



METHODOLOGY OF CLIMATE MODELLING USING LAND SURFACE TEMPERATURE DOWNSCALING: CASE STUDY OF GIRONDE (FRANCE)

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Abstract

Aim: Climate modelling in viticulture introduced new challenges such as high spatio-temporal monitoring and the use of dependable time series and robustness modelling methods. Land surface temperature (LST) is widely used and particularly MODIS thermal satellite images due to their high temporal resolution (four images per day). However, this data is not completely adapted to regional scale with its medium spatial resolution (1-km). Downscaling methods can improve spatial resolution using machine learning algorithms implementing multiple predictors as topographical variables and vegetation indices. In the last decades, classical bioclimatic temperature-based indices showed a specific spatial distribution depending on topographical variables and at once a significantly non-correlation with vegetation growing trend.

Methods and Results: In the current study, an assessment of SVM Machine learning method was used to downscaling daily LST using topographical variables and vegetation indices as predictors at multiple spatial resolution. The aims of this study were to (1) evaluate daily LST time series through 2012-2018 period, (2) assess the impact of topographical variables and evolution of vegetation indices during vegetative season and (3) calculation of bioclimatic indices on the wine-growing area of the Gironde. The dataset included: 1) daily time series of MODIS LST at 1-km (MOD11A1 and MYD11A1) and 2) topographical variables derived from Digital Elevation Model at 500 m (GMTED10). The first step was the pre-processing and reconstruction of time series. The second step was the downscaling of LST using SVM with topographical variables as predictors. For each day, a model was calibrated and validated to predict daily LST at finer spatial scale. The third step was the calculation of bioclimatic indices (Winkler and Huglin). The methodology was applied for the fourth LST MODIS products acquired at different times. For example, for the 2012 wine growing season Huglin index and Winkler index were calculated with the daily predicted LST (without vegetation indices as predictors but only topographical variables) on the Gironde area and have a globally similar spatial structure. The lowest values ($\approx 1900^{\circ}\text{C}$ for Huglin and 1340°C for Winkler) are concentrated on the coastline to the west and south of the Gironde. The highest index values ($> 2000^{\circ}\text{C}$ for Huglin and $> 1700^{\circ}\text{C}$ for Winkler) are located from the centre of the Gironde to the north-east. These warmer sectors are concentrated in the valley bottoms of the Dordogne and Gironde with higher values in the south of Libourne. LST predictions should be downscaled for the whole period (2012-2019) and the second experiment of the downscaling method includes vegetation indices as predictors.

Conclusion: The advantage of LST is their temporal and spatial covers in all the areas. However, data availability and bias must be taken into account and minimized.

Significance and Impact of the Study: At the scale of Gironde region, this downscaling method has been tested for the first time with MODIS Land Surface Temperature derived from thermal satellite images in a wine-growing context.

Keywords: Climate modelling, topographical downscaling, thermal satellite imagery, bioclimatic indices, Gironde

Introduction

Climate, one of the main components of terroir, varies according to the local environment and it influences vine development and grape quality and composition (Van Leeuwen *et al.*, 2004; Van Leeuwen and Seguin, 2006). For decades, wine-growing regions have been characterized and classified by temperature-based bioclimatic indices (Amerine and Winkler, 1944; Winkler, 1962; Huglin, 1978; Tonietto and Carbonneau, 2004; Parker *et al.*, 2011, 2013). The impact of local factors on climatic conditions (Quénol, 2014b.) mainly temperature is widely studied throughout the winegrowing regions (van Leeuwen *et al.*, 2004; Jones *et al.*, 2009).

In viticulture, the study of climate or meteorology included three types of temperature data: 1) the air temperature, 2) Temperature from Regional Climate Models (RCM) and the Land Surface Temperature. The air temperature (ground-based measurements) mainly for regional or local application is provided by regional meteorological stations or networks of temperature sensors installed in the vineyard plots either in the canopy or at the beginning of the vine rows. The air temperature data is essential for local thermal monitoring and the understanding of the local thermal environment of the vine, however it is limited in time, space and cost. Globally, for regional scale, some studies have used a second type of temperature data retrieved and gridded from Regional Climate Models (RCM) (Jones *et al.*, 2009; Fraga *et al.*, 2014; Sturman *et al.*, 2017; Bois *et al.*, 2018; Le Roux *et al.*, 2018). The third type of temperature data is Land Surface Temperature from thermal remote sensing, in some cases combined with optical or radar data, had made it possible to improve spatial and/or temporal resolutions in particular for agricultural and precision agricultural applications. Daily thermal satellite data at medium spatial resolution has potential in the study of thermal structure variability. Current and potential wine-growing regions can be widely studied and compared in time and space with similar data. Currently, several daily or even intra-day thermal satellite data, as ASTER or MODIS images around 1km resolution, have not sufficient spatial resolution to monitor the impact of thermal conditions inside a winegrowing region. Statistical methods are widely studied to provide spatial scale downscaling of these thermal satellite data using topographical factors.

This study focused on the winegrowing region of Bordeaux in the Gironde department in France. This winemaking region has been widely studied in climate change applications: in phenology (Parker *et al.*, 2011, 2013), the influence of climate change in wine quality (van Leeuwen *et al.*, 2009; Baciocco, Davis and Jones, 2014; van Leeuwen and Darriet, 2016), temperate based zoning (Bois *et al.*, 2018), potential adaptation (van Leeuwen *et al.*, 2019), European comparison (Quénol *et al.*, 2014) and more locally in Saint-Emilion-Pomerol area with a network of 90 air temperature sensors and phenological measurements (Le Roux *et al.*, 2017a; de Rességuier *et al.*, 2020).

The objectives of this study were: 1) the characterisation of daily 1 km-MODIS Land Surface Temperature time series between 2012-2018 from daily products (M*D11A1) and 8-days composite (M*D11A2) overall the Gironde department, 2) Application and evaluation of daily downscaling Land Surface Temperature method with terrain attributes (slope, elevation, coordinates, exposition) using SVM algorithm and 3) Calculation and mapping of bioclimatic indices using daily Land Surface Temperature downscaled at 500 m for the 2012-2018 period.

Materials and Methods

Study Site

The wine-growing region of Bordeaux is located in the south-west of France in the department of Gironde at latitudes 44.5°N to 45.5°N. With a western facing on the Atlantic Ocean, this department is classified as an oceanic temperate climate (Cfb) by the Kotték *et al.*, (2006) classification with moderate summers without dry season. This study site includes a variety of land uses and elevations extending up to 150 km inland to the east. It is along the main river Gironde and the Dordogne River crossing the region from East to West that the Bordeaux vineyards are located. The Bordeaux wine growing region was characterized by previous studies as a sub-humid climatic conditions with a dryness index between 50 and 150 mm (class 1 of the dryness index) and by cool nights characteristic of class CI+1 of the night freshness index (Tonietto, 2004). The study focused on a seven year wine-growing period between 2012 to 2018 including months between March to October corresponding to the wine growing season of the northern hemisphere.

Data Description

Land surface temperatures were acquired by two satellites: Terra (MOD) in descending orbit crossing the equator at about 10:30 and 22:30; Aqua (MYD) in ascending orbit at about 01:30 and 13:30. For this study, two types of

surface temperature data accessible freely were used: daily data (M*D11A1) and data from an 8-day composite (M*D11A2) is an average of all the corresponding daily pixels collected within that 8-day period. Each of this data is divided in four products: two acquired during daytime (MOD_DAY and MYD_DAY) and two during nighttime (MOD_NIGHT and MYD_NIGHT). This data is extracted at 1 km spatial resolution from bands 31 (10.78-11.28 μm) and 32 (11.77-12.27 μm) from version 6 using the split-window algorithm. The MODIS data used in this study was downloaded between 2012 and 2018 via AppEars and corresponds to the products "MODIS Land Surface Temperature/Emissivity Daily L3 Global 1 km SIN Grid V006" and "MODIS Land Surface Temperature/Emissivity 8-days L3 Global 1 km SIN Grid V006". They were cropped at the border of the Gironde department (including the tiles "h17v4" and "h18v4"), re-projected in the WGS84 system and converted into degrees Celsius.

The elevation data was produced by GMTED2010 - Global Multi-resolution Terrain Elevation Data (Danielson and Gesch, 2011) at the resolution 15 arc-seconds (~500 meters). This data has been downloaded from EarthExplorer. Topographic variables are derived from the DEM: elevation (metres), slope (degrees), North-South orientation (degrees), East-West orientation (degrees), and geographic coordinates (latitudes/longitudes).

Daily and 8-days LST Times Series Reconstruction and Downscaling Method

The reconstruction and downscaling method applied for daily and 8-days Land Surface Temperature using topographical variables is detailed in this section (Figure 1).

A) The reconstruction of daily time series were performed by combining the daily LST (MYD11A1 and MOD11A1) with the 8-day composite LST is an average of all the corresponding daily pixels collected within that 8-day period (MYD11A2 and MOD11A2) (Z. Wan *et al.*, 2015) both including two daytime products and two nighttime products at 1-km. To limit dependency of previous and later temporal window reconstruction, this study is based on the replacement of NA with 8-day composite value.

B) The downscaling method was developed with the Support vector Machine (SVM) algorithm used as a machine learning regression model in this study. The SVM initially developed by Cortes and Vapnik (Cortes and Vapnik, 1995) for classification studies has also been used as a regression method. This algorithm uses a hyperplane to classify the input variables into a m-dimensional feature space with maximal margin. In this study, the caret package (Kuhn, 2012) and the e1071 package (Meyer *et al.*, 2014) in R software version 4.0.1 were used for regression implementation using a radial kernel, and optimal values of the hyper-parameters (cost and epsilon) were determined through 5-fold cross validation as developed in Le Roux *et al.* (2017b) for air temperature spatialisation.

C) The first index used is the standard Growing Degree-Days (GDD), also known as the Winkler Index (WI) (Amerine and Winkler, 1944). It corresponds to the accumulation of degrees above 10°C during the seven months of the growing season (1st April to 31st October, Northern Hemisphere). This index makes it possible to compare several regions of the world, especially after the evolution of the upper and lower limits (Jones *et al.*, 2009). The heliothermal Huglin index "HI" (Huglin, 1978) is calculated using daily mean and maximum temperatures above 10° C, over six months (1st April to 30th September, Northern Hemisphere) and takes into account a coefficient (k) to adjust the length of the day depending on latitudes. A "k" value of 1.03 was used for this study.

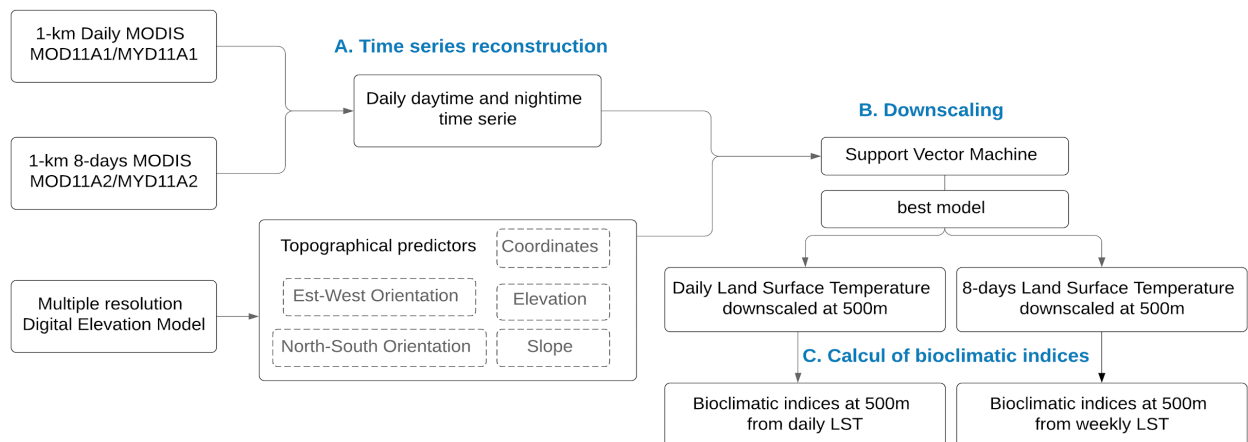


Figure 1: Processing flow applied to downscale daily and 8-days Land Surface Temperature with topographical variables.

Results and Discussion

Downscaling Performance

The method of downscaling surface temperatures to 500m from topographic variables using the SVM algorithm was applied for each MODIS product and on two types of data (daily or weekly). The performance of the SVM downscaling method was variable depending on the type of data (daily or weekly) and the four Land Surface Temperature products derived (Figure 2). The analysis of the daily data showed results very close to the weekly data. The coefficients of determination of the daily performances vary from $0.40 \geq R^2 \geq 0.55$ with $1.0^\circ\text{C} \geq \text{RMSE} \geq 2.1^\circ\text{C}$ and the 8-days data vary from $0.37 \geq R^2 \geq 0.55$ with $0.9^\circ\text{C} \geq \text{RMSE} \geq 1.9^\circ\text{C}$. In both cases, night products have better results due to the stability of atmospheric exchange during acquisition (Zeng, 2015; Huang, 2015; Shen, 2016).

The correlation coefficients are moderate, which could be explained by the diversity of land cover over the entire Gironde region. Different types of soil are covered: urban, agricultural areas, forests, or mixed areas, which can lead to a low precision in this type of method. However, this first study allows to evaluate several surfaces in this method of downscaling between surface temperatures and topographic variables at this scale.

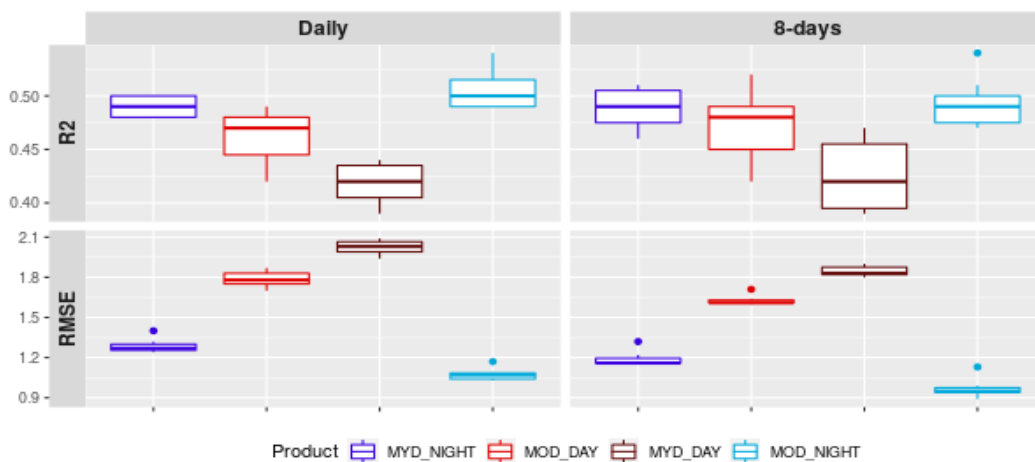


Figure 2: Performance of the downscaling of Daily and 8-days land surface temperature using SVM algorithm at 500m.

Seasonal Bioclimatic Indices: Winkler and Huglin

Differences in bioclimatic index values were observed between the growing seasons from 2012 to 2018 (Figure 3). The variations were also marked between the two data used to calculate these bioclimatic indices: weekly land surface temperatures and daily land surface temperatures. Figure 3 shows the difference in index values between the weekly LSTs compared to the daily LSTs. The results showed for the Winkler index less variability in the values than for the Huglin index. On an interannual scale, a profile between 2012 and 2016 was obtained with close and little variable values of the difference between the two indices (8 days - daily). Whereas for 2017, for example, the values tend towards a difference of $+100^\circ\text{C}$ and for 2018 which tend towards a difference of -100°C . On the intra-annual aspect, index differences were generally stable. For the Winkler index, there was a trend of higher positive difference values in the eastern part of the region. For the Huglin index the maps showed a gradient of negative to positive values marked from the northwest to the southeast of the region.

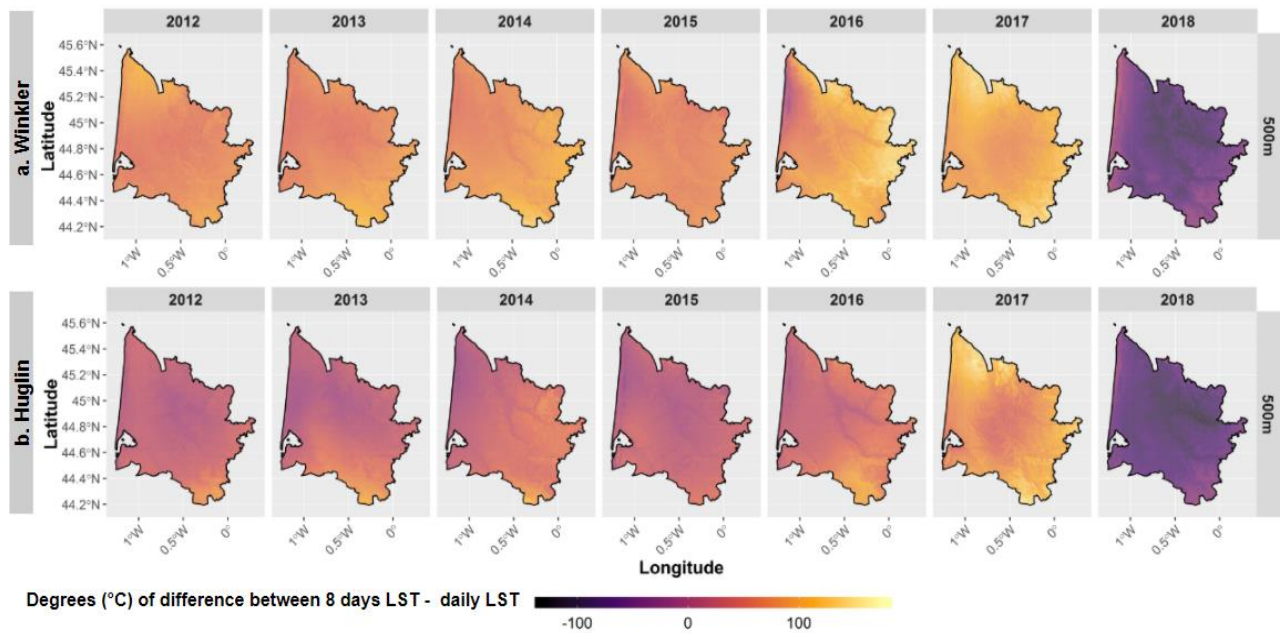


Figure 3: Differences between bioclimatic indices calculated with weekly Land Surface Temperature and daily Land Surface Temperature in degrees (°C) between 2012 and 2018 at 500m : a) Winkler, b) Huglin.

Conclusion

The objective of this study was to evaluate the potential use of daily and weekly MODIS thermal images in the mapping of bioclimatic indices at the scale of the Gironde vineyard between 2012 and 2018. Over seven growing seasons, the variability of surface temperatures between these two types of data was globally stable in space but changed according to the seasons. The next step would be to evaluate more precisely these intra-seasonal variabilities and to better understand the effects of topographic variables on these thermal values accumulated over the season. In addition, other studies have demonstrated the positive effects in the downscaling method of using data on the evolution of vegetation such as vegetation indices in remote sensing, which would make it possible to follow the thermal accumulation according to the phenological stages and link this to bioclimatic indices.

Acknowledgments

This research was supported by funding from IRP VINADAPT, LIFE ADVICLIM and AVVENIR programs.

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