Impact of climate dynamics on cyclical properties of wine production in Douro region using time-frequency approach

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Abctract. In this paper we model the impact of climate dynamics on wine production temporal cycles for the period 1933 to 2013 in the Douro wine region. We identify the cyclical properties of wine production and which cycles are determined by spring temperature and soil water levels during summer. We achieve that by applying a time-frequency approach, which is based on Kalman filter regressions in the time domain. The time-varying autoregressive model can explain 79% of the variability of wine production in Douro region. We then transfer the results in the frequency domain and can show that wine production is characterized by two cycles of 5.7 and 2.5 years around the long run trend. The in-season spring temperature as well as the temperatures of two and three years ago could explain about 65% of the variability of wine production. When the soil water level in summer is incorporated, the R^2 increases to 83% and the Akaike criterion value is lower. The effects of soil water in wine production are depending on the timing. The in-season effect of an increase in soil water is negative, whilst soil water from two and three years ago have a positive effect on wine production. There is a stable but not constant link between production and the spring temperature. The temperature is responsible for two long-medium cycles of 5.8 year and 4.2 years as well as a short one of 2.4 years that began since the 80s. The soil water level can explained 60%of the 7 years cycles of wine production as well as a short one of 2.3 years cycle which has been happening since the 90s. We can recognise a shift of the relative importance away from temperature to soil water. Despite using a new an extended dataset, our results largely confirm the results of the impact of climate on the wine production in Douro region in our previous research. Modelling the impact of climate on the wine production can be an important instrument contributing for mitigation strategies facing the projected climate conditions in order to remain competitive in the market.

Keywords. Climate variability, Wine production, Time-varying spectra, Kalman filter, Douro region.

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1. Introduction

Grapevines are the number one perennial crop, with more than seven million ha of grapevine, ranging from 50º N, through the tropics, to 43º S, in all continents except Antarctica. Portugal is number five in

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the European wine producers' ranking and number eleven worldwide (OIV, 2016), growing grapes in over 30 different denominations of origin wine regions. Arguably the most known of these wine regions is the Douro Valley, which has gained notoriety from the quality of its main product - Port wine (IVDP, 2016).

In Douro region, as in many other wine regions worldwide, the last decades were characterized by large inter-annual variations of wine production (WP) with adverse effects for the wine producers (Cunha & Richter, 2012; Jones, 2012). This may be further exacerbated by climate change in the future, despite the noticeable advances in vineyard technologies. Unpredictable variations in wine production are a major threat to the wine industry (e.g. Clingeleffer et al., 2001). Therefore, there is a strong demand for improved wine yield forecasting in order to improve the efficiency of vineyard and winery operations as well as to support commercial strategies. Also, the Governments and European Commission's policy makers can use forecast information to implement regulatory mechanisms provided under the Common Organization of Wine Market for moderating the interannual wine variability effects (e.g. price policy, assign economic aid, crop insurance contracts, production quotas, and stock management (Cunha et al., 2010; Quiroga & Iglesias, 2009). However, there is still a great lack of knowledge concerninglong term forecasting of wine production, particularly in the context of the climate changes scenarios.

The mounting evidence of global climate change has been at the heart of academic discussion of the scientific community both at national and supranational level in order to mitigate the negative effects for example for the wine industry and to adapt to the changing conditions. Future climate conditions in the Douro region were examined by Jones (2012) and Santos et al. (2013) using IPCC SRES projections from the HADCM3 ensemble models for three greenhouse gas emission scenarios (B2, A1B, and A2) and three future time slices (2020, 2050, and 2080). The future projections for the climate in the region from this assessment agrees with other works for Europe, Iberian-Peninsula, and Portugal (Fraga et al., 2016; Giorgi & Lionello, 2008; IPCC, 2007; Moriondo et al., 2015). The average annual temperatures are predicted to rise for all emission scenarios range from 1.4-3.3°C by 2050. During the growing season the region may experience substantial dry periods with precipitation reductions of more than 20% by 2080.

Previous work suggests that warming climate during spring period could lead to higher wine production (WP) in the Douro region (Cunha et al., 2003; Gouveia et al., 2011; Santos et al., 2013),which can be explained by the better thermal conditions for the flowering and fruit-set (May, 2004), as well as anticipation of the phenological stages (Bindi et al., 2001), avoiding both hydric stress (Duchêne & Schneider, 2005) and the impact of diseases (Caffarra et al., 2012).

In the context of the aforementioned climate scenarios for Douro region, which pointed tohigher temperatures and more infrequent rainfalls, soil water in summer could be the limiting resource for WPand, therefore, could become relatively more important for the WP than spring temperature where irrigation is not necessary. The magnitude of the referred mean changes impliesthe unsuitability of current wine varieties in those regions at or near the optimal threshold of ripening potential. This may in turn lead to a change of overall production and/or the development of new wine varieties (Bisson *et al.*, 2002; Moriondo *et al.*, 2013). Improved analysis of the trend and cyclicality of wine production, what motivated them, their duration and periodicity, is paramount importance for the future wine industry policy contributingfor mitigation strategies facing the projected climate scenarios in order to remain competitive in the market.

Recently, researchers have proposed different approaches to study quantitatively the impacts of climate change or climate scenarios on sectors such as agriculture, but little has been done in the viticultural subsector (Lavalle *et al.*, 2009; Long *et al.*, 2006; Mosedale *et al.*, 2016). Crop growth models and data–driven models are the basis of the most popular approaches for assessments of the climate changes on crop development and yield. Crop models performs an abstraction of the dynamic mechanistic of the plant's physiological stages by fitting them into a mathematical model (e.g. Bindi *et al.*, 1996; Cola *et al.*, 2014). According to an evaluation performed by Mosedale *et al.* (2016) and Everingham *et al.* (2009) this kind of models are expensive in terms of time and data requirements being impractical for application. Moreover, global warming and CO_2-enriched environments were not taken into account in the process-based models, which limits the applicability of these models for assessing the impact of climate scenarios on wine production (Moriondo *et al.*, 2015).

On the other hand, data-driven predictive models when built empirically, do not require a deep knowledge on biophysical mechanisms which in turn produced the data. Such techniques are inexpensive relatively easy to apply, and do not need a predefined structure of the model. Consequently, data-driven models have been widely applied in the last years using regressions analysis (Bock *et al.*, 2013; Fraga *et al.*, 2014; Gouveia *et al.*, 2011; Moriondo *et al.*, 2015; Santos *et al.*, 2010) and time-frequency methods (Cunha & Richter, 2012; Cunha & Richter, 2016; Esteves & Orgaz, 2001). Statistical models are represented by parametric structures optimisedby sum-of-squares residuals, validated by hypotheses test and confidence intervals. The main data-driven models applications to assess the impact of climate change on crop yield assume stationarity of the data generating process and typically assume a constant linear trend mimicking technological progress. Although this stationary assumption could describe the overall long-term trend in production, it does not reflect the inherent cyclicality in production and the information contained therein and obviously cannot model changes in the data generating process as caused

by climate change (Chen & Chang 2005). The inconclusive results on wine production modelling obtained in the previous studies may have been the result of using a correlation analysis which averages the degree of contemporaneous impact across all frequencies. That is problematic because two variables could share a trend or short-term shocks, but show no coherence between their cycles. That would imply low or possibly negative contemporaneous correlations, and give no picture of the true linkage or dependence between them.

The stationary assumption of wine production distribution in the Douro region, as in many other wine regions worldwide, has long been compromised allegedly by climatic changes and improved management techniques (Cunha & Richter, 2012; Jones, 2012). During the last decades several studies based on autoregressive model (Cunha & Richter, 2012), climate (Esteves & Orgaz, 2001; Fraga *et al.,* 2014) or measures of radial growth cycles (Maxwell *et al.,* 2016) pointetowards a clearly identifiable cyclicality of wine production. The conditions during the previous and current years growing season can affect the amount of carbon fixed and allocated to growth and especially grapevines where the current year buds, and therefore fruitfulness, are set during the previous year. As a result, an increase in production has to be offset later.

Therefore, a time-varying spectral analysis, capable of separating out changes at different cyclical frequencies in the regional WP, is capable to provide the flexibility to capture these features. Similarly, a time varying approach will be necessary if we are to accommodate the structural breaks which must be expected with WP and climate variability (Cunha & Richter, 2016). Moreover, if these changes argue for a time-varying approach to measuring the coherence between variables, then they also argue for a decomposition of the different cycles that make up wine production performance. Hence our choice of a time-frequency approach.

This paper provides a temporal analysis of the cycles of WP from 1933 to 2013 in Douro region. Firstly, the wine production's variance was decomposed in order to find the dominating cycles. The second step, identify the importance of climate variability for the cyclical properties of wine production, and analyse the predictability of these events. We apply a time-frequency approach, which not only gives us the cyclical properties, but also how they changed over time (if they changed at all) possibly due to climate variability. A Kalman Filter is used to estimate the parameters of the discrete time Fourier transform. References are made to experimental data and methodological approaches which provide support to the hypotheses on the interaction of cyclical wine production and climate (multi-year) carry over effects, namely through soil water interaction.

2. Material and methods

2.1. Wine industry, Douro region

The Douro valley is one of the most arid wine regions of the world, with strong and consistent post-flowering water and thermal stress. These situations are especially frequent in summer and appear as a consequence of the low soil water content (stony soils), due to low rainfall and the elevated gradients of the water vapour pressure between the leaves and the air (Chaves & Rodrigues, 1987). Since most of the vineyards in Douro region are no-irrigated and most of rain occurs outside the vegetative growth cycle, available soil water should be an important drive of the temporal variation of wine production in the Douro region (Jones, 2012).

The Douro Region, located in northeast Portugal, has an area of 250,000ha and vineyards cover approximately 15.4% of all the land in the region. Viticulture, the main activity of most farmers in the region, takes place under particularly rigorous climatic conditions, on stony soil which is unsuitable for other agricultural use.

Out of the entire amount of land used as vineyards in the Douro region, only 26,000ha (about 68%) are authorised for the production of Port Wine. The vines which are considered appropriate for this wine type are selected according tocriteria of quality based on a scoring method (considers soil, climatic, varieties, age of the vines), and classified according to a scale of quality that ranges from A to F.The importance of climate conditions for wine production in Douro is emphasised by the score leading to the A–F classification were the parameter related with climate conditions represents 62.5% (IVDP, 2016).

According to Köppen's classification, the region belongs to group Csb (temperate, with dry summer, which is not very hot but extensive), while Thornthwaite's rational climate classification (Thornthwaite, 1948) describes it as B1B′2s2a′ humid (hydric index: 25.3%; B1), mesothermic (thermal efficiency index: 778 mm evapotranspiration; B′2), with great shortage of water in the summer (aridity index: 38%; s2) and thermal efficiency summer concentration index: 47% (above 20% = typically continental).

The mean annual precipitation in the Douro region vary from 400 to 900 mm and the mean monthly temperatures range from 5 to 8°C (January) up to 21–24°C (July). During the period April–October, the mean temperature is about 19.5°C and according to the climate maturity grouping (Jones, 2007), the growing season can be defined as "warm" (April– October; mean temperature between 19 and 24°C). In the ripening period (20 July to 20 September), the rainfall in 80% of years is ≤28 mm (Reis & Lamelas, 1988) and the available water reserve at the end of the ripening period is lower than 20% (Cunha et al., 2003).

2.2. Wine production data

In this paper, we use the annual wine production data (1933–2013) for the Douro region provided by the *Instituto dos Vinhos do Douro e Porto* (IVDP, 2016). In the Douro region, the drawback of wine yield estimations is the lack of annual detailed regional data of the dynamics of new plantings, replanting, removal and age composition of vineyard. Moreover, no reliable information is known about the rate of changes in vineyard area for each year.

However, the percent share of young vineyards (less than 4 years)in 1998 is less than 4% in comparison to all other vineyards (IVDP, 2016). Therefore, our modelling assumption is that this share of young vineyardsremained constant in our sample and is reasonably small not to jeopardise the stability of the productivity link.

In this context, the expected upward long-term trend in the times series of wine production is mainly a reflection of the increasing production area (known factor). As the trend does not depend on climate, it must be removed before subjecting the data to regression analysis.

2.3. Meteorological data

The meteorological observations for the years 1933–2013 were collected in the weather station of Peso da Régua (41º10′N, 7º47′W), located within the Douro region. The meteorological data consist of daily observations for mean, maximum and minimum temperature (Tm; °C) and precipitation (R; mm).

The target variable (wine production) has only one value per year and the explanatory variables are presented on daily base. Therefore, the daily climate was aggregated to extract some soil-climate metrics (e.g. available soil water) and also converted to temporal seasonal periods: Spring temperature (ST) and Soil Water (SW) in the summer. The ST relate to the period of maximum shoot growth, flowering and fruit-set of the grapevine growth in the region. The SW during the summer period are related with the period of grape development and the period between veraison and harvest.

The daily climate data for the period 1933 to 1950 were obtained from the "Serviço Meteorológico Nacional – Mapa de apuramento mensal" (records in paper). For this period the climate data are complete (no missing data) and it was not possible to know the quality control (if any) used for climate data inspection. For the period 1950 to 2013 the climate data was subject manual examination to assess missing data.

Daily climate data covering all the period analysed (1933 to 2013) were subject to quality control to examine outliers, adjusted missing data values, and check the temporal homogeneity of the data, using the procedures developed by Peterson *et al.* (1998) and applied by Jones (2012) to climate data in Douro region. The software package RHtestsV4 [Retrieved from]. was used for assessment of the quality of the meteorological data. This is an

R application written developed and maintained by Xiaolan Wang and Yang Feng (Environment Canada).

2.4. Soil water balance

In this paper metrics of vineyard soil water status for the period 1933 to 2013 were simulated by using the Vineyard Soil Irrigation Model (VSIM). The VSIM has been used for simulation of daily and seasonal soil water balance for vineyard based on climate (rainfall, temperature), soils (texture, rooting depth), and leaf area index (LAI). The background and computation of VSIM is fully described in Pierce *et al.* (2015).

In VSIM, soil water balance (eq. 1) is described using a simple bucket approach over the entire root zone of the plant, which takes into account, on a daily (d) basis, the gains and losses of water flow through the vine and soil:

$$SW_d = SW_{d-1} + R - ETc - Runoff \tag{1}$$

This model is initialized with soil moisture information and the input flows are rainfall (R) and available soil water (SW_{d-1}), than output flows as crop evapotranspiration (ETc, eq. 2) from the soil-plant system, and surface water "Runoff".

Daily ETcwithin VSIM is evaluated to a modified FAO crop model (Allen *et al.*, 1998), based on reference evapotranspiration (ETo) and a crop coefficient (kc, eq. 3) adjusted for stress conditions (ks, eq. 4):

$$ET_c = ET_0 \times (Kc \times Ks) \tag{2}$$
$$Kc = 1 - e^{(-ext\_coeff \times LAI)} \tag{3}$$
$$Ks\ (0\text{-}1) = 1 - (WPmax - WPday)/WPmax - WPmin) \tag{4}$$

The model computes daily vine canopy LAI, from bud-break through canopy leaf fall using a relationship between LAI and Growing Degree Days (GDD) (e.g. Williams & Ayars, 2005). The crop coefficient (Kc) is a curvilinear function of LAI growth, based on the Beer's Law and on canopy light extinction coefficient (Campbell & Norman, 1997). The Kc estimated from LAI is adjusted downwards by a scalar (0-1; Ks) designed to down-regulate Kc under increasing vine water stress in order to simulate the effects of increasing water stress on reducing stomatal conductance. The maximum soil water-holding capacity, wilting point and field capacity as well as soil/leaf water potential used in Ks is obtained from the calculated soil moisture using the model based on soil texture developed by Saxton *et al.* (1986). The daily estimated vine water potential (WPday) is compared to the water potential under maximum stomatal conductance (WPmax = - 4 Mpa) and to water potential under which stomatal conductance is at minimum (WPmin = -1.5 MPa) (e.g. Schultz, 2003).

The VSIM model has been validated for vineyards in different wine regions with good results (e.g. Johnson *et al.*, 2006). We validated the VSIM

for the Douro region with field measurements of vine water potential acquired in a commercial vineyard (Quinta dos Aciprestes, Real Companhia Velha) in Soutelo do Douro (41.21º N of latitude and 7.43ºW of longitude) between June and September of 2014 (Cunha & Richter, 2016).

The climate, soil water and LAI parameters as well as the inputs for Kc used for VSIM's validation in Douro region are presented in table 1. The daily reference evapotranspiration were estimated by using the Ref_ET programme for windows (Allen, 2015). The VSIM calculates the water potential using the soil water content vs. water potential characteristic curve (Saxton *et al.*, 1986), and assuming that the grapevine water potential is equal to soil water potential.

Table 1. *Description of the inputs parameters used in the vineyard soil irrigation model (VSIM) to simulate the available soil water in Douro for the years 1933 to 2013*

Variable/input	Name	Units	Value
GDD at Budbreak (TBase = 0ºC)	GDD_{Bb}	ºC d	865
GDD at peak LAI (TBase = 10ºC)	GDD_{Pk}	ºC d	600
Light extinction coefficient (Beer's Law)	LEc	[ ]	0.6
Yearday of leaf drop and canopy senescence	Ld	DOY	285
Distance between rows	RW	m	2.1
Distance between vines	L	m	1.1
Soil moisture storage at field capacity	FC	mm/m	295.2
Soil moisture storage at wilting point	WP	mm/m	140.8
Maximum soil water-holding capacity	MSWHC	mm/m	154.4
Optimal midday stem water potential	LWP_{op}	MPa	0.9
Vine water potential to initiate reduction in Kc	LWP_{Kcmax}	MPa	0.5
Vine water potential at which Kc = 0	$LWP_{Kc=0}$	MPa	1.2

Notes: GDD Growth Degree Day calculated for a growing period (budbreak or peak LAI) using a temperature base (TBase). LAI Leaf Area Index

3. Time-frequency analysis of the wine production

3.1. Estimation in the time domain

In the first step, we estimate the cyclic behaviour of each individual variable, i.e. wine production (WP), spring temperature (ST) and soil water (SW) using an Autoregressive Model of order "p" (AR(p)), where p is determined by statistical tests. In order to allow for the possible changes in the parameters, we will employ a time-varying model AR(p) by applying a Kalman filter to the chosen model as follows:

$$y_t = \alpha_{0,t} + \sum_{i=1}^{9} \alpha_{i,t} y_{t-i} + \varepsilon_t \tag{5}$$

with

$$\alpha_{i,t} = \alpha_{i,t-1} + \eta_{i,t}, \text{ for } i=0...9 \tag{6}$$

and $\varepsilon_t, \eta_{i,t} \sim \text{i.i.d.}\left(0, \sigma^2_{\varepsilon, \eta_i}\right)$, for i=0...9.

In order to run the Kalman filter we need initial parameter values. The initial parameter values are obtained estimating them by Ordinary Least Squares (OLS) using the entire sample (see also Wells, 1996). Of course, using the entire sample implies that we neglect possible structural breaks. The initial estimates might therefore be biased. The Kalman filter however corrects for this bias since, as Wells (1996) shows, the Kalman filter will converge to the true values independently of the initial values. Hence, our start values have no effect on the parameter estimates, i.e. our results are robust. Given these starting values, we can then estimate the parameter values using the Kalman filter. We then employ a general to specific approach to obtain a final specification for (eq.5), eliminating insignificant lags using the strategy specified in the next paragraph below. The maximum number of lags was determined by the Akaike Criterion (AIC). The AIC takes indirectly into account whether a variable is significant or not. If not then the AIC value usually drops. Each time we ran a new regression we used a new set of initial parameter values. Then, for each regression we applied a set of diagnostic tests, shown in the tables in the following sections, to confirm the final specification found. The final parameter values are therefore filtered estimates, independent of their starting values.

Using the specification above implies that we get a set of parameter values for each point in time. Hence, a particular parameter could be significant for all points in time; or at some periods but not others; or it might never be significant. These parameter changes are at the heart of this paper as they imply changes in the lag structure and hence changes in the spectral results. If a parameter was significant for some periods but not others, it was kept in the equation with a parameter value of zero for those periods in which it was insignificant. This strategy minimised the AIC criterion, and led to a parsimonious specification. Finally, we tested the residuals in each regression for auto-correlation and heteroscedasticity.

The final specification (eq.5 and 6) was then *validated* using two different stability tests. Both tests check for the same null hypothesis (in our case a stable AR(9) specification) against differing temporal instabilities. The first is the fluctuations test of Ploberger *et al.* (1989), which detects *discrete* breaks at any point in time in the coefficients of a (possibly dynamic) regression. The second test is due to LaMotte & McWorther (1978), and is designed specifically to detect *random* parameter variation of a specific unit root form (our specification). We found that the random walk hypothesis for the parameters was justified for each model (results available on request). We also test for autocorrelation of the residuals. For this purpose we use the Ljung-Box test, which allows for autocorrelated residuals of order p. In all our regressions, we could reject the hypothesis of autocorrelation.

Finally we chose the fluctuations test for detecting structural breaks because the Kalman filter allows for structural breaks at any point in time and the fluctuations test is able to accommodate this. It should be noted,

that all our tests of significance, and significant differences in parameters, are being conducted in the time domain, *before* transferring to the frequency domain. This is because no statistical tests exist for calculated spectra (the data transformations are nonlinear and involve complex arithmetic). Stability tests are important here because our spectra are sensitive to changes in the underlying parameters. But, given the extensive stability and specification tests conducted, we know there is no reason to switch to another model that fails to pass those tests.

Once this regression is done, it gives us a time-varying AR(p) model. From this AR(p) we can then *calculate* the short–time Fourier transform as outlined below, and as originally suggested by Gabor (1946), in order to *calculate* the associated time-varying spectrum.

3.2. Spectral analysis

As a first step we analyse the power spectral density function of the wine production in Douro region. The power spectral density function (PSD) shows the strength of the variations (energy) of a time series at each frequency of oscillation. In other words, it decomposes the variance of a time series into its periodicities. In a diagram it shows at which frequency variations are strong/powerful, and at which frequencies the variations are weak (expressed in "energy"). The unit of measurement in the PSD is energy (variance) per frequency, frequency band or cycle length.

For example, if a time series $X_t = \varepsilon_t$, where $\varepsilon_t \sim i.i.d.\left(0, \sigma^2\right)$ and constant over time, the power spectrum would look like figure 1.
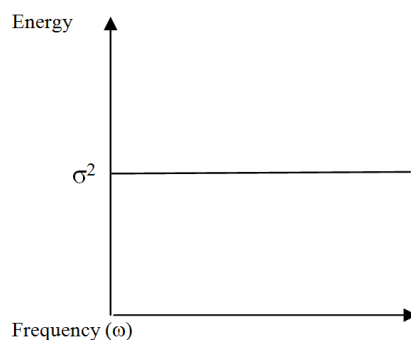

Figure 1. *Hypothetical spectrum for a constant variance*

As one can see from figure 1, a white noise process is characterised by the fact that no specific frequency has a bigger impact than any other frequency, for $\omega = 0, ..., \pi$. However, if the data were dominated by long wine production cycles, then the diagram would have higher power (variances) at the low or middle frequency bands respectively; and lower power at the high frequencies. In the spectral diagrams that follow, we use the term "power" rather than "energy" to denote relative variances.

In order to calculate the spectrum from an estimated representation of (eq.5), we use the Fast Fourier Transform. The Fast Fourier Transform is an

efficient algorithm for computing a discrete Fourier transformation or in our case a Discrete Time Fourier Transform (DTFT) for discrete points in time. In our case it creates a *frequency domain* representation of the original *time domain* representation of the data (eq.5). Hence, our analysis of the spectra and coherences that follow are based on a regression done in the time domain, but then transformed into a frequency domain function by the Fourier transform. However, in this paper we also allow the coefficients of our regressions to vary over time. Therefore we derive one DTFT for each point in time. For technical details please refer to Appendix.

Thus, when we present our empirical results below, they are based on the time-varying of short time Fourier transform (STFT) calculations (eq. A1 and A2, appendix). The only difference from figure 1 is that we have to add a time dimension to show how the spectra have changed over time. The result is then a 3-dimensional diagram.

3.3. Cross-spectral analysis

In this paper we also investigate the linkage between different wine production cycles. In the frequency domain, the natural tool to do that is the coherence. The spectral coherence $\left(K_{XY}^2 \right)$ is a statistic that can be used to examine the relation between two signals or data sets. Values of the coherence will always satisfy $0 \leq K_{XY}^2 \leq 1$. For a strictly proportional linear system with a single input x_t and single output y_t, the coherence will equal one. If x_t and y_t are completely unrelated then the coherence will be zero. If K_{XY}^2 is less than one but greater than zero it is an indication that output y_t is being produced by input x_t as well as by other inputs. Hence, the coherence is nothing else than the R^2 in the frequency domain. Since we are calculating the coherence using the short time Fourier transform, the coherence may also be time-varying. So we have to extend K_{XY}^2 by a time index. For the rest of this paper we will write $K_{XY,t}^2$.

Suppose now we are interested in the relationship between two variables $\{ y_t \}$ and $\{ x_t \}$, where $\{ y_t \}$ is the wine growth rate and $\{ x_t \}$ is the temperature variability for example. We assume that they are related in the following way:

$$V(L)_t \, y_t = A(L)_t \, x_t + u_t, \quad u_t \sim \text{i.i.d.} \left(0, \sigma^2 \right) \tag{7}$$

where $A(L)_t$ and $V(L)_t$ are filters, and L is the lag operator such that $Lz_t = z_{t-1}$. Notice that the lag structure, $A(L)_t$, is time-varying. That means we need to use a state space model (we use the Kalman filter again) to estimate the implied lag structure. That is

$$v_{i,t} = v_{i,t-1} + \varepsilon_{i,t}, \text{ for } i = 1, ..., p \text{ and } \varepsilon_{i,t} \sim \left(0, \sigma_{\varepsilon_i}^2\right)$$

$$a_{i,t} = a_{i,t-1} + \eta_{i,t}, \text{ for } i = 0, ..., q \text{ and } \eta_{i,t} \sim \left(0, \sigma_{\eta_i}^2\right)$$

(8)

As before, we test for the random walk property using the LaMotte-McWorther test, and for structural breaks, we employ the fluctuations test (Ploberger *et al.,* 1989). Finally, we use our previous general to specific approach to estimate (eq. A.3, appendix); starting off with lag lengths of nine and p=q, and dropping those lags which were never significant (as we did before).

Having estimated the coefficients in equation 7, we can calculate the gain, coherence and cross spectra based on the time-varying spectra just obtained. This allows us to overcome a major difficulty in this kind of analysis: namely that a very large number of observations would usually be necessary to carry out the necessary frequency analysis by direct estimation. That would be a particular problem in the case of structural breaks, since the sub-samples would typically be too small to allow the associated spectra to be estimated directly.

As the coherence is equivalent to the R^2 statistic it can be interpreted accordingly. The gain is equivalent to the regression coefficient or the impact/transmission effect of x_t on y_t, in the time domain. Thus the coherence measures, for each frequency, the degree of fit between x_t and y_t: equivalentto the R^2 between each of the corresponding cycles in x_t and y_t. Hence $A(\omega)_t$ and $K_{YX,t}^2$ (see appendix) measure the link between two variables at time t. For example, if the coherence has a value of 0.6 at frequency 1.2, then it means that the variable (e.g. spring temperature) cycle at frequency of 1.2 determines wine production cycle at that point in time by 60%. Similarly a gain of 0.5 means that half the variance in spring temperature cycle at that frequency is transmitted to the wine production cycle. In this paper, we are concerned with the coherence and gain, not with measuring the phase shift elements as such. But we are able to detect changes in phase relationships from changes in the relative importance of different cycles in the cross-spectral components.

4. Results

In the figures shown in this section, we first present the time-varying spectrum and then the coherence and gain. One can see from the figures that the spectra change. However, one cannot infer directly from those figures that the changes in the spectra are also statistically significant. The figures for the time-varying spectra/cross-spectra have to be accompanied by the fluctuation test results. Once a structural break has been identified by the fluctuations test, the results will show up as a significant change in the associated spectrum or coherence or gain. The results of the fluctuation tests are available from the authors upon request.

4.1. Single spectra of Douro wine production

Figure 2 shows the time series of wine production in the Douro Region from 1933 to 2013. There is evident up-ward trend in wine production. Also, for most of the sample this time series shows a lot of variation, which can be caused by structural breaks (which in turn may be caused by climate effects). In any case, this variation makes a common regression very difficult, as it does not really capture the variation. In contrast, time-varying parameter approaches can capture those parameter changes in a systematic way.
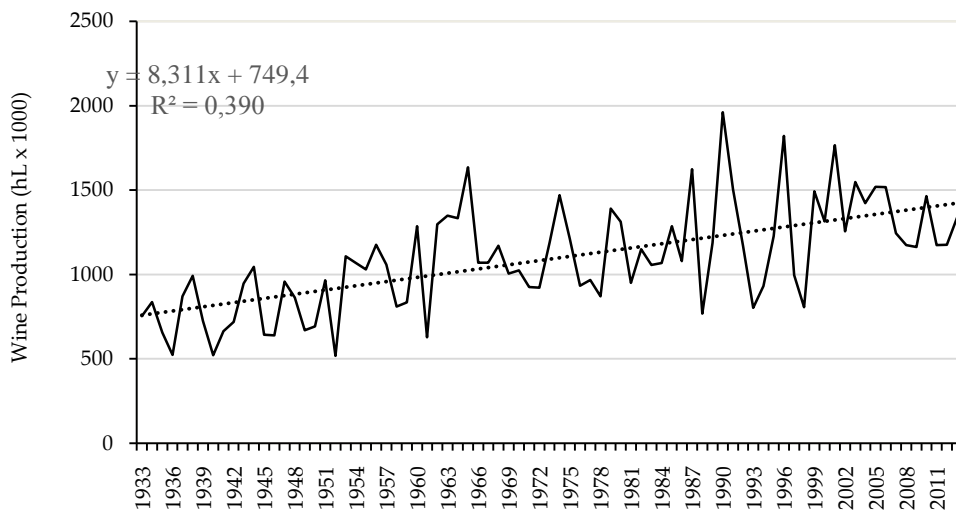
Figure 2. *Time series and estimated linear trend ofwine production for the period 1933 to 2013in the Douro wine region.*

Equation 9 shows the regression result for the series of wine production (WP) based on estimation by Kalman filter using 70 observations, i.e. the end of the sample. Table 2 presents the statistics for adequacy of this autoregressive model.

WP (hL x 10³) = 559.7775 - 0.01042WP1 + 0.018633WP2 + 0.014452 WP3 + 0.456167 WP5   (9)

SE	20.82468	0.135716	0.118789	0.09716	0.04362
z_statistic	26.88048	-0.07676	0.156856	0.148747	10.45765

The number after each dependent variable represents the lag of the actual season. For example WP3 and WP5 are, respectively, the 3nd and the 5th lag of WP. We employed a general to specific approach (starting with 9 observations) to obtain a final specification for the equation 5. This AR(5) model is the basis for the spectrum shown in the figure 3.

Table 2. *Regression results for wine production volume (WP), mean spring temperature (ST) and soil water in summer (SW) for the period 1933-2013 in Douro region. Estimation by Kalman filter using 70 observations.*

Model Statistics	Autoregressive model (WP)	Spring Temperature (ST)	Soil Water in Summer (SW)
Degrees of freedom	66	65	64
Mean value for Variable	1138.68	16.74	162.58
Std Error for variable	296.81	1.04	22.22
Radj-Square	0.794	0.654	0.832
Standard error of estimate	267.61	267.30	231.75
Sum squares of residuals	5013062	5001563	3759665
Akaike Information Criterion	538.90	317.29	283.06
Ljung-Box Test: Q	25.11	22.11	20.89

As one can see from table 2, the autoregressive model is robust as there is no autocorrelation (Ljung–Box test; Q> 21). For the chosen model, this was in fact, the lowest AIC value (results not showed). The adjusted R_{adj}-squared is relatively high with 79%, but there is still some unexplained variance. Although the first four lags are statistically not significant at the end of the sample, they were at other sample points in time, which is why we kept them in the regression (Eq. 5). Hence, this equation only shows the final regression for the last observation for reason of restricted space.

The time-varying spectrum, which is based on regression presented on equation9 shows the dynamic characteristics of the wine production. Over the entire frequency band, there are three distinctive peaks: at 0.1, 1.3 and 2.5 (Fig. 3). A frequency of 0.1 basically represents the long run trend. In figure 3 the trend can be seen in the upper left hand corner.
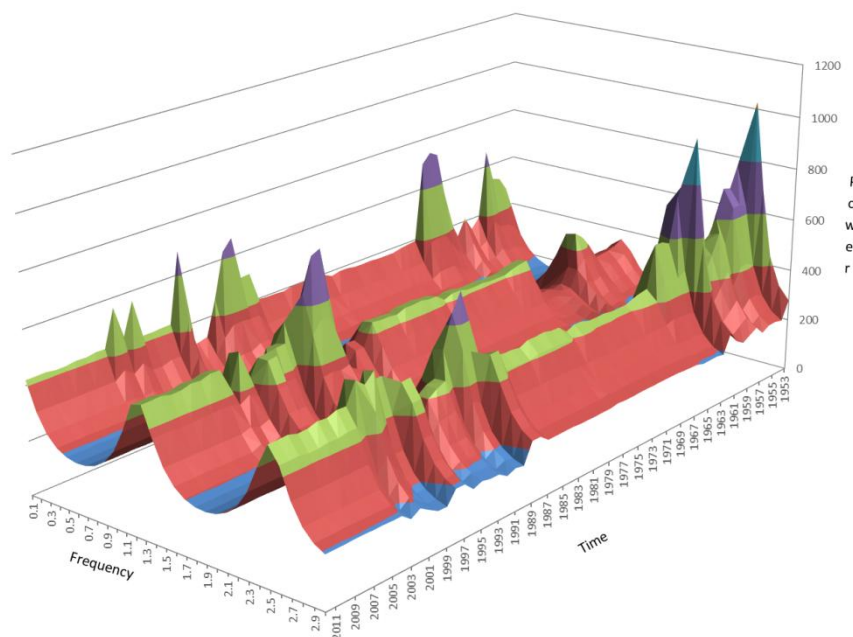

Figure 3. *Time-varying spectrum of the wine production for the period 1933-2013 in Douro region*

It has a spectral mass of about 1.1 and 2.5. Hence these three cycles are equally important. This is particularly true for the last five years of the sample. That was no always the case, for example during the 1990s (Note: the link between period (P) and frequency (ω) is P=2*π/ω). Hence, currently wine production is characterised by a long run trend and two shorter cycles of 5.7 years and 2.5 years, respectively. This means the time span from one peak in WP to another is approximately 6 and 2.5 years respectively.

4.2. Cross spectra of Douro wine production

4.2.1. The effect of temperature on wine production

Having established what characterises the wine production cycles, the next question is what causes them. The spectrum in itself cannot answer this question. It is purely descriptive.

We had the choice of several exogenous variables which may have an impact on wine production. Notably, we have time series of temperature and soil water for the period 1933 to 2013. The aim was to find a determinant that can explain the observed production pattern and therefore the "most important" variable. As it turned out among all models containing different temperature variables (daily minimum and maximum temperature for all seasons), the one that produced the lowest AIC value was the one containing mean temperature in spring (data not showed).

Equation 10 shows the regression results for wine production (WP) and spring temperature (ST, ºC) based on estimation by Kalman filter using 70 observations.

$$WP \ (hL \times 10^3) = -237.34 - 0.074 \ WP1 + 0.217 \ WP5 + 104.36 \ ST - 6.87ST2 - 22.59 \ ST3 \tag{10}$$

SE	1.46×10^{-5}	0.047	0.043	3.14	2.66	2.86
z_statistic	-1.60×10^7	-1.564	4.989	33.19	-2.58	-7.90

The number after each dependent variable represents the lag of the actual season. This model is the basis for the spectrum shown in the figure 4.

In comparison to the autoregressive model(table 2), the regression with STpresents lower values for R_{adj}-square (65%).However, this model with the ST is preferable to the autoregressive one for the lower AIC value (317 in comparison to 539; table 2).

Equation 10shows that WP can be modelled using ST. At the end of the sample the current STas well as the temperatures of previous two and three yearshave significant impact on the WP. In opposite to the current ST, an increase in the past temperature have a negative impact on WP. Also, the first and the 5th lag of wine production are significant.

Although, our model does not say, what exactly causes the increase of the impact of temperature on WP, we argue that this is due to global warming (IPCC, 2007; Jones *et al.*, 2005).

Figure 4 shows the coherence between wine production and spring temperature. We can see from this figure that WP is determined by ST through three main cycles (although other cycles matter as well, but we focus on the important ones): the long run cycle at a frequency of 1.1 (5.8 years), the medium term cycle at 1.5 (4.2 years) and the short term cycle 2.9 (2.2 years). Since 2003, the link for the long run cycle has decreased from over 60% to just over 50%. The medium cycle remained largely constant at 40%, whilst the short term cycle decreased from 50% to 40% as well. This means that medium cycles have the same impact on WP than short term fluctuation. Having said that, the coherence is largely at a value where it was for a long time from the 1960s to the 1990s. Therefore, relatively "low" values for the coherence can be considered as a return to previous values. The higher coherences were an exception than the rule.
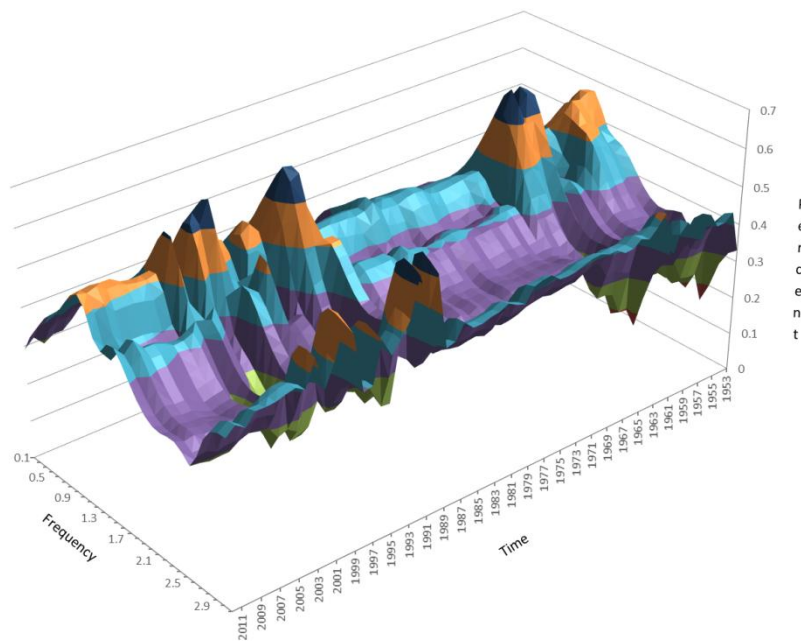

Figure 4. *Coherence between wine production and spring temperature for the period 1933-2013 in Douro region.*

4.2.2. The effect of soil water on wine production

In this section we investigate the effects of SW on wine production. As before we present only the last regression result. From all models of SW in turned out that the most important SW is the one that is in summer. In other words wine production depends more on SW in summer than in spring, for example. Hence, our regression only contains summer soil water (Equation 11 and table 2).

Equation 11 shows the regression results for the series of wine production based on estimation by Kalman filter using 70 observations.

Equation 11 shows the regression results for wine production (WP) and SW is the soil water level (mm) based on estimation by Kalman filter using 70 observations. This model is the basis for the spectrum shown in the figure 5.

$$WP \ (hL \times 10^3) = 598.12 + 0.046WP1 + 0.127WP3 + 0.332 \ WP5 - 5.42 \ SW + 2.04 \ SW2 + 2.76 \ SW3 \tag{11}$$

SE	42.53	0.076	0.104	0.106	0.23	0.15	0.20
z_statistic	14.06	0.605	1.217	3.14	-23.40	13.36	13.74

In comparison to the autoregressive and the spring temperature model (table 2), the R_{adj}-square is now higher (83%). As this model has the lowest AIC value (283 in comparison to 317), this is the most preferred model of the models presented in this paper (table 2). Hence, SW is clearly more important to wine production than ST when it comes to predicting wine production. Although, temperature is also important for WP as pointed out above.

The effects of SW in WP are depending on the timing (Eq. 11). The immediate effect of an increase in SW is negative, whilst the soil water that is in the ground, i.e. from the previous two and three years have a positive effect on wine production.

Given this information we are interested in what dynamic effects are caused by available soil water. As we did in the previous section, we are now looking at the coherence between wine production and soil water (Fig. 5).
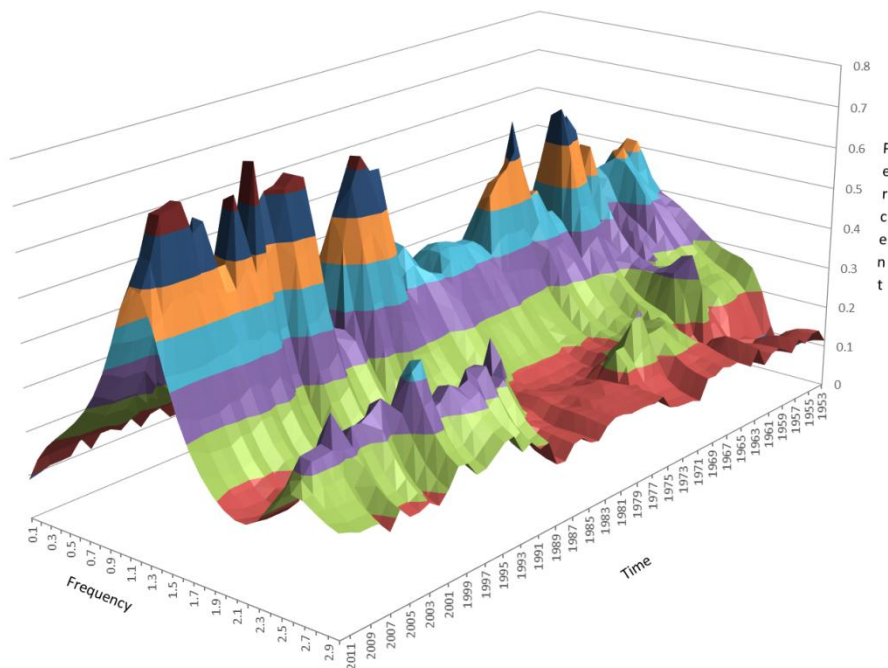

Figure 5. *Coherence between wine production and soil water for the period 1933-2013 in Douro region.*

Figure 5 shows that the coherence between WP and SW is quite stable and centred around a frequency of 0.9 or 7 years as well as a short one of 2.4 years which has been happening since the 1990s. However, it is evident that SW can explain 7 year cycles by 60% in recent years (since the late 1990s). In previous years this link was inbetween 40%- 50%. So there is evidence that the impact SW has on WP increased over time. With regards to the 2.4 year cycle, this is even more evident: before the late 90s soil water could only explain on average 12% of the 2.4 year cycle. This has increased to 30%. Remarkably, both changes took place in the same time period. So from the late 90s onwards, SW became particularly important for the long term WP and the shorter term WP. The fact that both events occurred at the same time (where both changes are statistically significant) indicates that this was not a random behaviour.

5. Discussion

We have modelled the cyclical wine production in Douro region using a time-frequency approach based on Kalm filter regressions for the period 1933 to 2013. The short time Fourier transform was used to decompose the link between WP and spring temperature and soil water in summer. We show how much of the WP cycle and what cycle in particular is explained by the ST and SW. We used two individual regressions in order to avoid multicollinearity, i.e. the two explanatory variables may be correlated with each other making the model not estimable anymore. More importantly, modelling the impact of the two variables separately allows us to decide via the AIC criterion which model/variable is preferable to each other with a clear statistic. This underlines our results as the AIC is 283 in case of SW and 317 in case of ST. This alternative approach was partially presented in previous work for analyses the impact of climate dynamics on wine production (Cunha & Richter, 2012; Cunha & Richter, 2016), vegetation growth Cunha & Richter (2014) and for economics applications (Hughes Hallett & Richter, 2003a; Hughes Hallett & Richter, 2006).

The developed atime-varying autoregressive model that explains 79% (Table 2) of the variability of WP in Douro region which is characterized by two cycles of 5.7 and 2.5 years around the long run trend (Fig. 3). In previous work, Cunha & Richter (2012) developed a time-varying model for the Douro WPbased on the ST for the period 1966 to 2007. It is worth noting that although the regression results are very similar to Cunha & Richter (2012) for the Douro WP for the period 1966 to 2007, the availability of new data (1933 to 2013) meant that the second important cycle is now 5.7 years instead of 4.7 years. That is, the new data shifted the second cycle by one year. Remarkably, these two wine cycles (5.7 and 2.5 years) are also consistent with other previous studies for Douro (Fraga *et al.,* 2014) and Dãowine region in the north-central part of Portugal (Esteves & Orgaz, 2001).

The in-season ST as well as the ST of previous two and three years could explained about 65% of the variability of wine production (eq. 10 and table

2). The current impact of ST is positive, i.e. an increase in ST in any one year will lead to a rise in WP, while previousST have a negative impact on WP. The biggest negative impact on WP has the ST of previous three years. The positive impact of the ST on the WP are in line with previous results (Cunha *et al.,* 2016; Cunha & Richter, 2012; Gouveia *et al.,* 2011; Santos *et al.,* 2013) suggests that actual ST is generally below the optimum level of the main grape temperature-dependent physiological processes related with crop yield, that occurs during spring such as flowering development, anthesis and fruit-set (May, 2004; Vasconcelos *et al.,* 2009). High spring temperature play an important role in triggering the different phenological stages with great impact on avoiding both soil water stress (Duchêne & Schneider, 2005) and diseases (Caffarra *et al.,* 2012) and, consequently on wine production. Further, high spring temperatures are negatively correlated with damage in wine production caused by late frosts spells. The positive effect of in-season spring temperature on WP agree with the previous study for Douro region (Gouveia *et al.,* 2011; Santos *et al.,* 2013) and, northwest de Portugal (Fraga *et al.,* 2014), northwest Spain (Lorenzo *et al.,* 2013), lower Franconia Germany (Bock *et al.,* 2013) and California (Lobell *et al.,* 2007).

When the soil water level in summer was incorporated, the R_{adj}-square increases and the AIC was lower. The current SW as well as the SW of two and three years ago could explained about 83% of the variability of WP. In opposite to the current SW, a decrease in the previous 2 or 3 years have a negative impact on wine production (Eq. 11 and table 2). The significant negative effect of SW in the WP of the current year is in line with the findings of other author for different regions (Bock *et al.,* 2013; Fraga *et al.,* 2014; Jones & Davis, 2000; Lorenzo *et al.,* 2013).

The rationale behind the existence of these cycles could be explained by the development of diseases and/or bud fertility. A high water content in the soil generally favour the development of epidemic diseases in that year with a strong negative impact on WP (Caffarra *et al.,* 2012). Contrariwise, non-irrigated vineyards exposed to consecutive years with both hot ST and low SW, may decreased accumulated reserves of carbon and nutrients in the permanent structure (e.g. May, 2004; Vasconcelos *et al.,* 2009). These reserves can play a critical role in bud fertility (Guilpart *et al.,* 2014), which is directly related with the WP of the following seasons as indicated by our results. Therefore, the predictors used in the developed model are biophysically sound and are supported by the relationship between both ST, SW and the eco-physiological development of the major grapevine yield components.

We use the short time Fourier transform to decompose the link between wine production performance and spring temperature and soil water in summer. The ST is responsible for two long-medium cycles of 5.8 year and 4.2 years as well as a short one of 2.4 years of wine production which has been happening since the 80s (Fig. 5). In difference to Cunha & Richter (2012), the higher number of observations of our model (1933 to 2013) led to

two more variables to be significant: the first lag of wine and the second lag of mean temperature. Because of that it is not surprising that the coefficient values are not identical as in Cunha & Richter (2012), but they are similar. For example, the coefficient on the current temperature is 104 (Eq. 10), whilst in the previous paper it was 149. This implies that despite the lower number of observations, the initial regression was quite robust. In summary, there is a stable but not constant link between production and the spring temperature. The temperature is still important for explaining about 60% the long term and short term behaviour of wine production, but its importance has decreased (Fig. 4).

There is a stable link between production and the soil water level in summer, and 60% of the 7 year wine production cycle is explained by SW. Since the early 1990s soil water is also becoming important for shorter cycles (2.3 years). Soil water can explain around 20% of the short term cycle. The simple appearance of another cycle that has become important is an indicator in itself that available soil water has become more important for wine production.

Whilst the improved analysis of the impacts of climate and climate scenarios on wine production and the mechanisms of adaptation will benefit, it will not in itself ensure adaptive decision-making in the Douro region which therefore needs more research.

6. Conclusion

Regional time series of wine production are emanated from complex system of which we know little. Predictable behaviour of such system like trends and cyclicality, is therefore of great interest. Spectral analysis is an effective tool to search for cyclical behaviour in time series of unknown periodicities. They has the potential to deal with nonstationary data while most of the modelling process assume stationarity, which may or may not be apparent in wine time series data.

The results of the developed model support the hypothesis that wine production are physiologically dependent in several ways on thermic and hydric conditions of the previous years. In this context developing a multiyear' model is very difficult as many of the carry-over effects on growth are not well understood. Therefore, the proposed approach based on time-varying spectral approach, capable of separating out changes at different cyclical frequencies and points in time with respect to wine production, are need to provide the flexibility to capture these features and the important ecophysiological information contained therein. We can recognise a shift of the relative importance away from temperature to soil water. Despite soil water explaining about 70% of wine production cycle, temperature still explains about 50% of those cycles. We interpret this that if in future temperature changes or we experience more infrequent rainfalls as pointed by climatic scenarios, soil water in summer will be the limiting resource for wine production and, therefore, will become relatively more important than temperature.

Whilst the developed model can only give an indication of causal impact of climate on wine production cycles, it contributes to the mounting evidence for causal hypothesis generation, namely, for the multi-year plant-soil interactions through the soil water. This information could be used by the wine industry to support sustainable measures to mitigate the negative effects of climate variability and adapt them to the changing conditions in the Douro region, as well as in other non-irrigated dry regions that represent a large part of the vineyards worldwide. The quantification of the relative impact of climate on the wine cycles is still a huge challenge for developing strategies at an operational vineyard-scale which could be tested where other data sources will be available.

Appendix

The Short Time Fourier Transform (STFT)

In discrete time, this means data to be transformed has been broken up into frames (which usually overlap each other). Each frame is then Fourier transformed, and the (complex) result added to a matrix which records its magnitude, phase and frequency at each point in time. This can be expressed as:

$$STFT\left\{x[n]\right\} \equiv X\left(m,\omega\right) = \sum_{n=-\infty}^{\infty} x[n]\,w[n-m]\,e^{-j\omega n}$$

(A.1)

In this case, m and n are different points in time; ω is the frequency and is continuous; and $j = \sqrt{-1}$. But in most typical applications the STFT is performed using the Fast Fourier Transform, so all variables are discrete and "n-m" would be the estimation window. In our application the window is not constant, but increasing with each new observation. Moreover, we derive the STFT using Kalman filter estimates of (eq. A.1): see section "cross-spectrum analysis" below. The squared magnitude of the STFT then yields the spectrogram of the function:

$$Spectrogram \quad \left\{x_t\right\} \equiv \left|X\left(\tau,\omega\right)\right|^2$$

(A.2)

The remaining question is what algorithm do we use to calculate the Fast Fourier Transform? One algorithm often used to calculate the Fast Fourier Transform is the Bluestein algorithm (Bluestein, 1968), which is also called the chirp z-transform algorithm. In particular, it can compute any transform of the form:

$$X_k = \sum_{n=0}^{N-1} x_n z^{nk}, \text{ where } k = 0, ..., M-1$$

(A.3)

for an *arbitrary* complex number z and for *differing* numbers N and M of inputs and outputs (see also: Rabiner *et al.,* 1969). Hence, the algorithm we apply to calculate the Fast Fourier Transform is a well-established algorithm and widely used in engineering (Boashash, 2003; Boashash & Reilly, 1992).

Finally Boashash & Reilly (1992) have shown theoretically that, once equation 6 (see also section cross spectral analysis) has been estimated, its coefficients $\alpha_{i,t}$ can be used to calculate the short time Fourier Transform and the power spectra directly (by applying the Bluestein algorithm). That has the convenient property that the traditional formulae for the power spectral density function (PSD) are still valid and may still be used, but they have to be recalculated at each point in time. The time-varying spectrum of the growth rate series can therefore be calculated as follows (see also: Lin, 1997):

$$P_t\left(\omega\right) = \frac{\sigma^2}{\left|1 + \sum_{i=1}^{9} \alpha_{i,t}\exp\left(-j\omega i\right)\right|_t^2}$$

(A.4)

where ω is angular frequency and j is a complex number. The main advantage of this method is that, at any point in time, a power spectrum can be calculated instantaneously from the updated parameters of the model. Hence, we are able to generate a power spectrum even if we have a short time series and even if that time series contains structural breaks.

For the Cross Spectral Analysis, we use the methods introduced in Hughes Hallett & Richter (2009a; 2009b; 2009c). The time-varying cross spectrum, $f_{YX}(\omega)_t$, using the STFT can be written as:

$$f_{YX}\left(\omega\right)_t = \left|T\left(\omega\right)\right|_t f_{XX}\left(\omega\right)_t \tag{A.5}$$

where $T(\omega)_t$ is the transfer or filter function is defined by (eq. A.5) and calculated as follows:

$$T\left(\omega\right)_t = \left(\frac{\sum_{b=0}^{q} a_{b,t}\exp\left(-j\omega b\right)}{1-\sum_{i=1}^{p} v_{i,t}\exp\left(-j\omega i\right)}\right), \text{ for } t = 1, ..., T \tag{A.6}$$

The last term in (eq. A.5), $f_{XX}(\omega)_t$, is the spectrum of predetermined variable. This spectrum may be time varying as well. However, in this paper we are interested in the coherence and in the composition of the changes to that coherence over time. So we need to establish expressions for the coherence and gain between x_t and y_t to show the degree of association and size of impact of x_t on y_t. The spectrum of any dependent variable is defined as (Jenkins & Watts, 1968; Laven & Shi, 1993; Nerlove $et\ al.$, 1995; Wolters, 1980):

$$f_{YY}\left(\omega\right)_t = \left|T\left(\omega\right)_t\right|^2 f_{XX}\left(\omega\right)_t + f_{vv}\left(\omega\right)_t \tag{A.7}$$

From (eq A.4) we get the time varying residual spectrum

$$f_{vv}\left(\omega\right)_t = \frac{f_{uu}\left(\omega\right)_t}{\left|1-\sum_{i=1}^{p} v_{i,t}\exp\left(-j\omega i\right)\right|^2} \tag{A.8}$$

and the gain as $A\left(\omega\right)_t = \left|T\left(\omega\right)_t\right|^2$. Finally, given knowledge of $f_{YY}(\omega)_t$, $\left|T\left(\omega\right)_t\right|^2$, and $f_{XX}(\omega)_t$, we can calculate the coherence at each frequency as:

$$K_{YX,t}^2 = \frac{1}{\left\{1+f_{VV}\left(\omega\right)_t\Big/\left(\left|T\left(\omega\right)_t\right|^2 f_{XX}\left(\omega\right)_t\right)\right\}} \tag{A.9}$$

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