mlp[, -15], ir_mlp[, 15], ratio = 0)
# Data standardization
df <- normTrainingAndTestSet(df)
gx.mlp <-
  mlp(
    df$inputsTrain,
    df$targetsTrain,
    size = 15,
    learnFunc = "SCG",
    learnFuncParams = c(0, 0, 0, 0),
    # learnFunc = "Std_Backpropagation", learnFuncParams = c(0.2, 0),
    # learnFunc = "BackpropBatch", learnFuncParams = c(10, 0.1),
    # learnFunc = "Quickprop", learnFuncParams = c(0.1, 2.0, 0.0001, 0.1),
    maxit = 1000,
  )

```

```

metric = "RMSE",
)
#summary(gx.mlp)
# training accuracy
pre_mlp <- predict(gx.mlp, newdata = df$inputsTrain)
pre_mlp <- as.numeric(pre_mlp)
frecoff<-
  cor.test(
    pre_mlp,
    df$targetsTrain,
    method = "pearson",
    na.action = na.omit,
    conf.level = 0.95
  )
AC[k, 9] <- frecoff$estimate
AC[k, 10] <- accuracy(pre_mlp, df$targetsTrain)[1, 2]

# validation accuracy
ir_mlp2 <- as.matrix(ir2[, c(-1,-11,-12,-14)])
df2 <-
  splitForTrainingAndTest(ir_mlp2[, -15], ir_mlp2[, 15], ratio = 0)
# Data standardization
df2 <- normTrainingAndTestSet(df2)
pre_mlp2 = predict(gx.mlp, newdata = df2$inputsTrain)
pre_mlp2 <- as.numeric(pre_mlp2)
frecoff2 <-
  cor.test(
    pre_mlp2,
    df2$targetsTrain,
    method = "pearson",
    na.action = na.omit,
    conf.level = 0.95
  )
AC[k, 11] <- frecoff2$estimate
AC[k, 12] <- accuracy(pre_mlp2, df2$targetsTrain)[1, 2]

#Xgboost
gx.xgb <- xgboost(
  data = do.call(cbind, ir[, c(-1, -11, -12, -14, -19)]),
  label = ir[, 19],
  booster = "gbtree",

```

```

objective = "binary:logistic",
max.depth = 5,
eta = 0.5,
#nthread = 2,
nround = 1000,
min_child_weight = 1,
subsample = 1,
colsample_bytree = 1,
num_parallel_tree = 1
)

# summary(gx.xgb)
# training accuracy
pre_mlp<-
  predict(gx.xgb, newdata = do.call(cbind, ir[, c(-1, -11, -12, -14, -19)]))
#pre_mlp<- as.numeric(pre_mlp)
frecoff<-
  cor.test(
    pre_mlp,
    ir[, 19],
    method = "pearson",
    na.action = na.omit,
    conf.level = 0.95
  )
AC[k, 13] <- frecoff$estimate
AC[k, 14] <- accuracy(pre_mlp, ir[, 19])[1, 2]
# validation accuracy
pre_mlp2<-
  predict(gx.xgb, newdata = do.call(cbind, ir2[, c(-1, -11, -12, -14, -19)]))
pre_mlp2<- as.numeric(pre_mlp2)
frecoff2<-
  cor.test(
    pre_mlp2,
    ir2[, 19],
    method = "pearson",
    na.action = na.omit,
    conf.level = 0.95
  )
AC[k, 15] <- frecoff2$estimate
AC[k, 16] <- accuracy(pre_mlp2, ir2[, 19])[1, 2]
# Imorptance2[,k]=xgb.importance(model = gx.xgb)$Gain

```

```

#Support vector regression (SVR)
#Data normalization
ir_svm<- ir
ir_svm2<- ir2
ir_svm[, c(-1,-19)]<-
  scale(ir_svm[, c(-1,-19)], center = TRUE, scale = TRUE)
ir_svm2[, c(-1,-19)]<-
  scale(ir_svm2[, c(-1,-19)], center = TRUE, scale = TRUE)
gx.svm <-
  svm(
    SM ~ LST + EVI + NDVI + DEM + SLOPE + ASPECT + SAND + SILT + CLAY + LAI + NDWI +
    LSWI + NSDSI + ALBEDO,
    data = ir_svm,
    cost = 1,
    gamma = 0.1
  )
#summary(svm.fit)
pre_svm = predict(gx.svm, newdata = ir_svm)
frecoff3 <-
  cor.test(
    pre_svm,
    ir$SM,
    method = "pearson",
    na.action = na.omit,
    conf.level = 0.95
  )
AC[k, 17] <- frecoff3$estimate
AC[k, 18] <- accuracy(pre_svm, ir_svm[, 19])[1, 2]
# validation accuracy
pre_svm2 <-
  predict(gx.svm, newdata = do.call(cbind, ir_svm2[, c(-1,-11,-12,-14,-19)]))
pre_mlp2 <- as.numeric(pre_svm2)
frecoff2 <-
  cor.test(
    pre_svm2,
    ir2$SM,
    method = "pearson",
    na.action = na.omit,
    conf.level = 0.95
  )
AC[k, 19] <- frecoff2$estimate

```

```

AC[k, 20] <- accuracy(pre_svm2, ir_svm2[, 19])[1, 2]
}

## 2.The results of prediction
## In the prediction part of results, the optimal model was selected and the dependent variable, namely soil moisture, was obtained using the optimal model.
## Select the optimal model based on the average RMSE of training set and test set
rf_rmse <- (AC[k, 2] + AC[k, 4]) / 2
mlr_rmse <- (AC[k, 6] + AC[k, 8]) / 2
mlp_rmse <- (AC[k, 10] + AC[k, 12]) / 2
xgb_rmse <- (AC[k, 14] + AC[k, 16]) / 2
svr_rmse <- (AC[k, 18] + AC[k, 20]) / 2
min_rmse <- min(rf_rmse, mlr_rmse, mlp_rmse, xgb_rmse, svr_rmse)

# var explained
EVIFILE2 <-
raster(paste0(
'PATH/MODIS/MOD13A2/tif1000/',
date,
'.1_km_16_days_EVI.tif
))
NDVIFILE2 <-
raster(paste0(
'PATH/MODIS/MOD13A2/tif1000/',
date,
'.1_km_16_days_NDVI.tif
))
for (i in 1:16) {
date1 <- date + i - 1
filename1 <-
paste0('PATH/MODIS/MOD11A1/tif1000/',
date1,
'.LST_Day_1km.tif)
filename2 <-
paste0('PATH/MODIS/MCD43D58/tif1000/MCD43D58.A',
date1,
'.tif')
}

```

```

if (i < 9) {
  date2 <- date
} else{
  date2 <- date + 8
}

LAIFILE2 <-
raster(paste0('PATH/MODIS/MOD15A2/tif1000/',
              date2,
              '.Lai_500m.tif'))

FAPARFILE2 <-
raster(paste0('PATH/MODIS/MOD15A2/tif1000/',
              date2,
              '.Fpar_500m.tif'))

NDWIFILE2 <-
raster(paste0('PATH/MODIS/MOD09A1/tif1000/',
              date2,
              '_NDWI.tif'))

LSWIFILE2 <-
raster(paste0('PATH/MODIS/MOD09A1/tif1000/',
              date2,
              '_LSWI.tif'))

NSDSIFILE2 <-
raster(paste0('PATH/MODIS/MOD09A1/tif1000/',
              date2,
              '_NSDSI.tif'))

LAIFILE2[LAIFILE2 > 100] <- 0
FAPARFILE2[FAPARFILE2 > 100] <- 0

if (file.exists(filename1)) {
  LSTFILE2 <- raster(filename1)
  ALBEDOFILE2 <- raster(filename2)
  # #Output
  result <- LSTFILE2
  result[result >= 0] <- NaN
  train <-
    cbind(
      matrix(LSTFILE2),
      matrix(EVIFILE2),
      matrix(NDVIFILE2),
      matrix(DEMFILE2),

```

```

matrix(SLOPEFILE2),
matrix(ASPECTFILE2),
matrix(SANDFILE2),
matrix(SILTFILE2),
matrix(CLAYFILE2),
matrix(LAIFILE2),
matrix(NDWIFILE2),
matrix(LSWIFILE2),
matrix(NSDSIFILE2),
matrix(ALBEDOFILE2)

)
colnames(train) <- Factors
xuhao2 <-
  which(train[, 1] > 0 &
    train[, 6] > 0 &
    train[, 14] > 0 &
    rowSums(is.na(train)) == 0)
train <- train[xuhao2,]
if (min_rmse == rf_rmse) {
  churn.prediction <- predict(gx.rf, newdata = train)
} else if (min_rmse == mlp_rmse) {
  train<-data.frame(train)
  churn.prediction <- predict(gx.mlp, newdata = train)
} else if (min_rmse == xgb_rmse) {
  train <- as.matrix(train)
  df3 <- splitForTrainingAndTest(train, train[, 14], ratio = 0)
  # Data standardization
  df3 <- normTrainingAndTestSet(df3)
  churn.prediction <- predict(gx.mlp, newdata = df3$inputsTrain)
} else if (min_rmse == xgb_rmse) {
  churn.prediction <- predict(gx.xgb, newdata = train)
} else if (min_rmse == xgb_rmse) {
  train <- scale(train, center = TRUE, scale = TRUE)
  churn.prediction <- predict(gx.svm, newdata = train)
}

#Write the results
result[xuhao2] <- churn.prediction
date0 <- as.Date(as.character(date1), "%Y%j")
date0 = gsub("-", "", date0)
rf <-
  writeRaster(

```

```
result,
filename = paste0('PATH/SMAP/xibei10003/',
                  date0,
                  '.tif'),
overwrite = TRUE
)
#Timing
print(date0)
}
}
print(date)
## progress
info <- sprintf("Progress %d%%", round(k * 100 / n))
setTkProgressBar(pb, k * 100 / n, sprintf("Doing (%s)", info), info)
}
#Accuracy
write.csv(AC, file = "PATH/validation/AC.csv")
# write.csv(Imorptance1, file = "PATH/validation/importance1.csv")
# write.csv(Imorptance2, file = "PATH/validation/importance2.csv")
close(pb)
```