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ORIGINAL PAPER

Measuring the impact of temperature changes on the wine production in the Douro Region using the short time fourier transform

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Abstract This paper investigates the cyclical behaviour of the wine production in Douro region during the period 1932–2008. In general, wine production is characterised by large fluctuations which are composed of short-term and/or long-term cycles. The aim of this paper is twofold: firstly, we decompose the wine production's variance in order to find the dominating production cycles, i.e we try to explain whether wine production follows more long-term or short-term cycles. In the next step, we try to explain those cycles using a dependent variable, namely the medium spring temperature (Tm_Sp) for the period 1967–2008. We estimated a Time-Varying Autoregressive Model, which could explain 75% of the production that is characterised by 4.8- and 2.5-year cycles. We use the Short Time Fourier Transform to decompose the link between wine production and temperature. When the temperature was incorporated, the R^2 increased and the Akaike criterion value was lower. Hence, Tm_Sp causes a large amount of these cycles and the wine production variation reflects this relationship. In addition to an upward trend, there is a clearly identifiable cycle around the long-term trend in production. We also show how much of the production cycle and what cycle in particular is explained by the Tm_Sp. There is a stable but not constant link between production and the Tm_Sp. In particular, the temperature is responsible for 5.2- and 2.4-year cycles which has been happening since the 1980s. The Tm_Sp can also be used as an indicator for the 4.8- and 2.5-year cycles of production. The developed model suggests that stationarity is a questionable assumption, and this means that historical distributions of wine production are going to need dynamic updating.

Keywords Spectral analysis · Time-varying spectra · Kalman filter · Wine production modelling · Climate variability

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Introduction

Regional wine production is characterised by large inter-annual fluctuations with adverse consequences for everybody involved in vineyards and the wine industry as a whole. Moreover, the impact of these fluctuations have consequences concerning input use, land use and thus, indirectly, the environment.

Moreover, Santos et al. (2010) and Esteves and Orgaz (2001) investigated the impact of the climate on wine production in Portugal, that is in the Douro and Dao regions. Both studies found a significant impact of the climate on the wine production. In the Mediterranean region, climate is a major risk, probably due to the broad spectrum of possible negative climate events and to the uncontrolled aspects of natural hazards (Quiroga and Iglesias 2009). The main part of the inter-annual variability in the atmospheric circulation of the western European (Iberian) areas can be tied to large-scale geophysical mechanisms of which the most prominent is the North Atlantic Oscillation (NAO) (Hurrell 1995; Hurrell and Van

Loon 1997; Corte-Real et al. 1998). Through its control over regional temperature and precipitation variability, atmospheric teleconnections can affect vegetation dynamics (Vicente-Serrano and Heredia-Laclaustra 2004) and wine productivity and quality (Esteves and Orgaz 2001). In this context, climate regulates nearly every step of wine production from selection of a suitable grape variety to the type and quality of wines produced.

Detecting and characterising changes of the dynamics involved in wine production over time is the natural first step towards identifying the key determinants of this process. Various crop modelling approaches are proposed in the agricultural literature focusing on investigating the cyclical factors associated with crop production and studying how these crop cycles should be characterised and measured. In order to support management decisions, a number of parametric and non-parametric risk analysis models were developed (Ferris 2006; Goodwin and Ker 1998; Capitanio and Adinolfi 2009; Gemmil 1978; Chen and Chang 2005). However, there are only a few risk analysis models available for wine production (Folwell et al. 1994; Quiroga and Iglesias 2009). Usually, such analyses are based on probability distributions arising from historical data where the distributions developed are based on at least a partial assumption on stationarity and do not incorporate sensitivity tests or (estimate) changes in distribution outcomes (Chen et al. 2004; McCarl et al. 2008; Zhu et al. 2008). Evidence exists that climate change will shift the mean and variance of crop yields, challenging the stationary assumption (Milly et al. 2008). In this context, crop yield-related risk analysis would need to use distributions with non-stationary means and variances along with possibly shifting higher order moments (McCarl et al. 2008).

The link between wine production and in-season climate data has been studied through many research articles (Folwell et al. 1994; Cunha et al. 2003; Bindi et al. 1996). However, the perennial nature of grapevine means that every year is physiologically dependent in several ways on the previous years (May 2004; Vasconcelos et al. 2009). The permanent structures of grapevine provide reserves of carbon and nutrients but also carry effects from year to year. Therefore, developing multiple years' models is very difficult as many of the important carry-over effects on growth or cropping are not well understood.

The traditional approach to modelling the cyclicality of wine production is to assume normal climate and project crop yields as a linear extension of past trends. Although this linear trend describes the overall long-term trend in production, it does not reflect the inherent cyclicality in production and the information contained therein. Indeed, the explanatory power of a linear model is less than 50% (Phares 2000; European Commission 1997; Santos et al. 2010). This implies that, instead of using this model to forecast wine production, one could as well flip a coin.

When conducting a long-time cyclical analysis, one has to take into account that the analysis is affected by structural and climatic variability of the vineyard. At this time there is no regional analysis that co-integrates these two sources of information.These are the changes we wish to test for here. Enhanced production and climate effects will come in several parts: obviously, climate affects production via grapevine growth convergence (coherence, correlation), but production methods have changed themselves and there is a non-constant impact (or spillovers) of climate onto wine production, which translates into stronger lead/lag relationships between production and climate. We examine all three in this context, focusing on measures of coherence and gain, respectively. We can then ask: to what extent are production cycles becoming more correlated to climate?

We are therefore engaged in an exercise in identifying the linkages between climate and wine production using a time–frequency approach. We are not aware that this has been attempted before. In this paper, we show how to use a time-varying spectral analysis to determine the degree of impact at different frequencies and cycles, even where data samples are small and where structural breaks and changing structures are a part of the story. The inconclusive results obtained in the past 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.

A common feature of all the studies cited above is that the results are sensitive to: (1) the choice of coherence measure (correlation, concordance index); (2) the choice of cyclical measure (classical, deviation or growth cycles); and (3) the detrending measure used (linear, Hodrick-Prescott filter, band pass, etc.). This sensitivity to the detrending technique is a serious difficulty highlighted in particular by Canova and Dellas (1993) and Canova (1998). The advantages of using a time–frequency approach are therefore:

- It does not depend on any particular detrending technique, so we are free of the lack of robustness found in many recent studies. These methods also do not have an "end-point problem"
- No future information is used, implied or required as in band-pass or trend projection methods.
- There is no arbitrary smoothing parameter, such as in the HP algorithm, equivalent to an arbitrary band-pass selection (Artis et al. 2004).
- We use a coherence measure which generalises the conventional correlation and concordance measures.

Any spectral approach is tied to a model based on a weighted sum of sine and cosine functions. However, that is not restrictive. Any periodic function may be approximated arbitrarily over its entire range, and not just around a particular point, by its Fourier expansion (a suitably weighted sum of sine and cosine terms), and that includes non-differentiable functions, discontinuities and step functions. Hence, once we have time-varying weights, we can get almost any cyclical shape we want. Therefore, a time-varying spectral approach, capable of separating out changes at different cyclical frequencies in the regional wine production, will be needed 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 wine production methods and meteorological variability. However, 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.

Materials and methods

Wine industry, Douro region and sample data

Portugal is number five in the European wine producers ranking and the number ten world-wide (OIV 2010), and it accounted for 7% (246 10^3 ha) vineyard surface and around 4% (7.1 10^6 hL) of the total wine production in the EU-15.

The Douro Region, located in northeast Portugal, has an area of 250,000 ha 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 that cannot be put to any other use. The Douro region is characterised by having mountain viticulture, with more than 70% of vineyards planted on hillsides with a slope greater than 30% (IVDP 2010). The most noteworthy red wine varietals, all of them native to the region, are Touriga Franca, Touriga Nacional and Tinta Roriz (*tempranillo*).

Out of the entire amount of land used as vineyards in the Douro region, only 26,000 ha (about 68%) are authorised for the production of Port Wine. The vines which are considered appropriate for this wine type are selected according to a criteria 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% (Fonseca 1949).

The regulating institution of the sector (IVDP) stipulates annually the quantity of grapes produced in Douro Region that can be used for the production of Port wine. This typical quota policy, called “benefício” coefficient, is attributed annually among the vineyard that have that property right (classification A to F).

The meteorological observations for the years 1967–2008 were collected in station of Peso da Régua (41º10′N, 7º47′W, 139 m above sea level), located within the Douro region and has not been relocated over the period of record. The meteorological data consist of daily observations mean temperature (Tm; °C) and precipitation (R; mm), that are summed (R) or averaged (Tm) by seasons (spring and summer).

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 describes it as $B_1B'_2s_2a'$ humid (hydric index: 25.3%; B_1), mesothermic (thermal efficiency index: 778 mm evapotranspiration; B'_2), with great shortage of water in the summer (aridity index: 38%; s_2) and thermal efficiency summer concentration index: 47% (above 20% = typically continental).

The Douro‘s vineyards is one of the most non-irrigated arid regions of the Europe and a strong water stress is normally observed. These situations are especially frequent in summer and appear as a consequence of the low soil water content (stony soils), due to the low rainfall and the elevated gradients of the water vapour pressure between the leaves and the air (Chaves and Rodrigues 1987). It is well established that positive NOA is associated to a decrease in moisture conditions and drought episodes in southern Europe and in Mediterranean areas (Corte-Real et al. 1998; Knippertz et al. 2003) with great impact for the Douro Valley (Paredes et al. 2006).

The mean annual precipitation in 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 and Lamelas 1988) and the available water reserve at the end of the ripening period is always ≤20%, causing lower berry weight and, consequently, lower wine yield (Cunha et al 2003).

In this work, we use the annual wine production data (1932–2008) for the Douro Region provided by the Instituto dos Vinhos do Douro e Porto (IVDP 2010).

The regional wine yield in any given year is the net effect of all the planting decisions (technologies include) that modify both the regional vineyard area and the age composition of grapevine composition stock. In Douro regions, the drawback of wine yield estimations is the absolute lack of annual detailed regional data of the dynamics of new plantings, replanting, removal and age composition of vineyard. However, the percentage share of young vineyards (less than 4 years) in 1998 is less than 4% in comparison to all other vineyards (Casa-do-Douro 1999). In this context, our modelling assumption is that this share remained constant in our sample and is reasonably small not to jeopardise the stability of the productivity link.

Empirical techniques

Estimation in the time domain

We estimate the bilateral links between the wine production cycles. 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:

$$y_t = \alpha_{0,t} + \sum_{i=1}^{9} \alpha_{i,t} y_{t-i} + \varepsilon_t \tag{2.1}$$

with

$$\alpha_{i,t} = \alpha_{i,t-1} + \eta_{i,t}, \text{for i} = 0 \ldots 9 \tag{2.2}$$

and $\varepsilon_t, \eta_{i,t} \sim i.i.d.\left(0, \sigma^2_{\varepsilon,\eta_i}\right)$, 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. 2.1), 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 nonsignificant. 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. 2.1 and 2.2) 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 and 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 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.

Spectrum 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 $\varepsilon_t \sim i.i.d.(0, \sigma^2)$ and constant over time, the power spectrum would look like Fig. 1.

As one can see from Fig. 1, a white noise process is characterised by the fact that no specific frequency has a bigger impact than any other frequency, for $\omega = 0, \ldots, \pi$. However, if the data were dominated by long 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.[1]

In order to calculate the spectrum from an estimated representation of Eq. 2.1, 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. 2.1). 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 the Appendix.

Thus, when we present our empirical results below, they are based on the time-varying STFT calculations. The only difference from Fig. 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.

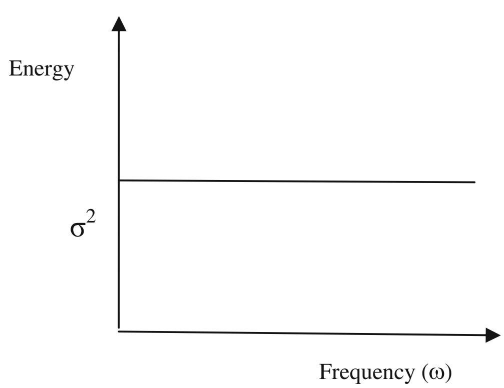


Fig. 1 Power spectrum of a white noise process

[1] In the spectral diagrams that follow, we use the term "power" rather than "energy" to denote relative variances.

Cross-spectrum 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 datasets. 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:

$$V(L)_t y_t = A(L)_t x_t + u_t, \mathrm{u_t} \sim i.i.d.\left(0, \sigma^2\right) \quad (2.3)$$

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

$$v_{i,t} = v_{i,t-1} + \varepsilon_{i,t}, \text{ for i} = 1, \ldots, \text{p and } \varepsilon_{\mathrm{i,t}} \sim \left(0, \sigma_{\varepsilon_i}^2\right) \quad (2.4)$$

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

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 Eq. 2.3, 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.

The coherence is equivalent to the R^2 statistic, and the gain is equivalent to the regression coefficient, impact or 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: equivalently the R^2 between each of the corresponding cycles in x_t and y_t. Hence $A(\omega)_t$ and $K^2_{YX,t}$ (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 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 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.

Results

In the figures shown in the next sections, we first present the time-varying spectrum and then the coherence and gain.[2]

Single spectra of Douro wine production

Figure 2 shows the time series of wine production in the Douro Region from 1940 to 2008. For most of the sample, this time series shows a lot of variation, which can be caused by structural breaks. 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.

Table 1 shows the regression results for the series production. This AR(5) model is the basis for the spectrum shown in Figs. 3 and 4. As one can see the regression is robust as there is no autocorrelation. For the chosen model, this was in fact, the lowest AIC value. The adjusted R_{adj}-squared is relatively high with 75%, but there is a lot of 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 (Table 1). Hence, this table only shows the final regression for the last observation for reason of restricted space.

The regressed series models the variation of the original series fairly well (Fig. 3). But the peaks are sometimes not as high as in the original series. This calls for an investigation of other determinants of the dynamic behaviour of the series. However, before we come to that, it is worthwhile to highlight the dynamic properties of the wine production series.

The time-varying spectrum, which is based on above regression, 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. 4). A frequency of 0.1 basically represents the long run trend. In Fig. 4, the trend can be seen in the upper left hand corner. Figure 2 contains an estimated trend and this trend is clearly upward sloping over the entire sample. It has a spectral mass of about 1.5 and hence is as important as the shorter cycles (Fig. 4). This is particularly true for the last 5 years of the sample. That was not always the case, for example during the 1990s.[3]

Hence, currently, wine production is characterised by a long run trend and two shorter cycles of 4.8 years and 2.5 years, respectively. In other words, wine production is following an (upwards) trend. To show that the trend is upward sloping, we regressed the raw data on trend.

The Fig. 5 shows the behaviour of wine production cycles in the Douro region "excluding trend". Since the two cycles of wine production have the same spectral density, i.e. have the same impact, that makes it difficult to distinguish between the two when considering the time series only. For example, the upswing of the 5-year cycle could be dampened by the downturn of the 3-year cycle.

The question now is how to determine the production peaks. Of course, one could always use some sophisticated time domain method, but we are looking for something more practicable. Assume we are interested in the 5-year cycle.[4] In order to create a time series that inhibits the 5-year cycle, we subtracted from our raw data the trend and the 3-year cycles. Figure 6 shows the resulting data.

With this series, we can now perform an out-of-sample test of the prediction power of our model. We would expect a maximum production every 5 years. Counting the maximum values shows that, of 17 maximum values we

[2] 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.

[3] The link between period (P) and frequency (ω) is $P=2\times\pi/\omega$.

[4] Of course, we could do the same analysis for the trend and the 3-year cycle.

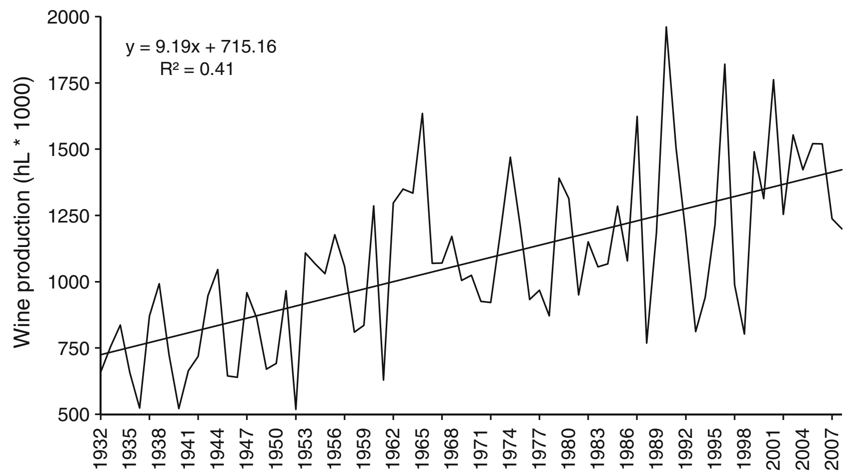


Fig. 2 Time series and estimated linear trend of wine production

predicted 12 correctly. So for a farmer to make a forecast based on the cyclical properties of wine production there is a 71% probability that the farmer will make the right prediction.

Cross-spectra of Douro wine production

Having established what characterises the 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 rainfall and temperature for the period 1967 to 2008. 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 variables, the one that produced the lowest AIC value was the one containing mean temperature in spring (Tm_Sp).

Figure 7 show the time series of Tm_Sp and, like the wine production series, it contains large variation. Visually, it seems there are three regimes: (1) one regime that starts the beginning of the sample until 1983; this period is characterised by a relatively high level of Tm_Sp variation (mean 16.0°C; σ 0.76); (2) the next period is from 1984 to 1994, where the variance is relatively low (mean 16.6°C; σ 0.47); and (3) in the last regime from 1994 to 2008, the variation is increasing again but also the Tm_Sp is higher (mean 17.9°C; σ 0.76) than in the previous periods. Given these structural breaks, it makes sense to incorporate Tm_Sp into our AR(5) model in a time-varying manner. Table 2 shows the regression results for the final point in time (2008). In comparison to Table 1, the R_{adj}^2 is now much higher (98%) and the AIC value is lower.

Figure 8 shows the behaviour of the Tm_Sp coefficient. As one can see, the coefficient varies a lot throughout the sample. However, towards the end of the sample, the coefficient stabilises on a relatively high level (149). Although, our model does not say what exactly causes the increase of the impact of temperature on wine production, we argue that due to global warming temperature (IPCC 2007) becomes a more important factor for wine production. At the end of the sample, a 1°C increase in the Tm_Sp will increase mean wine production in the same year by 13.4% (149,238 hL; Table 2). Over time though, after 3 years, an increase in Tm_Sp will reduce mean wine

Table 1 Kalman filter parameter estimates and summary statistics for time-varying spectral model of the wine production in the Douro Region

Dependent variable	PRD	Annual data from	1940–2008	Variable	Coeff.	SE	*t* values
Obs	69	*df*	64	Constant	363.712	29.88	12.17
R_{adj}^2	0.75	SE y	313.75	PRD(1)	0.1123	0.092	1.22
Mean	1,110.87	SSr	5,086,005	PRD(2)	0.0595	0.124	0.48
SE	281.90	LjB test	33.05	PRD(3)	0.0907	0.109	0.83
AIC	325.53			PRD(5)	0.3594	0.150	2.40

Obs Usable observations, *df* degrees of freedom, *PRD* Douro wine production, R_{adj}^2 adjusted coefficient of determination, *AIC* Akaike criterion, *LjB test* Ljung-Box Test: Q×(16), *SSr* sum of squared residuals, *SE y* standard error of dependent variable and of estimate (SE)

t values Significance levels for 64 *df*: $t>1.670$ ($p<0.05$); $t>2.387$ ($p<0.01$); $t>3.442$ ($p<0.0005$)

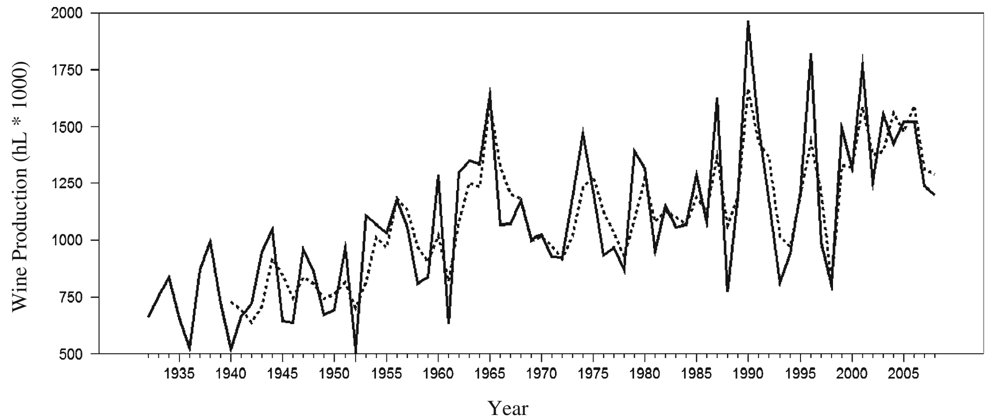


Fig. 3 Original time series (*black*) and regressed time series (*dotted*) of wine production in Douro Region

production by 6.0% (66,279 hL, Table 2).So the increase of the coefficient has “positive” effects as well as “negative”. Positive effects arise because higher temperature allows for higher wine production in the short term. In the long term though, higher temperatures lead to drier soils which lead to lower wine production.

The original idea to use Tm_Sp was to check whether this variable can explain the wine production cycles. Figure 9 shows the gain. What this figure is showing is that if the temperature changes it causes two major cycles: on the one hand, there is the cycle at a frequency of 1.2 or 5.24 years, and on the other, a frequency of 2.6 or 2.41 years. Those cycles are indeed very close to the production cycles.

Although the two most important cycles of the gain have always been the most important cycles, their impact is not constant as one can see from Fig. 9. Nevertheless, the 5.24-year cycle has always been the most important one. This result is in contrast to the previous results where the spectrum of the wine production was characterised by an equal impact of these cycles. Spring temperature on its own does not cause cycles of equal strength. Hence, temperature alone cannot fully explain the dynamic behaviour of wine production. Other impacts could come from meteorological variables not tested, grape prices or market regulating mechanisms, for example.

However, looking at Fig. 9, there is a stable impact on temperature on wine production. In Fig. 10, the coherence reveals that for some cycles (frequencies of 3 and 1.2) the correlation has since 1995 been on a higher level than before (if one omits the spike in 1986). We can therefore conclude that correlation between temperature and wine production is increasing for these cycles. What makes this result important is that, without having decomposed the cyclical behaviour, this effect would not have been visible. If we had looked at only the time domain results, this effect would have been “averaged out”.

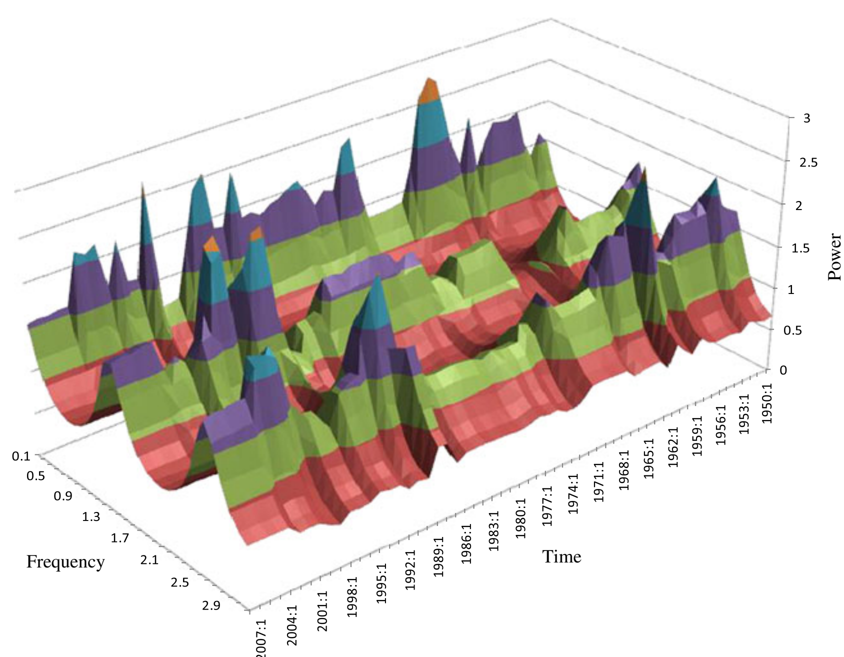


Fig. 4 Time-varying spectrum of the wine production

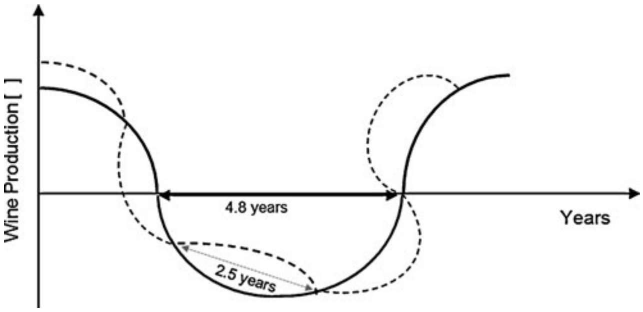


Fig. 5 Graphical interpretation of the wine production cycles in Douro region. There are two fluctuations of equal strengths: one has a length of 4.8 years (*solid line*) and there is a shorter one of 2.5 years (*dashed line*)

Having established that the spring temperature causes a dynamic behaviour of wine production close to the spectrum, the next question is: what can we learn from the actual behaviour of the temperature? For that, we consider the coherence which gives the current impact of temperature on wine production.

The coherence shows that Tm_Sp explains up to 50% of the 5-year cycle of wine production and about 40% of the current short run trend of production. Spring temperature also explains about 20% of the current 2.4-year cycle. The conclusion is twofold: temperature does have a contemporary effect on wine production. However, this impact is no more than 50%. Given that the contemporary effect is rather low, there must be other variables which explain the contemporary behaviour of wine production.

However, given that wine producers may be interested in the predictive power of temperature, further research is needed on how strong this predictive power is.

Discussion

From 1932 to 2008, the growing season for wine production in the Douro region has been subjected to cycles, but there has been a trend toward a continued increase in production. While some of the trend in high production can undoubtedly be attributed to vineyard structure changes and/or better viticultural and wine practices, climate exerts an influence on production variability. As previously stated, the linear model currently used by industry analysts accounts for less than 50% of the variation in grape production; our model based on spring temperature explains approximately 98% of wine production variability.

According to this time-varying model, the Tm_Sp is the meteorological variable which explains more of the cyclicality of Douro wine production. Despite the great importance of rainfall on grapevine production in Mediterranean climates (Quiroga and Iglesias 2009; European Commission 1997; Santos et al. 2010), mainly during the spring and summer period, no significant influence on wine production cycles was reported in this study. In the Douro region, summer rainfall is consistently low over the years, and it is difficult to consider it as an important factor to explain the great variability of wine production (Cunha et al. 2003). On the other hand, high spring temperature is usually combined with high sunshine levels, low precipitation levels and soil moisture.

Remarkably, spring temperature can be used to model the actual short-term variation of wine production. Mean spring temperature explains up to 35% of short-term variation of wine production (Fig. 8). Moreover, it also explains up to 37% of the current 5-year cycle and it still explains 15% of the current 2-year cycle (Fig. 10). Hence, if one follows the Tm_Sp, this information can be used to establish the stage the wine production cycle. This information is useful when it comes to forecasts concerning wine production in the current year.

These wine cycles are consistent with Esteves and Orgaz (2001) for another wine region of Portugal (Dão). These authors found, for the period 1960–1992, that temperature in May explained the 2.5- and 5.3-year wine cycles in the Dão region, frequencies very similar to the

Fig. 6 Time series of wine production filtered for the trend and the 3-year cycles

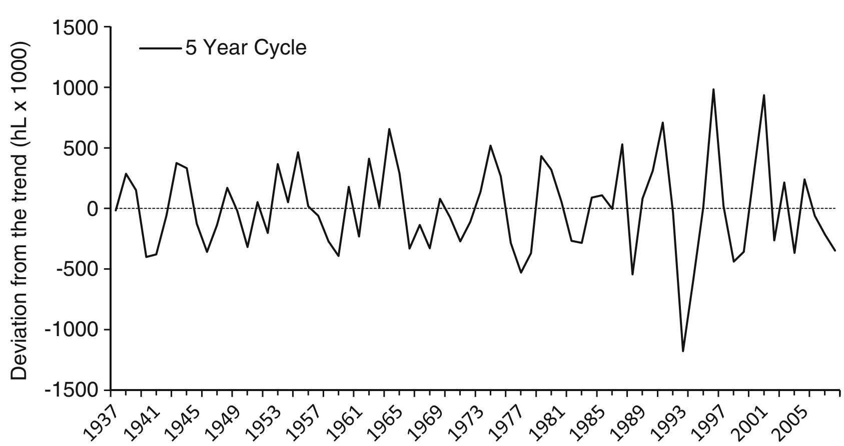
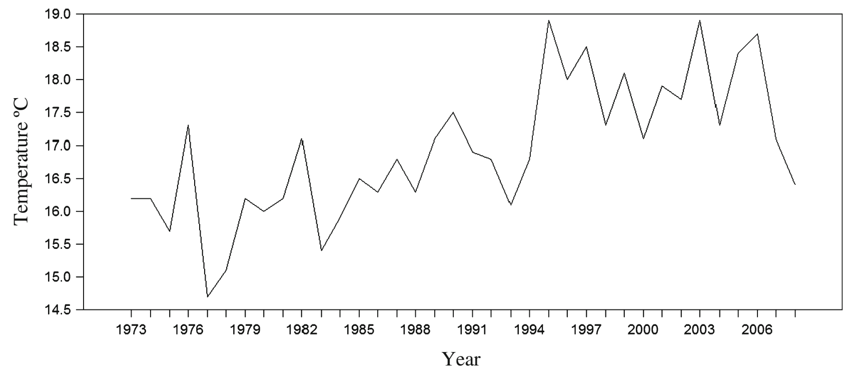


Fig. 7 Mean spring temperature in Douro region for the period 1973–2008



Douro wine cycles explained by the Tm_Sp.Furthermore, this spectra of wine series in the Dão region showed statistically significant oscillations coherent with those found in the series of teleconnection indices.Future observational research should be aware of the relationships between climate variability result from the impact of large-scale geophysical mechanisms and the cyclical behaviour of wine production.

The influence of previous and in-season spring temperature on the short-term wine cyclical production found in this study is consistent with previous studies on the grapevine ecophysiology behaviour and yield. As a perennial and deciduous plant, environmental conditions influence its vegetative and reproductive growth. The conditions of the previous year are important components of the wine production variability. This influence relates not only to the season in which the crop is produced but also to past seasons, mainly the two seasons before the one in which the harvest takes place (Cunha et al. 2010; Vasconcelos et al. 2009). As one of the premises for grape yield, grapevine bud fruitfulness has been the focus of many studies. Most of these studies have consistently determined that light and temperature are the most important climatic factors during the bud differentiation in the season before the one in which the harvest takes place (May 2004; Cunha et al. 2010). These studies support the positive impact of Tm_Sp of the current 2-year production cycle found in our work.

Hot spring temperatures are favourable, directly or indirectly, for photosynthetic assimilation and grapevine pollination/fertilisation, and result in high fruit-set (Cunha et al. 2003; Vasconcelos et al. 2009). Moreover, hot and dry spring conditions are generally associated with low impacts of grape diseases on production level. On the other hand, the earlier phenology development, associated to hot springs (Jones and Davis 2000; May 2004), allows the grapevine to be rain-fed and to capitalise on diminishing soil water from winter rains. All these effects are in accordance with positive impact of in-season spring temperature on the Douro wine production level observed in our study.

However, in the Mediterranean climate, no irrigated vineyard (like the Douro region) submitted to consecutive hot springs could reduce the soil moisture as well as depleting accumulated reserves of carbon and nutrients in the permanent structures (e.g. May 2004). These reserves can play a critical role in potential production of grapevine, mainly in years with unfavourable climate conditions during the spring (García-de-Cortázar-Atauri 2006). Modelling work suggests a negative relationship between wine production and the spring temperatures in the previous 5 years.

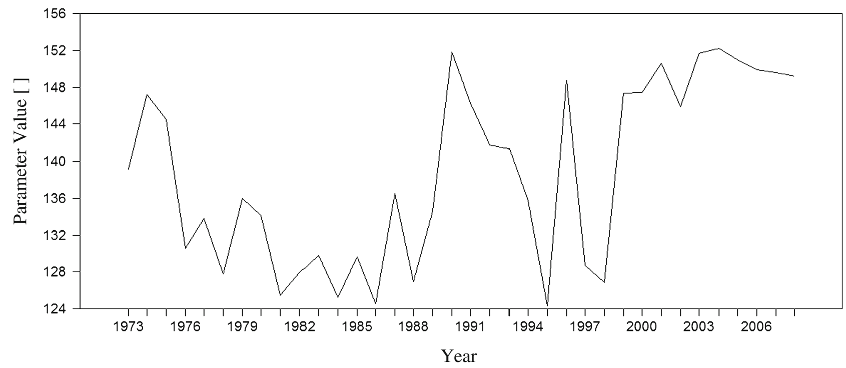
Table 2 Kalman filter parameter estimates and summary statistics for the time-varying model of wine production on temperature

Dependent variable	PRD	Annual data from	1973–2008	Variable	Coeff.	SE	*t* values
Obs	36	*df*	32	Constant	−502.368	19.645	−25.57
R^2ad	0.98	SE y	313.75	PRD(5)	0.3015	0.0275	10.96
Mean	1,110.87	SSr	2,040,501	Tm_Sp	149.238	9.7644	15.28
SE	252.52	LjB test	12.159	Tm_Sp(3)	−66.279	8.5834	−7.72
AIC	315.35						

Obs Usable observations, *df* degrees of freedom, *PRD* Douro wine production, R_{adj}^2 adjusted coefficient of determination, *AIC* Akaike criterion, *LjB test* Ljung-Box Test: Q×(16), *SSr* sum of squared residuals, *SE y* standard error of dependent variable and of estimate (SE)

t values Significance levels for 64 *df*: $t > 1.695$ ($p<0.05$); $t>2.452$ ($p<0.01$); $t >3.643$ ($p<0.0005$)

Fig. 8 Immediate impact of spring temperature

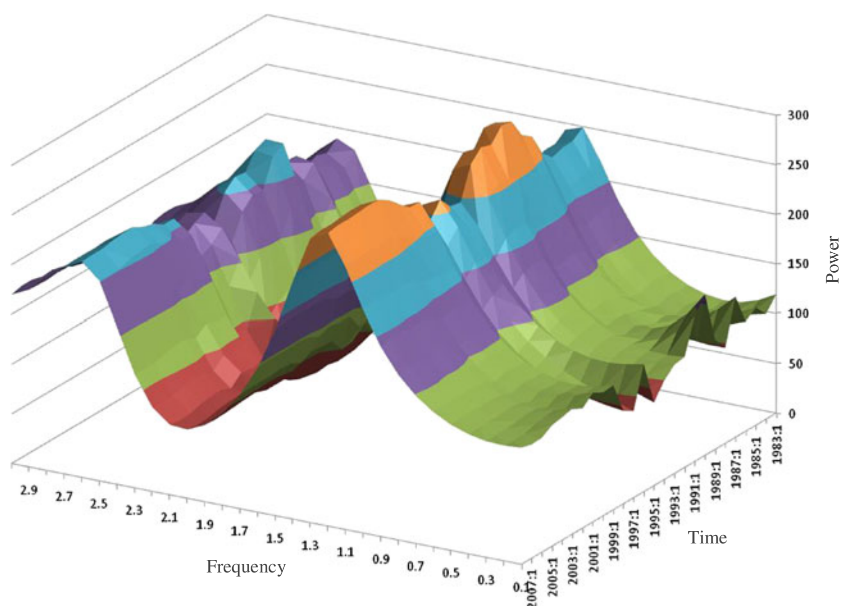


Modelling cyclical wine production with this time-varying model allows for accurate short-term as well long-term forecasts, providing long-term growth rates and short-term cycle lengths and intensities by different periods and climate scenarios.The projections of future climate in combination with the developed model of cyclical behaviour of wine production can provide a powerful tool for assessing potential future responses of viticulture and the wine industry to climatic variability, and allow statistical confidence limits to be attached to estimated responses. With respect to the future, we can expect climate risks to intensify in the Mediterranean (IPCC 2007) which represent an additional challenge for wine production in the Douro region. Based on the most recent and comprehensive ensembles of global and regional climate variability simulations, the Mediterranean may experience substantial warming (temperature increases of 3–5°C) by 2080; at the same time, inter-annual variability is projected to increase, especially in the spring period (Giorgi and Lionello 2008; IPCC 2007).According to our model, wine production would increase by 22% if temperatures rise by 3°C. This result is in line with Santos et al. (2010) who predict an increase in wine production of approximately 25% for the Douro region.

Viticultural regions, which produce premium wines, are usually located in narrow climatic niches (Bindi et al. 1996, 2001; Jones 2007). These climatic niches are very vulnerable to both short-term climate variability and long-term climate change. This in turn may cause adverse effects on the viticultural regions.

Due to the economic and social importance of the wine industry (EU 2006; OIV 2010), it behoves us to pay attention to this phenomenon, and especially to put effort into understanding how viticulture and the wine industry will respond and adapt to information about climate generally and modelling in particular. Our model suggests that stationarity is a questionable assumption, and this means that historical distributions of wine production are going to need dynamic updating. We should consider this

Fig. 9 Gain: temperature on production



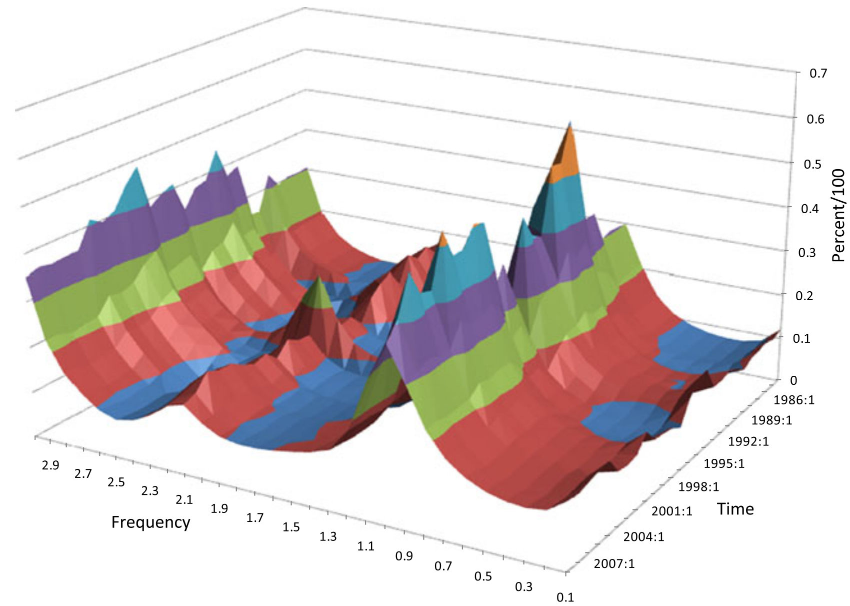


Fig. 10 Coherence between wine production and spring temperature

when developing wine production models where climate plays an important direct or indirect role and climate variability is increasing, as indicated by the recent IPCC reports.

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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:

$$STFT\{x[n]\} \equiv X(m,\omega) = \sum_{n=-\infty}^{\infty} x[n]w[n-m]e^{-j\omega n} \quad \text{(A.1)}$$

In this case, m and n are different points in time; ω is the frequency and is continuous; and j=√-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. 2.1; see "Cross-spectrum analysis" above. The squared magnitude of the STFT then yields the spectrogram of the function:

$$Spectrogram\ \{\chi_t\} \equiv |X(\tau,\omega)|^2 \quad \text{(A.2)}$$

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:

$$X_k = \sum_{n=0}^{N-1} x_n z^{nk}, \text{ where } k = 0, \ldots, M-1 \quad \text{(A.3)}$$

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 and Reilly 1992; Boashash 2003). It is not commonly used in economics, however.

Finally, Boashash and Reilly (1992) have shown theoretically that, once Eq. 2.2 (see "Cross-spectrum analysis" above) 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 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):

$$P_t(\omega) = \frac{\sigma^2}{\left|1 + \sum_{i=1}^{9} \alpha_{i,t} \exp(-j\omega i)\right|_t^2} \tag{A.4}$$

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

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

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

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

The last term in Eq. A.5, $f_{XX}(\omega)_t$, is the spectrum of predetermined variable. This spectrum may also be time-varying. 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 (Wolters 1980; Nerlove et al. 1995; Jenkins and Watts 1968; Laven and Shi 1993):

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

From Eq. A.4, we get the time-varying residual spectrum

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

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

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

References

Artis M, Marcellino M, Priorietti T (2004) Dating the euro area business cycle. In: Reichlin L (ed) The Euro area business cycle: stylised facts and measurement issues. Centre for Economic Policy Research, London

Bindi M, Fibbi L, Gozzini B, Orlandini S, Miglietta F (1996) Modelling the impact of future climate scenarios on yield and yield variability of grapevine. Climate Res 07(3):213–224

Bindi M, Fibbi L, Miglietta F (2001) Free Air CO2 Enrichment (FACE) of grapevine (Vitis vinifera L.): II. Growth and quality of grape and wine in response to elevated CO2 concentrations. Eur J Agron 14(2):145–155

Bluestein LI (1968) A linear filtering approach to the computation of the discrete Fourier transform. Northeast Electronics Research and Engineering Meeting Record 10:218–219

Boashash B (ed) (2003) Time frequency signal analysis and processing. Elsevier, Oxford

Boashash B, Reilly A (1992) Algorithms for time-frequency signal analysis. In: Boashash B (ed) Time-frequency signal analysis - methods and applications. Longman-Cheshire, Melbourne, pp 163–181

Canova F (1998) Detrending and business cycle facts. J Monetary Econ 41:475–512

Canova F, Dellas H (1993) Trade dependence and the international business cycle. J Int Econ 34:23–47

Capitanio F, Adinolfi F (2009) The relationship between agricultural insurance and environmental externalities from agricultural input use: a literature review and methodological approach. New Medit 8(3):41–48

Casa-do-Douro (1999) Dados estruturais da região do Douro. Cadastro da casa do Douro. Douro-Boletim da Casa do Douro, Peso-da-Régua, Portugal

Chaves M, Rodrigues L (1987) Photosynthesis and water relations in grapevines response to environmental factors. In: Tenhunen JD (ed) Plant Response to Stress-functional analises in Mediterranean ecosystems. Springe, Berlin, pp 279–290

Chen C, Chang C (2005) The impact of weather on crop yield distribution in Taiwan: some new evidence from panel data models and implications for crop insurance. Agric Econ 33:503–511

Chen CC, McCarl BA, Schimmelpfennig DE (2004) Yield variability as influenced by climate: a statistical investigation. Clim Change 66(1–2):239–261

Corte-Real J, Qian BD, Xu H (1998) Regional climate change in Portugal: precipitation variability associated with large-scale atmospheric circulation. Int J Climatol 18(6):619–635

Cunha M, Abreu I, Pinto P, De Castro R (2003) Airborne pollen samples for early-season estimates of wine production in a Mediterranean climate area of northern Portugal. Am J Enol Vitic 54(3):189–194

Cunha M, Marçal ARS, Silva L (2010) Very early prediction of wine yield based on satellite data from VEGETATION. Int J Remote Sens 31(12):3125–3142

Esteves MA, Orgaz MDM (2001) The influence of climatic variability on the quality of wine. Int J Biometeorol 45(1):13–21

EU (2006) Wine, Economy of the sector. European Commission, Directorate-General for Agriculture and Rural Development. Available online at http://ec.europa.eu/agriculture/markets/wine/studies/rep_econ2006_en.pdf (assessed 11 November 2009)

European Commission (1997) Oliwin Project: agrometeorogical models for the estimation at harvest of olive and vine yield; regional and national level. Final Report

Ferris J (2006) Forecasting World Crop Yields as a Probability Distributions. Paper presented at the International Association of

Agricultural Economists Conference, Gold Coast, Australia, 12–18 August
Folwell RJ, Santos DE, Spayd SE, Porter LH, Wells DS (1994) Statistical technique for forecasting concord grape production. Am J Enol Vitic 45(1):63–70
Fonseca A (1949) O benefício e a sua distribuição na Região Vinhateira do Douro. Federação dos Viticultores da Região do Douro, Peso-da-Régua, Portugal
Gabor D (1946) Theory of communication. J Inst Electr Eng 93 (3):429–457
García-de-Cortázar-Atauri I (2006) Adaptation du modèle STICS à la vigne (Vitis vinifera L.). Utilisation dans le cadre d'une étude du changement climatique à l'échelle de la France. PhD thesis, Ecole Supérieur Nationale d'Agronomie de Montpellier, Montpellier
Gemmil G (1978) Estimating and forecasting agricultural supply from times-series: a comparison of direct and indirect methods. Eur Rev Agric Econ 5(2):175–191
Giorgi F, Lionello P (2008) Climate change projections for the Mediterranean region. Glob Planet Change 63(2–3):90–104. doi:10.1016/j.gloplacha.2007.09.005
Goodwin BK, Ker AP (1998) Nonparametric estimation of crop yield distributions: implications for rating group-risk crop insurance contracts. Am J Agric Econ 80(1):139–153
Hughes Hallett A, Richter C (2009a) Economics in the backyard: how much convergence is there between China and her Special Regions? World Econ 32(6):819–861
Hughes Hallett A, Richter C (2009b) Has there been any structural convergnence in the transmission of european monetary policies? Int Econ Econ Policy 6(2):85–101
Hughes Hallett A, Richter C (2009c) Is the US No longer the economy of first resort? Changing economic relationships in the Asia-Pacific Region. Int Econ Econ Policy 6(2):207–234
Hurrell JW (1995) Decadal trends in the North Atlantic Oscillation: regional temperatures and precipitation. Science 269(5224):676–679. doi:10.1126/science.269.5224.676
Hurrell JW, Van Loon H (1997) Decadal variations in climate associated with the North Atlantic Oscillation. Clim Change 36 (3):301–326. doi:10.1023/a:1005314315270
IPCC (2007) Climate Change (2007). Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press
IVDP (2010) Instituto dos Vinhos do Douro e Porto, dados estatísticos sobre a produção de vinho do Douro e Porto na Região Demarcada do Douro
Jenkins GM, Watts DG (1968) Spectral analysis and its applications. Holden-Day, San Francisco
Jones GV (2007) Climate Changes and the global wine industry. Paper presented at the 13th Australian wine industry technical Conference, Adelaide, Australia, 28 July – 2 August
Jones GV, Davis RE (2000) Climate influences on grapevine phenology, grape composition, and wine production and quality for Bordeaux, France. Am J Enol Vitic 51(3):249–261
Knippertz P, Ulbrich U, Marques F, Corte-Real J (2003) Decadal changes in the link between El Nino and springtime North Atlantic oscillation and European-North African rainfall. Int J Climatol 23(11):1293–1311. doi:10.1002/joc.944
LaMotte LR, McWorther AJ (1978) An exact test for the presence of random walk coefficients in a linear regression. J Am Stat Assoc 73(364):816–820
Laven G, Shi G (1993) Zur Interpretation von Lagverteilungen. Discussion Paper, Johannes Gutenberg University, Mainz
Lin Z (1997) An Introduction to time-frequency signal analysis. Sensor Rev 17(1):46–53
May P (2004) Flowering and Fruitset in Grapevines. Lythrum Press, Australia
McCarl BA, Villavicencio X, Wu XM (2008) Climate change and future analysis: is stationarity dying ? Am J Agric Econ 90 (5):1241–1247. doi:10.1111/j.1467-8276.2008.01211.x
Milly PCD, Betancourt J, Falkenmark M, Hirsch RM, Kundzewicz ZW, Lettenmaier DP, Stouffer RJ (2008) Climate change - stationarity is dead: whither water management? Science 319 (5863):573–574. doi:10.1126/science.1151915
Nerlove M, Grether DM, Carvalho JL (1995) Analysis of economic time series. Academic, New York
OIV (2010) Organization Internationale de la Vigne et du Vin - Statistiques. Accessed 1 January 2010
Paredes D, Trigo RM, Garcia-Herrera R, Trigo IF (2006) Understanding precipitation changes in Iberia in early spring: weather typing and storm-tracking approaches. J Hydrometeorol 7(1):101–113. doi:10.1175/JHM472.1
Phares C (2000) Business cycles and the world wine market. Regional Research Institute, West Virginia University
Ploberger W, Krämer W, Kontrus K (1989) A new test for structural stability in the linear regression model. J Econ 40(2):307–318
Quiroga S, Iglesias A (2009) A comparison of the climate risks of cereal, citrus, grapevine and olive production in Spain. Agric Syst 101(1–2):91–100. doi:10.1016/j.agsy.2009.03.006
Rabiner LR, Schafer RW, Rader CM (1969) The chirp z-transform algorithm and its application. Bell Syst Tech J 48:1249–1292
Reis R, Lamelas H (1988) Statistical study of decade series of water balance and its components of potencial evapotranspiration calculated by Penman's method. vol 36. Instituto Nacional de Meteorologia e Geofisica, Lisbon
Santos JoA, Malheiro AC, Karremann MK, Pinto JG (2010) Statistical modelling of grapevine yield in the Port Wine region under present and future climate conditions
Vasconcelos MC, Greven M, Winefield CS, Trought MCT, Raw V (2009) The flowering process of vitis vinifera: a review. Am J Enol Vitic 60(4):411–434
Vicente-Serrano SM, Heredia-Laclaustra A (2004) NAO influence on NDVI trends in the Iberian peninsula (1982–2000). Int J Remote Sens 25(14):2871–2879. doi:10.1080/01431160410001685009
Wells C (1996) The kalman filter in finance vol. 32. Advanced studies in theoretical and applied econometrics. Kluwer, Dordrecht
Wolters J (1980) Stochastic dynamic properties of linear econometric models. Springer, Berlin
Zhu Y, Goodwin B, Ghosh S (2008) Time-varying yield distribuition and the implications for crop insurance pricing. Paper presented at the NC State Agricultural Economics Workshop, Raleigh, NC, 6 May