ESTIMATION OF CORK PRODUCTION USINGAERIAL IMAGERY[1]

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ABSTRACT – Inventory and prediction of cork harvest over time and space is important to forest managers who must plan and organize harvest logistics (transport, storage, etc.). Common field inventory methods including the stem density, diameter and height structure are costly and generally point (plot) based. Furthermore, the irregular horizontal structure of cork oak stands makes it difficult, if not impossible, to interpolate between points. We propose a new method to estimate cork production using digital multispectral aerial imagery. We study the spectral response of individual trees in visible and near infrared spectra and then correlate that response with cork production prior to harvest. We use ground measurements of individual trees production to evaluate the model's predictive capacity. We propose 14 candidate variables to predict cork production based on crown size in combination with different NDVI index derivates. We use Akaike Information Criteria to choose the best among them. The best model is composed of combinations of different NDVI derivates that include red, green, and blue channels. The proposed model is 15% more accurate than a model that includes only a crown projection without any spectral information.

Keywords: NDVI; Remote sensing; Akaike Information Criteria.

ESTIMAÇÃO DA PRODUÇÃO DE CORTIÇA USANDO IMAGENS DIGITAIS AÉREAS

RESUMO – A inventariação e previsão de descortiçamento ao longo do tempo e espaço tornam-se essenciais para os gestores florestais responsáveis pelo seu planejamento e logística (transporte, armazenamento etc.). Os métodos comuns de inventariação de campo que incluem a densidade de troncos, diâmetro e altura da estrutura são caros e geralmente baseados em pontos (parcelas). Além disso, a estrutura horizontal irregular dos povoamentos de sobreiro torna difícil, se não impossível, a interpolação entre os pontos (parcelas). Assim, propõe-se um novo método para estimar a produção de cortiça usando imagens digitais aéreas multiespectrais. Foi estudada a resposta espectral a árvores individuais nas faixas do visível e infravermelho próximo, e posteriormente foi correlacionada essa resposta com a produção de cortiça antes do descortiçamento. Foram usadas medidas terrestres de produção de árvores individuais para avaliar a capacidade preditiva do modelo. Propuseram-se 14 variáveis candidatas à predição de produção de cortiça baseadas no tamanho da copa combinada com diferentes índices derivados do NDVI. Foi usado o Critério de Informação de Akaike para escolher a melhor opção entre elas. O melhor modelo é composto por combinações de diferentes derivados de NDVI que incluem os canais do vermelho, verde e azul. O modelo proposto é 15% mais preciso que o modelo que inclui unicamente a projeção da copa sem qualquer tipo de informação espectral.

Palavras-chave: NDVI; Sensoriamento remoto; Critério de Informação de Akaike.

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1. INTRODUCTION

Cork, which is a valuable forest product, is derived from the bark of a cork oak (*Quercus suber* L.). Cork is an important forest product primarily grown in the forests of Portugal and Spain. Worldwide, about 90% of annual cork production comes from these two countries. The cork oak is generally grown in open forest stands with combined agrossilvipastoral activities, called "montado" in Portugal or "dehesa" in Spain (PINTO CORREIA et al., 2011). The socio-economic and conservation value of these ecosystems has been widely demonstrated in the literature (BUGALHO et al., 2011).

These woodlands are characterized by low stand density and high variability in the size and age-class of individual trees. Such high spatial heterogeneity makes forest inventory particularly difficult, yet forest managers need accurate spatially explicit estimations of potential harvest amounts to optimize forest management and harvest operations. Estimations of total annual harvest are especially important for planning before the harvest season.

Regular forest inventory assessments, disaster mapping, and disease monitoring projects that rely on remote sensing have made aerial imagery commonly available in Portugal. A number of recent studies have demonstrated the potential use of remote imagery for tasks such as mortality assessment (COSTA et al., 2010; RIBEIRO; SUROVÝ, 2008).

There are currently two methods for using aerial imagery to estimate cork production. The first, which could be considered a geometric approach, applies information about crown shape and size to a distance-dependent cork production model (SUROVÝ et al., 2004a; SUROVÝ et al., 2007). The second, which could be considered a spectral approach, relies on assessment of spectral reflectance what we describe in this paper.

1.1. Correlation between reflectance and productivity.

Relationship between canopy reflectance and plant characteristics has been widely studied. According to OLLINGER (2011), the search for the "NDVI" (normalized difference vegetation index) and "vegetation" yielded more than 2500 publications on ISI search at the time of the article writing. These include NDVI and LAI correlation (e.g., CHEN; CIHLAR 1996; HOUBORG; BOEGH2008), NDVI and foliar biomass, NDVI and water potential, NDVI and vegetation detection (COUTO JUNIOR, 2011), and NDVI and plant primary production (OLLINGER, 2011). Simple correlation between reflectance and productivity is influenced by external factors. For example, positive correlation between the amount of reflected near infrared (NIR) electromagnetic radiation and productivity is influenced by sun position, time of year among other factors. Thus, it is important to use relative values – indices that eliminate or minimize these effects. The most common index used in remote sensing is the already mentioned NDVI, defined as the ratio between NIR and visible spectral reflectance measurement (*vis*) (KRIEGLER et al., 1969):

$$NDVI = \frac{NIR - vis}{NIR + vis} \tag{1}$$

Cork growth and formation and its correlation with NDVI: In the first few years following cork harvest (which does not result in tree mortality), the tree invests most of its resources into the production of new cork, significantly decreasing xylem growth (COSTA et al., 2001; OLIVEIRA et al., 2002). Some authors suggest cork growth may be greatest in the second and third post-harvest years (CAÑELLAS; MONTERO, 2002). In any case, cork production correlates with net primary production (NPP), which is also well correlated with a tree's leaf area index (LAI), assuming climate variables are omitted. LAI has also been shown to directly correlate with net ecosystem CO_2 exchange (ADIKU et al., 2006; GITELSON et al., 2004) and ecosystem productivity (MOULIN et al., 1998; ZHANG et al., 2005).
Kogan (1995) showed that it is possible to estimate drought stress (or vegetation status) using NDVI. He derived a new index called the Vegetation Condition Index (VCI), which has proven to be an excellent tool for estimating the impact of drought on vegetation at sites around the world (ZHANG et al., 2004). Following Kogan (1995), Peters et al. (2002) developed another NDVI-based index to assess drought, the Standardized Vegetation Index, or SVI. Collectively, this research shows that NDVI is influenced both by leaf density (ZHANG et al., 2004) and drought or water availability (PETERS et al., 2002). For the purpose of this study, we assume NDVI can be used to estimate primary production because it reflects both leaf density (LAI) and climate conditions (water availability) – two potentially important factors that influence cork production.

We investigate the relationship between cork production and spectral reflectance values from remotely sensed data. We propose using a combination of NDVI derivates in a model that can predict cork production in kilograms per tree. We use ground measurements taken at the time of cork harvest to verify the model's predictive accuracy.

2. MATERIALAND METHODS

2.1. Ground truth data

The ground truth data was taken from individual trees in permanent research plots at Machuqueira de Grou, Coruche, Portugal (39°12´N, -08°30‘E); these trees were debarked in 2008. Using aerial photos, we manually identified 65 trees for inclusion in the study that had visible crown contours and no significant stem damage. Dry weight was estimated from the wet weight of the harvested material using an adjustment for moisture content. This adjustment was derived by drying a sample of the harvested material for 48 hours at 103 °C to determine moisture content.

2.2. Photo Imagery

We used un orthorectified digital aerial imagery taken in the fall of 2007. The camera used was DMC – Intergraph. The pixel spatial resolution was 0.5m.The image size was 7.680 x 13.824 pixels, which approximately corresponds to an area of 26.54 km^2 (the other technical details can be found on web page of the Instituto Geográfico Portugues (www.igeo.pt, the institute which kindly offered images for this study) Digital photo files were stored in an uncompressed Tagged Image File Format (TIFF) that included all four channels (R, G, B, NIR). For un orthorectified photography we manually delineated the edges of individual trees in permanent inventory plots. This task was completed in the field so that it would be possible to directly compare aerial photographs with ground observations.

The resultant data layer was used to construct a mask layer, which was later used to extract the reflectance of individual pixels. The reflectance is here understood as digital numbers of individual pixels (ESPIRITO-SANTO; SHIMABUKURO, 2005). We used a previously published method to get the values of individual pixels from TIF file (SUROVÝ et al., 2004a); and simultaneously from mask file while performing bitwise and operator. However, this kind reflectance can be extracted using any image processing software capable of reading mask values from an underlying image (e.g., Image J, IDRISI, and others).

2.3. Statistical analysis for model selection

Statistical analyses were conducted to select the best linear model for estimating cork production. We began by preparing a set of explanatory variables (Table 1) based on 14 combinations of four basic observation variables for a second-degree polynomial function. We conducted a complete search for the best linear model using these 14 variables and use Akaike information criteria (AIC) (AKAIKE, 1974) to select the best model. To avoid missing useful combinations through the selection process, we did not use a stepwise multiple regression approach. In Table 1, *Cpr* is the horizontal crown projection in pixels and NDVIr, NDVIg, and NDVIb are the estimated average NDVI reflectance per crown for the red, green, and blue channels, respectively.

Let y be a response variable vector, $X = (x_1, x_2, \ldots x_{n-1}, x_n)$ with xi as the *i*-th explanatory variable vector, so that our linear model is expressed by the following:

$$y = X.\mathrm{diag}(b^p_i).\ a + a_0 1_p + \varepsilon \qquad (2)$$

where b^p_i is a (px1) vector. Its *k*-th element corresponds to the *k*-th digit number of a 0-1 integer value in the base-2 system converted from the integer value of i(i = 0...2^p) in the base-10 numerical system within the p-digit dimension. For example, $b^5_3 = (1,1,0,0,0)$ because3 becomes 11 when it is converted from a base-10 to a base-2 numerical system; given the 5-digit expression in the above rule, 3becomes 00011, resulting in (1,1,0,0,0). $\mathrm{diag}(B^p_i)$ is a diagonal matrix with b^p_i in its diagonal elements, e.g.

$$\mathrm{diag}(\boldsymbol{b}_3^5) = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{pmatrix} \qquad (3)$$

a = (a1,a2...ap)'is a (px1) coefficient vector, a_0 is also a coefficient with 1 as a*p*-dimensional unit vector, and ε is an error vector. In our case *p* was set to 14 with *i* from 0 to 2^{14}; thus, there were a total of 16,384 distinct candidate models. We estimated all candidate models, and then selected the model with the smallest AIC. We discuss the proposed model, which is based on a combination of candidate variables, and compare it to a simplified model that is only based on the horizontal crown projection (*Cpr*) with no spectral information.

Table 1 – List of explanatory variables used in the model selection process.
Tabela 1 *– Lista de variáveis explanatórias utilizadas no processo de selecção do modelo.*

Variable name	Expression	Variable name	Expression
x_1	Cpr	x_8	NDVIr . NDVIg
x_2	NDVIr	x_9	NDVIr . NDVIb
x_3	NDVIg	x_{10}	NDVIg . NDVIb
x_4	NDVIb	x_{11}	Cpr^2
x_5	Cpr . NDVIr	x_{12}	$NDVIr^2$
x_6	Cpr . NDVIg	x_{13}	$NDVIg^2$
x_7	Cpr . NDVIb	x_{14}	$NDVIb^2$

3. RESULTS

Figure 1 shows mirrored charts for correlation between dry weight cork production and tree crown characteristics obtained from aerial images.

As it can be observed in Figure 1, there is a strong correlation between dry cork weight per tree and crown projection area. This suggest that the cork production can be easily estimated using only the geometrical information of crown. Trends can also be seen between dry weight and NDVI derivates for individual bands (red, green, and blue).

Table 2 shows the optimal combination of variables for each of the model classes considered, which included anywhere from 0 to 14 variables. The inclusion of a candidate variable in the final model is marked with 1, the absence is marked with 0. Only the best model (with the lowest AIC) for each classis displayed.

Figure 2 shows all possible model combinations with differing numbers of candidate variables and their corresponding AIC values. The upper group in this figure consists of models that do not include the horizontal crown projection. In total, up to nine different candidate variables can be included in a model without using *Cpr* information. As Figure 2 shows, the lowest AIC value was derived from a model with four variables. The coefficients for this optimal model are as follows: x5, x6, x7, x12 or expressed in the explanatory form: *Cpr . NDVIr, Cpr . NDVIg, Cpr . NDVIb,* $NDVIr^2$.

We also considered a simplified model that only included horizontal crown projection (*Cpr*) data with no spectral information. As mentioned before this kind of model offers reliable estimates of cork production, which may be easily adopted by forest decision makers.

Figure 3 shows a comparison of the residual distributions after fitting the full model (left side) and the simplified model (right side). The standard deviation associated with the simplified model is larger than that associated with the full model.

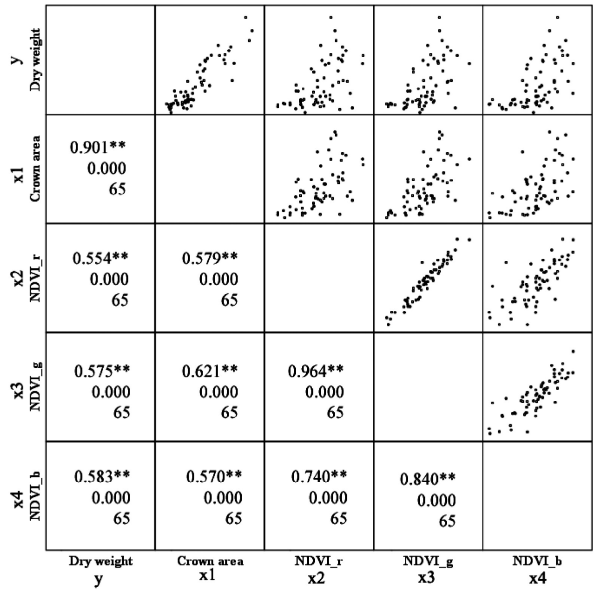

Figure 1 – Correlation between dry cork weight per tree (kg), crown area, and average NDVI derivates for red, green, and blue, respectively.
Figura 1 *– Correlação entre o peso seco de cortiça por árvore (kg), projecção da copa, e derivados de NDVI para o vermelho, verde e azul, respectivamente.*

4. DISCUSSION

There is a substantial amount of literature about the assessment of crop production using remotely sensed imagery (e.g., CURRAN, 1985; MOULIN, et al., 1998; JENSEN, et al., 2007). Less work has focused on estimating tree productivity, though there have been some significant contributions (e.g., YE, et al., 2008; TORRES, et al., 2008). In this paper we presented a method for using remotely sensed imagery to directly estimate cork production on a research plot in Portugal.

We surmised that cork production is primarily dependent on tree size, leaf density (LAI), and each tree's physiological status. The LAI, apart from being a good predictor of future growth, can also be used to determine overall tree health, specifically water availability (SMETHURST, et al., 2003); thus, LAI can be used to estimate productivity. As mentioned in the

Table 2 – The best model selected for each class (rows) with corresponding AIC values.
***Tabela 2** – O melhor modelo selecionado para cada classe (linhas) com os correspondentes valores da AIC.*

Number of Variables	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}	x_{11}	x_{12}	x_{13}	x_{14}	AIC
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	594.5745
1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	481.3082
2	0	0	0	0	1	0	0	0	0	0	0	0	1	0	481.9156
3	0	0	0	0	1	1	1	0	0	0	0	0	0	0	473.7503
4	0	0	0	0	1	1	1	0	0	0	0	1	0	0	471.9928
5	0	0	1	0	1	1	1	1	0	0	0	0	0	0	472.9546
6	1	1	0	0	1	1	1	0	0	0	0	1	0	0	474.1796
7	0	1	1	0	1	1	1	0	1	1	0	0	0	0	474.1203
8	0	1	1	0	1	1	1	0	1	1	0	0	0	1	475.4508
9	0	1	1	0	1	1	1	0	1	1	0	1	0	1	476.7056
10	0	1	1	0	1	1	1	1	1	1	1	0	0	1	478.0795
11	0	1	1	1	1	1	1	1	1	1	1	0	0	1	480.0338
12	1	1	1	1	1	1	1	1	1	1	1	0	0	1	481.9437
13	1	1	1	1	1	1	1	0	1	1	1	1	1	1	483.9077
14	1	1	1	1	1	1	1	1	1	1	1	1	1	1	485.8632

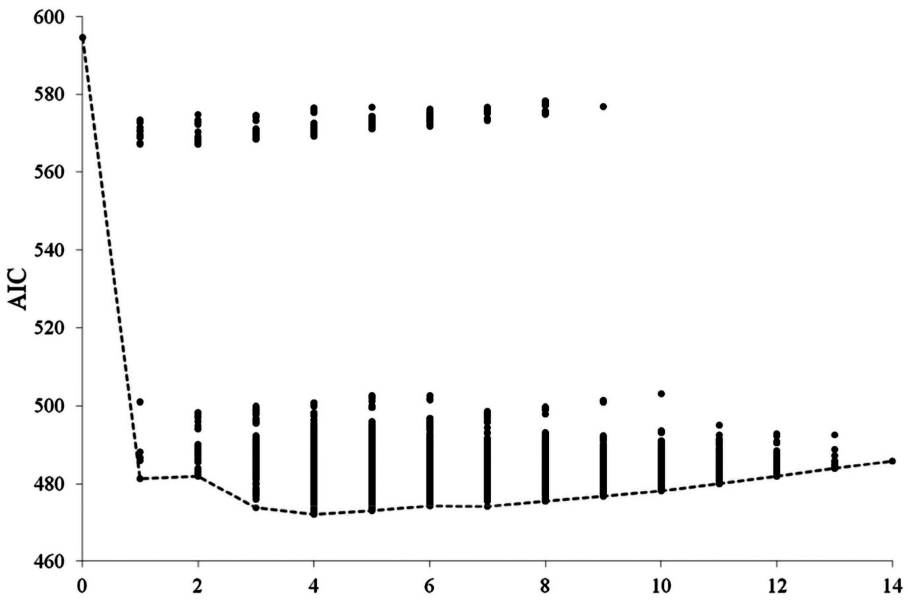

Figure 2 – AIC values for all possible model combinations with minimum values highlighted in each class. The lowest AIC value was derived from a model with four variables.
***Figura 2** – Valores AIC para todos os possíveis modelos com valores mínimos em cada classe. O menor valor de AIC foi encontrado na classe de modelo com quatro variáveis.*

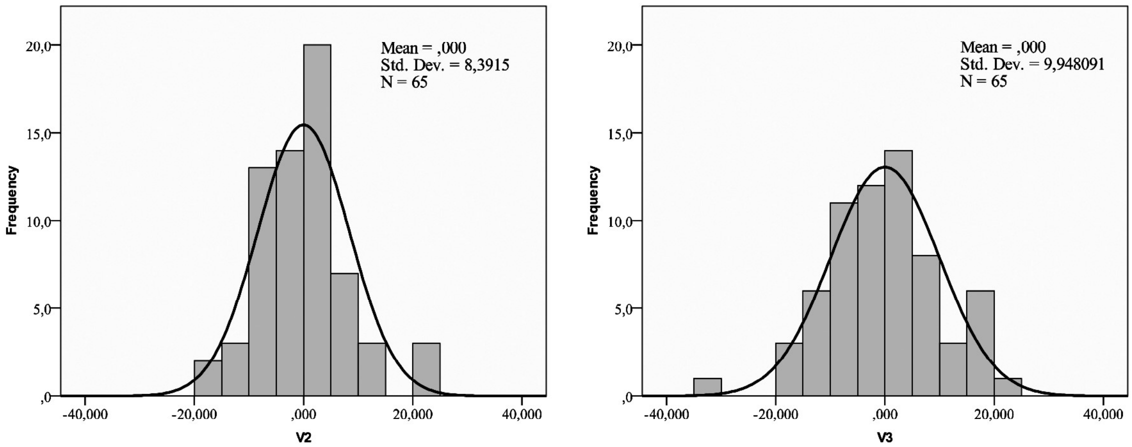

Figure 3 – Residual distributions for the full model (left side) with four variables and the simplified model (right side) with no spectral information.

Figura 3 – *Distribuições de residuais para o modelo completo (lado esquerdo) com quatro variáveis e para o modelo simplificado (lado direito), sem nenhuma informação espectral.*

Introduction many works have demonstrated correlation between indices derived from remote sensed imagery (like NDVI) and LAI. Thus, we hypothesized that there can be correlation between the NDVI and cork production of cork oak.

We found very good correlation between horizontal crown projection and total weight of cork production (Figure 1). Horizontal crown projection is also well correlated with the stem's cross-sectional area, which is the primary predictor for most cork weight models (RIBEIRO et al., 2006; TOMÉ et al., 2001). However, trees with full crowns produce more cork than those frequently pruned or with low leaf density. From a physiological perspective, $NDVI_r$ (NDVI based on NIR and the red band) may be a good descriptor of photosynthetic activity (the more red light that is absorbed by leaves, the higher the potential photosynthetic activity). On the other hand, NDVI based on the blue band ($NDVI_b$) may have better capacity to describe leaf density because the blue band is known to be a good descriptor for distinguishing between vegetation and other background imagery. Our data (Figure 1) supports this hypothesis.

The Enhanced Vegetation Index (EVI) (ALMEIDA et al., 2008), for instance is based on combination of near-infrared, red, and blue wavelengths. Following Knyazikhin et al. (1998) who suggested using all possible information from MODIS and MISRto assess LAI, our analysis is based on all bands from the available remote imagery. A statistical evaluation of the data from our study suggests the inclusion of spectral information can improve the accuracy of productivity assessments. We compared a model that included both structural (horizontal crown projection) and spectral information to a simplified model that included only structural information *without* the spectral component. The use of spectral information increased the accuracy of the model by decreasing the variance of residuals by approximately 15% when compared to the simplified model.

5. CONCLUSION

Inventory and prediction of cork harvest over time and space is important to forest managers who must plan and organize harvest logistics. We present a method for direct estimation of cork production using remotely sensed aerial imagery that is commonly available in Portugal. We show that there is a correlation between reflectance in individual bands obtained from this imagery (NIR, RGB) and indices derived from this reflectance (NDVIr, NDVIg, NDVIb), which can be used to predict cork production. We propose using a model that combines all of these NDVI derivates to predict cork production. This model can help not only during decision-making processes about the management of cork oak stands, but also to understand the spatial distribution of cork production and the influence of site-specific factors like water or nutrient availability.

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