BORDEAUX SCIENCES AGRO

Internship report

AGROMET project : Investigating spatial interpolation of temperature using Multiple Linear Regression

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Preface

This document is my internship report for Bordeaux Sciences Agro as part of my formation in “Digital for Agriculture” and my 3-month internship in the CRA-W.

It was completely written with RMarkdown and LaTeX.

Abstract

The European directive 2009/128/CE imposes member-states to set up tools that allow for a more rational use of crop protection products. The AGROMET project, led by CRA-W, aims to generate a high spatial resolution network which diffuses interpolated weather data provided by physical weather stations using geostatistical tools. The internship aimed to spatialize temperature using Multiple Linear Regression method. To do that, the internship was integrated in in data acquisition and data analysis steps. As a first step, data which can explain temperature were collected and organised to integrate them in machine learning algorithms. Then, the objective is to compare different combinations of explanatory variables and to identify which one provides the lowest error using multiple linear regression as learning method. The results obtained from a database containing more than 23000 hours show some interesting combinations as the one based on spatial coordinates and elevation or the one based on the variables with the best linear correlation computed every hour. Other variables will be integrated afterward to try to reduce prediction errors.

La directive européenne 2009/128/CE impose aux états-membres de mettre en place des outils visant à une utilisation rationnelle des produits phytosanitaires. Le projet AGROMET, dirigé par le CRA-W, a pour but de genérer un réseau de stations virtuelles à haute résolution spatiale qui diffusera des données météorologiques interpolées à partir de données issues de stations physiques et d'outils géostatistiques. Le stage avait pour objectif de spatialiser la température à l'aide de la Régression Linéaire Multiple. Pour ce faire, le stage s'est intégré dans la phase d'acquisition des données et d'analyse des données. Dans un premier temps, des données qui pourraient expliquer la température ont été récoltées et organisées afin de les intégrer dans des algorithmes de machine learning. L'objectif est ensuite de comparer les différentes combinaisons de variables explicatives et d'identifier celle qui fournit les prédiction avec l'erreur la plus faible en utilisant la régression linéaire multiple comme méthode d'apprentissage. Les résultats obtenus à partir d'une base de données de plus de 23000 heures mettent en évidence plusieurs combinaisons intéressantes comme celle utilisant les coordonnées géographiques et l'altitude ou celle utilisant les variables avec la meilleure corrélation linéaire à chaque heure. D'autres variables seront par la suite intégrées pour tenter de réduire les erreurs de prédiction.

Abbreviations

- API : Application Programming Interface
- ANN : Artificial Neural Networks
- CRA-W : Walloon agricultural research center
- CRS : Coordinate Reference System
- IDW : Inverse Distance Weight
- JSON : JavaScript Object Notation
- KNMI : Royal Netherlands Meteorological Institute (Dutch national weather service)
- MAE : Mean Absolute Error
- RMI : Royal Meteorological Institute
- RMSE : Root Mean Square Error
- OS : Operating System
- SSH : Secure Shell
- WGS84 : World Geodetic System 1984

Glossary

- to nest : *imbriquer*
- late blight : *mildiou*
- wheat septoria : *septoriose du blé*
- rain gauge : *pluviomètre*
- orange midge : *cécidomyie orange du blé*
- leaves wetness : *humidité du feuillage*
- forecast : *prévision*

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Introduction

Use of pesticides and other crop protection products is a topical issue in an environmental and societal context. These products are increasingly criticized for their risks and impacts on human health and environment. Crop monitoring models are developed and their efficiency is well demonstrated. Acting at the right time in plots is inscreasingly possible thanks to these models. In Belgium, the Walloon agricultural resarch centre (CRA-W) is a research centre where a lot of issues are explored to bring solutions.

From May 21st to August 20th, I did an internship in the CRA-W. I worked on the AGROMET project which is a project about agrometeorology where the aim is to provide a near real-time hourly gridded datasets of weather parameters at the resolution of 1 km^2 for the whole region of Wallonia characterized by a quality indicator. This project is led by the Farming Systems, Territory and Information Technologies Unit.

The objective of the internship was to investigate a spatial interpolation of the temperature using multiple linar regression with the best combination of explanatory variables.

First, the report will present the CRA-W, its organisation, the Unit where I worked and the AGROMET project. Then, my workflow will be detailed in two parts : the data acquisition and preparation and the machine learning methods used. Finally, the results will be presented and discussed.

Chapter 1

Presentation of the AGROMET project and the CRA-W

1.1 CRA-W and Farming Systems, Territory and Information Technologies Unit

The CRA-W was founded in 1872 and depends on the Regional Goverment of Wallonia. It aims to maintain and develop the scientific excellence and societal usefulness and contributes to sustainable development of the agricultural industry in Wallonia in its economic, ecological and cultural dimension. 120 scientifics are working in the CRA-W on three sites (Gembloux, Libramont and Mussy-la-Ville) representing 300 ha of fields, greenhouses, laboratories and offices. The CRA-W is a place for scientific research but also to provide services in agricultural and agri-food sector keeping a perspective view on the development of agriculture.

The research is divided into 4 main fields where more than 100 projects are currently in progress. :

- Precision agriculture
- Precision livestock farming
- Risk management
- Understanding products

The CRA-W is divided into 4 departments with 4 research units each :

- Life sciences
- Production et sectors
- Valorisation of agricultural products
- Agriculture and natural environment

The unit 11 *Farming Systems, Territory and Information Technologies* where I realized my internship belongs to the *Agriculture and natural environment* department. This Unit develops tools to meet society's new expectations and decision support

systems to improve the technico-economic and environmental performance of farming systems. There are actually 28 projects in progress.

The main activities of the Unit are the following :

- Adaptation of agrosystems to global change : definition of references
- Adaptation of agrosystems to global change through bottom-up approaches
- Support to the development of agrosystems in line with territory projects
- Decision support systems and information technologies for the management of multifunctional agriculture
- Spatial information systems for the management of rural areas.

PAMESEB is a non-profit organisation handled by the CRA-W which aims to promote agrometeorology by considering weather conditions in the context of walloon agriculture. PAMESEB manages a network of 30 automated weather stations in Wallonia. These stations provide measures for ways to fight crop diseases like late blight and wheat septoria. Stations have a local acquisition unit for hourly data recording. The AGROMET project uses weather data provided by the PAMESEB network as its primary data source.

Each PAMESEB station is equipped with 5 basic sensors :

- Temperature sensor
- Relative humidity sensor
- Solar sensor
- Wind sensor
- Rain gauge

1.2 The AGROMET project

1.2.1 Context

The European directive 2009/128/CE imposes member-states to set up tools that allow for a more rational use of crop protection products. Among these tools, agricultural warning systems, based on crop monitoring models for the control of pests and diseases are widely adopted and have proved their efficiency. However, due to the difficulty to get meteorological data at high spatial resolution (at the parcel scale), they still are underused. The use of geostatistical tools (Kriging, Multiple Regressions, ANN, etc.) makes it possible to interpolate data provided by physical weather stations in such a way that a high spatial resolution network (mesh size of 1 km2) of virtual weather stations could be generated.

The purpose of the AGROMET project is to build a web platform that makes such “spatialized” weather data available to crop monitoring models. That will help other CRA-W’s units and partners to act against crop diseases like potato late blight or orange midge which depends on meteorological conditions.

The project was inspired by several academic papers dealing with spatial interpolation of data like *Use of geographic information systems in warning services for late blight* (Zeuner, 2007), *Decision Support Systems in Agriculture : Administration of Meteorological Data, Use of Geographic Information Systems(GIS) and Validation Methods in Crop Protection Warning Service* (Racca *et al.*, 2011) and *Spatial interpolation of ambient ozone concentrations from sparse monitoring points in Belgium* (Hooyberghs, 2006).

1.2.2 Objectives

The project aims to set up an operational web-platform designed for real-time agrometeorological data dissemination at high spatial (1km2) and temporal (hourly) resolution. To achieve the availability of data at such a high spatial resolution, we plan to "spatialize" the real-time data sent by more than 30 connected physical weather stations belonging to the PAMESEB and RMI networks. This spatialization will then result in a gridded dataset corresponding to a network of 16 000 virtual stations uniformly spread on the whole territory of Wallonia.

These "spatialized" data will be made available through a web-platform providing interactive visualization widgets (maps, charts, tables and various indicators) and an API allowing their use on the fly, notably by agricultural warning systems providers. An extensive and precise documentation about data origin, geo-statistic algorithms used and uncertainty will be also available.

The meteorological data the project aims to spatialize are :

- Temperature (1.5 meters above the ground)
- Relative humidity (1.5 meters above the ground)
- Leaves wetness
- Rainfall will be spatialized from RMI rain radar data.

In order to perform spatial predictions of these variables, known independent variables are required. Depending of the weather parameter to be spatialized, various independent variables will be considered. We can mention :

- Digital elevation model and its derivatives like aspect and slope
- Solar irradiance
- Other variables discussed to improve the prediction : distance to sea, CORINE land cover...

The Figure 1.1 shows the global steps of the project and steps before data diffusion.

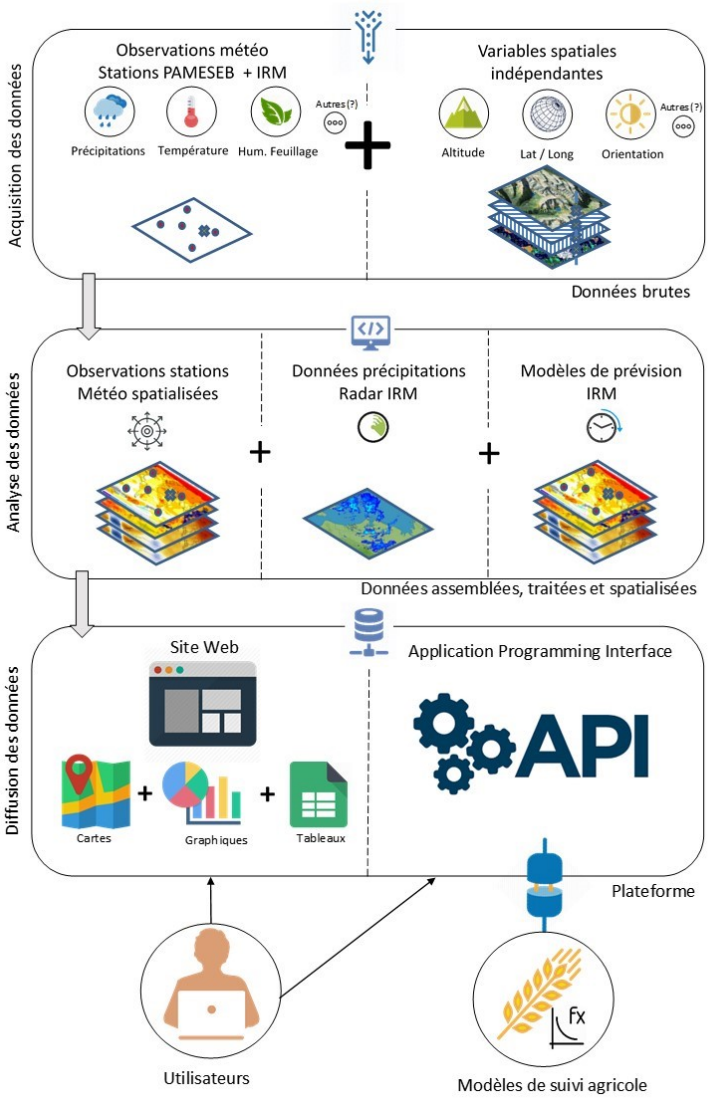


Figure 1.1: Global steps of the AGROMET project

1.3 Scope of the internship : using multiple linear regression for temperature predictions

To perform spatial predictions of meteorological variables, several statistical methods can be tested like multiple linear regression, ANN and several kriging methods.

Two workpackages were clearly defined for my internship :

- acquiring and preparing independent variables that have been identified as potential explanatory variables for temperature
- benchmarking various combinations of independent variables used with the **multiple linear regression** algorithm as spatial prediction method for the **temperature**

I used R because it is a free software for statistical computing and graphics. Spatial data were collected from different sources and involved the use of specific R libraries to manipulate them. I needed to handle these libraries to manipulate vector and raster geodata. Then, these data have been organised with the tidyverse library to respond to the structure imposed by the chosen modeling library and to help reduce computation time. The modeling library used is mlr, dealing with machine learning algorithms, responds to a special architecture and logic that I needed to understand. Then, the data have been integrated to build models through a benchmark and analysis. Visualization was done thanks to a plotting system for R, ggplot2, able to create graphics and maps.

The benchmark was run on two large years (from 2015-11-11 to 2018-06-30) because some data were not yet available before this period.

1.4 About the working environment

1.4.1 Applications and tools

Working in development field often imposes to be methodic. In particular for bug tracking or code versioning to detect errors and keep an history of code modifications. Being methodic is also important for code readability (adding comments for example) and code reproducibility. For the reason that the AGROMET project is public, this last point is important for transparency.

That's why preparing the working environment is important to help achieve these good practices.

First, I have installed **Ubuntu GNOME**, a distribution of Linux on my laptop. Indeed, this is an open-source OS prefered by developers. It has a large community which is important to solve problems and bugs and to improve the OS. Because it is free, anyone can install it and that is important for reproducibility. Due to its large community of developers, Linux is safer because they monitor for issues and can repair them. Moreover, Linux has only 3% of the market and hackers prefer target a large segment of users as Windows. This installation of Ubuntu was done thanks to a USB drive with a boot of Ubuntu GNOME.

Once I had Ubuntu installed on my laptop, I used an **ANSIBLE script** to automatically install all the applications I need. Moreover, this script handles the updates of these applications. That is a very useful way to earn some time and it helps science reproductibility because anyone with the script will end up with the exact same installation.

Accessing to servers has to be secured to be protected against intrusions and monitor logs. That's why every developer should have a **SSH** key. This key or token is unique and enable people to access to servers. It is useful to access to Git repositories for example. It also helps to save some time because anyone who wants to connect

a service does not need to provide a login and password each time using an SSH connection instead.

GitHub is a hosting service for version control. It facilitates the collaborative work on a same code, the handle of code versions and the use of code developed by other users. It is a very common tool for developers because it ensures a public and online access.

For my internship, I had to collaboratively work on code development with my mentor. This is why we have been using GitHub. For each of the code folders that I had to work on, I made a fork that I've downloaded on my laptop for further local developments. Then, I have a copy that I can modify and I can send my modifications on GitHub. To clone these repositories, my SSH key was useful.

The current development version of the AGROMET platform already offers an **API** that allows to retrieve weather data from the stations. A specific API token with reading rights has been created for my internship. The API provides data in both JSON and GeoJSON formats which are open-standard file formats. These formats are easy to parse by machines and are easy to read by humans.

Among the different programming languages, R has been chosen because it is is a free software environment for statistical computing and graphics. It is adapted to data analysis because R was developed by statisticians and easy to use even for people without programming skills. R has a large community to help people to solve bugs and problems and packages are well documented.

Docker is a software for containerizing platforms. This container approach has many advantages compared to the use of virtual machines : lightweight, quick and modular. Moreover, Docker facilitates reproducible science because with a single pull command of the container, anyone gets the exact same working environment.

There are two main reasons to use R in conjunction with Docker. First, it allows you to quickly and easily share your work whatever the OS and R configuration of your collaborators. Second, it allows you to work in an isolated environment. This means that you will never pollute your OS and e.g. run in time-consuming re-installation procedures due to broken configuration. In case of OS crash, simply relaunch your Docker R container with a single command and you are ready to work.

1.4.2 Reproducible science

Reproducible science refers to the idea that full working environment of a research can be used by anyone to reproduce the results and create a new work based on it. That ensures reliability and credibility because the entire work is available.

In the case of the AGROMET project, the purpose of choosing open-source is to allow reproducible science and transparency about the chosen methods and therefore the meaning of the produced datasets.

Transparency is promoted thanks to open science. That means the content and the results of the project will be accessible to others. Indeed, transparency is superior

to trust and is an ideal (Munafo, 2017).

Development represents the major part of the project. Today, open science is widely used and tools have been developed for that. The availability of code on GitHub ensures that anyone can check the code and inspect it. Then, some people can improve codes and increase efficiency of work.

Moreover, this transparency makes sure that people can inspect and understand the origin of the data produced by the platforms. Users will have a deep insight of the data they will be working with.

For these reasons, transparency and open science will give more credibility and reliability to the project.

Chapter 2

Data acquisition and preparation

Explanatory variables (i.e. independent variables) are required to build models able to predict the response variable (i.e. dependent variable). In our case the dependent variable is air temperature. We will call this variable our *target variable*. As set of explanatory variables have been identified and integrated in our modeling approach. These will be presented here below.

2.1 Target variable

The AGROMET project aims to provide weather data used as input for various crop models. These parameters are temperature, relative humidity, leaves wetness and rainfall. The last one is retrieved from the RMI (Belgian Météo France equivalent). The others are measured by weather stations from PAMESEB network, data are stored in a PostgreSQL database and users can query it using the API. Using the API, users retrieve untyped data and they have to type the data using specific functions.

Temperature is the target variable concerned by my internship.

2.2 Explanatory variables

As a reminder, the purpose of my internship was to implement the multiple linear regression algorithm as a spatialization method. This means that, for each set of hourly records from the network of stations, I need to find an equation where the target variable can be modeled from one or more explanatory variables. The equation will have the form : $Y = b_0 + b_1.X_1 + b_2.X_2 + ... + b_n.X_n$ where Y is the response variable and X_n your n explanatory variables related to their estimated parameter b_n.

These explanatory variables which have an influence on temperature are already known and some academic papers already have dealt with them (Zeuner 2007, Janssen 2011).

Two types of explanatory variables can be discriminated : static variables, i.e. variables not time-dependent but depending on the spatial position and dynamic variables, i.e. time-dependent and position-dependent variables.

2.2.1 Static variables

Land cover

All PAMESEB weather stations are localized in agricultural or herbaceous areas. That is a way to reduce errors about measures. However, the surrounding environment (100 meters around the station) of each station might be different and can have an impact on measures. For example, a station could have a different behaviour if a forest is near its area or if an artificial surface (road, construction) is near it.

CORINE land cover is an inventory updated every 6 years by **Copernicus**, the European Union's Earth Observation Programme. These data can also be found on the **Belgian geo-portal**. CORINE Land Cover has been already used to make a spatial interpolation of air pollution (Janssen *et al.* 2011).

CORINE Land Cover is divided in 47 different land covers. 26 of them are found in Wallonia. However, we made a clustering to group land covers that we judge to have the same kind of impact on temperature. Then, we made 5 classes :

- **Agricultural areas** : areas where crops can be tall
- **Herbaceous vegetation** : cleared areas like pastures and grasslands
- **Artificial areas** : roads, rails and constructions where anthropogenic material can impact temperature
- **Forest** : large areas providing shadow and cold
- **Water bodies** : areas like river, lake, wetlands and bogs. Finally, this class has been removed because of the fact that no stations are located near a water body

R handles the two types of spatial data : vector and raster. Vector model is based on points inside a CRS. Vector data can be points or lines or polygons. In R, `sp` and `sf` packages can handle this data type. The major difference between `sp` and `sf` is that `sf` objects can be treated as data frames in most operations and has better performances (Lovelace 2018). Raster model is based on a matrix representing equally spaced pixels and contains informations about the CRS, the extent and the origin. `raster` package handles this data type. These three packages can work together to convert data from a type to another one.

CORINE land cover data downloaded on the geo-portal was a shapefile, i.e. vector data, with WGS84 CRS. This geographic CRS has coordinates expressed in degrees. Then, to read them in R, `sp` was necessary but I converted data to `sf` format because this package facilitates the handling for data clustering in classes.

A conversion of CRS was also done from WGS84 to Belgian Lambert 2008. In contrast to WGS84, Lambert 2008 is a projected CRS expressed in meters. It facilitates our work to characterize the surrounding environment of the stations defining buffers around them. A projected CRS facilitates the definition of the radius of the buffer using meters instead of degrees.

Table 2.1: Distribution of land covers around physical stations

sid	crops	artificial	forest	herbaceous
1	63.85818	4.265755	0.00000	31.83038
4	64.11932	35.834990	0.00000	0.00000
7	75.28137	0.000000	0.00000	24.67295
9	99.95431	0.000000	0.00000	0.00000
10	69.91902	0.000000	30.03530	0.00000
13	89.50912	0.000000	10.44519	0.00000

Thanks to these buffers, part of each class of land cover is computed and then stored in a table. These buffers have a radius of 100 meters for physical stations and 500 meters for virtual stations (because each station covers 1 km²). The Table 2.1 below shows the structure of the data frame where each station identified by an ID has the percentage of cover for each class.

Digital Terrain Model

In the same way as land cover, the terrain characteristics could have an impact on temperature of the environment. These variables have been integrated in the models made by Zeuner *et al.* (2007) and the relevance has been demonstrated several times.

Elevation data have been recovered for Wallonia from **NASA's SRTM** providing a high-resolution (90 meters) topographic data. Then, slope, aspect and roughess of terrain have been calculated with spatial libraries implemented in R.

2.2.2 Dynamic Variables

Solar irradiance

Some explanatory variables for temperature can be time-dependent. In this case, we can be interested in solar irradiance. Indeed, solar irradiance has an impact on weather changes (Dewitte *et al.* 2004).

Data are recovered from **EUMETSAT**, the European Organisation for the Exploitation of Meteorological Satellites. They are produced every 30 minutes and expressed in W/m². These data are aggregated in hourly data and they are queried using the API of AGROMET.

There are 875 points distributed in Wallonia where records are available, this is not sufficient in our case where the objective is to provide predictions with a precision of 1 km². The handle of these spatial data with R packages was necessary to spatialize the records. To do that, the IDW spatial interpolation method was used.

These data are available from 2015-11-11. As a consequence, models built before this date do not use solar irradiance as explanatory variable. However, solar irradiance is an interesting explanatory variable, that's why no model was benchmarked before this date for my internship.

In parallel with that, PAMESEB stations also measure solar irradiance. But only 27 stations are useable. The measures from weather stations are used to build models from physical stations whereas the EUMETSAT measures will be used later for the spatialization on the spatial grid of Wallonia.

Temperature forecasts

The AGROMET project is supported by the RMI, the Belgian equivalent of Météo France. As a partner, RMI will provide temperature forecasts based on their own algorithms. It was planned to integrate these data as explanatory variables but at the time of my internship these were not yet available.

2.3 Data preparation

Once all the data are available, an important task is to organize them to perform modeling. This organisation needs to respond to a methodic approach :

- help reduce computation time
- respond to the structure imposed by the chosen modeling library

Our choice turned to the use of the `mlr` package because it provides an interface for machine learning using a lot of statistical methods. The objective of data preparation is to make our data mlr-compliant because the package needs data with a specific structure. In particular, I needed to organize data to have one line for each station containing values for every explanatory variable. Moreover, this organisation must be done for every hour.

The first step consists of grouping data. Static and dynamic variables are grouped in a data frame. Then, to reduce computation time and to prepare the integration of the data frame for the modeling task, there is a way to nest data frames with the library purrr. In this way, it is possible to have one single row for each hour but every row contains data frames inside. The Figure 2.1 shows how it looks. This nested data frame is a efficient way to manipulate many sub-tables at once.

Table 2.2: Example of nested data frame in a row corresponding to 2016-05-19 15:00:00

altitude	slope	aspect	roughness	crops	artificial	forest	herbaceous	ens	tsa	X	Y
473.6300	3.392046	211.6529	12.917668	63.85818	4.265755	0.00000	31.83038	348	12.4	721240.2	568849.6
345.7340	1.908891	162.7127	9.446796	64.11932	35.834990	0.00000	0.00000	389	12.8	714221.2	543453.8
348.8835	2.611751	165.0716	10.269126	75.28137	0.000000	0.00000	24.67295	779	14.1	750500.7	550825.6
497.7260	1.823958	137.0710	8.165029	99.95431	0.000000	0.00000	0.00000	916	13.5	753130.6	581716.9
389.9188	6.510637	310.6517	22.573696	69.91902	0.000000	30.03530	0.00000	916	14.9	734687.9	580969.6
259.7389	1.669001	288.5355	6.330072	89.50912	0.000000	10.44519	0.00000	774	15.2	641664.8	588814.6

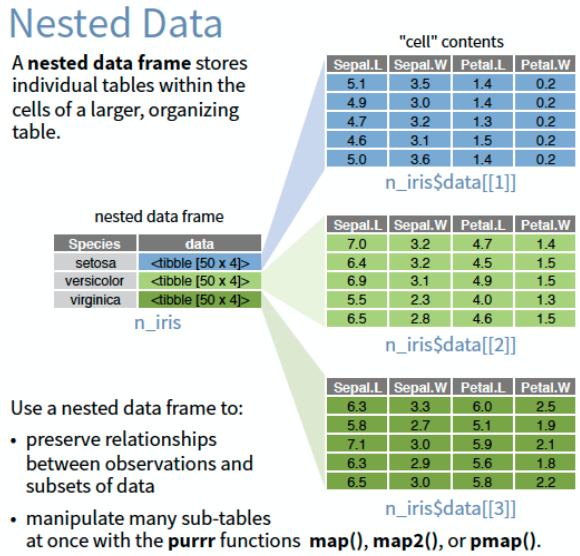


Figure 2.1: Structure of a nested data frame

In the case of the project, the nested data frame contains one row for each hour which in turns contains a nested data frame holding the data from all the stations for this hour. In the Table 2.2, there is a preview of the data frame contained into each row.

Chapter 3

Modeling with machine learning methods

Once the dataset is ready, the next step is to model spatial predictions of temperature. Two approaches can be used. Either physical models or Machine learning. My mentor and the project leaders have chosen the machine learning approach because it is easier to implement than physical models for which a deep understanding of the equations governing all the physical processes involved in the definition of the temperature at a specific point in the space an time is required.

3.1 Principle of machine learning

3.1.1 Definition

Machine learning is the idea that there are generic algorithms that can tell you something interesting about a set of data without you having to write any custom code specific to the problem. Instead of writing code, you feed data to the generic algorithm and it builds its own logic based on the data. In other words, Machine learning is a subset of deep learning or Artificial Intelligence that provides an ability to "learn" with data.

> There are 2 types of machine learning : supervised and unsupervised learning. In practice, most of machine learning uses supervised learning.
>
> From *machinelearningmastery.com* :
>
> > Supervised learning is where you have input variables (x) and an output variable (Y) and you use an algorithm to learn the mapping function from the input to the output : Y = f(X).
> > The goal is to approximate the mapping function so well that when you have new input data (x), you can predict the output variables (Y) for that data.
> > It is called supervised learning because the process of an algorithm learning

from the training dataset can be thought of as a teacher supervising the learning process

For supervised machine learning, the algorithm tries to learn from examples we give to it and then it returns a model of prediction. Classification and regression are supervised machine learning.

This is the case of the AGROMET project where regression models are used.

The unsupervised machine learning is not relevant in the context of my work because this kind of machine learning does not need reference to infer patterns and cannot be directly applied to regression problems.

3.2 Machine learning approach in the AGROMET project

The objective is to spatially predict weather parameters (temperature, relative humidity, leaves wetness). We use data from meteorological stations and from other sources like EUMETSAT for solar irradiance and COPERNICUS for land cover as explanatory variables for these weather parameters and to build our models.

Here is our approach :

We choose a weather parameter to predict, it is our **target**. In the context of my internship, *temperature* is my target variable.

Then, from the historical dataset of hourly weather records from PAMESEB database, a representative subset of records is filtered. Stations are filtered to only keep the useful ones which are active. For each hourly set of records, a benchmark experiment is run with multiple linear regression algorithm, the **learner**, applied to various regression **tasks**, i.e. the target response variable (temperature) and all the chosen **explanatory variables** (elevation, slope, land cover...). The different combinations of explanatory variables using multiple linear regression algorithm are compared and ranked using a **cross-validation resampling strategy**. Several methods exist but we will use the Leave-One-Out cross-validation method (LOOCV). It consists to establish, for each hourly dataset, a model based on every weather stations except one which will be the one where the model output will be compared to the observation to compute the error. this procedure is repated iteratively on each station. Model performance metrics (RMSE and MAE) are stored for each of these iterations.

These performance metrics are two of the most common metrics used to measure accuracy for continuous variables and for validation step in machine learning.

MAE measures the average magnitude of the errors in a set of predictions, without considering their direction. It is the average over the test sample of the absolute differences between prediction and actual observation where all individual differences

have equal weight.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_j - \widehat{y}_j|$$

RMSE is a quadratic scoring rule that also measures the average magnitude of the error. It is the square root of the average of squared differences between prediction and actual observation.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_j - \widehat{y}_j)^2}$$

The entire methodology is detailed in the *Appendix A* (Spatialization methodology).

3.3 Machine Learning in R

All of our work is done using R. Moreover, a R package which provides the infrastructure to run machine learning is available. This package, **mlr**, is very complete to build models, make predictions and evaluate performances.

Machine learning in R offers a common and simplified interface for all statistical methods implemented in the package. With this package, running a benchmark that compares several statistical methods, i.e. a set of combinations of learners and explanatory variables, can easily be performed on a large dataset covering a long period of hourly records. This benchmark returns a lot of information :

- about learners and task descriptions used in the benchmark
- about models, test performance values, predictions from the benchmark

The package includes several ways to analyze benchmark results. Plots are integrated to visualize results and learning algorithms can be compared and ranked. It is possible to compare learners and tasks through measures of error like RMSE or MAE. In the case ofmy internship, the learner is always the same, multiple linear regression, and tasks change because I modify the set of explanatory variables used.

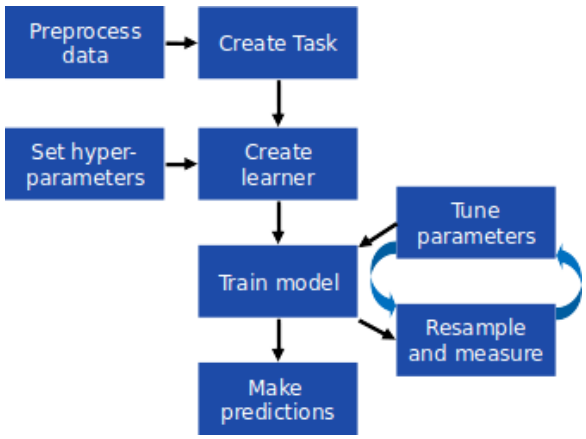


Figure 3.1: mlr workflow

The Figure 3.1 shows the general workflow of `mlr`.

This package has an important community which improves it regularly. A lot of statistical methods are implemented from other packages like *tgp*, *kknn* or *DiceKriging*.

Chapter 4

Results and discussion

4.1 Benchmark

4.1.1 Methodology

A LOOCV strategy of the multiple linear regression learning algorithm has been applied to each set of hourly records. The aim is to assess combinations of explanatory variables provides, on average, the best spatial predictions. This is achieved by comparing and ranking the various combinations of explanatory variables with respect to their performance measures (MAE and RMSE) averaged on the whole set of hourly records. Hence we actually end up with a so-called mlr benchmark experiment that is run on each set of hourly records.

The initial objective was to run these benchmarks on 5 years of data to establish which combination of explanatory variables provides, on average, the best predictions. But at this moment, solar irradiance data from EUMETSAT was not available for the whole period. These benchmarks were therefore performed on 23089 sets of hourly records from 2015-11-11 00:00:00 to 2018-06-30 00:00:00 (the period for which the solar data is already available).

The learners were defined with filter methods implemented in `mlr`. These filter methods are applied to a statistical algorithm (multiple linear regression) to choose explanatory variables using conditions. The different conditions used to filter explanatory variables are the following :

- for each hourly dataset, linear correlation with temperature is computed for every explanatory variable. Other filter methods are available (chi-squared, anova...) but linear correlation seems to be the most relevant one for a regression problem.
- then, explanatory variables are kept according to conditions : variables with the best hourly linear correlation with temperature (the number of variables to keep is specified) or all the variables which have a linear correlation greater than a specific value from 0 to 1.
- I can also choose explanatory variables that I want to build models regardless of their linear correlation

Table 4.1: Combination of explanatory variables used

Statistical Method	ID	Explanatory variables
Multiple Linear Regression	lm.Long.Lat	Longitude & Latitude
Multiple Linear Regression	lm.Long.Lat.Elev	Longitude & Latitude & Elevation
Multiple Linear Regression	lm.SolIrr+1bestVar	Solar Irradiance & best variable based on an hourly linear correlation computation
Multiple Linear Regression	lm.SolIrr+2bestsVar	Solar Irradiance & 2 best variables based on an hourly linear correlation computation
Multiple Linear Regression	lm.SolIrr+3bestsVar	Solar Irradiance & 3 best variables based on an hourly linear correlation computation
Multiple Linear Regression	lm.2bestsVar	2 best variables based on linear correlation computation for every hour
Multiple Linear Regression	lm.3bestsVar	3 best variables based on linear correlation computation for every hour
Multiple Linear Regression	lm.4bestsVar	4 best variables based on linear correlation computation for every hour
Multiple Linear Regression	lm.Vars.r>0,5	Variables with a linear correlation greater than 0.5
Multiple Linear Regression	lm.Vars.r>0,3	Variables with a linear correlation greater than 0.3

All these filter methods where applied to **Multiple Linear Regression** learner in the case of my internship.

The Table 4.1 shows the different combinations that were created using filter methods.

Because a benchmark is performed on each set of hourly records, computation of the linear correlation is also performed on an hourly basis scale and mlr choose automatically the variables using the filter methods. Thus, it must be stressed out that the selected combination of explanatory variables may differ from one hour to another.

Performing the benchmarks on the 23089 sets of hourly records took about 30 hours, i.e. 3 hours per method. Computations are very long and results are very large. Each method represents more than 1 Gigabyte of data.

4.1.2 Comparison of methods

Once the 23089 benchmarks are performed, we can compare their outputs averaged on the whole period. This comparison is based on the error of measures. In our case, RMSE and MAE were computed because they both express average model prediction error in units of the variable of interest. Both metrics can range from 0 to ∞ and are indifferent to the direction of errors. They are negatively-oriented scores, which means lower values are better.

Since the errors are squared before they are averaged, the RMSE gives a relatively high weight to large errors. This means the RMSE is more useful because large errors are particularly undesirable in the project. (Chai, 2014)

The figure 4.1 shows the averaged RMSE and MAE for the 10 methods implemented. The two metrics both return the same ranking of the methods and they both show methods which stand out from the other ones.

The method only using coordinates, i.e. longitude and latitude, to build models has a large error, this combination is not relevant to spatially predict temperature in Wallonia. The method using explanatory variables with a linear correlation with temperature greater than 0.3 has an error larger than the other methods too, this filter

method is not selective enough to return valid spatial predictions. A few methods have a similar error. In particular, that is the case when 4 variables are chosen to build models.

Among the 3 methods that, on average, perform the best, the one that builds the spatial prediction models with longitude, latitude and altitude as explanatory variables, provides the lowest errors. The two other methods are based on the hourly computation of the linear correlations with temperature, with or without solar irradiance as mandatory variable and keeping the 2 other best variables have a similar error. However, in spite of their larger error, they can be interesting because the equation is dynamic throughout hours and, in this way, the models are adapted to the evaluated hour.

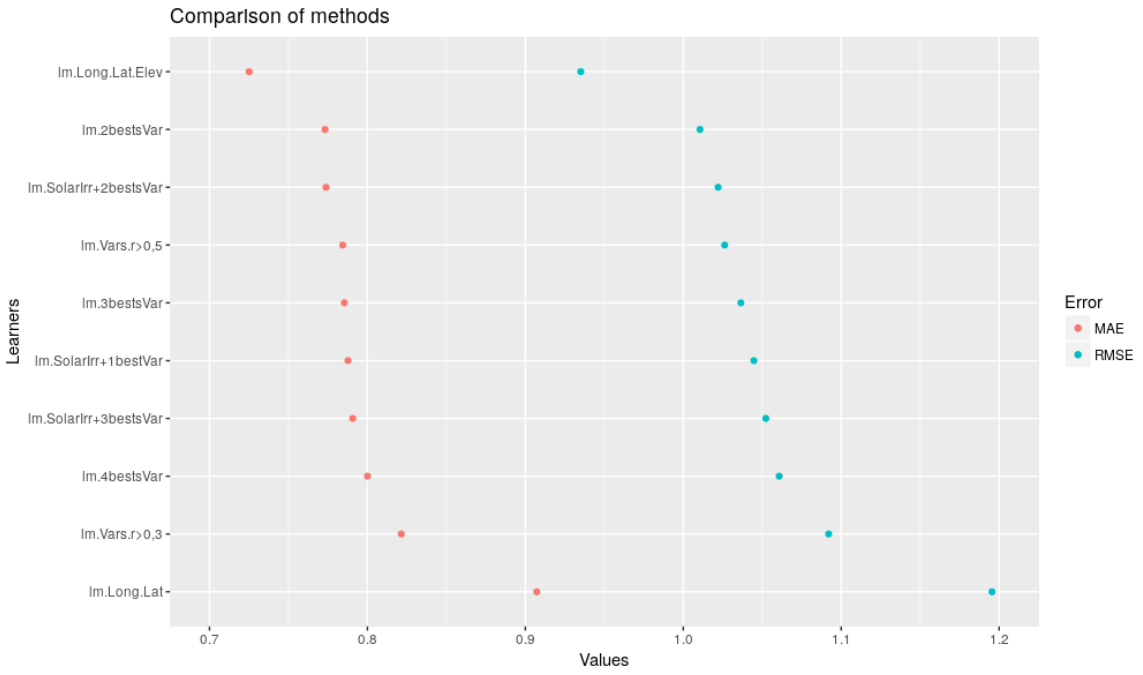


Figure 4.1: Errors (RMSE and MAE) of methods

Errors are between 0.72 and 0.91 for MAE and between 0.93 and 1.20 for RMSE. These errors should be near zero. Both of MAE and RMSE are expressed in degrees such as temperature. An error of 1 degree is relatively important and has to be taken into consideration.

Performances of methods can be compared computing their rank for each hour. The Figure 4.2 compares the three best methods :

- the 2 variables with the best hourly linear correlation with temperature
- longitude, latitude and elevation
- solar irradiance and the 2 variables with the hourly best linear correlation with temperature

Table 4.2: Models with their equations

	Datetime	Equation	BestVar1	BestVar2	RMSE	MAE
16135	2017-09-13 06:00:00	T = 14.656695 + -0.008887.altitude + 1e-06.X	altitude	X	0.5674956	0.4107285
16136	2017-09-13 07:00:00	T = 14.722147 + -0.00574.altitude + 0.012719.ens	altitude	ens	0.6122121	0.4529545
16137	2017-09-13 08:00:00	T = 15.676696 + -0.004304.altitude + -0.011732.herbaceous	altitude	herbaceous	0.9375293	0.7287999
16138	2017-09-13 09:00:00	T = 13.701668 + -0.012835.herbaceous + 0.00415.ens	herbaceous	ens	1.2198397	0.9671947
16139	2017-09-13 10:00:00	T = 14.987154 + -0.001473.altitude + -0.009431.herbaceous	altitude	herbaceous	1.0206276	0.8224733
16140	2017-09-13 11:00:00	T = 14.131936 + -0.003737.altitude + 0.005707.ens	altitude	ens	0.8312792	0.5979420
16141	2017-09-13 12:00:00	T = 11.852128 + -0.002653.altitude + 0.012421.ens	altitude	ens	0.9727891	0.7488237
16142	2017-09-13 13:00:00	T = 22.557946 + 0.003638.ens + -1.4e-05.Y	ens	Y	1.2605875	0.9444467
16143	2017-09-13 14:00:00	T = 15.441184 + 0.000484.altitude + -0.015099.herbaceous	altitude	herbaceous	1.0796645	0.8760026
16144	2017-09-13 15:00:00	T = 10.730857 + -0.003947.altitude + 9e-06.Y	altitude	Y	0.9526830	0.7777128

This barchart corroborates the precedent graph. The method based on coordinates and elevation is widely better than the two others which are more similar but with a relevant difference. The ranks 1.5 and 2.5 correspond to cases where two methods have exactly the same error for a same task.

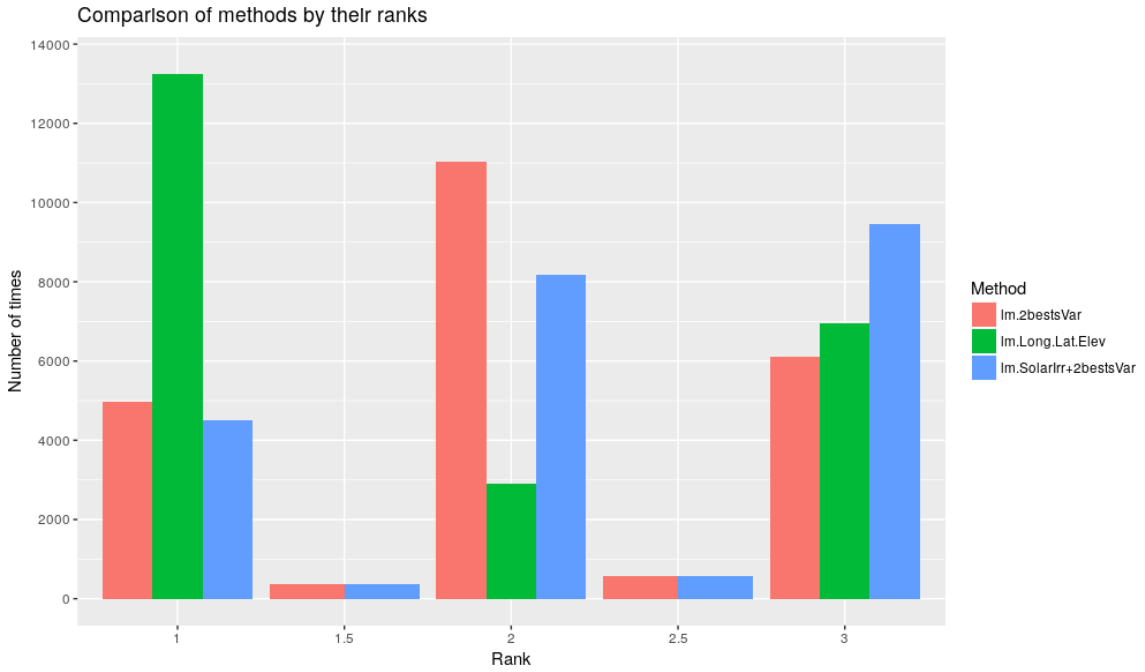


Figure 4.2: Comparison of methods by rank

`mlr` benchmark allows to extract the equations of the computed models. This is useful if we want to build spatialized temperature maps. The Table 4.2 shows an example of the structure of the equations in the case where explanatory variables can be different from one hour to another (lm.2bestsVar). The table also shows what are the best variables and display the related error.

4.1.3 Visualization

Spatial predictions built upon these models can be shown on maps. For that purpose, functions building maps have been made with ggplot2 library from R for static maps

and leaflet library for interactive maps.

Models built from physical stations data are applied to the 1 km² grid cells. Then, the spatialized temperature is mapped with a color palette similar to the one of RMI. Class breaks are based on quantiles of temperature values. Standard error is computed for each cell and it is shown on the map with a white layer which has different levels of transparency according to the error. A large standard error is related to an opacity and vice-versa. This transparency trick to display the attached standard error was inspired from the article of Hengl (2011) which explains the uncertainty of the prediction at each interpolation point.

The Figure 4.3 shows an example of output that I can produce for one hour based on the method where explanatory variables are Solar irradiance and the 2 variables with the best linear correlation with temperature. To build this map, some objects are needed : an object containing data (temperature and standard error) for the grid and a spatial vector object containing boundaries of Wallonia, but also the name of the variable to display. Then, some conditions can be chosen, like the display of the layer containing error, the display of the legend for error, the way to build the legend and its classes. Some arguments enable to customize the map with titles and comments. The function is thus reusable for other usages. For example, this function has also been used to build maps of spatialized hydric deficit in Wallonia during this year summer drought.

The choice I made was to use quantiles to make class breaks because that is more relevant than homogeneous breaks. Indeed, the last one has an unequal count of 1 km² cells per grid whereas groups made with quantile classification have the same quantity. A reference about the difference between these classifications is available in *Appendix C*

The figure shows 2 maps. The map on the left shows the spatialized temperature. The map on the right shows the spatialized temperature combined with the standard error (uncertainty) of the prediction. It is possible to see larger errors in the Ardennes, in the Meuse river valley near to Liège and in the east of Hainaut province.

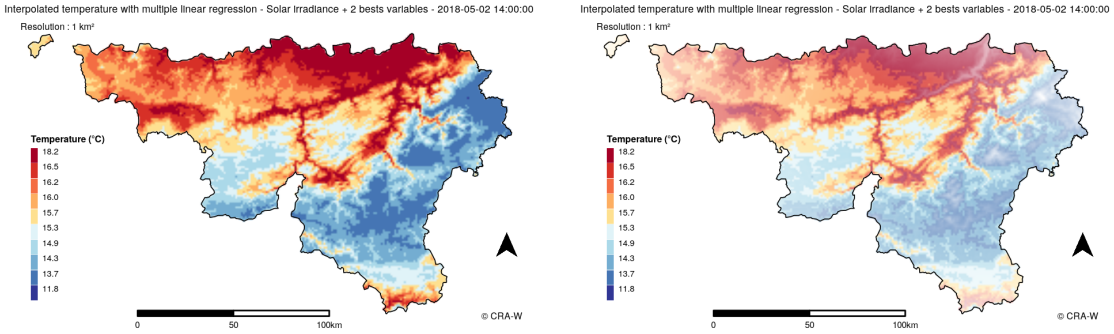


Figure 4.3: Example of an output for 2018-05-02 14:00:00 (left : without standard error ; right : with standard error)

This figure shows the output based on a model depending on the method where explanatory variables are Solar irradiance and the 2 variables with the best linear correlation with temperature, the equation of the model is the following one :

$$T = 15.59716 + -0.00629 \times Elevation + -0.00197 \times Herbaceous + 0.00206 \times SolarIrradiance$$

The *Appendix B* shows exemplative maps made with all methods for one hour. These maps show differences in the relevance of each model. For example, the model depending on longitude and latitude is very simplistic compared to the others. The other models are more similar but show that some of them are more reliable because the standard error is smaller. The better model is the second one on the first row. It is corresponding to the the model depending on longitude, latitude and elevation. For this hour, the equation of the best model is :

$$T = -9.375042 + -0.010431 \times Elevation + 1.02e{-}05 \times Longitude + 1.59e{-}05 \times Latitude$$

Longitude and latitude are expressed in meters because the CRS used is Belgian Lambert 2008. That is why their coefficients are about $1e$-05. For information, values of the coordinates are about 6e06.

4.2 Discussion

As a reminder, the objective of the project is to provide spatialized weather data with the lowest uncertainty and the lowest prediction error in the agricultural areas of

Wallonia. These predictions will feed decision support tools to monitor crop diseases like potato late blight and to operate in fields at the right times.

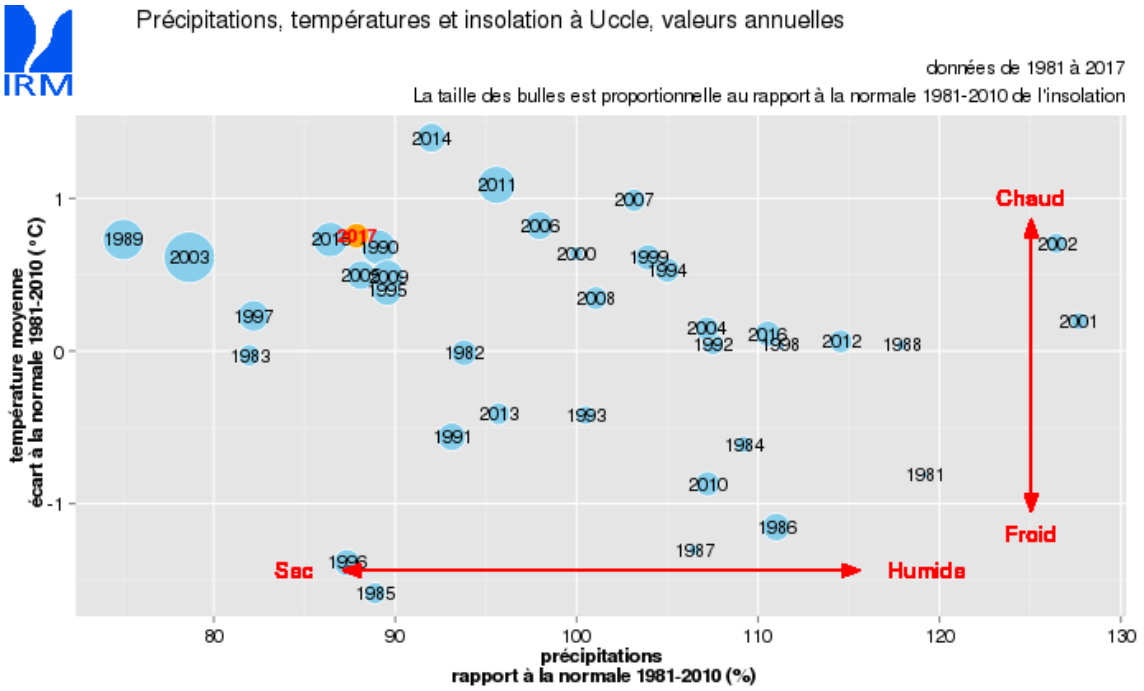


Figure 4.4: Precipitations, temperatures and insolation, annual values

Results have some limits that have to be discussed. The first limit is the period used to build models. Indeed, models were built with data from 2 and a half years. This period could be too short to be relevant. Moreover, this period is not necessarily representative of a mean period. According to RMI, 2015, 2017 and 2018 are hot and dry years compared to normal year, 2016 were a wet year. This is shown on the Figure 4.4.

Even if visualization of outputs is not the main objective of the project, the choice I made to compute class breaks with quantiles can be discussed. In the case of temperature, that seems relevant but other methods exist.

Models were built with some explanatory variables but they may be insufficient. Adding new variables like temperature predictions from RMI could improve models. Only 27 stations are used to build these models, adding new variables like next hour temperature predictions from RMI could improve models too. However, weather stations from different networks have differences in their measures, checking interoperability is very important for that and making corrections is essential.

Multiple linear regression is the only statistical method used to build models, but going forward, other methods will be compared like ANN and different kriging methods. The major constraint will be time computation which is relatively long.

There is a lot of possible combinations of explanatory variables to compare, choices must be done because of the time computation. These choices sometimes can be subjective and not based on scientific literature.

Beyond these limits, other points can be discussed. Solar irradiance data are provided by EUMETSAT and by PAMESEB stations. These data have to be compared because both sources are used. Data from stations are used to build models, data from EUMETSAT for spatialization. To do this comparison, I have searched for the nearest point of record from EUMETSAT to each PAMESEB station. Then, I compared each couple on the period where I realised the benchmark. This comparison shows a correlation around 0.95. As a consequence, there is nothing wrong with it.

The ranking of the methods show that the method using the hourly 2 best variables provides a smaller error than the same method adding solar irradiance in every task. That is interesting because intuitively, adding an explanatory variable should reduce the error. I noticed that solar irradiance provides a large error for a few tasks, that might explain these results.

With the aim to provide data for agronomic utilisation, there is an interest to compare mean error observed in Wallonia and this error in agricultural areas to be sure of the accuracy of predictions. That has not be done yet.

Rather than choosing the best spatial prediction method on average to perform the hourly spatialization, we could also decide to choose, for each hourly spatialization, the best method according to the benchmark even if this method could be different for each hour. This would not be a problem as long as the methodology is transparent.

Conclusion

At the end of this internship, the progress of the project is great. Principal data have been recovered to be integrated as explanatory variables and first models have been built. Now, the routine is ready to build further models that could make use of other learning algorithms as various forms of kriging, ANN, etc.. First results are encouraging because models are relatively relevant and they can be improved adding new explanatory variables and using other statistical methods.

The project will end in 2020, that leaves time for building better models and developing decision support tools for crop monitoring. Therupon, the project will have an importance and some foreign organisations are already interested by the project (Germany and Slovenia).

Beyond the technical skills I have developed during my internship, like the use of R language to interpolate spatial data and manipulating them, the discovery of developer applications and tools like Docker or Ubuntu, I also developed skills in collaborative work, in particular with GitHub and Riot.im. It was a very enriching experience.

Outside the AGROMET project, I worked for other projects. I contributed to the report on drought in this summer 2018 in Wallonia, upgrading graphics and building a template of the map of Wallonia. I also contributed to provide data from the API of the project to co-workers for other projects.

Appendix A

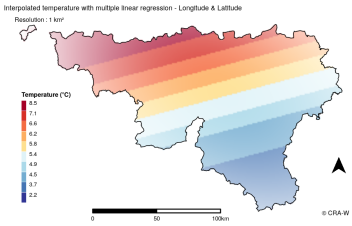
Resources on AGROMET and my work

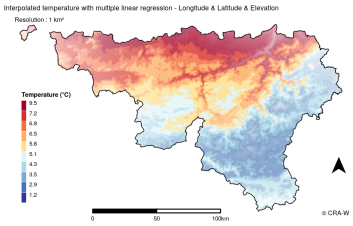
- European directive 2009/128/CE : https://eur-lex.europa.eu/legal-content/EN/ALL/?uri=celex%3A32009L0128
- PAMESEB network : https://www.pameseb.be/
- Spatialization methodology available here : https://pokyah.github.io/agrometeor-methodo-spatial/assets/uml_images/spatialization-methodology.svg
- All my codes are available on my Github account : https://github.com/ldavadan
- My personal blog, made with Blogdown : ldavadan.github.io
- Contribution to "Crop and Grassland conditions in early August" report : http://www.cra.wallonie.be/fr/etat-des-cultures-et-des-prairies-en-ce-debut-du-mois-daout-2018

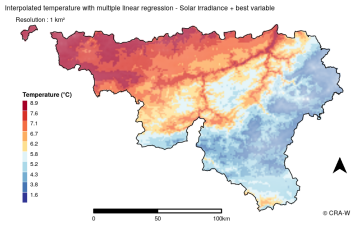
Appendix B

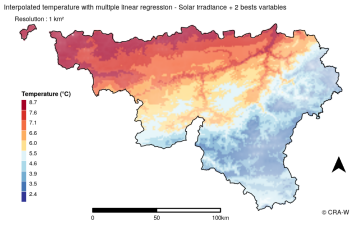
Outputs with different methods

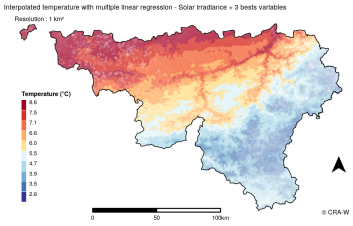
Methods from left to right and top to bottom follow the order presented in Table 4.1. Models built for 2018-03-07 14:00:00.

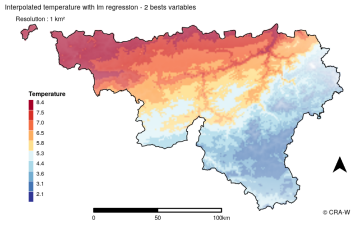


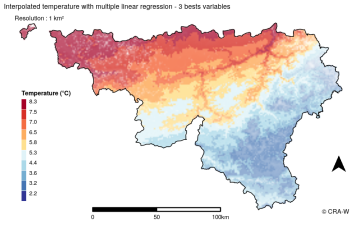


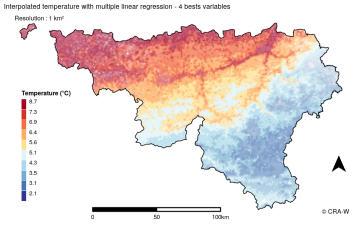


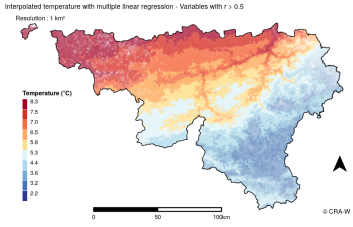


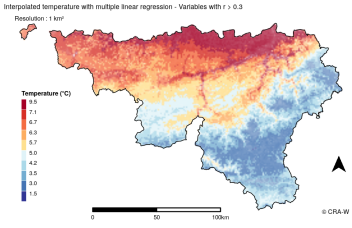












Appendix C

Additional resources

- Ubuntu GNOME : https://ubuntugnome.org/
- ANSIBLE : https://www.ansible.com/
- SSH : https://www.ssh.com/
- GitHub : https://github.com/
- API : https://medium.freecodecamp.org/what-is-an-api-in-english-please-b880a3214a82
- R : https://www.r-project.org/
- Docker : https://www.docker.com/what-docker
- Copernicus : https://land.copernicus.eu/pan-european/corine-land-cover/view
- Belgian Geoportal : https://www.geo.be/#!/catalog/details/bcd19aa9-c320-4116-971b-6e4376137f13?l=en
- NASA's SRTM : https://lta.cr.usgs.gov/SRTM
- EUMETSAT : https://landsaf.ipma.pt/en/products/longwave-shortwave-radiation/dssf/
- Differences between machine learning and physical models approaches : https://medium.com/(**???**)
- Machine Learning Mastery Blog : https://machinelearningmastery.com/supervised-and-unsupervised-machine-learning-algorithms/
- Machine Learning in R : http://mlr-org.github.io/mlr/index.html
- Data classification : https://gisgeography.com/choropleth-maps-data-classification/

Appendix D

Structure of the code using mlr package

```
# define learners
lrns.l <- list(makeFilterWrapper(learner = makeLearner(cl = "regr.lm", id = "lm.L
               makeFilterWrapper(learner = makeLearner(cl = "regr.lm", id = "lm.L

# define resampling strategy
resampling.l = makeResampleDesc(method = "LOO")

#run benchmark
benchmark <- benchmark(
  learners = lrns.l[1],
  tasks = data.stations.n.df$tasks, # 1 task = 1 hour
  resamplings = resampling.l,
  # additionnal parameters
  keep.pred = FALSE, # boolean specifying if predictions have to be kept
  show.info = TRUE, # boolean specifying if informations have to be shown when ru
  models = FALSE, # boolean specifying if models have to be kept
  measures = list(rmse, mae, timetrain) # list of measures to do
)
```

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