Brazilian Journal of Development

Monitoring *Thaumastocoris peregrinus* (Hemiptera: Thaumastocoridae) in *Eucalyptus* plantations with remote sensing
/
Monitoramento de *Thaumastocoris peregrinus* (Hemiptera: Thaumastocoridae) em plantios de *Eucalyptus* com sensoriamento remoto

Isabel Carolina de Lima Santos
Doutora em Engenharia Florestal pela Universidade Federal de Lavras
Engenheira Florestal, Pesquisadora voluntária
Endereço: Rua dos Crentes, 121 – Cavalhada 2, 78216-646, Cáceres – MT, Brasil
E-mail: isabelcarolinadelima@gmail.com

Jerffersoney Garcia Costa
Estudante de Engenharia Florestal
Instituição: Instituto Federal do Mato Grosso – Campus Cáceres
Endereço: Caixa Postal 244, 78210-970, Cáceres – MT, Brasil
E-mail: jerffersoney.garcia@gmail.com

Anderson Melo Rosa
Estudante de Engenharia Florestal
Instituição: Instituto Federal do Mato Grosso – Campus Cáceres
Endereço: Caixa Postal 244, 78210-970, Cáceres – MT, Brasil
E-mail: andersonrosa.melo@gmail.com

Alexandre dos Santos
Doutor em Entomologia pela Universidade Federal de Lavras
Instituição: Instituto Federal do Mato Grosso – Campus Cáceres
Endereço: Caixa Postal 244, 78210-970, Cáceres – MT, Brasil
E-mail: alexandre.santos@cas.ifmt.edu.br

ABSTRACT
Thaumastocoris peregrinus (Hemiptera: Thaumastocoridae), the eucalyptus bronze bug, is among the many species of insect pests that affect commercial eucalyptus forests in Brazil. *T. peregrinus* reduces the photosynthetic capacity of trees and, in some cases, can lead to the complete death of plants. The objective of this research was to evaluate the potential of medium spatial resolution images, available for free, in the mapping and prediction of attacks caused by *T. peregrinus* in eucalyptus plantations in Brazil, using Partial Least Squares Discriminant Analysis (PLS-DA). The PLS-DA regression model selected three main components, with a cross-validation error rate of 0.245 for the prediction and mapping of stands attacked by *T. peregrinus*. The important bands were selected from the PLS-DA model, using variable importance in the projection (VIP). The VIP bands predicted healthy and

Brazilian Journal of Development

attacked stands with an accuracy of 97.7% in an independent validation dataset. This study demonstrates the potential of medium spatial resolution images as a viable alternative to successfully characterize and map *T. peregrinus* attacks in planted forests in Brazil.

Keywords: Insects pests; medium resolution images; multivariate analysis; Partial Least Squares Discriminant Analysis.

RESUMO

Thaumastocoris peregrinus (Hemiptera: Thaumastocoridae), percevejo bronzeado, está entre as muitas espécies de insetos-praga que afetam as florestas comerciais de eucalipto no Brasil. *T. peregrinus* reduz a capacidade fotossintética das árvores e, em alguns casos, pode levar à morte completa das plantas. O objetivo desta pesquisa foi avaliar o potencial de imagens Landsat 5 TM, de média resolução espacial, disponibilizada gratuitamente, no mapeamento e predição de ataques causados por *T. peregrinus* em plantações de eucalipto no Brasil, usando a Análise Discriminante dos Mínimos Quadrados Parciais (PLS-DA). O modelo de regressão PLS-DA selecionou três componentes principais, com erro de 0,245 na validação cruzada na predição e no mapeamento de talhões atacados por *T. peregrinus*. Bandas importantes foram selecionadas a partir do modelo PLS-DA, utilizando a importância variável na projeção (VIP). As bandas VIP previram talhões saudáveis e atacados com uma precisão de 97,7% em um conjunto de dados de validação independente. Este estudo demonstra o potencial das imagens de média resolução espacial como uma alternativa viável para caracterizar e mapear, com sucesso, ataques de *T. peregrinus* em florestas plantadas no Brasil.

Palavras-chave: Análise discriminante dos mínimos quadrados parciais; Análise multivariada; Insetos-praga; Imagens de média resolução.

1 INTRODUCTION

The bronze bug *Thaumastocoris peregrinus* Carpintero & Dellapé, 2006 (Hemiptera: Thaumastocoridae), exotic species originally from Australia, it became a pest in eucalyptus plantations, with an outbreak in several countries (Nadel and Noack 2012; Nadel et al. 2010). *T. peregrinus* was detected in Brazil in 2008 (Wilcken et al. 2010), with large populations, with large populations causing damage to eucalyptus plantations, characterized by chlorosis, bronzing, drying and leaf fall (Soliman et al. 2012).

The attack of *T. peregrinus* alters the physiological processes of plants, and it is possible to identify through satellite images (Transon et al. 2018). The canopy of healthy trees have a high absorption of leaf pigments in the red spectral regions and high reflectance in the near-infrared and begin to absorb or reflect spectra at different wavelengths when exposed to biotic and abiotic stresses (Pinter Jr. et al. 2003; Vygodskaya et al. 1989). High water content in healthy trees canopy is usually found when the contrast between the near (NIR) and distant

Brazilian Journal of Development

(SWIR) infrared is analyzed, and the reverse pattern occurs for those unhealthy or under adverse conditions (Fraser and Latifovic 2005; Vogelmann and Rock 1989).

Satellite images allow the detection of different spectral patterns between healthy and damaged trees (Santos et al. 2017). These can be used to build maps to monitor attacked areas and the dynamics of insect pest infestation over time (Townsend et al. 2012). This information, combined with the development of an efficient algorithm, allows decision making on targets of interest (Rodríguez-Cuenca et al. 2015), which, in the case of eucalyptus plantations in Brazil, add up to thousands of hectares to be monitored.

Researches applying indexes to characterize changes in canopy forests (Cohen and Goward 2004; De Beurs and Townsend 2008; Zheng and Moskal 2009) are informative but resulting in unique values. This modifies the magnitude of the spectral band values (Singh 1989), essential for the development and sensitivity of this study.

The objective of this study was to evaluate the potential of medium spatial resolution multispectral images and partial least squares discriminant analysis to monitor the infestation of the bronze bug *Thaumastoris peregrinus* Carpintero & Dellapé, 2006 (Hemiptera: Thaumastocoridae), in eucalyptus plantations.

2 MATERIAL AND METHODS

2.1 STUDY AREA

The study was developed in 170.07 hectares with *Eucalyptus urophylla* x *Eucalyptus grandis* hybrid clones of 60 months old in the municipalities of Antônio Dias, Ipaba, and Periquito, Minas Gerais state, Brazil. The climate, according to the Köppen classification, of the municipality of Antônio Dias is Cwb, humid subtropical with dry winter and temperate summer, average annual precipitation of 1,489 mm, and average annual temperature of 19.8 ºC. The climate of the Ipaba and Periquito municipalities is Aw, tropical with dry winter, average annual precipitation of 1,344 and 1,290 mm and average annual temperature of 22.3 and 22.9 ºC, respectively (Alvares et al. 2013)

The healthy (54.65ha) and attacked (115.42ha) stands were determined by prior monitoring "*in loco*" to verify the presence or absence of *T. peregrinus* and its injuries on plants. Stands free of insects or injuries were considered healthy and stands with insects, chlorosis, bronzing or dry leaves were considered to be attacked.

Brazilian Journal of Development

2.2 ACQUISITION AND PRE-PROCESSING OF SATELLITE IMAGES

Satellite images of Landsat 5 in the bands 1, 2, 3, 4, and 5 (Table 1) in orbit 217 and point 73 with a spatial resolution of 30 m passage of sensor TM (Thematic Mapper) on June 6, 2010, were acquired at the site of the National Institute for Space Research in http://www.dgi.inpe.br/CDSR/.

Table 1. The spectral resolution of the Landsat TM bands to study health *Eucalyptus* stands or those damaged by *Thaumastocoris peregrinus* (Hemiptera: Thaumastocoridae)

Landsat TM Bands	Spectral resolution (micrometers)
Band 1 - blue	0.45 - 0.52
Band 2 - green	0.52 - 0.60
Band 3 - red	0.63 - 0.69
Band 4 - near infrared	0.77 - 0.90
Band 5 – short-wave infrared	1.55 - 1.75

The geometric and radiometric correction of images were performed in two steps. First, the digital image numbers were converted to at-satellite radiance through the calibration coefficients $B_{rescale}$ (W/m^2.sr.μm) and $G_{rescale}$ (W/m^2.sr.μm.DN) (Chander et al. 2007) and at-satellite radiance to at-satellite reflectance by the apparent reflectance method ($\rho\lambda$) (Chander et al. 2009), by the equation: $\rho\lambda = \pi\ L_\lambda\ d^2/\ ESUN_\lambda\ cos(\theta)$; where: L_λ is the apparent binomial radiance (W/m^2.sr.μm); d sun-earth distance in astronomical units; $ESUN_\lambda$ exoatmospheric average solar radiance (W/m^2.μm); and the θ solar zenith angle.

The images also passed by topographic correction using the C-correction approach (Teillet et al. 1982) with a terrain elevation image (19S435ZN); acquired at the site of INPE TOPODATA in http://www.dsr.inpe.br/topodata/; by the equation: $\rho H = \rho T\ (cos(\theta_z)+c/IL+c)$; where: ρH is the radiance observed in the horizontal surface; ρT the radiance observed on the surface with relief; θ_z the solar zenith angle; IL solar angle on a surface with relief; and $c= b/m$, where m and b regression coefficients specific for each band.

The images at the end of the pre-processing step were cropped based on the contour of the stands to obtain the new images canopy reflectance of eucalyptus trees for each of the spectral bands. The corrections and processing were performed using the R program (R Core Team, 2010) with the raster (Hijmans 2014), rgdal (Bivand et al. 2014), splancs (Rowlingson and Diggle 2013), landsat (Goslee 2011) and shapefiles (Stabler 2013) packages.

2.3 SPECTRAL CHARACTERIZATION OF *T. PEREGRINUS*

The targets of this study had 88 pixels to the smallest area of 7.95 ha to 567 pixels for the largest one with 51.03 ha on satellite images. Seventy random pixels per band were chosen for a non-unbalanced analysis of the data. The canopy reflectance values of each spectral band were analyzed with Permutational Multivariate Analysis of Variance (PERMANOVA) (Anderson 2001) with Mahalanobis distance (Perumal and Bhaskaran 2010) to reduce the bias of the analysis, with a significance level of $p<0.05$ and 9,999 replications. This analysis was conducted to verify differences in the bands between healthy and damaged areas. Analyses were performed using the R software (R Core Team 2010) and the vegan package (Oksanen et al. 2015).

2.4 PREDICTION AND MAPPING *T. PEREGRINUS*

The partial least squares discriminant analysis (PLS-DA), a special case of regression by partial least squares (PLSR) for categorical variables (Pérez-Enciso and Tenenhaus 2003) was used to predict the areas damaged by *T. peregrinus*. Five multispectral bands were subjected to PLS-DA regression, where the collinearity effect of the model data can be reduced more effectively, and the correlation between the variables of predictor spectral band and variable response maximized (Mevik and Cederkvist 2004). The partial least squares regression is described by the equation, $X= TP' + E$, $Y= UQ' + F$, where X is the predictor matrix; Y is the response matrix; T-scores$= X$; U$= Y$-scores; $P= X$-loadings; $Q= Y$-loadings; $E= X$-residuals; and $F= Y$-residuals (Geladi and Kowalski 1986; Ye et al. 2008).

The number of main components was selected according to the classification error rate as predicted by the cross-validation process by leave-one-out to minimize PLS-DA errors in the regression fitted (Mevik and Wehrens 2007). The predictor variables included in the regression PLS-DA, were chosen with the calculation of the important variables in the projection (VIP) (Tenenhaus 1998). These variables determine the contribution of each band in the data set and identifies those most important to predict areas damaged by *T. peregrinus*. The PLS-DA regression adjustment and calibration were performed in 102.21 ha attacked and 46.7 ha healthy, and the prediction in 13.21 ha attacked and 7.95 ha healthy ones to validate the data set model.

The infestation by *T. peregrinus* was mapped with the result of predicting pixel by pixel with the PLS-DA regression adjusted on the validation areas. The areas were mapped with the following classes: red for damage and gray for health areas in the interior of stands.

Brazilian Journal of Development

The accuracy of the maps was obtained by the simple ratio between the number of pixels correctly classified and the total pixels per area. Analyses were performed using the R software (R Core Team 2010) and mixOmics (Dejean et al. 2013) and raster (Hijmans 2014) packages.

3 RESULTS

The spectral bands of damaged and healthy areas showed differences with the Permutational Multivariate Analysis of Variance using Mahalanobis distance (pseudo-F= 50.489, p= 0.00001, DF= 1, n= 559) (Figure 1).

The Partial Least Square Discriminant Analysis (PLS-DA) adjusted had an error rate of cross-validation with three main components of 0.245. The differences in the accuracy of the adjusted models were higher with 1 and 2 main components, respectively, 0.305 and 0.285 (Figure 2a). Errors showed lower variation from three components (Figure 2a). The determination of the most important predictor bands to identify healthy and damaged areas by *T. peregrinus* with the selection of variables important in the projection (VIP) is the next step after defining the number of main components of the model. VIP showed that three major bands in the model are respectively the band 4 (near-infrared) (VIP= 1.12465), band 1 (blue) (VIP= 1.05784) and band 3 (red) (VIP = 1.02895) (Figure 2b).

The areas damaged by *T. peregrinus* showed more multidimensional variation for the most important bands to select areas with healthy eucalyptus plantations (Figure 3). This variation can be inferred that the probability of error of the PLS-DA regression is higher when predicting healthy areas as damaged by this pest than the inverse.
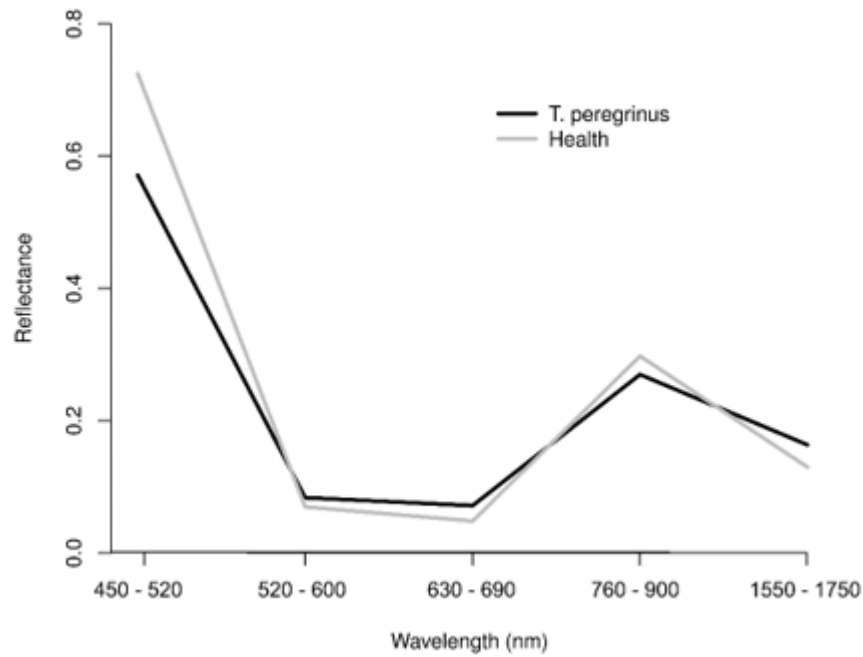
Brazilian Journal of Development

Figure 1. The reflectance of the bands 1, 2, 3, 4, and 5 of the Landsat 5 TM in healthy and attacked areas by *Thaumastocoris peregrinus* (Hemiptera: Thaumastocoridae).
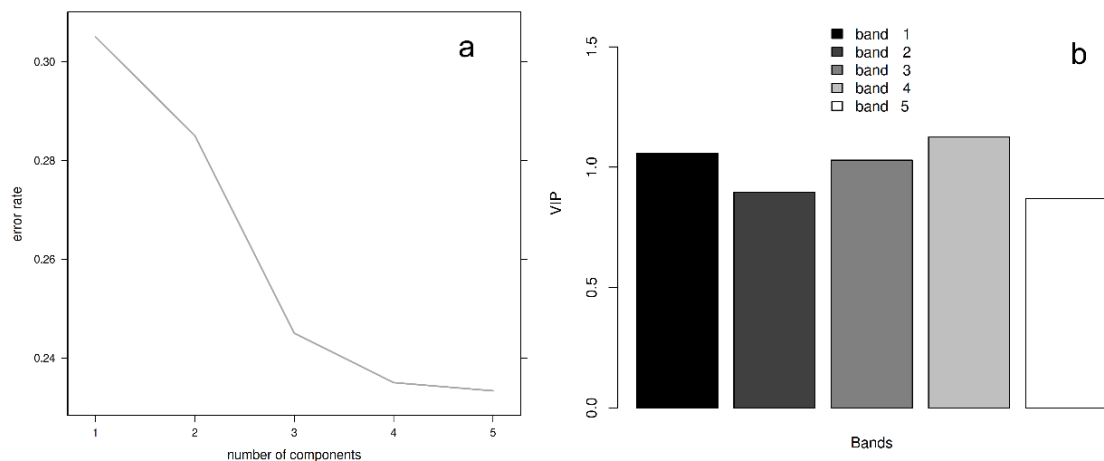

Figure 2. Classification of the cross-validation error rate (a) and variables important in the projection (VIP) (b) for adjustment of the regression with partial least squares discriminant analysis (PLS-DA).
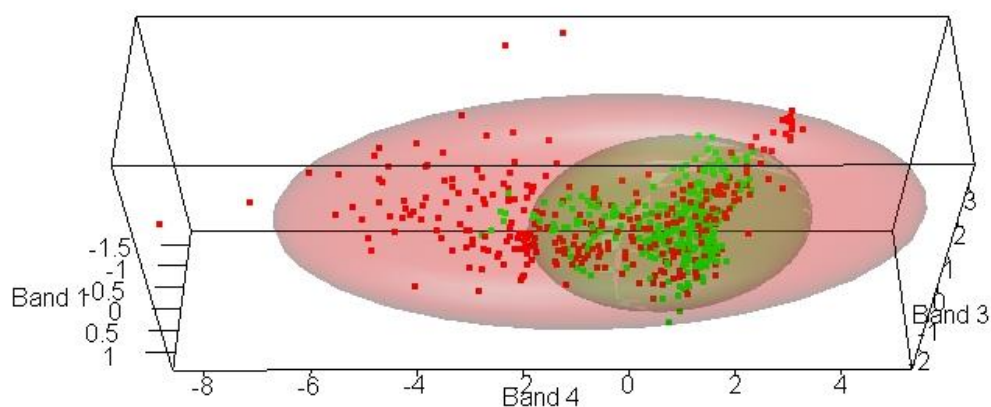
Figure 3. Scatter plot with confidence ellipse (95%) of the regression discriminant analysis partial least squares (PLS-DA) to separated healthy from damaged areas by *Thaumastocoris peregrinus* (Hemiptera: Thaumastocoridae) using bands 4, 1 and 3.

The fitted PLS-DA regression allowed predicting pixel to pixel, in order to map the status of two plant stands, not utilized in the adjustment and calibration stages, respectively, as damaged (Figure 4a) and healthy (Figure 4b). The mapping accuracy was 97.7% (100* (211 pixels correctly classified/216 pixels in the areas), showing a highly satisfactory approach to classify areas damaged or not by *T. peregrinus*.

Status classification
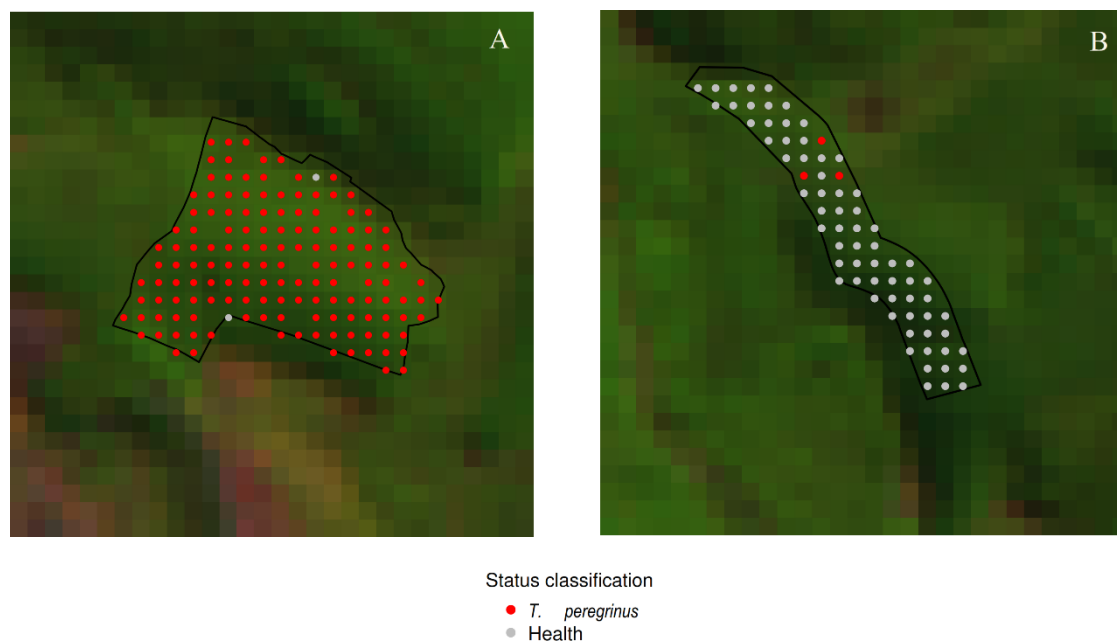- T. peregrinus
- Health

Figure 4. Mapping estimated by discriminant analysis by partial least squares (PLS-DA) for a target 13,21ha damaged by *Thaumastocoris peregrinus* (Hemiptera: Thaumastocoridae) (A) and healthy (B) with 7.95 ha combining the spectral bands 5, 4 and 3 Landsat 5 TM (false color).

Brazilian Journal of Development

4 DISCUSSION

The characterization of the spectral signature of 60 months old plants with damage by *T. peregrinus* shows variations along the spectrum which corroborate changes in their morphology (external and internal) and biochemical responses as observed for those of *Eucalyptus smithii* with this insect (Oumar and Mutanga 2012). The analysis of the reflectance curves for the healthy and attacked stands allowed for the spectral characterization of *T. peregrinus* damage across the Landsat OLI bands in 5-year-old forest stands of *Eucalyptus urophylla* x *Eucalyptus grandis* hybrid clones (Santos et al. 2017). This shows that the use of medium spatial resolution images can be used to monitor the attack of *T. peregrinus* in eucalyptus plantations. Difference between bands 1 (blue) and 2 (green) of healthy and damaged plantations could not be explained by the relationship between the visible spectrum and the concentration of photosynthetic pigments, as carotenoids and xanthophylls, which vary with the health status of the vegetation (Rock et al. 1986; Peñuelas and Filella 1998). Differences in the average reflectance of the infrared spectrum (band 5) show a change in water and other compounds absorption in the canopy of healthy or damaged plants by *T. peregrinus* (Peñuelas and Filella 1998; Santos et al. 2017). The band 5 (0.85–0.88 μm) showed higher reflectance in attacked stands as compared to healthy stands (Santos et al. 2017), and in this study, the inverse was observed. The plant physiology showed a peak in band 4 for healthy areas, in the length of 760 to 900 nm, indicating a higher water content in plant leaf tissues in those areas compared to the damaged ones (Rock et al. 1986). However, in monitoring the attack of *T. peregrinus* in eucalyptus plantations, the highest peak in band 4 was observed for the attacked areas (Santos et al. 2017). The band 3 of damaged areas showed higher reflectance, indicating lower concentration chlorophyll in leaves of damaged than in healthy ones (Horler et al. 1980; Filella and Peñuelas 1994; Santos et al. 2017).

The errors showed less variation with three main components, and similar results were obtained by Santos et al. 2017, who also found the smallest cross-validation error for the PLS-DA model with three main components in a study of *T. peregrinus* attack in eucalyptus plantations. The selection of bands 3 and 4 as important variables in projection (VIP) for predicting the phytosanitary status of areas damaged or not by *T. peregrinus* corroborates result with the WorldView-2 satellite images for *Eucalyptus smithii*, except for band 1, included in this work as a variable to identify plants with damage by this Hemiptera as reported for Oumar et al. 2013. However, Landsat OLI bands 2 (blue), 3 (green), and 6 (short-wave

Brazilian Journal of Development

infrared) were selected as important variables by VIP for the prediction of *T. peregrinus* attacked stands (Santos et al. 2017).

The of 97.7% accuracy of the mapping presented in this paper supports the use of the combination of multispectral sensors, like Landsat, and Partial Least Squares Regression (PLSR) as a robust approach for predicting damage by *T. peregrinus* as reported for the use of hyperspectral sensors in South Africa eucalyptus plantations (Oumar et al. 2013), and for the use of Lansat OLI images for predicting damage by *T. peregrinus* in eucalyptus plantation in Brazil (Santos et al. 2017). The sensor Thematic Mapper (TM) Landsat identified insect infestations, as *Adelges tsugae* Annand, 1924 (Hemiptera: Adelgidae) in *Tsuga Canadensis* (Pinaceae) (Bonneau et al. 1999) and defoliation by *Choristoneura pinus* Freeman, 1953 (Lepidoptera: Tortricidae) in *Pinus banksiana* (Pinaceae) (Radeloff et al. 1999). The high percentage of correct classification with Landsat 5 images, has the disadvantage discontinuation of imaging by this satellite in South America. On the other hand, other satellites, like the Landsat 8 and Sentinel, have similar features and enhancements and could be used with the approach proposed in this research.

The spectral response of the areas damaged by *T. peregrinus* as a result of an average spectrum of 90 trees per pixel (30x30 m), with 3.33x3.00 m plant spacing. However, the infestation which allows detection by the method proposed is not also known, because it was thoroughly examined only in healthy crops and those completely damaged by *T. peregrinus*. Satellites with better spatial and temporal resolution as the WorldView-2, respectively 2 x 2m in multispectral bands and 1.1 days for new imaging, have a higher sensitivity to predicting and mapping *T. peregrinus* (Oumar and Mutanga 2012). However, the Landsat images are free, while the WorldView-2 has a high cost.

Remote sensing combined with an unsupervised classification algorithm allows, at the appropriate time, monitoring and mapping of attacks by *T. peregrinus* in eucalyptus plantations (Ennouri and Kallel 2019).

5 CONCLUSION

The multispectral signature damage by the bronzing bug *T. peregrinus* was characterized. The approach using discriminant analysis by partial least squares showed the potential to develop an algorithm for remote sensing monitoring of medium resolution of this Hemiptera insect in eucalyptus plantations.

Brazilian Journal of Development

REFERENCES

Alvares CA, Stape JL, Sentelhas PC, Gonçalves JLM, Sparovek G. Köppen's climate classification map for Brazil. **Meteorologische Zeitschrift**, v. 22, n. 6, p. 711-728, 2013. doi: 10.1127/0941-2948/2013/0507

Anderson MJ. A new method for non-parametric multivariate analysis of variance. **Austral Ecology**, v. 26, n. 1, p. 32–46, 2001. doi: 10.1111/j.1442-9993.2001.01070.pp.x

Bivand R, Keitt T, Rowlingson B. **rgdal: Bindings for the geospatial data abstraction library**. R package version 0.8-16, 2014. http://CRAN.R-project.org/ package=rgdal

Bonneau LR, Shields KS, Civco DL. A technique to identify changes in hemlock forest health over space and time using satellite image data. **Biological Invasions**, v. 1, n. 2-3, p. 269-279, 1999. doi: 10.1023/A:1010081832761

Chander G, Markham BL, Barsi JA. Revised Landsat-5 Thematic Mapper radiometric calibration. **Ieee Geoscience and Remote Sensing Letters**, v. 4, n. 3, p. 490-494, 2007. doi: 10.1109/LGRS.2007.898285

Chander G, Markham BL, Helder DL. Summary of current radiometric calibration coefficients for Landsat MSS, TM, ETM+, and EO-1 ALI sensors. **Remote Sensing of Environment**, v. 113, n. 5, p. 893-903, 2009. doi: 10.1016/j.rse.2009.01.007

Cohen WB, Goward SN. Landsat's role in ecological applications of remote sensing. **BioScience**, v. 54, n. 6, p. 535-545. doi: 10.1641/0006-3568(2004)054[0535:LRIEAO] 2.0.CO;2

De Beurs KM, Townsend PA. Estimating the effect of gypsy moth defoliation using MODIS. **Remote Sensing of Environment**, v. 112, n. 10, 3983–3990, 2008. doi: 10.1016/j.rse.2008. 07.008

Dejean S, Gonzalez I, Cao KAL. **mixOmics: Omics data integration project**. R package version 5.0-1, 2013. http://CRAN.R-project.org/package=mixOmics

Ennouri, K., & Kallel, A. Remote sensing: An advanced technique for crop condition assessment. **Mathematical Problems in Engineering**, v. 2019, p. 1–8, 2019. doi:10.1155/2019/9404565

Geladi P, Kowalski BR. Partial least-squares regression: A tutorial. **Analytica Chimica Acta**, v. 185, n. 1, 1 –17, 1986. doi: 10.1016/0003-2670(86)80028-9

Filella I, Peñuelas J. The red edge position and shape as indicators of plant chlorophyll content, biomass and hydric status. **International Journal of Remote Sensing**, v. 15, n. 7, 1459-1470, 1994. doi: 10.1080/01431169408954177

Fraser RH, Latifovic R. Mapping insect-induced tree defoliation and mortality using coarse spatial resolution imagery. **International Journal of Remote Sensing**, v. 26, n. 1, p. 193-200, 2005. doi: 10.1080/01431160410001716923

Goslee SC. Analyzing remote sensing data in R: The Landsat package. **Journal of Statistical Software**, v. 43, n. 4, 1-25, 2011. doi:b10.18637/jss.v043.i04

Pinter Jr. PJ, Hatfield JL, Schepers JS, Barnes EM, Moran MS, Daughtry CST, Upchurch DR. Remote sensing for crop management. **Photogrammetric Engineering & Remote Sensing**, v. 69, n. 6, p. 647–664, 2003.

Hijmans RJ. **raster: Geographic data analysis and modeling.** R package version 2.2-31, 2014. http://CRAN.R-project.org/package=raster

Horler DNH, Barber J, Barringer AR. Effects of heavy metals on the absorbance and reflectance spectra of plants. **International Journal of Remote Sensing**, v. 1, n. 2, p. 121-136, 1980. doi: 10.1080/01431168008547550

Mevik BH, Cederkvist HR. Mean squared error of prediction (MSEP) estimates for principal component regression (PCR) and partial least squares regression (PLSR). **Journal of Chemometrics**, v. 18, n. 9, p. 422-429, 2004. doi: 10.1002/cem.887

Mevik BH, Wehrens R. The pls package: Principle component and partial least-squares regression in R. **Journal of Statistical Software**, v. 18, n. 2, 1-24, 2007. doi: 10.18637/ jss.v018.i02

Nadel RL, Noack AE. Current understanding of the biology of *Thaumastocoris peregrinus* in the quest for a management strategy. **International Journal of Pest Management**, v. 58, n. 3, p. 257-266, 2012. doi: 10.1080/09670874.2012.659228

Nadel RL, Slippers B, Scholes MC, Lawson SA, Noack AE, Wilcken CF, Bouvet JP, Wingfield MJ. DNA bar-coding reveals source and patterns of *Thaumastocoris peregrinus* invasions in South Africa and South America. **Biological Invasions**, v. 12, n. 5, p. 1067-1077, 2010. doi: 10.1007/s10530-009-9524-2

Peñuelas J, Filella I. Visible and near-infrared reflectance techniques for diagnosing plant physiological status. **Trends in Plant Science**, v. 3, n. 4, 151-156, 1998. doi: 10.1016/S1360 -1385(98)01213-8

Pérez-Enciso M, Tenenhaus M. Prediction of clinical outcome with microarray data: A partial least squares discriminant analysis (PLS-DA) approach. **Human Genetics**, v. 112, n. 5-6, p. 581-592, 2003. doi: 10.1007/s00439-003-0921-9

Oksanen J, Blanchet FG, Kindt R, Legendre P, Minchin PR, O'Hara RB, Simpson GL, Solymos P, Stevens MHH, Wagner H. **vegan: Community Ecology**. R package version 2.3-2, 2015.

Perumal K, Bhaskaran R. Supervised classification performance of multispectral images. **Journal of Computing**, v. 2, n.2, p. 124-129, 2010.

Oumar Z, Mutanga O. Using WorldView-2 bands and indices to predict bronze bug (*Thaumastocoris peregrinus*) damage in plantation forests. **International Journal of Remote Sensing**, v. 34, n. 6, 2236-2249, 2012. doi: 10.1080/01431161.2012.743694

Oumar Z, Mutanga O, Ismail R. Predicting *Thaumastocoris peregrinus* damage using narrow band normalized indices and hyperspectral indices using field spectra resampled to the Hyperion sensor. **International Journal of Applied Earth Observation and Geoinformation**, v. 21, n. 1, p. 113-121, 2013. doi: 10.1016/j.jag.2012.08.006

R Core Team. **R: A language and environment for statistical computing.** Vienna: R Foundation for Statistical Computing, 2010.

Radeloff VC, Mladenoff DJ, Boyce MS. Detecting jack pine budworm defoliation using spectral mixture analysis: separating effects from determinants. **Remote Sensing of Environment**, v. 69, n. 2, 156–169, 1999. doi: 10.1016/S0034-4257(99)00008-5

Rock BN, Vogelmann JE, Williams DL, Vogelmann AF, Hoshizaki T. Remote detection of forest damage. **BioScience,** v. 36, n. 7, p. 439-445, 1986. doi: 10.2307/1310339

Rodríguez-Cuenca B, García-Cortés S, Ordóñez C, Alonso MC. Automatic detection and classification of pole-like objects in urban point cloud data using an anomaly detection algorithm. **Remote Sensing**, v. 7, n. 10, p. 12680-12703, 2015. doi: 10.3390/rs71012680

Rowlingson B, Diggle P. **splancs: Spatial and space-time point pattern analysis**. R package version 2.01-34, 2013. http://CRAN.R-project.org/package=splancs

Santos A, Oumar Z, Arnhold A, Silva N, Silva CO, Zanetti R. Multispectral characterization, prediction and mapping of *Thaumastocoris peregrinus* (Hemiptera: Thamascoridae) attack in *Eucalyptus* plantations using remote sensing. **Journal of Spatial Science**, v. 62, n. 1, p. 127-137, 2017. doi: 10.1080/14498596.2016.1220873

Singh A. Review article digital change detection techniques using remotely sensed data. **International Journal of Remote Sensing**, v. 10, n. 6, p. 989-1003, 1989. doi: 10.1080/01431168908903939

Soliman EP, Wilcken CF, Pereira JM, Dias TKR, Zache B, Dal Pogetto MHFA, Barbosa LR. Biology of *Thaumastocoris peregrinus* in different eucalyptus species and hybrids. **Phytoparasitica** v. 40, p. 223-230, 2012. doi: 10.1007/s12600-012-0226-4

Stabler B. **shapefiles: Read and write ESRI shapefiles**. R package version 0.7, 2013. http://CRAN.R-project.org/package=shapefiles

Teillet PM, Guindon B, Goodenough DG. On the slope-aspect correction of multi-espectral scanner data. **Canadian Journal of Remote Sensing**, v. 8, n. 2, p. 84-106, 1982. doi: 10.1080/07038992.1982.10855028

Tenenhaus M. **La régression PLS: théorie et pratique**. Paris: Editions Technip, 1998. 254p.

Townsend PA, Singh A, Foster JR, Rehberg NJ, Kingdon CC, Eshleman KN, Seagle SW. A general Landsat model to predict canopy defoliation in broadleaf deciduous forests. **Remote Sensing of Environment**, v. 119, n. 1, p. 55-265, 2012. doi: 10.1016/j.rse.2011.12.023

Transon J, d'Andrimont R, Maugnard A, Defourny P. Survey of hyperspectral earth observation applications from space in the Sentinel-2 context. **Remote Sensing**, v. 10, n. 2, p. 1-32, 2018. doi: 10.3390/rs10020157.

Vogelmann JE, Rock BN. Use of Thematic Mapper data for the detection of forest damage caused by the pear thrips. **Remote Sensing of Environment**, v. 30, n. 3, p. 217–225, 1989. doi: 10.1016/0034-4257(89)90063-1

Vygodskaya NN, Gorshkova I, Fadeyeva YV. Theoretical estimates of sensitivity in some vegetation indices to variation in the canopy condition. **International Journal of Remote Sensing**, v. 10, n. 12, p. 1857-1872, 1989. doi: 10.1080/01431168908904016

Wilcken CF, Soliman EP, Sá LAN, Barbosa LR, Dias TKR, Ferreira Filho PJ, Oliveira RJR. Bronze bug *Thaumastocoris peregrinus* Carpintero and Dellapé (Hemiptera: Thaumastocoridae) on *Eucalyptus* in Brazil and its distribution. **Journal of Plant Protection Research**, v. 50, n.2, p. 201-205, 2010.

Ye X, Sakai K, Sasao A, Asada S. Potential of airborne hyperspectral imagery to estimate fruit yield in citrus. **Chemometrics and Intelligent Laboratory Systems**, v. 90, n. 2, p. 132-144, 2008. doi: 10.1016/j.chemolab.2007.09.002

Zheng G, Moskal LM. Retrieving leaf area index (LAI) using remote sensing: Theories, methods and sensors. **Sensors**, v. 9, n. 4, 2719-2745, 2009. doi: 10.3390/s90402719