Computers and Electronics in Agriculture 127 (2016) 680–689

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

Site-specific management of common olive: Remote sensing, geospatial, and advanced image processing applications

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ARTICLE INFO

Article history:
Received 28 March 2015
Received in revised form 25 March 2016
Accepted 28 July 2016
Available online 8 August 2016

Keywords:
Site-specific crop management (SSCM)
Olive
Remote sensing (RS)
Geospatial technology
Geographic information systems (GIS)
Normalized digital vegetation index (NDVI)
Soil adjusted vegetation index (SAVI)
Vegetative vigor index (VVI)
Multivariate regression model

ABSTRACT

Site-specific crop management (SSCM) is a part of precision agriculture which is helping increase production with minimal input. It has enhanced the cost-benefit scenario in crop production. The main goal of this paper was to use advanced geospatial techniques in data acquisition, remote sensing (RS), image processing, geographic information systems (GIS), global positioning systems (GPS) and statistical modeling to determine the correlation between image digital information and healthy olive trees growth and production management characteristics. It is to be noted that assumptions were based on the overall canopy greenness of the olive trees as healthy trees. This research was carried out during 2012–2014 in an irrigated olive orchards located in the Tarom region, Zanjan province of Iran. The following data were gathered: fruit set percent in shoot, canopy volume (CV), shoot length (SL), trunk diameter (TD), trunk height (TH), soil plant analysis development (SPAD), leaf area index (LAI), leaf dry matter percent (LDMP), leaf properties like nitrogen (N) and potassium (K) content in leaves, soil properties/characteristics like amount of Clay, Silt, Sand, Sodium adsorption rate (SAR), organic matter (OM), available phosphorous (P_{av}), available potassium (K_{av}), boron (B), total neutralizing value (TNV), electrical conductivity (EC), chloride (Cl), available iron (Fe_{av}). Advanced land observing satellite-Advanced visible and near infrared radiometer type 2 (ALOS-AVNIR-2) image was used in this experiment. A set of six clusters of olive trees existing in a compacted parcel of olive orchards were chosen. The image indices developed for this study were the normalized digital vegetation index (NDVI), newly developed vegetative vigor index (VVI) and the soil adjusted vegetation index (SAVI). Multivariate regression models were developed using remotely sensed image digital values in relation to the site specific crop growth parameters as mentioned above. As is stated above, individual band DN value statistics as input parameters and plant growth characteristics such as CV, SL, TD, TH, SPAD, LAI, and LDMP as output parameters were used in the multivariate regression models development. Multicollinearity analyses were completed on the input parameters to reduce redundancy of data usage. Multicollinearity analysis of the image related variables shows that VVI and b1 are highly correlated with other variables. It was also observed that NDVI – b3 and b2-b4 are highly correlated and hence omitted from the input parameter list. The multivariate regression models developed with NDVI and SAVI along with individual band (Green, Red and Infrared bands) as input parameters for olive crop growth parameters like TD, TH and SPAD provided excellent coefficient of determination (R^2) values of 0.98, 0.99 and 0.99, respectively. SAVI, Red-, Green-, and Blue-band image information together best estimated the olive tree canopy volume with R^2 value of 0.84. Similarly, SAVI, Red-, Green-, and Blue-band image information together also best estimated the olive tree SL and LA with R^2 value of 0.88 and 0.96, respectively. SAVI, NDVI, Red-, Green-, and Blue-band image information as input parameters estimated the olive tree trunk diameter with R^2 value of 0.98. The same SAVI, NDVI, Red-, Green-, and Blue-band image information together best predicted the olive tree trunk height with maximum correlation ($R^2 = 0.99$). Similarly SPAD and LDMP were estimated with excellent correlations ($R^2 = 0.99$ and 0.79, respectively) using image related input parameters of SAVI, NDVI, Red-, Green-, and Blue-band. Algorithms developed with this study could be used by farmers or orhard managers for estimating the olive tree physical characteristics in similar environmental conditions that prevailed in our study area using remotely sensed imagery in a non-invasive, economic, and efficient manner.

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http://dx.doi.org/10.1016/j.compag.2016.07.031

1. Introduction

Growth observation, impact assessment, and timely strategic response to small variations in crop production on spatial basis are known as precision agriculture (Panda et al., 2010). It has been used in a wide range of agricultural activities. Site-specific crop management (SSCM) is a part of precision agriculture which involves spatial referencing, crop and climate monitoring, attribute mapping, decision support systems, and differential management actions to increase production with minimal input (Panda et al., 2010). SSCM is carried out with a greater degree of precision through the use of geospatial technologies which is a combination of four essential tools: remote sensing (RS), geographic information systems (GIS), global positioning systems (GPS), and information technology (IT) or data management (Panda et al., 2010).

During recent years, SSCM has become very common in field and row crops management but its application for non-traditional horticultural crops has not been very widespread yet (Panda et al., 2009). Horticultural crops like fruits and nuts are high value crops for which SSCM may potentially increase net returns and optimize resource use (Panda et al., 2009). The delineation of horticultural orchards and geospatial technology based spatial analysis can provide additional information for horticultural crop management decision support including fruit yield determination and quantification, precise and proper fertilizer application scheduling, need-based irrigation scheduling, and pesticides application for pest and disease management in the orchard. Usha and Singh (2013) highlighted the potential of remote sensing in horticulture with focus on the development of updated and accurate database for systematic planning and decision making for better management of the existing crops.

Several studies have demonstrated the potential of SSCM in fruit and nut crops (Sevier and Lee, 2005). Scientists in the Space Application Center of the Indian Space Research Organization successfully used low resolution IRS LISS III and IRS AWiFS (23-m and 55-m, respectively) images to characterize apple orchards in the apple growing districts of Himachala Pradesh, India (Sharma and Panigrahy, 2007). They used the NDVI data to create blocks of apple orchards in the districts which accounted for a coverage area of 376.30 sq. km. Shrivastava and Gebelein (2006) performed a study in Florida classifying the land-use to delineate citrus groves in order to analyze the economic assessment. They used Landsat Enhanced Thematic Mapper Plus (ETM+) imagery and high resolution aerial imageries for this study. However, they reported that Landsat ETM$^+$ satellite did not work efficiently compared to aerial imageries for citrus groves delineation. Their conclusion, warranted us to use high resolution imageries for our study of olive orchard SSCM. O'Connell and Goodwin (2005) have used remotely-sensed imagery to identify the tree canopy of a peach orchard for orchard yield forecasting and estimation of future crop water requirement with cover ranging from 20% to 66% (coefficient of variation = 20%, n = 56) of $\geqslant$4 year old trees.

Sepulcre-Canto et al. (2005) used high spatial resolution thermal remote sensing imagery to assess crop water stress in an olive grove. García Torres et al. (2008) conducted a study to distinguish olive tree orchards using remote sensing images by clustering assessment or image classification techniques. They used remote sensing to project the yield potential and olive tree characteristics. Researchers at the MAICH Institute in Crete, Greece, conducted extensive studies on remote sensing for olive trees for environmental risk assessment (Karydas et al., 2005). López-Granados et al. (2002) and López-Granados et al. (2004) studied soil variation and site-specific application of nutrients in olive farms in southern Spain based on the spatial variation of leaf nutrients. To the best of our knowledge there has been no yield mapping of a large field of olive trees and this is due to the high labour cost associated with manual harvesting of olives. Peña-Barragána et al. (2004) developed a methodology to determine vegetation cover in olive groves using aerial images taken at diverse times of the year and using several vegetation indexes. Their study was designed to determine the orchard health but they did not provide any suggestion towards the SSCM of the olive orchard. Ramosa et al. (2007) measured and identified soil movement in olive orchards in various gradients using GPS, GIS. Alamo et al. (2012) established a methodology for integrating Geographic Information Systems (GIS) and Global Positioning System (GPS) to implement precision agriculture in a specific olive grove in southern Spain. However, advanced image processing techniques including vegetation indices such as soil adjusted vegetation indices and crop vigor indices along with field environmental data including soil and tree structure attributes would help in SSCM development of olive orchard as conducted by the authors of this study.

Knowledge for the selection of an image platform, basically the image resolution, is essential for any kind of SSCM study including the olive orchard SSCM (Panda et al., 2009). In recent times, high resolution imageries are available at low cost ($ per sq. km.). Even, one can take advantage of available high resolution imageries available in Google Earth with Google Inc.'s permission. Remote Sensing images are composed of pixels. Pixels contain digital/numerical information that can be manipulated and extracted using image processing techniques in software such as ArcGIS, eCognition, ERDAS Imagine, and Idrisi. This extracted digital information can be used to infer meaning to the objects within an image (Richards and Xiuping, 2013). RS systems due to regular, synoptic, multispectral and multitemporal coverage of an area provide accurate database on spectral behavior of crops as well as their growing environment.

The goals of this study were to use advanced techniques in data acquisition, remote sensing, and statistical modeling to determine the correlation between image digital value and olive trees characteristics to determine the health of the orchard in relation to fruit production. Moreover, the specific objective of the study was to determine the statistical significance of various image digital values in combination and their resulting correlation to output values.

2. Materials and methods

2.1. Study area

This research was carried out during 2012–2014 in an irrigated olive orchard located in east of Tarom in northwestern of Iran (between 48°56′ and 50°5′E; and 36°47′ and 37°36′N). The study site was a set of six clusters of 14-years old olive trees within a large mature olive (*Olea europaea* L. cv. Zard) plantation. The clusters were approximately 3.69 km east at a heading of 107.59° from Chavarzagh (A part of Tarom) (Fig. 1). The clusters are located at 425–500 m elevation.

2.2. Field measurements and sampling

Data was taken from 6 clustrs in the orchard. A 98 m × 98 m grid pattern was established, and each intersection point (node) represented a sampling point. The position of each node was geo-referenced using a commercial GPS (Garmin Co., Oregon 300, 2-m resolution).

The following plant and soil data were gathered in the field: Fruit set percent in shoot, canopy volume (CV), shoot length (SL), trunk diameter (TD), trunk height (TH), soil plant analysis development (SPAD) chlorophyll meter, leaf area index (LAI), leaf dry matter percent (LDMP), leaf nitrogen content (N), leaf potassium content (K), amount of Clay, Silt, Sand, Sodium adsorption rate