# faoswsImputation: A package for the imputation of missing time series data in the Statistical Working System

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**Abstract**

This vignette provides a detailed description of the usage of functions in the **faoswsImputation** package.

*Keywords*: Imputation, Linear Mixed Model, Ensemble Learning.



## 1. Setup

Before we begin, we will need to load the required libraries

```
## Load libraries
library(faoswsImputation)
library(faoswsUtil)
library(data.table)
```

Additionally, we'll load the production library for an example dataset

```
library(faoswsProduction)
```

To illustrate the functionality of the package, we take the Okra data set as an example. The implementation requires the data to be loaded as a *data.table* object. This is also the default when data are queried from the API of the Statistical Working System (SWS).

```
str(okrapd)

## Classes 'data.table' and 'data.frame': 912 obs. of  14 variables:
##  $ geographicAreaM49                          : int  3 3 3 3 3 3 3 3 3 3 ...
##  $ areaName                                   : chr  "Albania" "Albania" "Albania" "Albani
##  $ itemCode                                   : int  430 430 430 430 430 430 430 430 430 4
##  $ itemName                                   : chr  "Okra" "Okra" "Okra" "Okra" ...
##  $ timePointYears                             : int  1995 1996 1997 1998 1999 2000 2001 20
##  $ Value_measuredElement_5312                 : num  800 600 750 750 740 780 790 780 700 6
##  $ flagObservationStatus_measuredElement_5312: chr  "T" "T" "T" "T" ...
##  $ flagMethod_measuredElement_5312            : logi  NA NA NA NA NA NA ...
##  $ Value_measuredElement_5416                 : num  7.25 8 8 8 7.97 ...
##  $ flagObservationStatus_measuredElement_5416: chr  "T" "T" "T" "T" ...
```

```
##  $ flagMethod_measuredElement_5416           : logi  NA NA NA NA NA NA ...
##  $ Value_measuredElement_5510                : num  5800 4800 6000 6000 5900 6200 6500 67
##  $ flagObservationStatus_measuredElement_5510: chr  "T" "T" "T" "T" ...
##  $ flagMethod_measuredElement_5510           : logi  NA NA NA NA NA NA ...
##  - attr(*, ".internal.selfref")=<externalptr>
##  - attr(*, "index")= atomic
##   ..- attr(*, "flagObservationStatus_measuredElement_5510")= int  9 10 11 35 36 37 49 50
##   ..- attr(*, "flagObservationStatus_measuredElement_5416")= int  9 10 11 35 36 37 49 50
##   ..- attr(*, "flagObservationStatus_measuredElement_5312")= int  9 10 11 35 36 37 49 50
##   ..- attr(*, "areaName")= int  1 2 3 4 5 6 7 8 9 10 ...
```

Note: the okrapd dataset is a good example of the data available in the SWS. However, as such, the column names aren't very clear. As a quick explanation, 5312 refers to area harvested, 5416 refers to yield, and 5510 refers to production. Each variable has three columns for it's value and the two status flags.

In addition to the data, the implementation also require a table to map the hierachical relation of the observation flags. It provides a rule for "flag aggregation" (the process of assigning a new observation flag to an observation which is computed from other observations). An example of the table is given below. For more details on flags and how to create/interpret such tables, please see the vignette of the **faoswsFlag** package.

```
swsOldFlagTable = faoswsFlagTable
faoswsFlagTable$flagObservationStatus =
    as.character(faoswsFlagTable$flagObservationStatus)
swsOldFlagTable
```

```
##   flagObservationStatus flagObservationWeights
## 1                                         1.00
## 2                     T                   0.80
## 3                     E                   0.75
## 4                     I                   0.50
## 5                     M                   0.00
```



## 2. Functions

This section describes the step-by-step usage of functions which are used to perform imputation. The steps/functions illustrated here are for demonstration purposes only, as usually these functions will all be called by a one-step imputation function `imputeProductionDomain` (i.e. a "wrapper function").

### 2.1. Data processing

The first step of the imputation is to remove any previous imputations. Even when using the same methodology and settings, prior imputations will change as more information is received over time. This step is highly recommended but optional and depends on the judgement of the analyst.

To remove the prior imputations, one will need to specify the column name of the value and corresponding observation and method flags. Further, the character value which represents an imputation and the character value for a flag representing missing values must be provided.

The function will convert the previously imputed values to NA and the flags from previous imputations will be set to the missing flag value.

```
okraProcessed = copy(okrapd)

## Removing prior imputation for production
table(okraProcessed$flagObservationStatus_measuredElement_5510)

##
##       E   M   T
## 487 239 131  55

removeImputation(data = okraProcessed,
                 value = "Value_measuredElement_5510",
                 observationFlag =
                     "flagObservationStatus_measuredElement_5510",
                 methodFlag = "flagMethod_measuredElement_5510",
                 imputedFlag = "E",
                 missingObservationFlag = "M",
                 missingMethodFlag = "u")
table(okraProcessed$flagObservationStatus_measuredElement_5510)

##
##       M   T
## 487 370  55

## Removing prior imputation for area harvested
table(okraProcessed$flagObservationStatus_measuredElement_5312)

##
##       E   M   T
## 430 289 131  62

removeImputation(data = okraProcessed,
                 value = "Value_measuredElement_5312",
                 observationFlag =
                     "flagObservationStatus_measuredElement_5312",
                 methodFlag = "flagMethod_measuredElement_5312",
                 imputedFlag = "E",
                 missingObservationFlag = "M",
                 missingMethodFlag = "u")
table(okraProcessed$flagObservationStatus_measuredElement_5312)

##
##       M   T
## 430 420  62

## Removing prior imputation for yield
table(okraProcessed$flagObservationStatus_measuredElement_5416)
```

```
##
##       E   M   T
## 410 313 131  58

removeImputation(data = okraProcessed,
                 value = "Value_measuredElement_5416",
                 observationFlag =
                     "flagObservationStatus_measuredElement_5416",
                 methodFlag = "flagMethod_measuredElement_5416",
                 imputedFlag = "E",
                 missingObservationFlag = "M",
                 missingMethodFlag = "u")
table(okraProcessed$flagObservationStatus_measuredElement_5416)

##
##       M   T
## 410 444  58
```

After removing prior imputations, the next step is to replace zero values with a missing flag to values of NA. This is an issue from previous data: some observations will be labeled as missing but given a value of zero instead of a value of NA.

```
okraProcessed[geographicAreaM49 == 12 & timePointYears >= 2005,
              .(Value_measuredElement_5312,
                flagObservationStatus_measuredElement_5312)]
removeOM(data = okraProcessed,
         value = "Value_measuredElement_5312",
         flag = "flagObservationStatus_measuredElement_5312",
         naFlag = "M")
okraProcessed[geographicAreaM49 == 12 & timePointYears >= 2005,
              .(Value_measuredElement_5312,
                flagObservationStatus_measuredElement_5312)]

##    Value_measuredElement_5312 flagObservationStatus_measuredElement_5312
## 1:                         NA                                           M
## 2:                         NA                                           M
## 3:                         NA                                           M
## 4:                         NA                                           M
## 5:                         NA                                           M
## 6:                         19
## 7:                         19
## 8:                         19
## 9:                         19                                           T
```

Note how the zeroes have been changed into NA's above. Let's do the same for production and area harvested:

```
removeOM(data = okraProcessed,
         value = "Value_measuredElement_5416",
         flag = "flagObservationStatus_measuredElement_5416",
         naFlag = "M")
```

```
removeOM(data = okraProcessed,
         value = "Value_measuredElement_5510",
         flag = "flagObservationStatus_measuredElement_5510",
         naFlag = "M")
```

In order for the linear mixed model (one of the models in the ensemble that we will later fit) to fit successfully, at least one observation is required for each country. Thus, this function removes countries which contain no non-missing observations.

```
okraProcessed[geographicAreaM49 == 245,
              .(Value_measuredElement_5416,
                flagObservationStatus_measuredElement_5416)]

##     Value_measuredElement_5416 flagObservationStatus_measuredElement_5416
##  1:                         NA                                           M
##  2:                         NA                                           M
##  3:                         NA                                           M
##  4:                         NA                                           M
##  5:                         NA                                           M
##  6:                         NA                                           M
##  7:                         NA                                           M
##  8:                         NA                                           M
##  9:                         NA                                           M
## 10:                         NA                                           M
## 11:                         NA                                           M
## 12:                         NA                                           M
## 13:                         NA                                           M
## 14:                         NA                                           M
## 15:                         NA                                           M
## 16:                         NA                                           M
## 17:                         NA                                           M
## 18:                         NA                                           M
## 19:                         NA                                           M

removeNoInfo(data = okraProcessed,
             value = "Value_measuredElement_5416",
             observationFlag = "flagObservationStatus_measuredElement_5416",
             byKey = "geographicAreaM49")
okraProcessed[geographicAreaM49 == 245,
              .(Value_measuredElement_5416,
                flagObservationStatus_measuredElement_5416)]

## Empty data.table (0 rows) of 2 cols: Value_measuredElement_5416,flagObservationStatus_mea
```

Note for advanced users: All other remove* functions from the utils package perform by modifying the data.table in place (and thus you do not need to assign a new data.table to the result of a function). removeNoInfo should work in the same way, but there is currently not a way to delete rows in a data.table without copying the data.table. Thus, the object cannot be modified in place. For this function to behave like the other functions, then, we assign the data.table object in an environment (by default, the calling environment of removeNoInfo). This should be changed once the **data.table** package adds this functionality.

Next, we must create a list that contains specific parameters on how the processing should be performed.

```
processingParams = defaultProcessingParameters()
processingParams

## $productionValue
## [1] "Value_measuredElement_5510"
##
## $productionObservationFlag
## [1] "flagObservationStatus_measuredElement_5510"
##
## $productionMethodFlag
## [1] "flagMethod_measuredElement_5510"
##
## $yieldValue
## [1] "Value_measuredElement_5416"
##
## $yieldObservationFlag
## [1] "flagObservationStatus_measuredElement_5416"
##
## $yieldMethodFlag
## [1] "flagMethod_measuredElement_5416"
##
## $areaHarvestedValue
## [1] "Value_measuredElement_5312"
##
## $areaHarvestedObservationFlag
## [1] "flagObservationStatus_measuredElement_5312"
##
## $areaHarvestedMethodFlag
## [1] "flagMethod_measuredElement_5312"
##
## $yearValue
## [1] "timePointYears"
##
## $byKey
## [1] "geographicAreaM49"
##
## $removePriorImputation
## [1] TRUE
##
## $removeConflictValues
## [1] TRUE
##
## $imputedFlag
## [1] "E"
##
## $naFlag
## [1] "M"
```

Now, we will pass processingParams through all of the individual processing functions. The

function `processProductionDomain` is a wrapper that executes all the data processing above.

```
okraProcessed = copy(okrapd)
processProductionDomain(data = okraProcessed,
                        processingParameters = processingParams)
```

## 2.2. Imputation

Now we are ready to perform the imputation. First, we'll impute the yield. The function `imputeVariable` allows the user to perform imputation on the dataset, and it accepts a list of imputation parameters which control how the imputation is done.

To run the imputation, we need to construct a list with the default imputation parameters (similar to the list with the processing parameters) and adjust them as necessary for our specific use case. The documentation page for defaultImputationParameters() provides some detail on what each of the different elements of this list are. Also, let's delete some of the data (having too many countries can clog up some of the later plots).

```
okraProcessed = okraProcessed[geographicAreaM49 <= 60, ]
imputationParams = defaultImputationParameters(variable = "yield")
sapply(imputationParams, class)
```

```
##              yearValue                  byKey         ensembleModels
##            "character"            "character"                 "list"
##        restrictWeights         maximumWeights         plotImputation
##              "logical"              "numeric"              "logical"
##              errorType          errorFunction             groupCount
##            "character"             "function"              "numeric"
##            missingFlag         imputationFlag          newMethodFlag
##            "character"            "character"            "character"
##              flagTable               variable  imputationValueColumn
##           "data.frame"            "character"            "character"
##   imputationFlagColumn imputationMethodColumn    newImputationColumn
##            "character"            "character"            "character"
```

One very important part of this list is the ensembleModels element. This element specifies all of the models which should be used to form the final ensemble. By default, ten models are used. However, let's use a simpler example with just three models:

```
names(imputationParams$ensembleModels)
```

```
##  [1] "defaultMean"       "defaultLm"         "defaultExp"
##  [4] "defaultLogistic"   "defaultLoess"      "defaultSpline"
##  [7] "defaultArima"      "defaultMars"       "defaultNaive"
## [10] "defaultMixedModel"
```

```
imputationParams$ensembleModels =
    imputationParams$ensembleModels[1:3]
names(imputationParams$ensembleModels)
```

```
## [1] "defaultMean" "defaultLm"   "defaultExp"
```

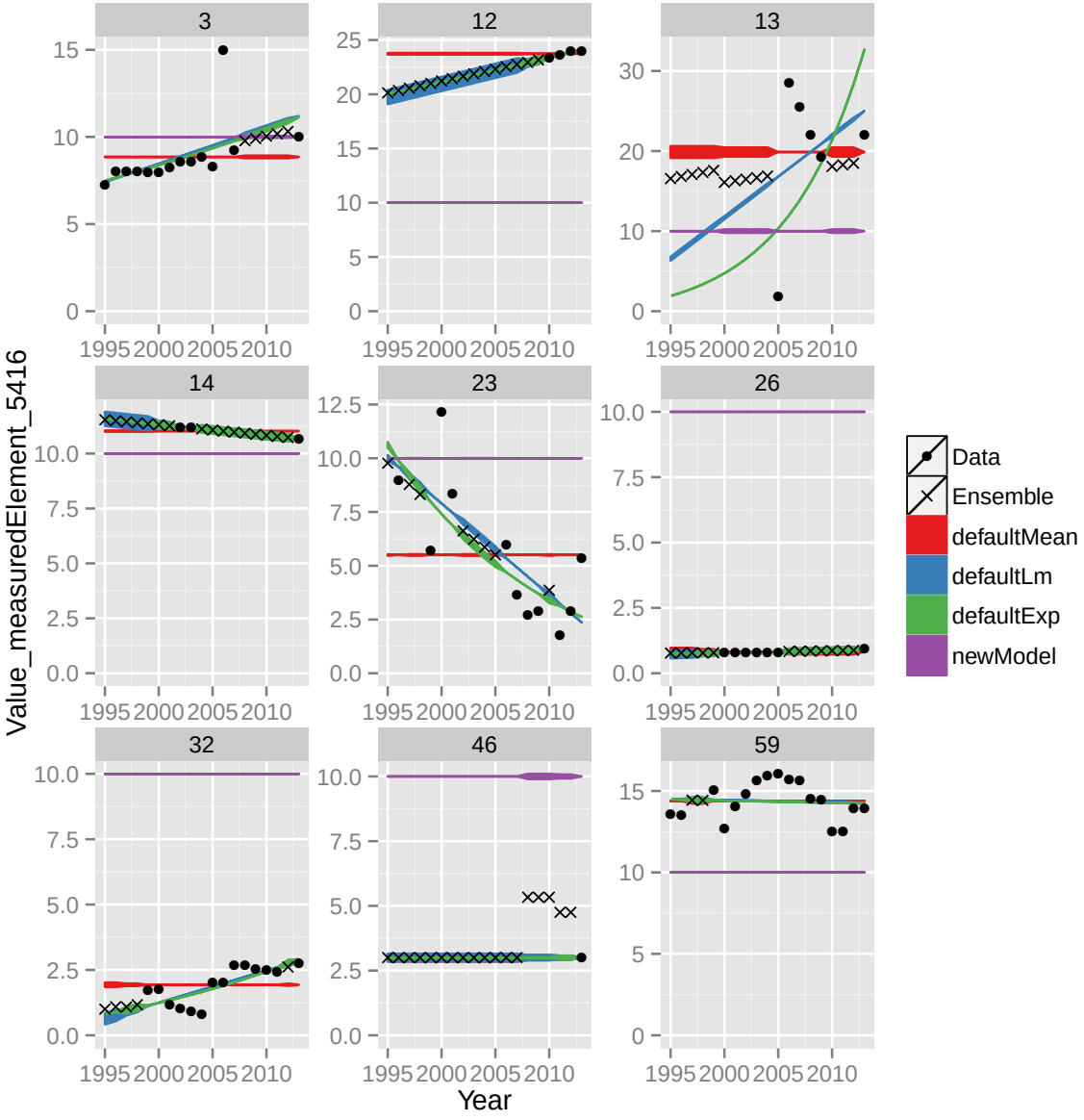
You can also manually create your own model for use. See the documentation page for ?ensembleModel for more details, and below for an example:

```
newModel = ensembleModel(
    model = function(data){
        rep(10, length(data))
    },
    extrapolationRange = 5,
    level = "countryCommodity")
is(newModel)

## [1] "ensembleModel"

imputationParams$ensembleModels = c(imputationParams$ensembleModels,
                                    newModel = newModel)
names(imputationParams$ensembleModels)

## [1] "defaultMean" "defaultLm"   "defaultExp"  "newModel"
```

This new model returns a constant prediction of 10. It's not a good model, but it's a simple example of how to create a new model. The extrapolation range specifies that the model can be used in an ensemble up to 5 observations outside the range of the data, but no more. The level argument specifies that the model should operate on data for all countries for a fixed commodity (as opposed to one model for each unique country-commodity pair).



```
imputationParams$newImputationColumn = "test"
imputeVariable(data = okraProcessed, imputationParameters = imputationParams)
colnames(okraProcessed)

##  [1] "geographicAreaM49"
##  [2] "areaName"
##  [3] "itemCode"
##  [4] "itemName"
##  [5] "timePointYears"
##  [6] "Value_measuredElement_5312"
##  [7] "flagObservationStatus_measuredElement_5312"
##  [8] "flagMethod_measuredElement_5312"
##  [9] "Value_measuredElement_5416"
## [10] "flagObservationStatus_measuredElement_5416"
## [11] "flagMethod_measuredElement_5416"
## [12] "Value_measuredElement_5510"
## [13] "flagObservationStatus_measuredElement_5510"
## [14] "flagMethod_measuredElement_5510"
## [15] "Value_test"
## [16] "flagObservationStatus_test"
## [17] "flagMethod_test"
```




Before discussing the output, first note that the newImputationColumn parameter was updated in the imputationParams object. This parameter allows you to store the imputations from the model in three new columns (value, observation flag, and method flag). This allows you to examine several different ensembles and compare their performances. The default value of imputationParams$newImputationColumn is just an empty string, and in this case the imputation will place the imputations into the processed data.table.

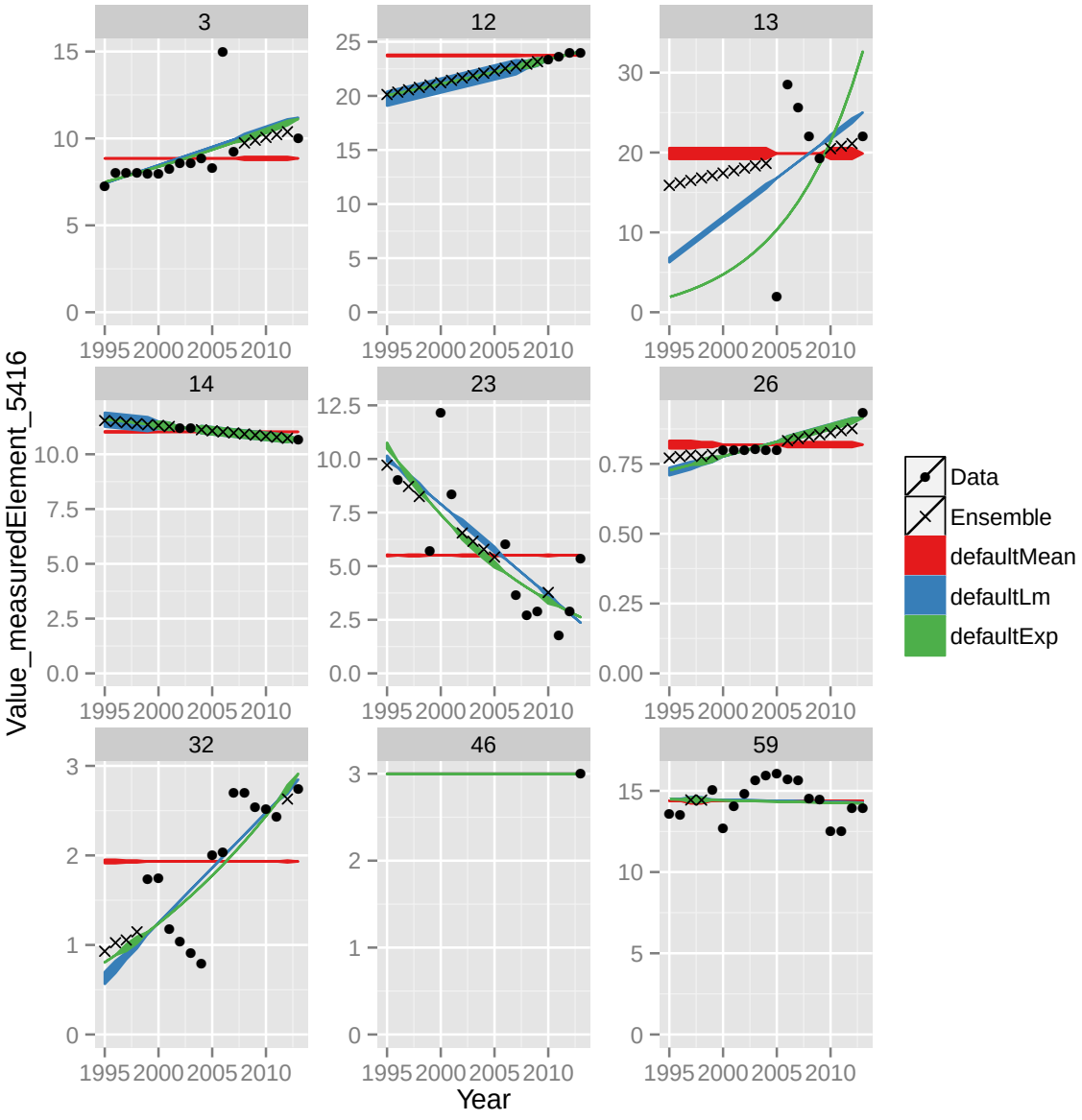
The graphs contain a lot of information. First, the dots represent observed values, and the crosses represent the imputations. The different colored lines show the different fits, and the thickness of the line is proportional to the weight it received in the ensemble. Of course, if the data point is an observation then no imputation is done, so all lines have the same thickness there. Also, the computed weights will be constant for all imputed values with one exception: models that are not allowed to extrapolate may have positive weights for some imputations and 0 for others. Moreover, if an observation is outside the extrapolation range of a model, then the weight of all other models will need to be rescaled so all values add to 1.

We see that the purple line (the model corresponding to our naive model which always estimates the value 10) rarely gets any weight. This makes sense, as it's not a very good model. However, in some particular cases (i.e. geographicAreaM49 = 13), no models do very well.

The mean model thus gets most of the weight, but our naive model also gets a little weight. You can also see how it only has weight up to 5 observations outside of the range of the data; this is because we gave the model an extrapolation range of 5.

Now, suppose we wanted to remove the naive model which always predicts 10. We can do that and re-examine what our ensemble looks like:

```
imputationParams$ensembleModels = imputationParams$ensembleModels[-4]
names(imputationParams$ensembleModels)

## [1] "defaultMean" "defaultLm"   "defaultExp"

imputeVariable(data = okraProcessed, imputationParameters = imputationParams)
```

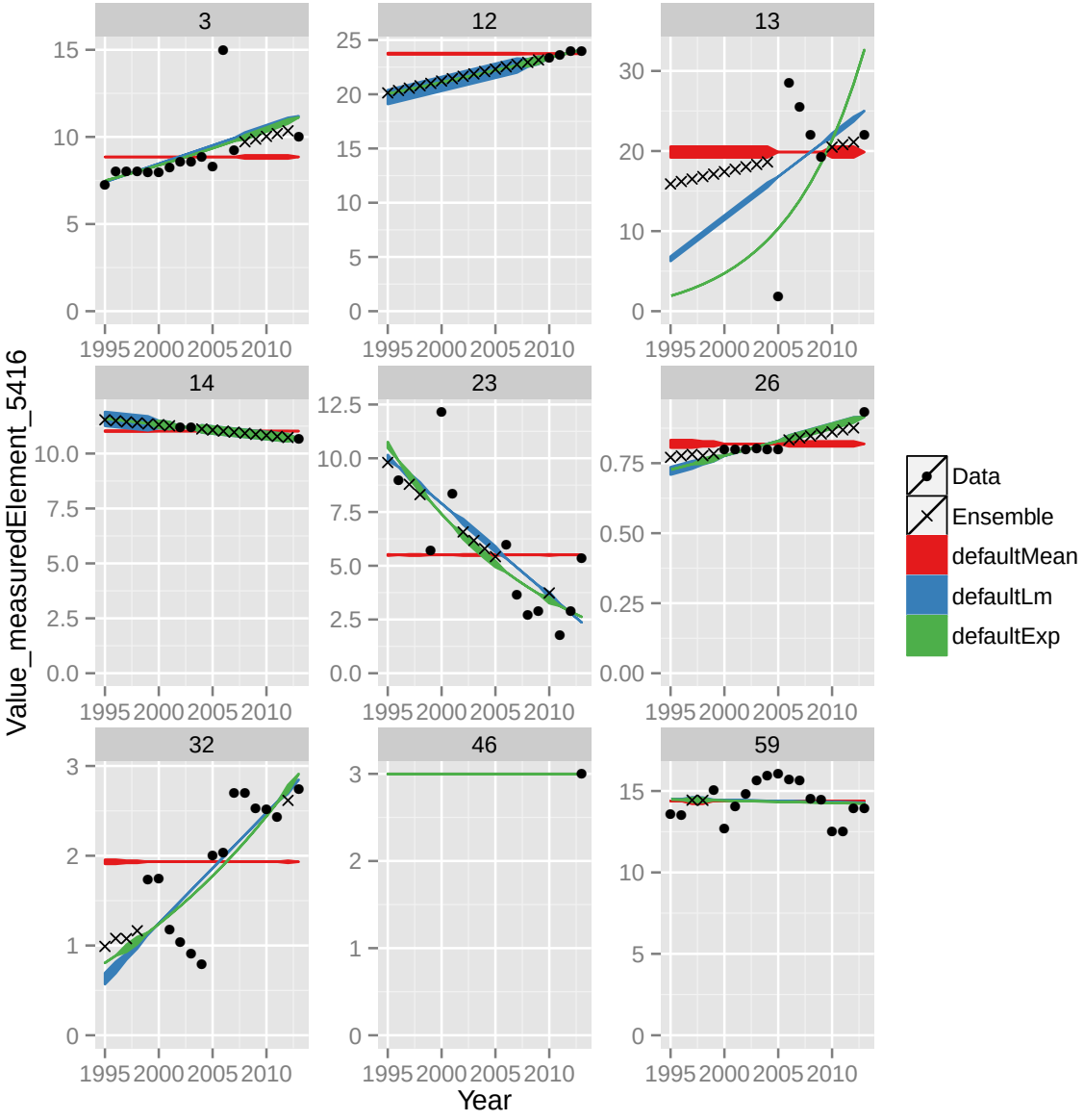



If we're happy with this model, we can assign these imputed values back to the original variable:

```
imputationParams$newImputationColumn = ""
imputeVariable(data = okraProcessed, imputationParameters = imputationParams)
okraProcessed[, c("Value_test", "flagObservationStatus_test",
                  "flagMethod_test") := NULL]
```

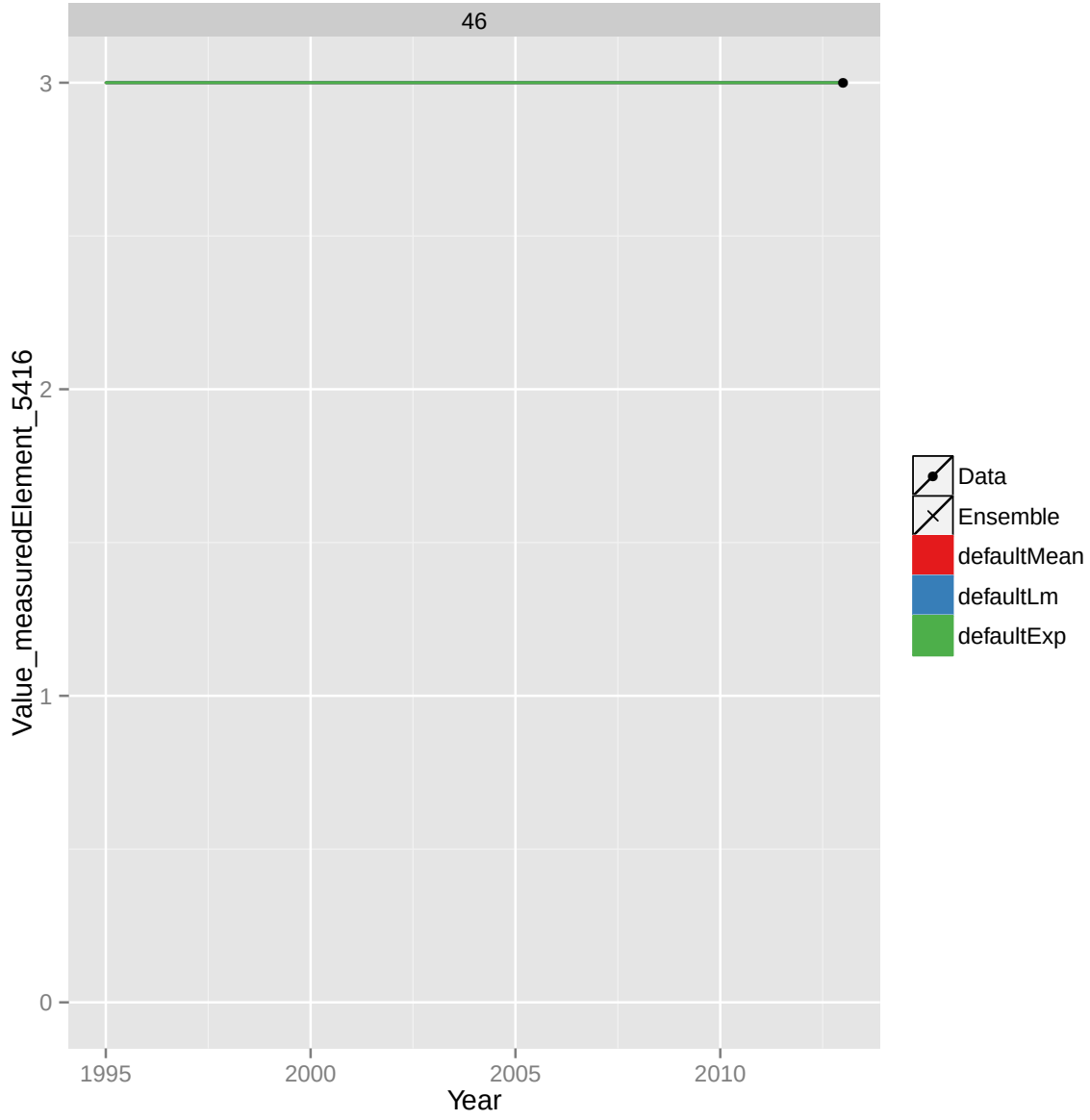
```
##      geographicAreaM49 areaName itemCode itemName timePointYears
##   1:                 3  Albania      430     Okra           1995
##   2:                 3  Albania      430     Okra           1996
##   3:                 3  Albania      430     Okra           1997
##   4:                 3  Albania      430     Okra           1998
##   5:                 3  Albania      430     Okra           1999
##  ---
## 205:                59    Egypt      430     Okra           2009
## 206:                59    Egypt      430     Okra           2010
## 207:                59    Egypt      430     Okra           2011
## 208:                59    Egypt      430     Okra           2012
## 209:                59    Egypt      430     Okra           2013
##      Value_measuredElement_5312 flagObservationStatus_measuredElement_5312
##   1:                        800                                           T
##   2:                        600                                           T
##   3:                        750                                           T
##   4:                        750                                           T
##   5:                        740                                           T
##  ---
## 205:                       9325
## 206:                       6885
## 207:                       6725
## 208:                       6957
## 209:                       6957                                           T
##      flagMethod_measuredElement_5312 Value_measuredElement_5416
##   1:                              NA                   7.250000
##   2:                              NA                   8.000000
##   3:                              NA                   8.000000
##   4:                              NA                   8.000000
##   5:                              NA                   7.972973
##  ---
## 205:                              NA                  14.441287
## 206:                              NA                  12.524619
## 207:                              NA                  12.496803
## 208:                              NA                  13.958315
## 209:                              NA                  13.958315
##      flagObservationStatus_measuredElement_5416 flagMethod_measuredElement_5416
##   1:                                          T                              NA
##   2:                                          T                              NA
##   3:                                          T                              NA
##   4:                                          T                              NA
##   5:                                          T                              NA
##  ---
## 205:                                                                        NA
## 206:                                                                        NA
## 207:                                                                        NA
```

```
## 208:                                                                  NA
## 209:                                       T                          NA
##      Value_measuredElement_5510 flagObservationStatus_measuredElement_5510
##   1:                       5800                                          T
##   2:                       4800                                          T
##   3:                       6000                                          T
##   4:                       6000                                          T
##   5:                       5900                                          T
##  ---
## 205:                     134665
## 206:                      86232
## 207:                      84041
## 208:                      97108
## 209:                      97108                                          T
##      flagMethod_measuredElement_5510
##   1:                              NA
##   2:                              NA
##   3:                              NA
##   4:                              NA
##   5:                              NA
##  ---
## 205:                              NA
## 206:                              NA
## 207:                              NA
## 208:                              NA
## 209:                              NA
```




If we now try to impute again, we see that imputation fails because we have no missing observations. Well, to be more accurate, we have missing observations in one country with only one valid observation. This country was not possible to impute because no leave-one-out cross-validation error can be calculated with a single observation and thus no ensemble weights can be choosen.

```
imputeVariable(data = okraProcessed, imputationParameters = imputationParams)
```



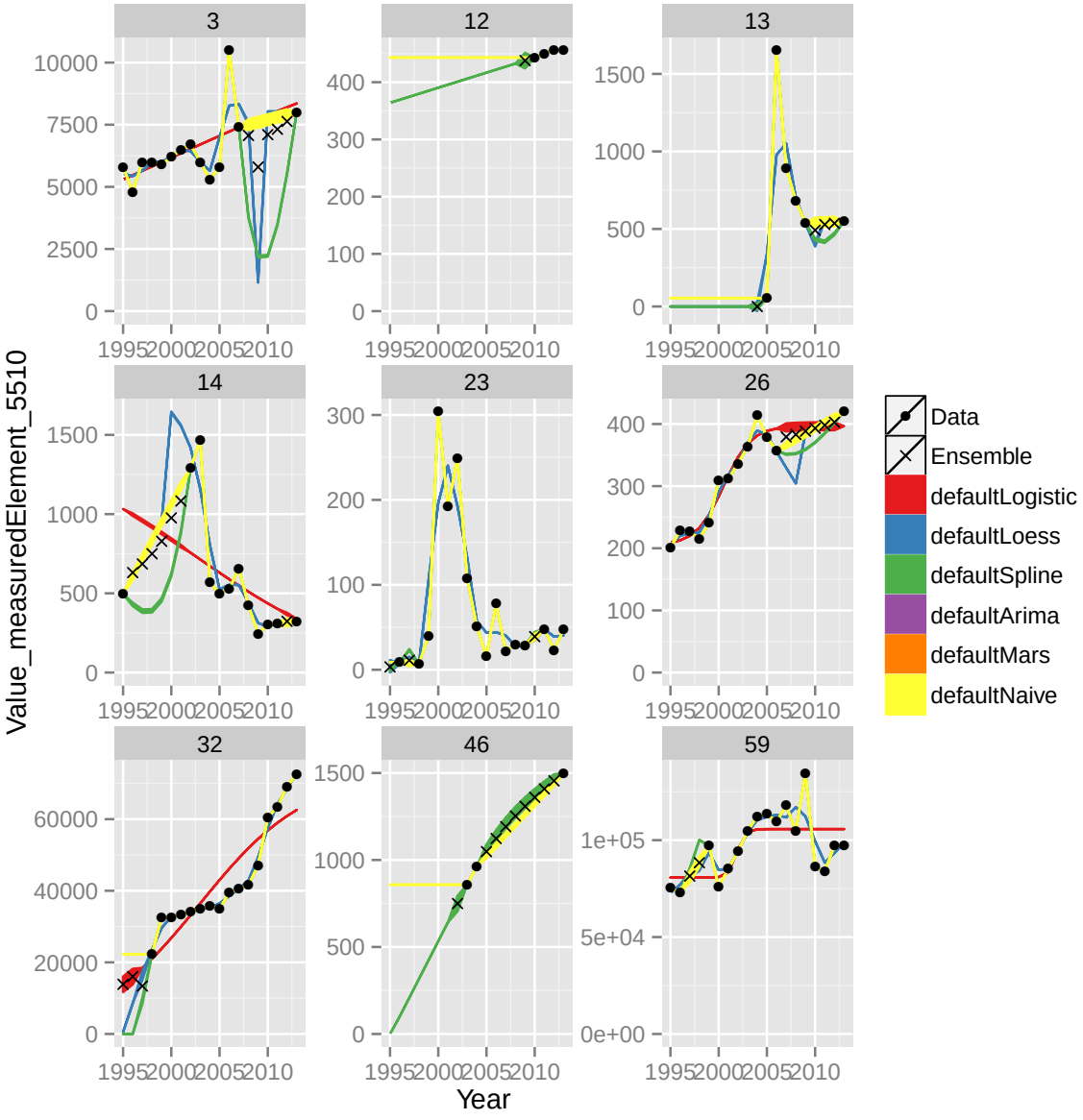

After the imputation of yield, we proceed to impute the production. The function `imputeVariable` is used again, but we first need to impute by "balancing," i.e. updating missing values of production when yield and area harvested both exist. This is because we have the relationship:

$$Y = P/A$$

where $Y$ is yield, $P$ is production, and $A$ is the area harvested. If no value for area harvested is available, then the function proceeds to impute the remaining production values with ensemble learning. Let's use some different models this time, just for the purpose of showing what's available.

```
balanceProduction(data = okraProcessed,
                  imputationParameters = imputationParams,
                  processingParameters = processingParams)
imputationParams = defaultImputationParameters("production")
imputationParams$ensembleModels =
    imputationParams$ensembleModels[4:9]
names(imputationParams$ensembleModels)
```

```
## [1] "defaultLogistic" "defaultLoess"    "defaultSpline"   "defaultArima"
## [5] "defaultMars"     "defaultNaive"

imputeVariable(data = okraProcessed,
               imputationParameters = imputationParams)
```




Note: imputations that are interpolations are always present, but some extrapolations are not imputed. The reason for this is that some models are not reasonable to extrapolate with (such as LOESS, Splines, etc.). For these models, an "extrapolation range" is defined, and this value dictates how far outside the range of the data a particular model is allowed to extrapolate. In our case, we have:

```
for(model in imputationParams$ensembleModels)
    print(model@extrapolationRange)

## [1] Inf
## [1] 1
```

```
## [1] 1
## [1] Inf
## [1] Inf
## [1] 0
```

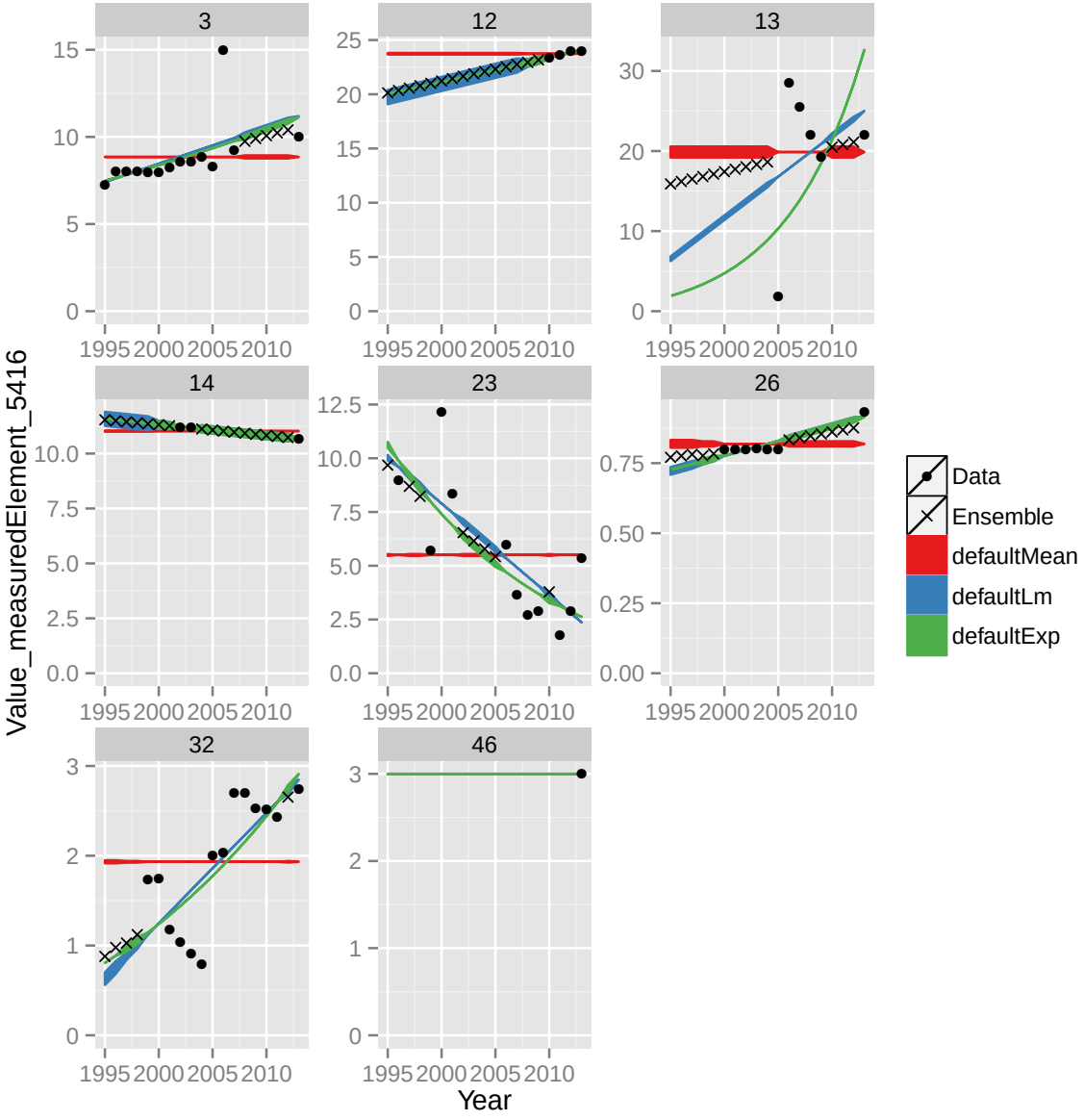
Thus, the Logistic, Arima, and Mars models are the only models that are allowed to extrapolate more than one observation away from the data. For most of the examples provided here, those three models all failed to fit to the data, and so imputations were not available.

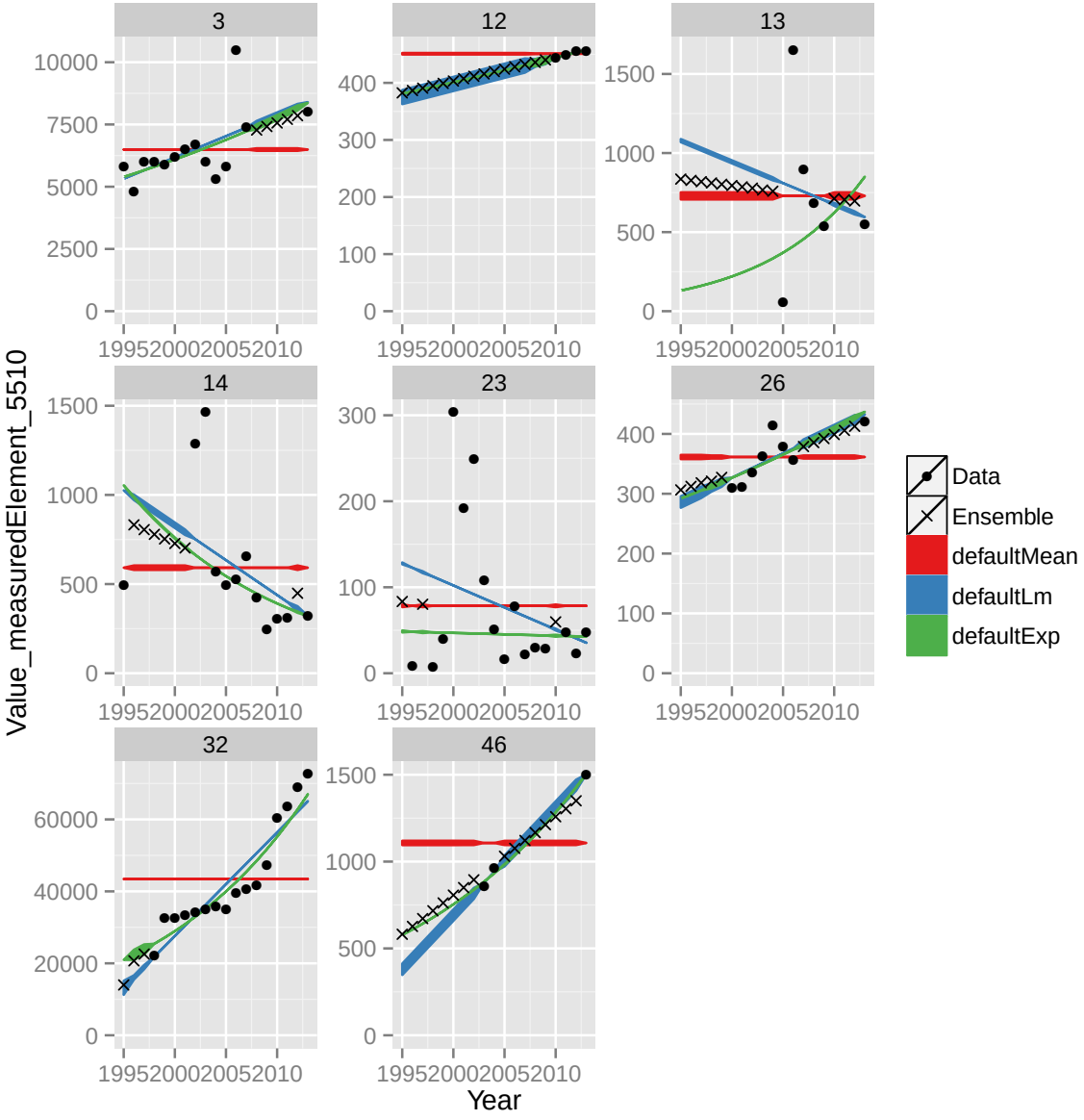
Finally, we can balance the area harvested after both production and yield have been imputed.

```
balanceAreaHarvested(data = okraProcessed,
                     imputationParameters = imputationParams,
                     processingParameters = processingParams)
```

The full procedure outlined in this section can be performed by a single function `imputeProductionDomain`. You will need to specify three parameter lists: the processing parameters (1) and the imputation parameters for both yield and production (2).

```
yieldParams = defaultImputationParameters("yield")
yieldParams$ensembleModels = yieldParams$ensembleModels[1:3]
productionParams = defaultImputationParameters("production")
productionParams$ensembleModels = productionParams$ensembleModels[1:3]
okraProcessed = okrapd[geographicAreaM49 <= 55, ]
system.time(
    {
        imputeProductionDomain(data = okraProcessed,
                               processingParameters = processingParams,
                               yieldImputationParameters = yieldParams,
                               productionImputationParameters =
                                   productionParams)
    })

## Initializing ...
## Imputing Yield ...
## Number of values imputed:  74
## Number of values still missing:  18
## Imputing Production ...
## Number of values imputed:  73
## Number of values still missing:  0
## Imputing Area Harvested ...
## Number of values imputed:  69
## Number of values still missing:  18
##    user  system elapsed
##   2.218   0.000   2.217
```


3
12
13
14
23
26
32
46
Value_measuredElement_5416
Year
Data
Ensemble
defaultMean
defaultLm
defaultExp




## 3. Ensemble model

Here we provide some details of how to implement user specific ensemble models.

First of all, the component models need to take a vector of values and return the fitted values. If the model failed, then a vector of NAs equal to the length of the input should be returned.

Shown below is the default linear model in the package. It is the analyst's job to ensure the component models return sensible values. For example, negative values are nonsensical for production, and in the current implementation negative values are replaced with zero.

```
defaultLogistic = function (x){
    stopifnot(is.numeric(x))
    stopifnot(length(x) > 1)
    time = 1:length(x)
    if (all(is.na(x)))
```

```
        return(as.numeric(rep(NA, length(x))))
    lmFit = predict(lm(formula = x ~ time), newdata = data.frame(time = time))
    lmFit[lmFit < 0] = 0
    lmFit
}
```

Now, to create an `ensembleModel` object, two other pieces of information must be provided: the extrapolation range of the model (i.e. how many years it can extrapolate outside the support of the data) and the "level" of the model (see the class documentation):

```
mod = ensembleModel(model = defaultLogistic, extrapolationRange = 1,
                    level = "countryCommodity")
is(mod)

## [1] "ensembleModel"
```

Now, `mod` is an object of type ensembleModel. We can construct a list of several of these models, but there are also some default models implemented. Calling allDefaultModels() returns a list of all of these models.

```
names(allDefaultModels())

##  [1] "defaultMean"       "defaultLm"         "defaultExp"
##  [4] "defaultLogistic"   "defaultLoess"      "defaultSpline"
##  [7] "defaultArima"      "defaultMars"       "defaultNaive"
## [10] "defaultMixedModel"

sapply(allDefaultModels(), is)

##       defaultMean         defaultLm        defaultExp   defaultLogistic
##   "ensembleModel"   "ensembleModel"   "ensembleModel"   "ensembleModel"
##      defaultLoess     defaultSpline      defaultArima       defaultMars
##   "ensembleModel"   "ensembleModel"   "ensembleModel"   "ensembleModel"
##      defaultNaive defaultMixedModel
##   "ensembleModel"   "ensembleModel"
```

Here we take the Okra production value of Bahrain as an illustration. After the component models have been designed and inserted into a list, we can compute the fits and weights then combine it to form the ensemble with the following functions.

First, we have to make sure we've correctly labeled any missing values as NA and not 0:

```
bahrainExample = okrapd[areaName == "Bahrain", ]
bahrainExample[1:4, .(areaName, timePointYears,
                      production = Value_measuredElement_5510,
                      productionFlag =
                          flagObservationStatus_measuredElement_5510)]

##    areaName timePointYears production productionFlag
## 1:  Bahrain           1995          0              M
## 2:  Bahrain           1996          0              M
```

```
## 3:  Bahrain           1997          0              M
## 4:  Bahrain           1998          0              M

removeOM(data = bahrainExample, value = "Value_measuredElement_5510",
         flag = "flagObservationStatus_measuredElement_5510")
bahrainExample[1:4, .(areaName, timePointYears,
                      production = Value_measuredElement_5510,
                      productionFlag =
                          flagObservationStatus_measuredElement_5510)]

##    areaName timePointYears production productionFlag
## 1:  Bahrain           1995         NA              M
## 2:  Bahrain           1996         NA              M
## 3:  Bahrain           1997         NA              M
## 4:  Bahrain           1998         NA              M
```

Next, we compute the model fits. We'll print the first three fits:

```
## Compute fit for all component models
imputationParameters = defaultImputationParameters("production")
modelFits = computeEnsembleFit(data = bahrainExample,
                               imputationParameters = imputationParameters)
modelFits[1:3]

## $defaultMean
##  [1] 659.3333 659.3333 659.3333 659.3333 659.3333 659.3333 659.3333 659.3333
##  [9] 659.3333 659.3333 659.3333 659.3333 659.3333 659.3333 659.3333 659.3333
## [17] 659.3333 659.3333 659.3333
##
## $defaultLm
##  [1] 1191.5667 1153.5500 1115.5333 1077.5167 1039.5000 1001.4833  963.4667
##  [8]  925.4500  887.4333  849.4167  811.4000  773.3833  735.3667  697.3500
## [15]  659.3333  621.3167  583.3000  545.2833  507.2667
##
## $defaultExp
##  [1] 181.4353 195.3650 210.3582 226.4962 243.8665 262.5630 282.6871 304.3477
##  [9] 327.6622 352.7568 379.7676 408.8407 440.1336 473.8159 510.0700 549.0922
## [17] 591.0939 636.3026 684.9631

length(modelFits)

## [1] 10
```

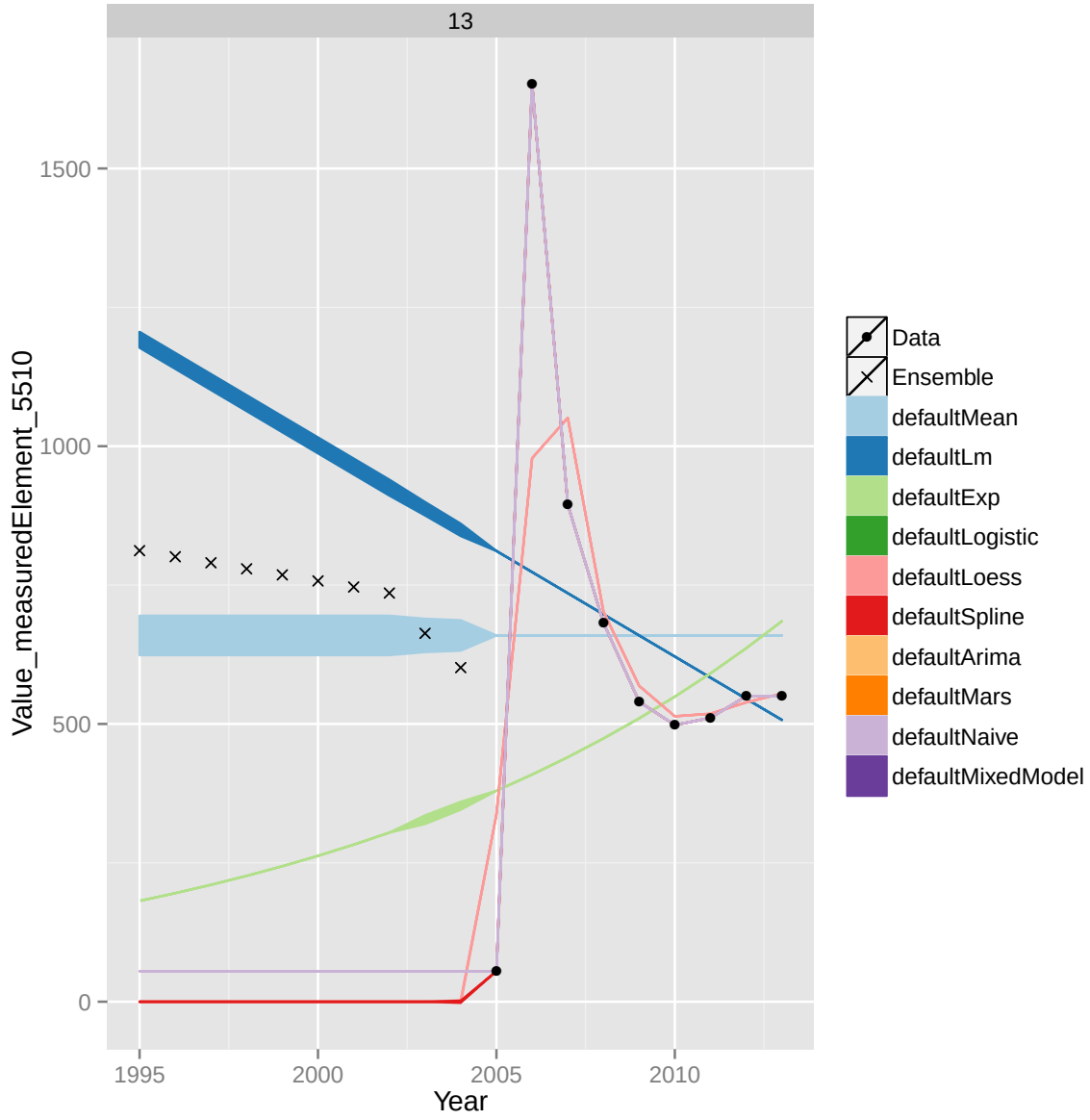
To compute weights, we need to use cross-validation. Each observation is assigned a cross-validation group. To compute the error of a particular model, we estimate the observed values in group i with all values not in group i. This allows us to measure how well a model predicts the data, and can help prevent overfitting. The model weights are then computed. Note the NA's; these exist when observations are real and values are not being imputed.

```
## Calculate the weight for each component model
cvGroup = makeCvGroup(data = bahrainExample,
                      imputationParameters = imputationParameters)
cvGroup

##  [1] NA NA NA NA NA NA NA NA NA NA 10  4  3  7  2  1  6  8  5

modelWeights = computeEnsembleWeight(data = bahrainExample,
                                     cvGroup = cvGroup,
                                     fits = modelFits,
                                     method = "inverse",
                                     imputationParameters =
                                         imputationParameters)
modelWeights[, .(defaultArima, defaultExp, defaultLm)]

##     defaultArima defaultExp defaultLm
##  1:            0  0.0000000 0.2867882
##  2:            0  0.0000000 0.2867882
##  3:            0  0.0000000 0.2867882
##  4:            0  0.0000000 0.2867882
##  5:            0  0.0000000 0.2867882
##  6:            0  0.0000000 0.2867882
##  7:            0  0.0000000 0.2867882
##  8:            0  0.0000000 0.2867882
##  9:            0  0.1551502 0.2422929
## 10:            0  0.1418587 0.2215361
## 11:           NA         NA        NA
## 12:           NA         NA        NA
## 13:           NA         NA        NA
## 14:           NA         NA        NA
## 15:           NA         NA        NA
## 16:           NA         NA        NA
## 17:           NA         NA        NA
## 18:           NA         NA        NA
## 19:           NA         NA        NA

dim(modelWeights)

## [1] 19 10
```

Lastly, combine the fits with the estimated weights to produce the final ensemble, and then plot it!

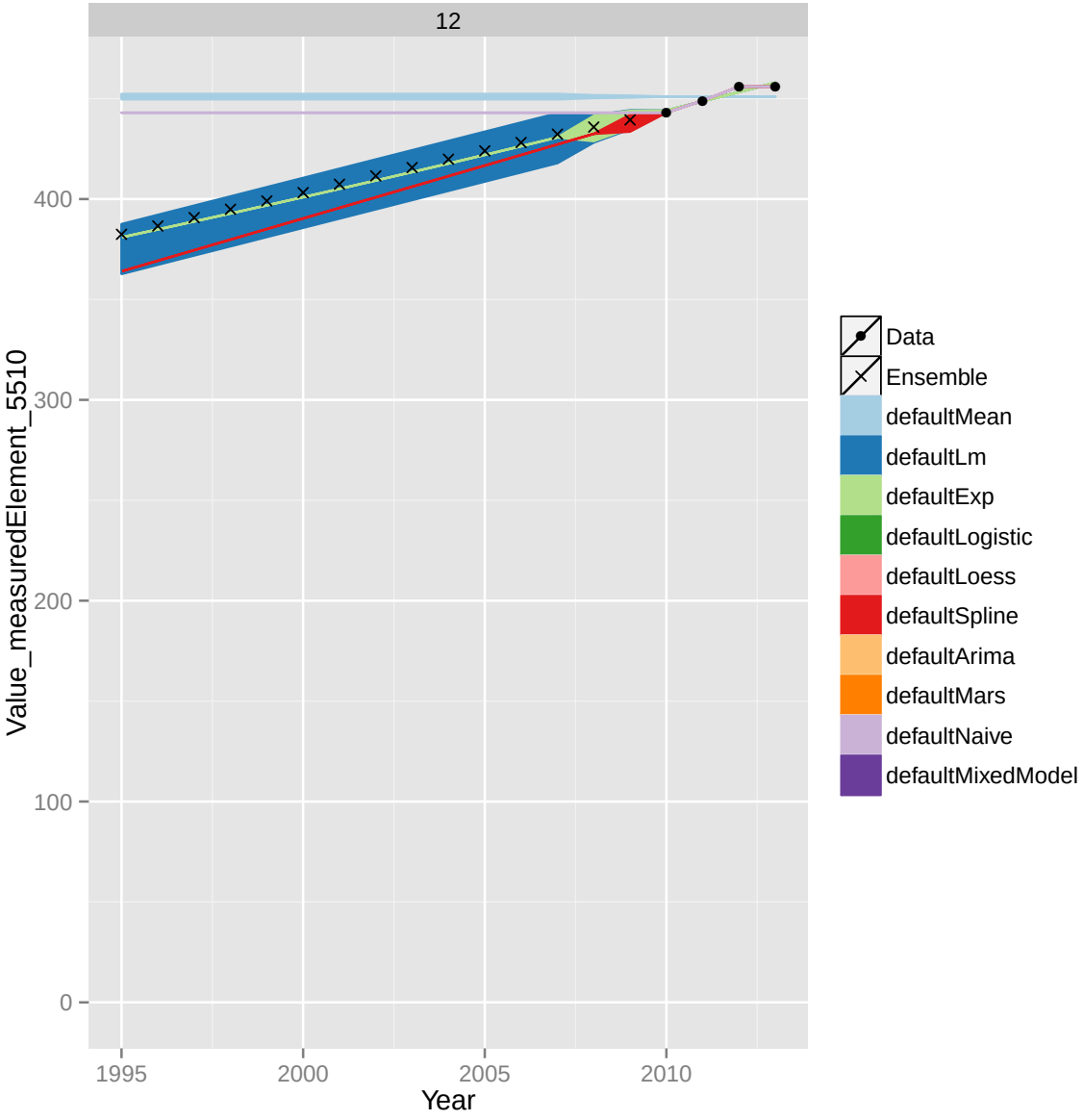
```
## Combine the models to obtain the ensemble
ensemble = bahrainExample[, Value_measuredElement_5510]
imputationFit = computeEnsemble(modelFits, modelWeights)
ensemble[is.na(ensemble)] = imputationFit[is.na(ensemble)]
plotEnsemble(data = bahrainExample, modelFits = modelFits,
             modelWeights = modelWeights, ensemble = ensemble,
             imputationParameters = imputationParameters)
```

```
## NULL
```




A one-step wrapper function is also available. There are also many other options you can specify when constructing an ensemble, such as the maximum weight that may be given to a model or a custom error function for choosing weights. See defaultImputationParameters for a description of all the options.

```
bahamasExample = okrapd[areaName == "Bahamas", ]
removeOM(data = bahamasExample, value = "Value_measuredElement_5510",
         flag = "flagObservationStatus_measuredElement_5510")
ensembleFit = ensembleImpute(data = bahamasExample,
                             imputationParameters = imputationParameters)
```




## 4. Models for Ensembling

This package implements many complex models that may not be familiar to the user, and so this section goes through the models and describes how the algorithm works as well as gives an example of the usage of that model. The order of this section is alphabetical, not by complexity. Let's first set up a dataset to use for this example, and we'll set

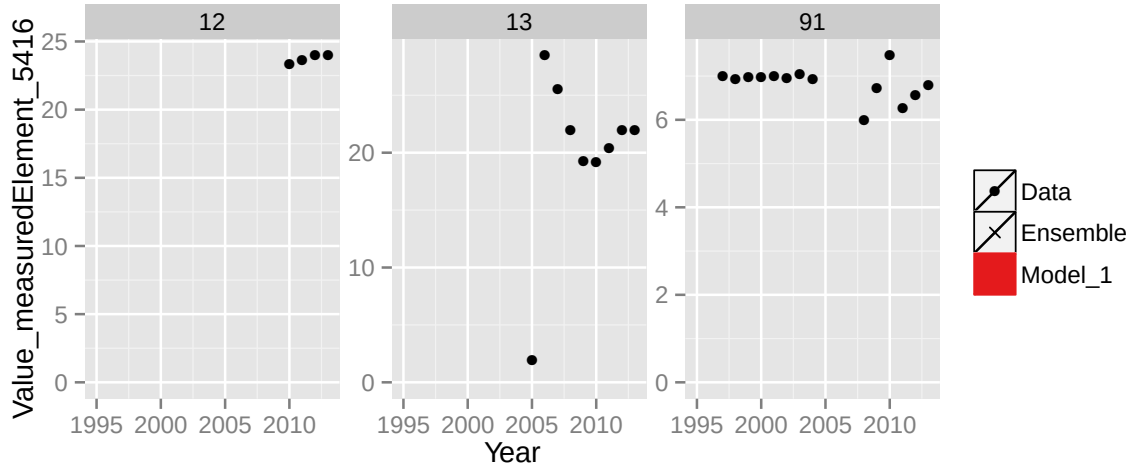
```
exampleData = okrapd[geographicAreaM49 <= 100, ]
removeOM(data = exampleData, value = "Value_measuredElement_5416",
         flag = "flagObservationStatus_measuredElement_5416")
removeNoInfo(data = exampleData,
             value = "Value_measuredElement_5416",
             observationFlag = "flagObservationStatus_measuredElement_5416",
             byKey = "geographicAreaM49")
imputationParameters = defaultImputationParameters("yield")
imputationParameters$newImputationColumn = "test"
```

```
invisible(exampleData[timePointYears %in% 2005:2007 &
                        geographicAreaM49 == "91",
                      c("Value_measuredElement_5416",
                        "flagObservationStatus_measuredElement_5416") :=
                        list(NA, "M")])
```

### 4.1. defaultArima

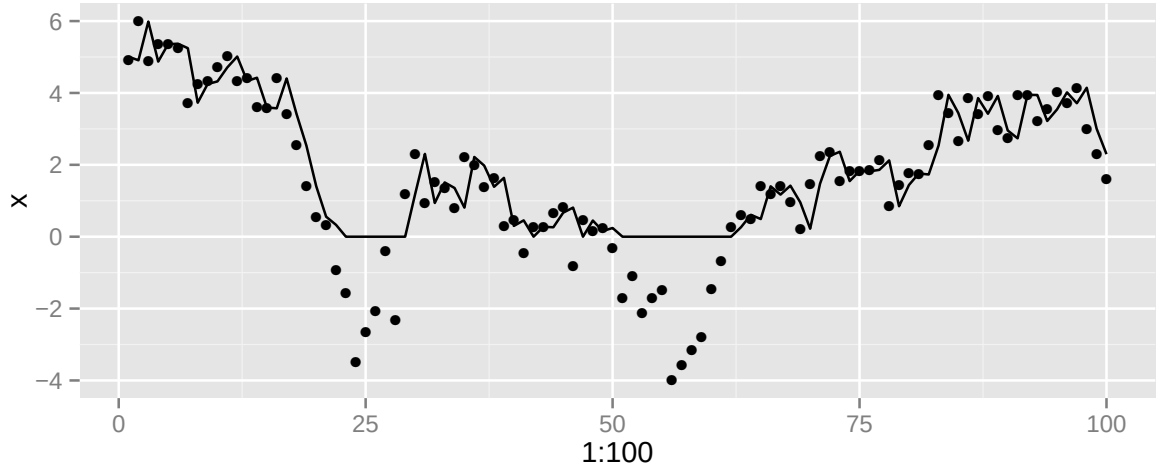
The defaultArima model first fits an AutoRegressive, Integrated Moving Average (ARIMA) model to the time series provided, and it attempts to find the best model using the auto.arima function from the **forecast** package. If such a model is found, that model is used (along with KalmanSmooth) to generate new smoothed estimates of the time series.

```
model = ensembleModel(model = defaultArima, extrapolationRange = Inf,
                      level = "countryCommodity")
imputationParameters$ensembleModels = list(model)
imputeVariable(data = exampleData, imputationParameters = imputationParameters)
```




This model often fails, on FAO time-series, and in such cases it is not used in the final ensemble. Below is an example of when it succeeds, though:

```
x = arima.sim(n = 100, model = list(ar = .9))
qplot(1:100, x) + geom_line(aes(y = defaultArima(x)))
```

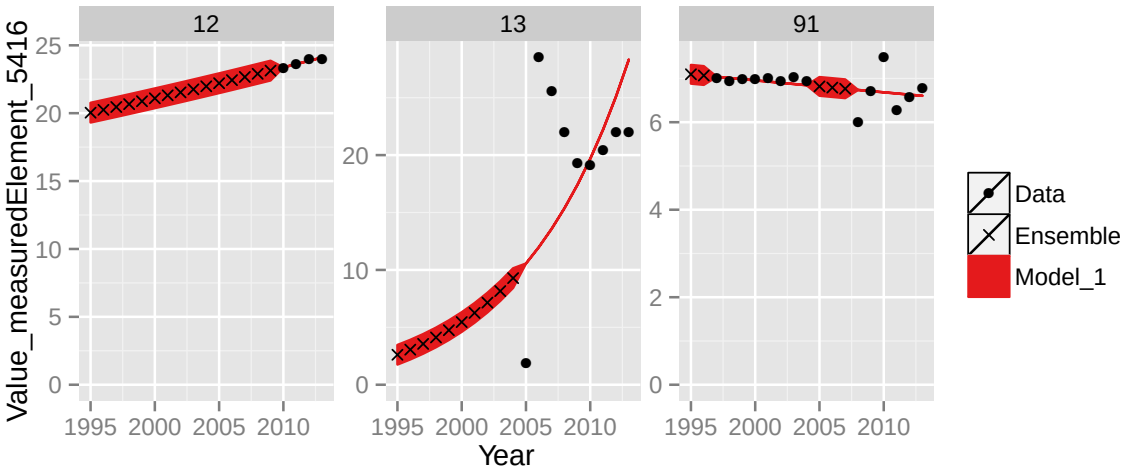



This example shows one of the common features of the default models: they often set negative values to 0 (as this is the most reasonable thing to do with most of the FAO data). However, there may be variables where negative values are reasonable, and in such cases an adjusted model should be used.

### 4.2. defaultExp

This algorithm fits the following model: $\log(Y+1) = \beta_0 + \beta_1 t$ where $Y$ is the dependent variable (i.e. production, seed rates, etc) $t$ is time, and $\beta_0, \beta_1$ are the estimated coefficients. This model is equivalent to $Y + 1 = e^{\beta_0 + \beta_1 t}$, hence the name exponential. The 1 in the formula ensures that $\log(Y+1)$ always exists (assuming $Y \geq 0$).

```
model = ensembleModel(model = defaultExp, extrapolationRange = Inf,
                      level = "countryCommodity")
imputationParameters$ensembleModels = list(model)
imputeVariable(data = exampleData, imputationParameters = imputationParameters)
```

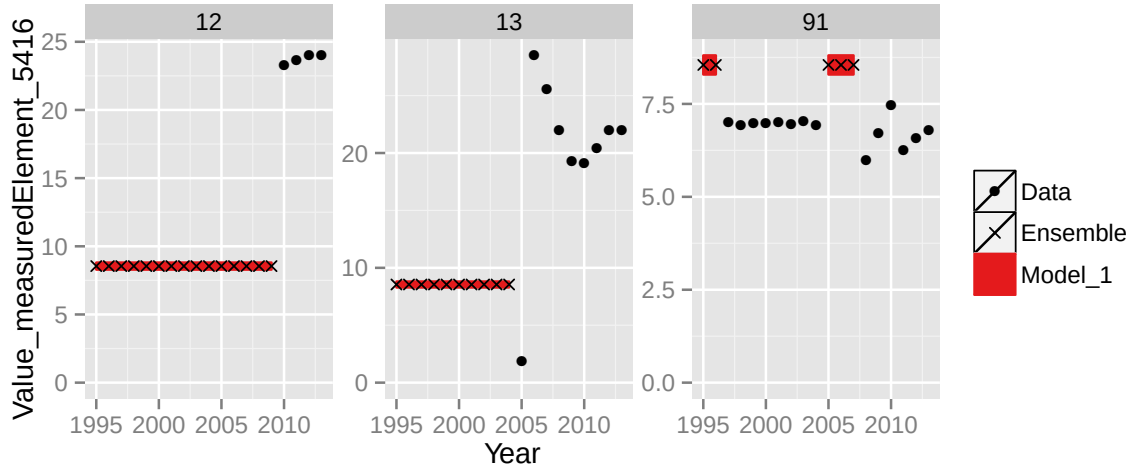



### 4.3. defaultGlobalMean

This model is quite simple: it computes the mean from all available observations and uses that value to impute any missing values. This model is not recommended for most domains; however, it may perform reasonably well when imputing rates or proportions, as the average

may not vary drastically from country to country. A variable like production is very different, values can vary drastically in scale and so a global mean is not appropriate.

```
model = ensembleModel(model = defaultGlobalMean, extrapolationRange = Inf,
                      level = "commodity")
imputationParameters$ensembleModels = list(model)
imputeVariable(data = exampleData, imputationParameters = imputationParameters)
```

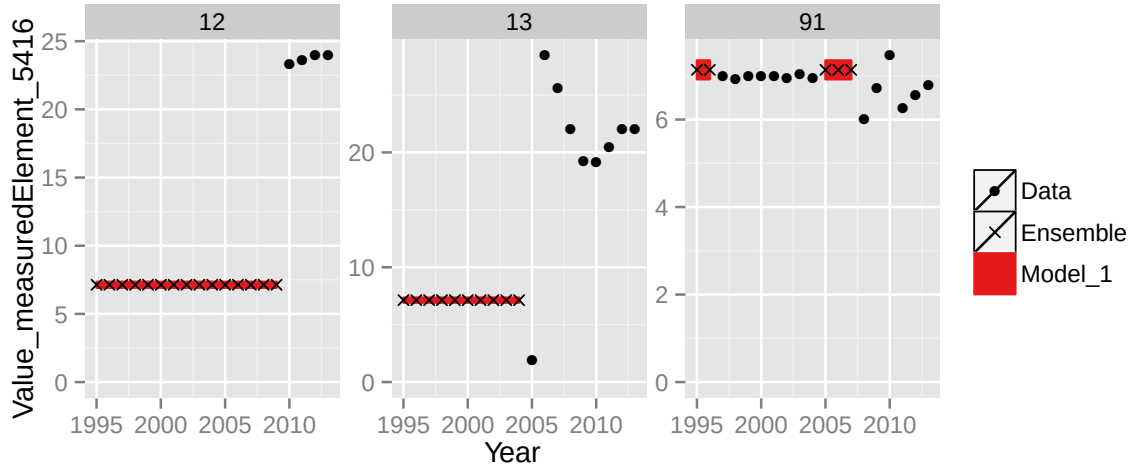



Note that in the above figure, the imputed values may appear to be different. However, this is simply due to the different scale in each of the grids; the imputed value is always about 8.

### 4.4. defaultGlobalMedian

The global median works exactly the same as the global mean, but computes the median instead of the mean. Again, this type of model should only be used when imputing rates or something similar (i.e. no drastic differences in scale across groups).

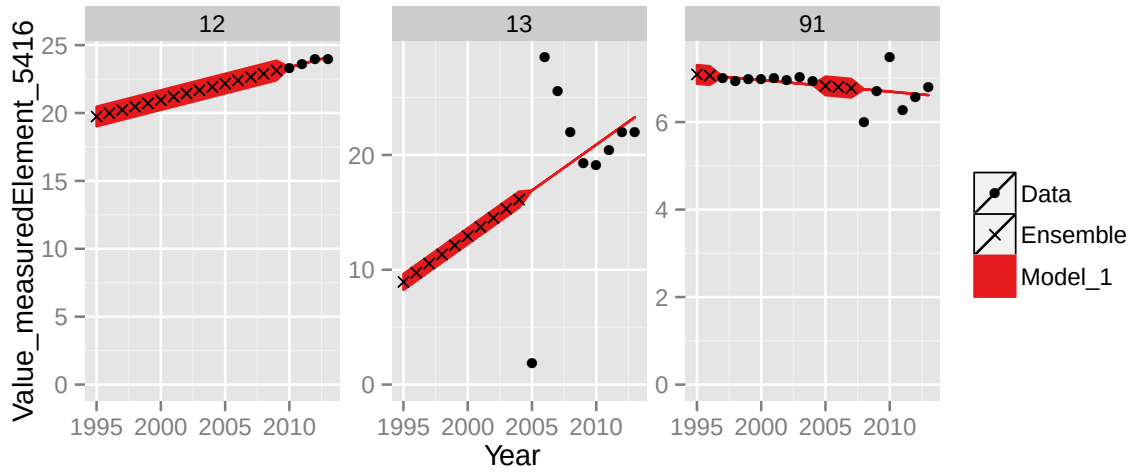
```
model = ensembleModel(model = defaultGlobalMedian, extrapolationRange = Inf,
                      level = "commodity")
imputationParameters$ensembleModels = list(model)
imputeVariable(data = exampleData, imputationParameters = imputationParameters)
```



### 4.5. defaultLm

The defaultLm model uses a simple linear regression model for imputation. It fits a model of the form: $Y = \beta_0 + \beta_1 t$, where $Y$ is the value to impute, $t$ is the time, and $\beta_0, \beta_1$ are estimated coefficients.

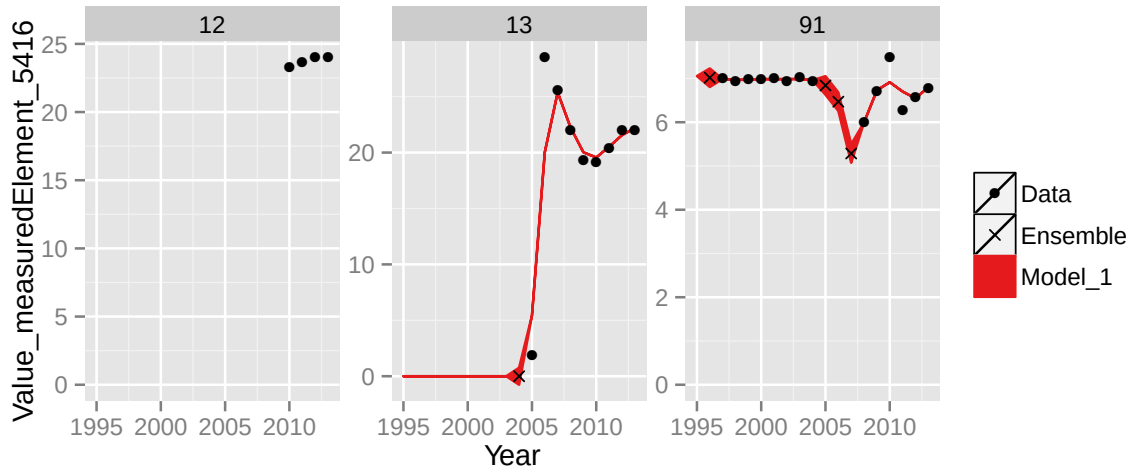
```
model = ensembleModel(model = defaultLm, extrapolationRange = Inf,
                      level = "countryCommodity")
imputationParameters$ensembleModels = list(model)
imputeVariable(data = exampleData, imputationParameters = imputationParameters)
```




### 4.6. defaultLoess

The defaultLoess model works by fitting a "local" linear regression model at each point in the model space. The model is local in the sense that the fit at time $t$ uses only nearby time points, say $t - k$ to $t + k$. Furthermore, points further away from $t$ are given less weight in the regression model. This type of model has several tuning parameters such as the size of the neighborhood and the degree of model to fit (i.e. we could fit local linear models, quadratic, etc.). For simplicity, we use a local linear model, and we choose the smallest span possible to allow for the most flexible model. Addditionally, the local nature of the loess model means that it likely will not extrapolate well, so the recommended extrapolation range is 1.

```
model = ensembleModel(model = defaultLoess, extrapolationRange = 1,
                      level = "countryCommodity")
imputationParameters$ensembleModels = list(model)
imputeVariable(data = exampleData, imputationParameters = imputationParameters)
```



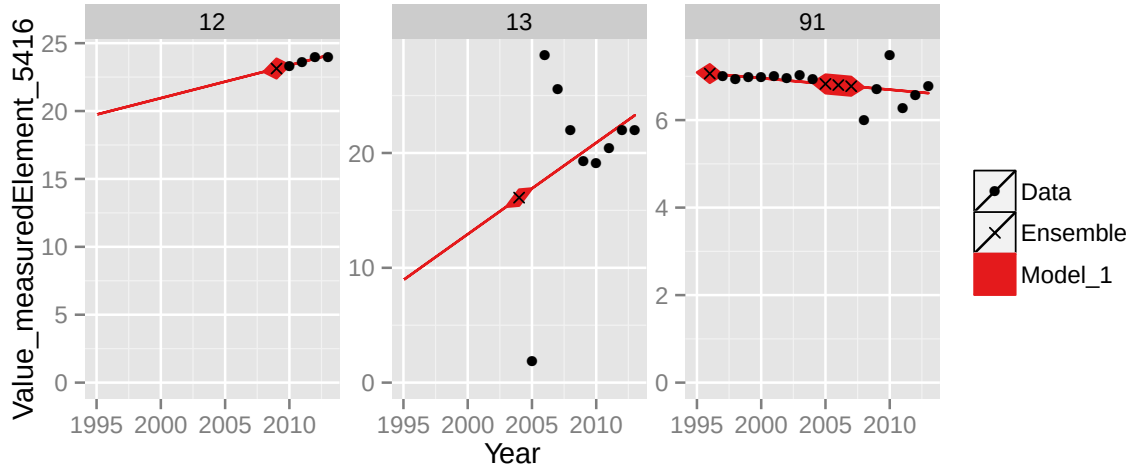

### 4.7. defaultLogistic

Logistic curves are S-shaped curves of the form

$$f(x) = A + \frac{B}{1 + e^{-C(t-D)}}$$

. These types of functions make sense in scenarios where a variable is increasing but may have some upper bound (i.e. production may increase greatly as technology improves, but there is some maximum production level a country can obtain). This algorithm attempts to first fit all four parameters above via numerical least squares. If that approach fails, $A$ is assumed to be 0 and numerical least squares are tried again. If that model also fails, $B$ is assumed to be the largest value and model fitting proceeds via generalized least squares.

```
model = ensembleModel(model = defaultLogistic, extrapolationRange = 1,
                      level = "countryCommodity")
imputationParameters$ensembleModels = list(model)
imputeVariable(data = exampleData, imputationParameters = imputationParameters)
```

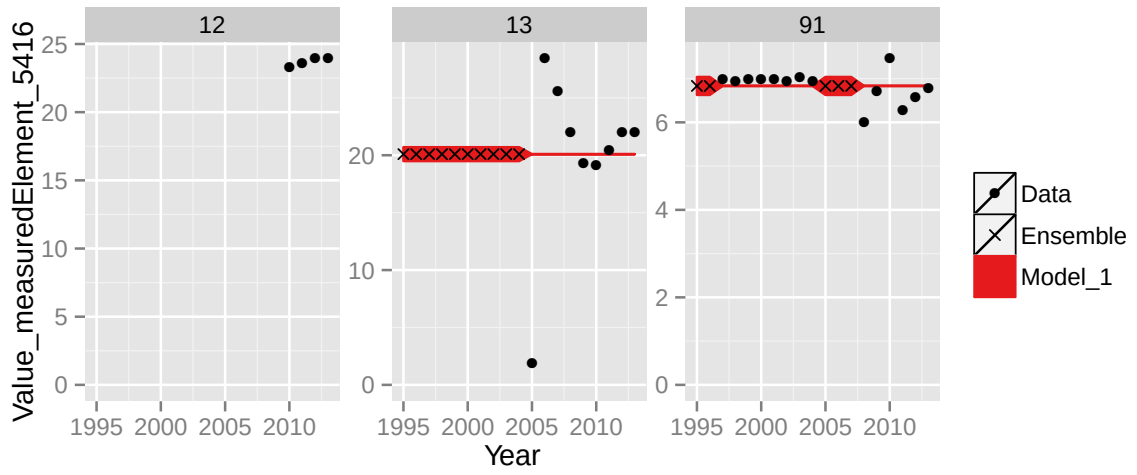



Note: in the first example, the logistic regression decays rapidly to 0. This may not be very reasonable, and thus we recommend using a small extrapolation range for this model.

### 4.8. defaultMars

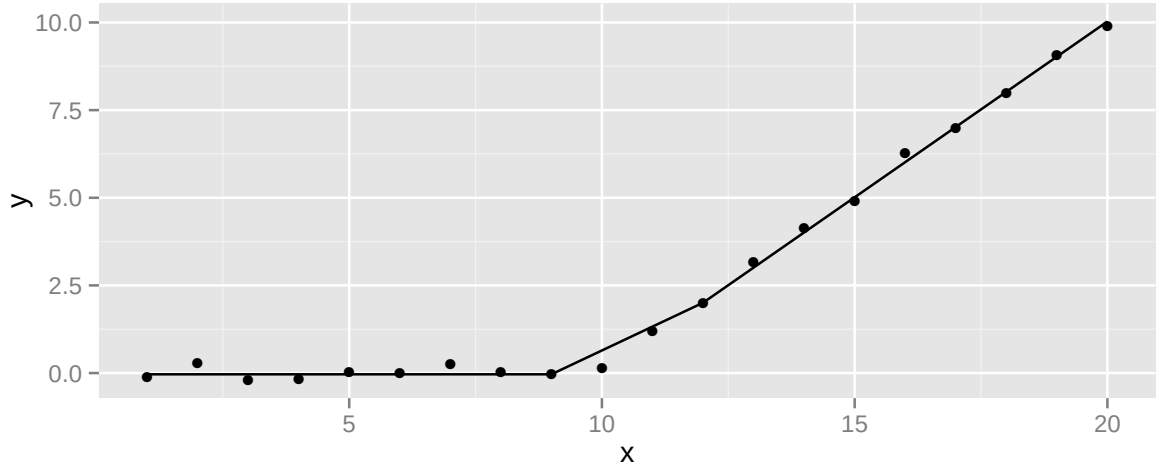
The defaultMars model uses a technique known as Multivariate Adaptive Regression Splines (MARS). This algorithm seeks to model the data using piecewise linear regression splines, and it determines the breakpoints of the splines using some optimization criterion. On our sample dataset, we don't see anything too interesting:

```
model = ensembleModel(model = defaultMars, extrapolationRange = Inf,
                      level = "countryCommodity")
imputationParameters$ensembleModels = list(model)
imputeVariable(data = exampleData, imputationParameters = imputationParameters)
```




To see how this model works, we can instead look at a little toy example. Suppose that our data is constant for the first 10 observations and then increases linearly for the following 10 observations. And, suppose that we can't measure our data perfectly, but that we have some observation error. The below R code implements such a model, and shows how the MARS approach will fit that data (MARS is named "earth" within R because MARS is a proprietary term).

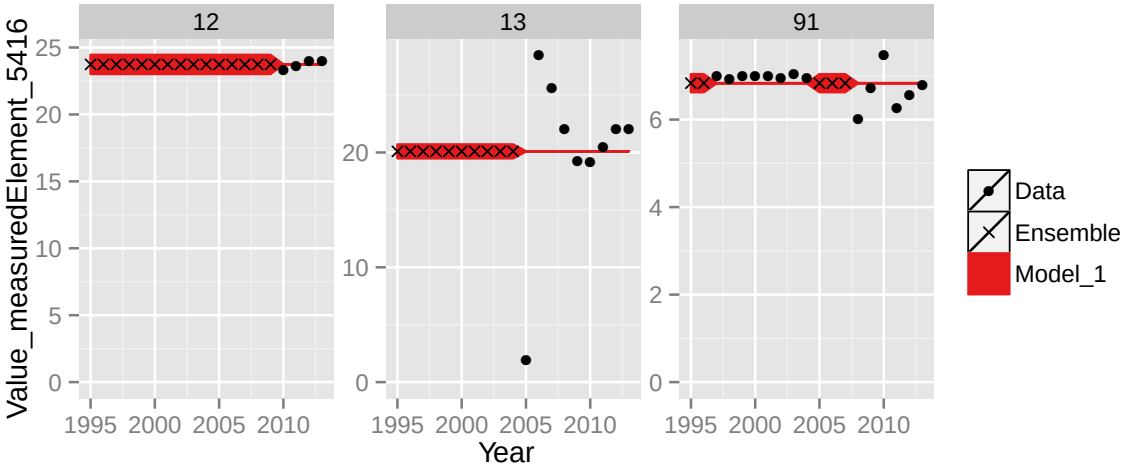
```
smallExample = data.table(x = 1:20, y = c(rep(0, 10), 1:10) +
                          rnorm(20, sd = .2))
fit = earth::earth(y ~ x, data = smallExample)
invisible(smallExample[, earthFit := predict(fit)])
ggplot(smallExample, aes(x = x, y = y)) + geom_point() +
    geom_line(aes(y = earthFit))
```




### 4.9. defaultMean

This model computes a mean on each subset of the data and uses that one value to impute any missing values.

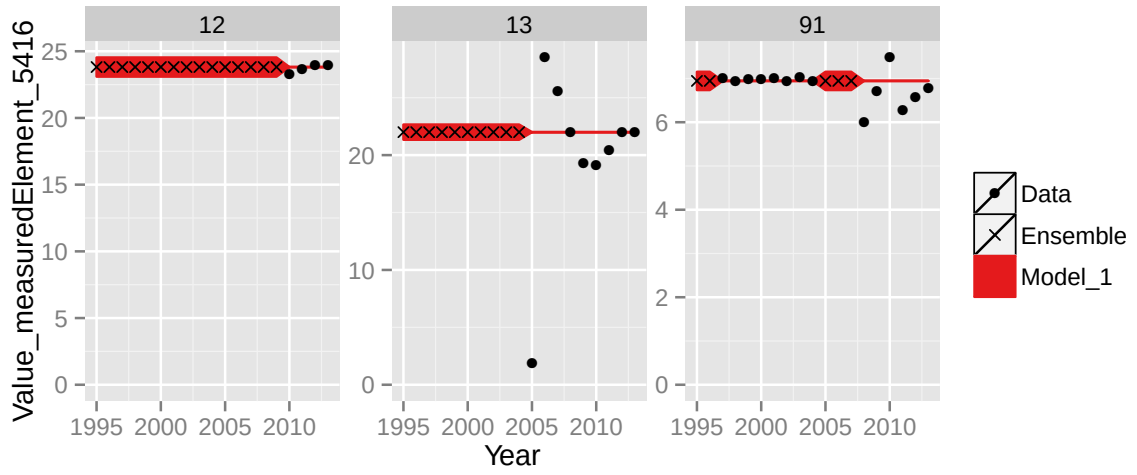
```
model = ensembleModel(model = defaultMean, extrapolationRange = Inf,
                      level = "countryCommodity")
imputationParameters$ensembleModels = list(model)
imputeVariable(data = exampleData, imputationParameters = imputationParameters)
```




### 4.10. defaultMedian

This model computes a median on each subset of the data and uses that one value to impute any missing values.

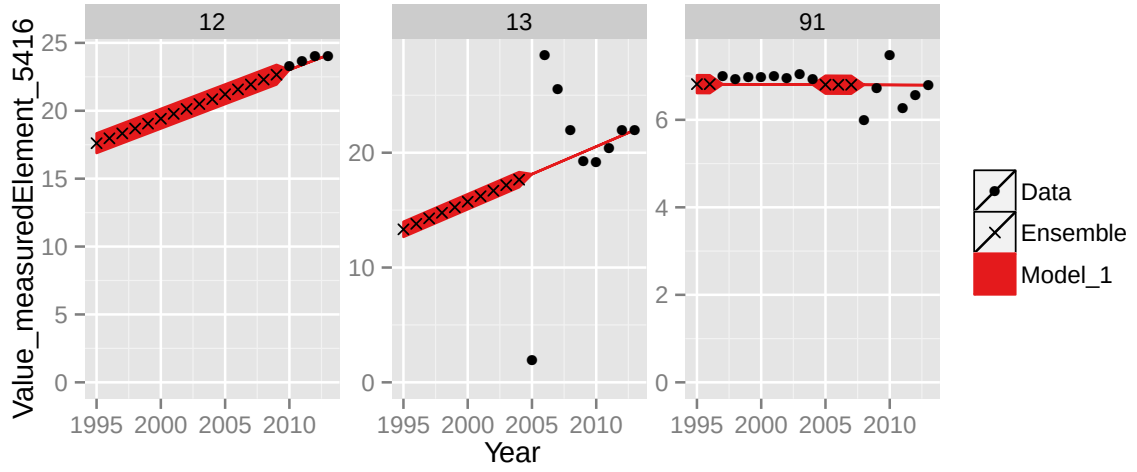
```
model = ensembleModel(model = defaultMedian, extrapolationRange = Inf,
                      level = "countryCommodity")
imputationParameters$ensembleModels = list(model)
imputeVariable(data = exampleData, imputationParameters = imputationParameters)
```




### 4.11. defaultMixedModel

The defaultMixedModel is a very flexible and powerful model. It's able to use all the data across countries when performing the fit, and for this reason it provides a much more flexible estimation than most other models.

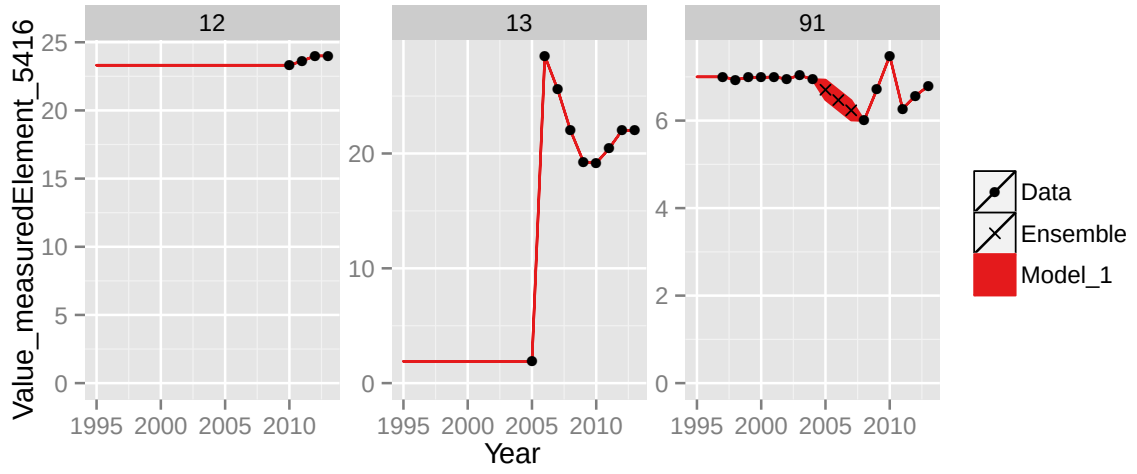
```
model = ensembleModel(model = defaultMixedModel, extrapolationRange = Inf,
                      level = "commodity")
imputationParameters$ensembleModels = list(model)
imputeVariable(data = exampleData, imputationParameters = imputationParameters)
```




### 4.12. defaultNaive

This model performs simple linear interpolation between available observations. However, if a missing value is outside the range of the data, then this model estimates that value by carrying back the first observation or carrying forward the last observation (depending on if the missing value is before the available data or after it). Because of this, this model is not recommended for extrapolation (and has a default extrapolationRange of 0 in allDefaultModels).

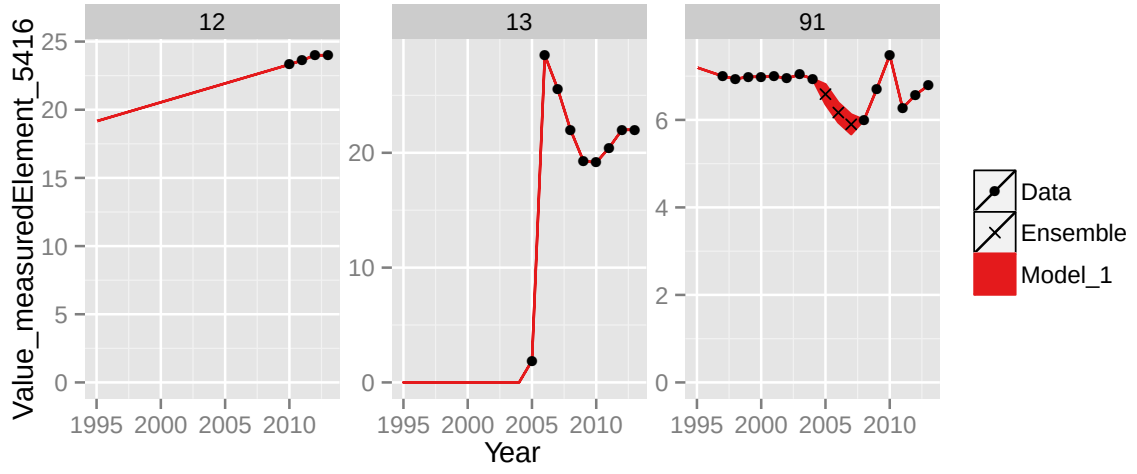
```
model = ensembleModel(model = defaultNaive, extrapolationRange = 0,
                      level = "countryCommodity")
imputationParameters$ensembleModels = list(model)
imputeVariable(data = exampleData, imputationParameters = imputationParameters)
```




### 4.13. defaultSpline

The defaultSpline model uses the spline function from the stats package (part of base) to fit a spline to the available observations. Missing observations are then imputed by the spline estimate at that location.

```
model = ensembleModel(model = defaultSpline, extrapolationRange = 0,
                      level = "countryCommodity")
imputationParameters$ensembleModels = list(model)
imputeVariable(data = exampleData, imputationParameters = imputationParameters)
```

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