Multispectral imaging: an effective tool to estimate garlic productivity and sanitary aspects

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Garlic is a relevant crop worldwide, with more than 1.6 M hectares and a production of 30 M tons. In Argentina the crop is located in the western part of the country, in the provinces of Mendoza and San Juan. The vast majority of the local production is exported, generating an average income of 150 M USD [1]. Garlic stakeholders and growers constitute a dynamic sector which constantly demands new tools to improve their efficiency, in a cost-effective manner. In this regard, previous experiments have evaluated the use of remote sensing to estimate garlic growth variables, particularly associated to irrigation and nutrition practices [2,3] and weather conditions [4]. However, the correlation with pest/disease outbreaks are scarce and often related to controlled conditions environments [5]. White rot (WR), caused by the soilborne fungus *Stromatinia cepivora*, is an increasing threaten to garlic crops worldwide. Reports mention that WR causes 50% of yield reduction and sometimes can lead to complete loss [6]. Once present in a field, the fungus produces resistance structures called sclerotia that remain in the soil for long periods of time, infecting any *Allium* crop for many years after that. Hence, the early detection of the presence of WR is essential for the sustainability of the garlic production in the region [7,8].

The objective of the present study was to evaluate the usefulness of multispectral images for the estimation of production variables and crop health in garlic.

The experiment was conducted during the 2020 season in a 1-hectare garlic parcel, located in Tupungato, Mendoza, Argentina. Twelve plots of 14.4 m^2 randomly selected in the parcel were employed as experimental units, consisting in ~450 plants each. The health status of the crop was rated in each experimental unit, considering the incidence and severity of WR. The incidence was calculated as the proportions of diseased/dead individuals over the total initial stand of plants, in the center of the experimental unit (~100 plants). The severity (corresponding to plant health status) was visually estimated in each experimental unit employing a 1-10 scale, where '1' corresponded to highly diseased/dead plants and '10' to healthy, optimal plants. Each plot was separately harvested to analyze the yield variables. Fresh weight was measured at harvest time, while dry yield was recorded after two months of drying, as well as dry weight of commercial bulbs. The number of bulbs produced in each plot was also recorded.

Multispectral images of the experimental field were taken on 8 October 2020. Data acquisition was performed with a Sequoia+ multispectral camera (Parrot Drone SAS), which is composed by 4 monochrome cameras with different narrow-band filters in the visible and near infrared (NIR) domain: green 530-570 nm, red 640-680 nm, red edge 730-740 nm and NIR 770-810 nm. Reflectance targets were used to assess the camera.

Their true reflectance factor was measured with a spectro-radiometer (Flame-S-VIS-NIR, Ocean Optics, USA) using SpectralonTM (LabSphere, USA) as reference. Aerial images were captured by one flight, attaching the camera to a UAV (Sensefly Ebee SQ), with an intended overlap of 85% to ensure image redundancy. The recorded images were aligned, mosaicked and geo-referenced using the software QGIS [9] and used to calculate the normalized difference vegetation index (NDVI). Field taken information, such as severity index, was also included as GIS data. The data were analyzed through lineal regression, using InfoStat [10]. The adjusted models were evaluated considering the coefficients of determination (R^2), residuals (QQ plots) and p-values.

The results showed highly significant coefficients for the lineal model regression ($p<0.0001$). High coefficients of determination, as well as minimal residuals, were found for the variables 'yield_number of harvested bulbs' ($R^2=0.939$, Fig. 1A), 'plant health status' ($R^2=0.804$, Fig. 1B), 'yield_fresh weight' ($R^2=0.965$, Fig. 1C) and 'yield_dry weight' ($R^2=0.938$, Fig.1D). The variables 'incidence' of white rot ($R^2=0.607$) as well as 'yield_mean bulb dry weight' ($R^2=0.669$) showed less adjustment to the NDVI values, but still acceptable.

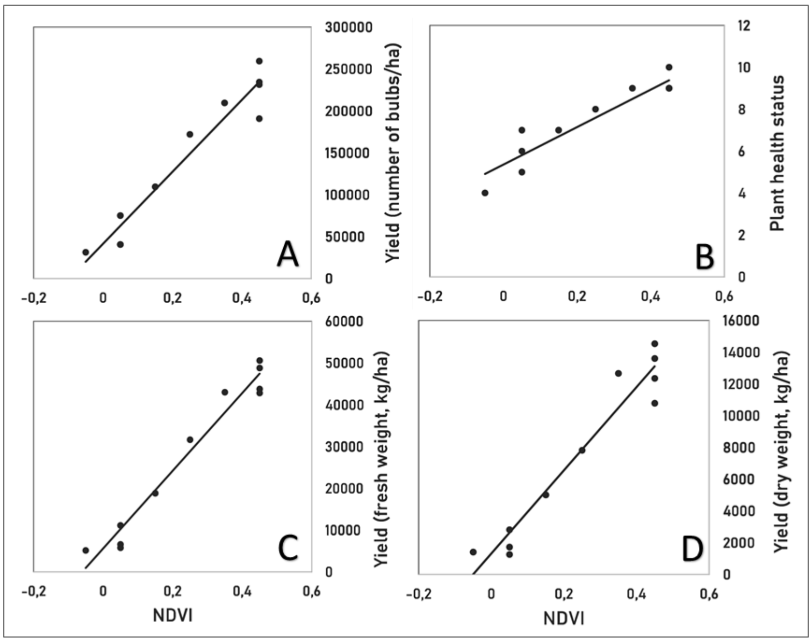

Fig. 1. NDVI as predictor of different yield and health aspects in a garlic crop. Fig. A: number of harvested bulbs; Fig. B: health status of the plot; Fig. C: fresh weight at harvest; Fig. D: dry yield. Date of data acquisition: 8 October 2020.

The use of aerial platforms to acquire images, for instance UAVs, display several advantages such as versatility, light-weight and low operational costs [2]. Previous studies have shown the potential application of NDVI to predict garlic yield in major cultivation regions [4]. In the present study, the fresh yield was accurately predicted, showing a better fitness in comparison to previous similar records [2]. Crop health aspects were also well estimated. However, new evaluations are needed to confirm and validate these results, as well as broader extension assays. The employment of normalized indexes, such as NDVI, constitute a suitable predictor variable to estimate productivity and sanitary aspects in garlic crops. The development of locally validated tools based on this approach could help garlic growers to estimate yields and early detect important pest and disease threatens, such as white rot [5]. The findings presented above constitute one of the first records of the application of remote sensing techniques in horticulture crops in the arid region of Argentina.

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