Available at www.sciencedirect.com

INFORMATION PROCESSING IN AGRICULTURE 11 (2024) 109–116

journal homepage: www.keaipublishing.com/en/journals/information-processing-in-agriculture/

A remote sensing approach to estimate the load bearing capacity of soil

Italo Rômulo Mendes de Souza [a], *Edson Eyji Sano* [b], *Renato Paiva de Lima* [c], *Anderson Rodrigo da Silva* [a,*]

[a] *Statistics and Geoprocessing Laboratory, Instituto Federal Goiano, Geraldo Silva Nascimento Road, Km 2.5, 75790-000 Urutaí, Goiás, Brazil*
[b] *Embrapa Cerrados, BR-020 Road, Km 18, Mailbox 08223, 73310-970 Planaltina, DF, Brazil*
[c] *Department of Soil Science, 'Luiz de Queiroz' College of Agriculture, University of São Paulo, Av. Pádua Dias, 235-Agronomia, Piracicaba, SP 13418-900, Brazil*

ARTICLE INFO

Article history:
Received 14 September 2021
Received in revised form
30 August 2022
Accepted 13 October 2022
Available online 20 October 2022

Keywords:
Soil compaction
SMAP
Preconsolidation stress
Brazilian Cerrado

ABSTRACT

Preconsolidation pressure (σ_P) of soil can be considered as an indicator of the Load Bearing Capacity (LBC), which is the tolerated surface pressure before compaction, often caused by the traffic of agricultural machinery. In this pioneering study, a remote sensing approach was introduced to estimate LBC through σ_P from soils of the "Rio Preto" Hydrographic Basin, Bahia State, Brazil, in a monthly time lapse from 2016 to 2019. Traditionally, σ_P is measured by a laborious and time demanding laboratory analysis, making it unfeasible to map large areas. The innovative methodology of this work consists of combining active–passive satellite data on soil moisture and pedotransfer functions of clay content and water matric potential to obtain geo-located estimates of σ_P. Estimates were analysed under different classes of soil use, land cover and slope; 95% confidence intervals were built for the time series of mean values of LBC for each class. The overall seasonal variation in LBC estimates is similar in areas with annual crops, grasslands and natural vegetation, and flat areas are less affected by soil moisture variations over the year (between seasons). LBC decreased, in general, at about 0.5% a year in flat areas. Therefore, these areas demand attention, since they occupy 86% of the Basin and are mostly subjected to agricultural soil management and surface pressure by heavy machinery.

1. Introduction

In the last few decades, Brazil has established itself as a major global agricultural power due to the intensified incorporation of technologies and mechanized operations in the production process, allowing the expansion of the agricultural frontier, especially in the Cerrado (Savanna) areas [1,2]. The high degree of soil weathering in the Cerrado promotes structural stability, which combined with the smooth topography, greatly favours soil management. On the other hand, incorrect management leads to structural degradation [3,4]. Therefore, it is necessary to have information about the potential for use and risk of damage of soils caused by different management systems, with the help of indicators that make it possible to keep or improve the soil physical quality [5].

* Corresponding author.
E-mail address: anderson.silva@ifgoiano.edu.br (A.R. da Silva).
Peer review under responsibility of China Agricultural University.
https://doi.org/10.1016/j.inpa.2022.10.002
2214-3173

The preconsolidation pressure can be used as a measure of the load bearing capacity (LBC) of soil, that is, the tolerable upper limit of surface pressure that precedes irreversible soil compaction [6,7]. In regions where the applied surface pressure is low, there is low probability of compaction, and the soil undergoes small, elastic or reversible deformations. The LBC reflects the history of pressures that a soil has already suffered. LBC has been used [2,8–10] to predict pressure levels which can be applied to the soil under different water contents without further compaction and to quantify the effects of agricultural operations on soil structure. Furthermore, the propagation of surface pressures through the soil profile can also be predicted [11].

Traditional methods applied to assess physical status of soil are generally laborious, time demanding in the field, costly, and sometimes dependent on laboratory analysis, which is the case when measuring LBC through compression tests. Thus, the development of alternative techniques for assessing the mechanical behaviour and physical attributes of the soils is both technically and economically relevant [12]. Soil physical and structural assessments can be done using modern sensors, through their spectral responses [13–19]. However, there is still a gap regarding the use of remote sensing techniques to estimate LBC. In practice, mapping that soil attribute would increase the performance of soil management procedures and the appropriate land use, but it would rather be feasible only through a remote sensing approach based on sensor data and accurate pedotransfer functions. Some pedotransfer functions were developed for the Brazilian Cerrado soils [2], but with incipient application in remote sensing studies. And, to the best of our knowledge, none using remote sensing data to estimate LBC of Brazilian soils.

Watersheds represent areas of natural resources of remarkable importance in Brazil, but they have been commonly exploited for human activities, especially for farming. This is the case of the “Rio Preto” Hydrographic Basin, located in western Bahia, in the region known as MATOPIBA, an agricultural frontier in the Brazilian Cerrado known to be highly exploited for cultivation of annual crops. Mechanized operations applied to soils with high moisture content must be planned according to the estimated LBC [20] to avoid structural degradation of the soils, especially when the machinery crosses the same area more than once.

The objective of this study was to combine remote sensing techniques and data with pedotransfer functions developed for Brazilian soils to estimate the LBC of the “Rio Preto” Basin under the effects of different classes of soil use, land cover and slope.

The methodological part of the paper was organized in order to: (a) describe the hydrographic basin in terms of geographic and topographic characteristics, and type of vegetation; (b) describe how satellite data were managed to classify the hydrographic basin in classes of land cover and slope; and (c) to show how remotely-driven soil physical data were organized in a spatial grid to estimate LBC. The results were organized into sections that allow one to verify the effect of those classes on the temporal estimates of LBC.

2. Material and methods

2.1. Study area

The data used in this study were driven from the “Rio Preto” Hydrographic Basin, which covers an area of 23 223 km^2, centred at the coordinates 11° 3′ 37.01″ S and 45° 12′8.55″ W, and located in the west of Bahia State (BA), Brazil. It reaches the states of Tocantins (TO) and Piauí (PI), draining the municipalities of Formosa do Rio Preto - BA, Santa Rita de Cássia - BA, Mansidão - BA, Riachão das Neves - BA and Mateiros - TO (Fig. 1).

The climate of the region, according to the Koppen classification system, is Aw (semi-humid tropical with summer rains) with mean annual rainfall ranging from 800 to 1 700 mm [21]. The vegetation consists of the Brazilian Cerrado (savanna) domain with physiognomies ranging from dense trees (*Cerradão*) to grassy-woody plants [22]. Yellow Latosol, Quartzarenic Neosols, Neosols-Litolics, Hydromorphic Planossols, Red-Yellow Argisols, and Haplastic Gleysol [23] are the dominant soil classes.

The landscape varies from flat to smoothly undulating topography, which favours agricultural practices and high yields of crops under intensive conventional agriculture. The topography contributes to the expansion of crop cultivation in the region, mostly soybean, corn, cotton, and common beans.

The next subsections describe the process of sensor data processing and estimation of load bearing capacity of the soils of the Basin, which defines the innovative methodology. Fig. 2 gives a graphical summary of that process. Firstly, LANDSAT 8 products were used to determine three classes of soil use and land cover: Annual crops/Livestock, Forest/Savanna, Grassland/Pasture. Next, elevation data retrieved from the Shuttle Radar Topography Mission (SRTM) were used to classify the soils of the Basin in three classes: Flat and Slightly Wavy Relief, Wavy Relief, Steep Slopes and Cliffs. Afterwards, gridded data on soil moisture were retrieved from SMAP, combined with clay content (from SOILINFO) data and then used in pedotransfer functions to obtain geo-located estimates of LBC.

2.2. Classification of soil use, land cover and slope

The hydrographic basin was classified according to the following classes of soil use and cover: Annual Crops/Livestock, Forest/Savanna Formation, and Grassland/Pasture Formation. The classification was based on images obtained from the LANDSAT 8 Operational Land Imager (OLI) satellite, from the United States Geological Survey [24] Earth Explorer platform, using the following bands: B2 - blue (0.450–0.515 μm), B3 - green (0.525–0.600 μm), B4 - red (0.630–0.680 μm), B5 - near infrared (0.845–0.885 μm), B6 - mid-near infrared (1.560–1.660 μm) and B7 - mid infrared (2.100–2.300 μm) [25] (NASA, 2019). The images were pre-processed by transforming digital numbers into radiance and reflectance using the Dark Object Subtraction (DOS) method. A supervised classifier based on the Maximum Likelihood method was trained by manually annotating pix-

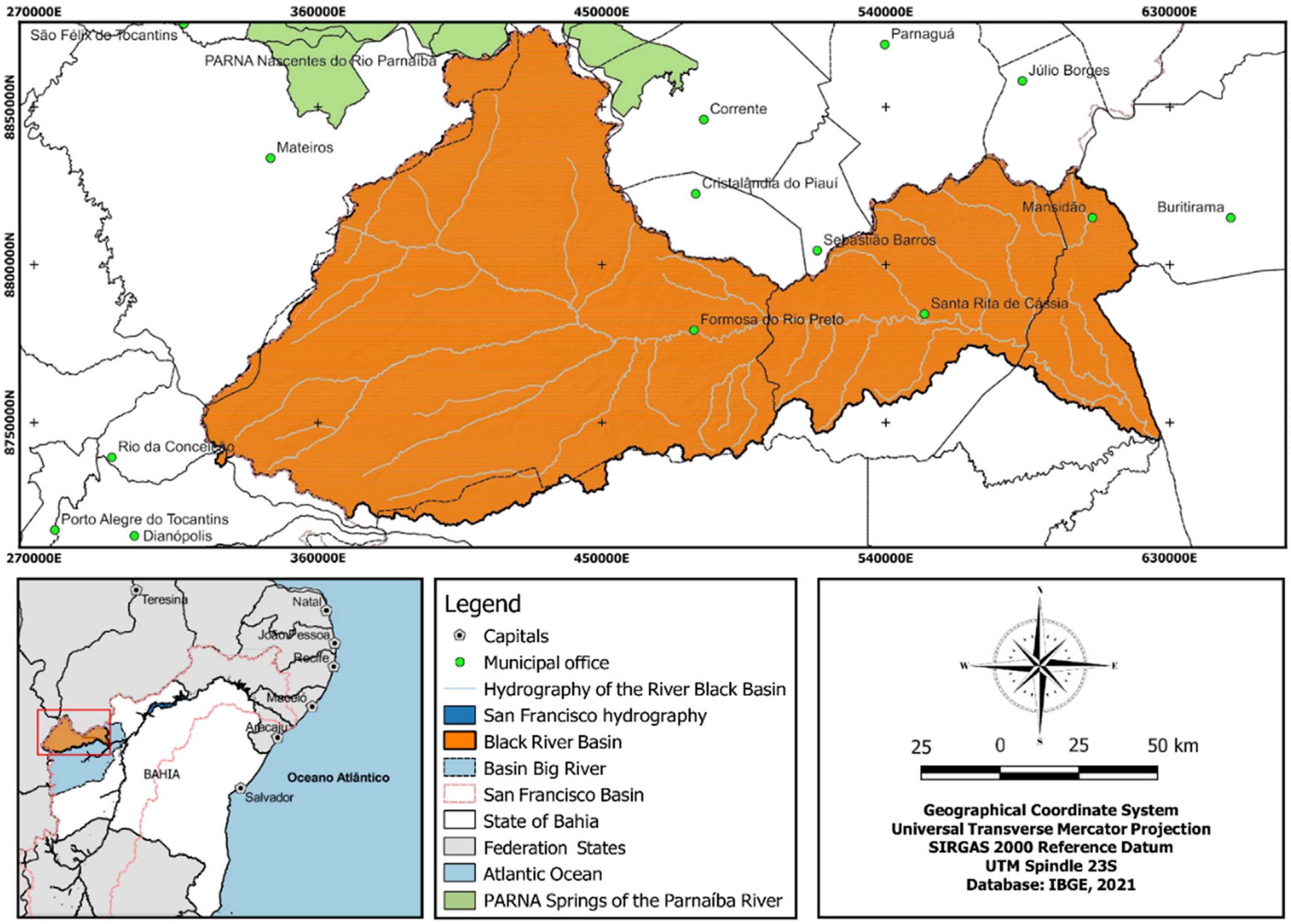

Fig. 1 – Location of the 'Rio Preto' Hydrographic Basin, western Bahia, Brazil.

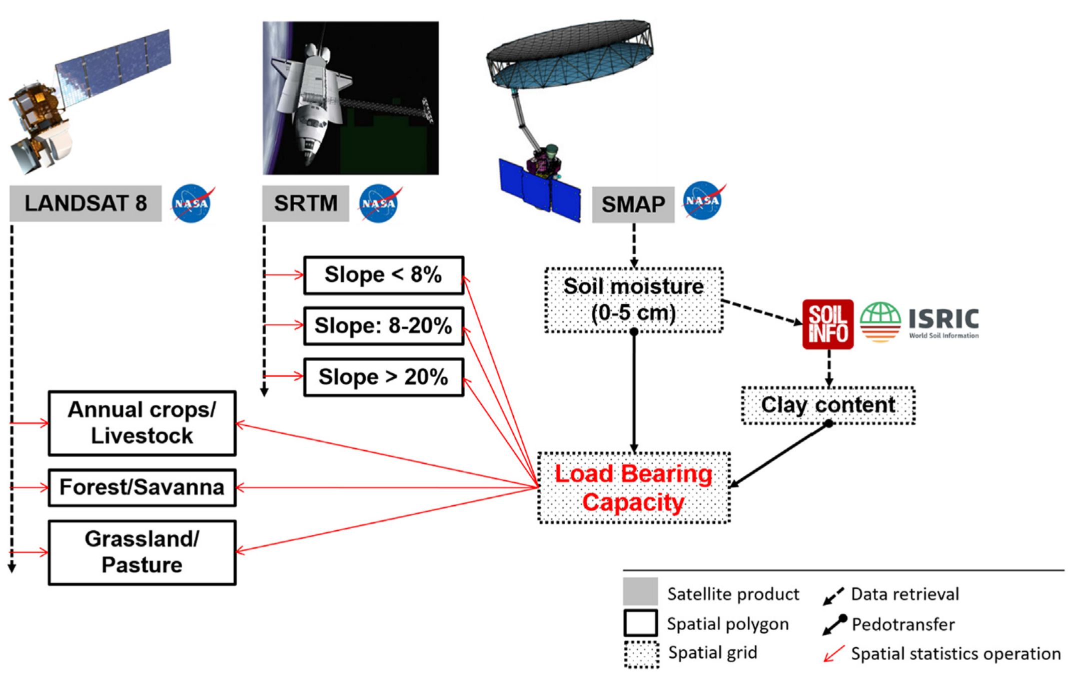

Fig. 2 – Flowchart of data processing for estimation of load bearing capacity of soil.

els in areas of previously known classes, being 200 pixels for Annual Crops/Livestock, 150 pixels for Forest/Savanna and 100 pixels for Grassland/Pasture. The annotated data were split into training (70%) and validation (30%) sets. The validation data set was used to compute the confusion matrix and the Kappa index, with values close to 1.0 indicating satisfactory classification. The classifier's algorithm calculates the probability of new pixels to belong to each of the three classes by assuming a multivariate Gaussian distribution for the vector of spectral bands, thus taking into consideration the covariance matrix of bands. Once the pixels were classified, the spatial polygons of the classes were obtained for further processing.

Classes of land slope were obtained using the methodology presented by the Brazilian Soil Classification System [26], based on the TauDEM (Terrain Analysis Using Digital Elevation Model [27], with data retrieved from the Shuttle Radar Topography Mission (SRTM, NASA). The following slope classes were considered: flat and slightly wavy relief (<8%); wavy relief (8%–20%); and topographies with strong and steep slopes and cliffs (>20%).

Images were processed using the software QGIS 3.4 Madeira (www.qgis.osgeo.org).

2.3. Soil physical data

Raster products containing soil moisture estimates were obtained from the Soil Moisture Active Passive (SMAP) satellite. The resolution of the L4_SM product used is 3 h at 9 km surface, collecting information in the 0–5 cm depth layer. The accuracy on estimating soil moisture is around 4% [28]. A regular grid of 280 points was obtained for the entire Basin. From January 2016 to December 2019, a month-representative raster was retrieved to build the time series grids of soil moisture. Based on the soil moisture grid over the Basin, data on soil density (Mg/m^3), silt, sand and clay contents (%) were retrieved from the World Soil Information (ISRIC), with the SOILINFO online platform (https://www.isric.org/). The data were processed with the packages *smapr* [29], *sp* [30] and *raster* [31] for the software R (www.R-project.org).

2.4. Estimation of load bearing capacity

The soil moisture data (θ, m^3/m^3) extracted from SMAP products and the clay content extracted from SOILINFO were used in an adapted set of pedotransfer functions developed and validated by [2] to estimate LBC (σ_P) for Brazilian soils as a function of matric potential and clay content (L, g/kg), with the equation:

$$\sigma_P = a\left\{\frac{1}{\alpha}\left[\left(\frac{\theta-\theta_R}{\theta_A}\right)^{\frac{n}{1-n}}-1\right]^{1/n}\right\}^b \quad (1)$$

Where a and b are empirical parameters used to describe σ_P as a log-linear function of the matric potential; α, n, θ_R, θ_A are parameters from the water retention model, where θ_R is the residual water content, θ_A is the difference between the water content at saturation and the residual water content, α and n represent a scale and a shape parameter, respectively. The estimates of these parameters are given in Table 1.

Predictions on the sampling grid were performed using the package *soilphysics* [7]. The LBC data were then grouped according to the classes of land use/cover and slope. Afterwards, 95% confidence intervals for the monthly mean of LBC of each class were built based on the t-Student distribution, for statistical comparisons.

3. Results and discussion

3.1. Soil use and land cover

For the classification of soil use and land cover, it was found a Kappa index of 0.94, indicating high accuracy, considering other works of similar nature [32]. Fig. 3 shows the estimates of average LBC for those classes. LBC varied with a similar pattern over the years, as a response to the seasonal behaviour of precipitation (Fig. 3(c)). This was also observed by Bergamin et al. [20] when they studied different management systems in Red-Dystrophic Oxisols from Mato Grosso State.

The lowest LBC estimates were found between February and April, with averages below 200 kPa for annual crop areas (Fig. 3(a),(d),(g),(j)), indicating that traffic of heavy machinery should be managed so that tyre inflation is carefully set for pressure distribution onto soil surface. In those areas, the grain harvest usually starts between March and April. Comparing this period with the months of highest estimates (September to October), it was observed a significant ($p < 0.05$) difference of about 20 kPa.

LBC tends to increase with the soil dryness, as the low water content makes the soil particles more cohesive with each other. At high soil moisture levels, the soil becomes more plastic and adherent, promoting an increase in the demand for power for traction of machines and implements [33,34]. The increase of soil water content reduces the internal resistance of soil matrix, since it forms a liquid film that surrounds soil particles and aggregates, reducing friction and increasing the deformation that can be intensified by external pressures exerted on the soil [35]. Also, the load applied to a soil associated with slippage degrades its structure which

Table 1 – Parameter estimates for pedotransfer functions of load bearing capacity, based on Severiano et al. [2].

Clay content (g/kg)	a	b	α	θ_R	θ_A	n	R^2
$L < 209$	129.0	0.15	0.79	0.050	0.42	1.72	0.95
$209 \leq L < 311$	123.3	0.13	0.72	0.087	0.45	1.56	0.94
$311 \leq L < 365$	85.0	0.17	1.73	0.110	0.47	1.51	0.94
$365 \leq L < 490$	70.1	0.16	2.04	0.126	0.50	1.47	0.96
$L \geq 490$	62.7	0.15	2.27	0.150	0.51	1.38	0.91

R^2: coefficient of determination.

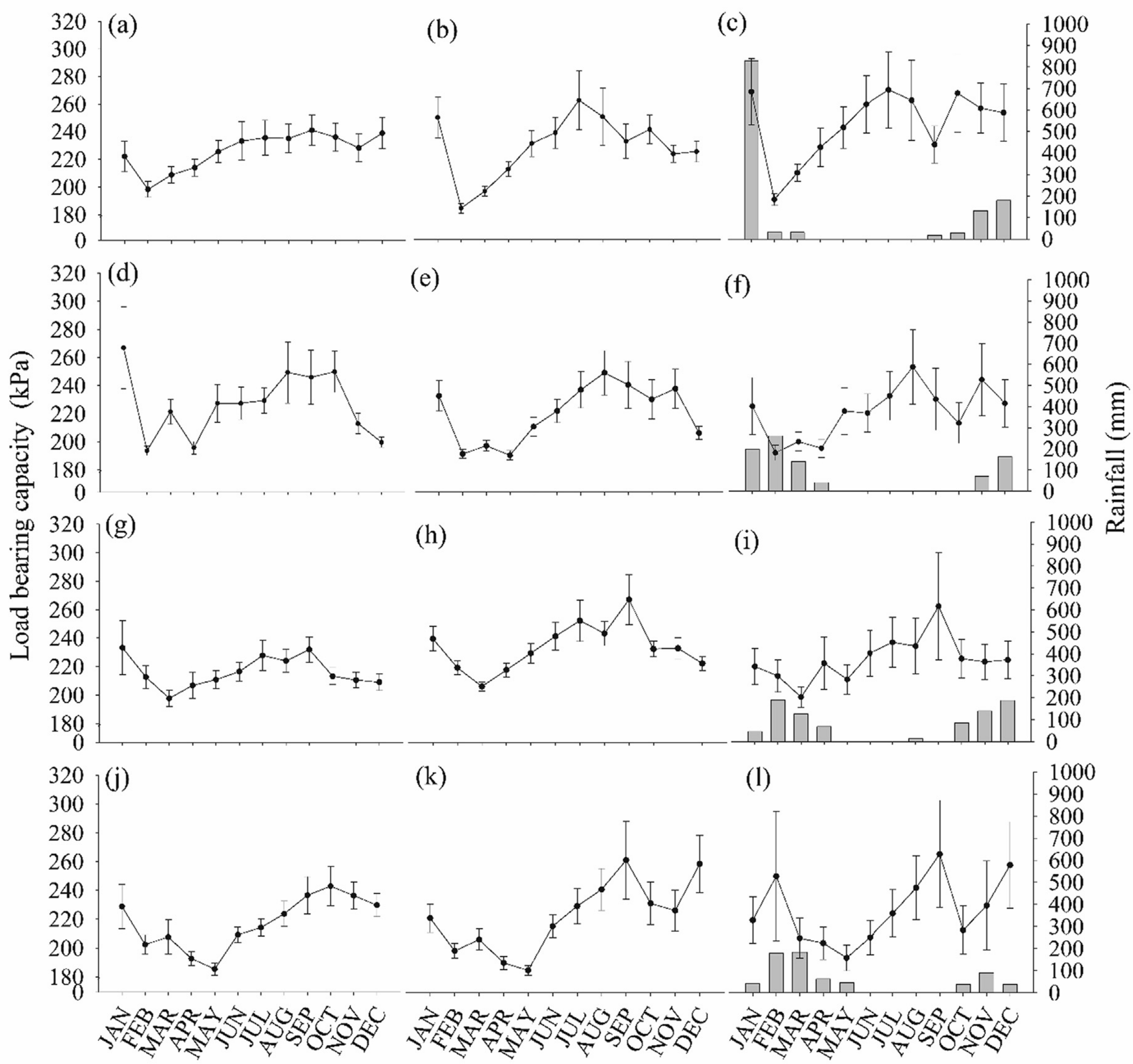

Fig. 3 – Predicted average load bearing capacity (kPa) of the soil classes of soil use and land cover. (a) Annual Crops/Livestock, (b) Forest/Savanna Formation, (c) Grassland/Pasture Formation in 2016; (d) to (f) the same soil classes in 2017, (g) to (i) in 2018; and (j) to (l) in 2019. Vertical lines indicate the 95% confidence interval for the mean. The same rainfall data were considered for all classes in a given year.

consequently contributes to the formation of compacted surface and subsurface layers.

Especially in the dry period (from August to September) of the last two years (2018–2019), soils cultivated with annual crops presented lower LBC than grasslands and natural vegetation. This is probably associated with the amounts of organic carbon (OC) and tillage practices at the surface layer, which reflects a greater potential for water retention and soil breakdown. Higher OC contents in the 0–3 cm soil layer provide greater potential for soil elasticity, contributing to the release of tensions [36]. Soils with high OC contents tend to be more resilient and have better structural recovery, which reflects lower mechanical strengths and low bulk density. Iori et al. found that soils under native forest presented higher values of LBC than soils cultivated with pasture, mainly due to the higher clay contents of soils under native vegetation, as a consequence of greater cohesion between particles [10].

Animal trampling, inadequate stocking rates and animal overload, depending on the availability of forage and/or semi-intensive or intensive livestock practices, can be factors that cause structural change if soils are at higher limits of surface pressure [37]. In a medium term, they can exert pressures that can cause compaction in the rainy season and breakdown in the dry period. In a long term, they contribute to the irreversible degradation of soils and vegetation.

3.2. *Land slope*

Fig. 4 shows the mean estimates of LBC for three classes of land slope (<8%, 8%–20%, and > 20%), assessed monthly from

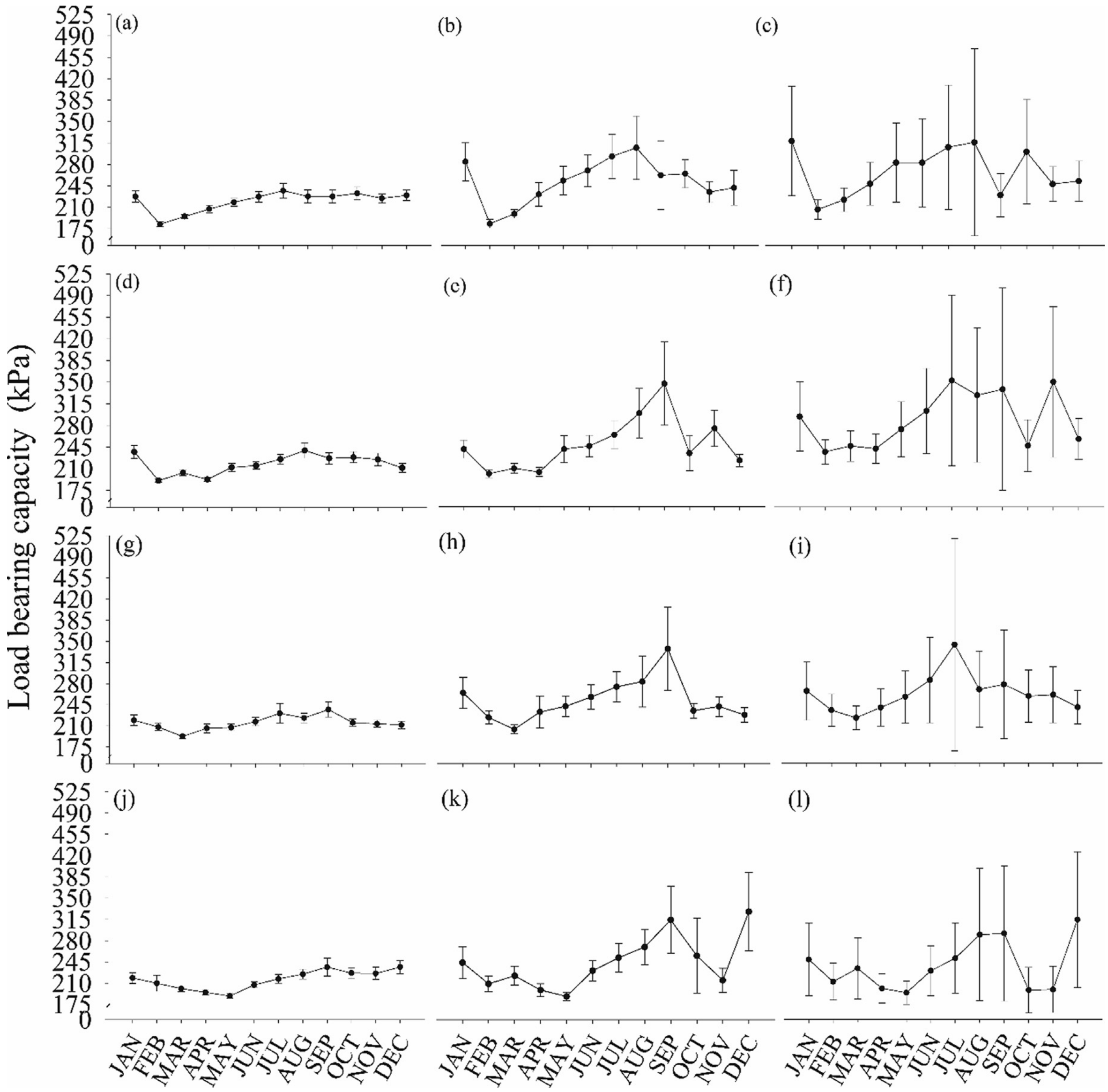

Fig. 4 – Predicted average load bearing capacity (kPa) of the soil classes of land slope. (a) < 8%, (b) 8%–20%, (c) > 20% in 2016; (d) to (f) the same classes in 2017; (g) to (i) in 2018; (j) to (l) in 2019. Vertical lines indicate the 95% confidence interval for the mean. The same rainfall data were considered for all classes in a given year.

2016 (top) through 2019 (bottom). Especially in the dry period, from May to September, significantly ($p < 0.05$) lower values were observed in areas with smooth topography (slope < 8%). On the other hand, areas with slope higher than 8% are more susceptible to water runoff, causing a reduction in the rate of water infiltration into the soil [38]. In addition, slope conditions the accumulation of soil carbon content, as observed by [39] in coffee plantations in flat areas (0%–3% slope).

About 86% of the Basin is flat to smoothly wavy, that is, slope < 8%. Nonetheless, the LBC estimates presented the lowest variability, based on confidence interval length. From July to September, areas with slope higher than 8% showed high variability of LBC.

In general, a temporal (2016–2019) reduction in LBC was observed for all classes of slope, in the following proportions: flat and smooth wavy reliefs (4 kPa or 1.8%); wavy reliefs (3.32 kPa or 1.2%); and rugged, mountainous reliefs (0.74 kPa or 0.31%).

4. Conclusion

In this study, the load bearing capacity of the soils from the “Rio Preto” Hydrographic Basin, Brazil was estimated using active–passive satellite data on soil moisture and validated pedotransfer functions based on clay content and water matric potential. Estimates were analysed under different classes of soil use, land cover and slope from 2016 to 2019. The estimation is governed by soil moisture at the superficial layer (5 cm depth), and is more affected by land slope than soil use and land cover. The overall seasonal variation in LBC estimates is similar in areas with annual crops, grasslands and native vegetation of the Brazilian Cerrado. LBC estimates in areas with slope < 8% are less affected by soil moisture variations over the seasons. In a four-year lapse, LBC decreased at about 1.8% in areas with slope < 8%. Therefore, these areas demand attention, since they are predominant in the Basin (86%) and mostly subjected to agricultural soil management and heavy machinery.

The approach presented in this work is pioneer and allows to map the dynamics of soil preconsolidation stress by combining validated predotransfer functions and satellite-driven data of physical properties. Future works shall be carried out to increase spatial resolution of soil moisture estimates.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This work was supported by NAWA – Polish National Agency for Academic Exchange [grant: PPN/ULM/2020/1/00025], CNPq – National Council for Scientific and Technological Development [grants: 309733/2021-9 and 316751/2021-9], and Instituto Federal Goiano. Renato P. de Lima also thanks the São Paulo Research Foundation - FAPESP (Process 2020/15783-4) for granting scholarships and financial support. Authors also thank Wojciech Cieôżkowski for revising the manuscript.

REFERENCES

[1] Santos CAP, Sano EE, Santos PS. Fronteira agrícola e a dinâmica de uso e ocupação dos solos no Oeste da Bahia. Acta Geográfica 2018;12:17–32.
[2] Severiano EC, Oliveira GC, Dias Júnior MS, Curi N, Costa KAP, Carducci CE. Preconsolidation pressure, soil water retention characteristics, and texture of Latosols in the Brazilian Cerrado. Soil Res 2013;51:193–202.
[3] Bonfim-Silva EM, Anicésio ECA, Silva FCM, Dourado LGA, Aguero NF. Compactação do solo na cultura do trigo em Latossolo do Cerrado. Enciclopédia Biosfera 2011;7:1–8.
[4] Severiano EC, Oliveira GC, Curi N, Dias Júnior MS. Potencial de uso e qualidade estrutural de dois solos cultivados com cana-de-açúcar em Goianésia (GO). Revista Brasileira de Ciência do Solo 2009;33:159–68.
[5] Soares MDR, Campos MCC, Oliveira IA, Cunha JM, Santos LAC, Fonseca JS, et al. Atributos físicos do solo em áreas sob diferentes sistemas de usos na região de Manicoré. AM. Revista de Ciências Agrárias 2016;59:9–15.
[6] Lima RP, Rolim MM, Oliveira VS, Silva AR, Pedrosa EMR, Ferreira RLC. Load-bearing capacity and its relationships with the physical and mechanical attributes of cohesive soil. J Terramech 2015;58:51–8.
[7] Da Silva AR, De Lima RP. soilphysics: An R package to determine soil preconsolidation pressure. Comput Geosci 2015;84:54–60.
[8] Kamimura KM, Dias Júnior MS, Oliveira MS, Santos GR, Guimarães PTG, Ajayi AE. Spatial variability of pre compression stress and volumetric water content of a Red-Yellow Latosol (Oxisol). Bioscience Journal 2020;36:142–51.
[9] Guimarães Júnnyor WS, Maria IC, Araújo-Júnior CF, Lima CC, Vitti AC, Figueiredo GC, et al. Soil compaction on traffic lane due to soil tillage and sugarcane mechanical harvesting operations. Scientia Agricola 2019;76:509–17.
[10] Iori P, Silva RB, Dias Júnior MS, Lima JM. Pressão de preconsolidação como ferramenta de análise da sustentabilidade estrutural de classes de solos com diferentes usos. Revista Brasileira de Ciência do Solo 2012;36:1448–56.
[11] De Lima RP, Da Silva AR, Da Silva AP. soilphysics: An R package for simulation of soil compaction induced by agricultural field traffic. Soil Tillage Res 2021;206:1–11.
[12] Lausch A, Baade J, Bannehr L, Borg E, Bumberger J, Chabrilliat S, et al. Linking remote sensing and geodiversity and their traits relevant to biodiversity – part I: soil characteristics. Remote Sensing 2019;11:1–51.
[13] Ghazali MF, Wikantika K, Harto AB, Kondoh A. Generating Soil Salinity, Soil Moisture, Soil pH from Satellite Imagery and Its Analysis. Information Processing in Agriculture 2020;7:294–306.
[14] Mendes WS, Medeiros Neto LG, Demattê JAM, Gallo BC, Rizzo R, Safanelli JL, et al. Is it possible to map subsurface soil attributes by satellite spectral transfer models? Geoderma 2019;343:269–79.
[15] Ma C, Li X, Wei L, Wang W. Multi-escale validation of SMAP soil moisture products over cold and arid regions in Northwestern China using distributed ground observation data. Remote Sensing 2017;9:1–14.
[16] Reichle RH, Lannoy GJM, Liu Q, Ardizzone JV, Colliander A, Conaty A, et al. Assessment of the SMAP level-4 surface and root-zone soil moisture product using in situ measurements. J Hydrometeorol 2017;18:2621–45.
[17] Demattê JAM, Bellinaso H, Araújo SR, Rizzo R, Souza AB. Spectral regionalization of tropical soils in the estimation of soil attributes. Revista Ciência Agronômica 2016;47:589–98.
[18] Younis SMZ, Iqbal J. Estimation of soil moisture using multispectral and FTIR techniques. Egypt J Remote Sens Space Sci 2015;18:151–61.
[19] Bezerra BG, Santos CAC, Silva BB, Perez-Marin AM, Bezerra MVC, Bezerra JRC, et al. Estimation of soil moisture in the root-zone from remote sensing data. Revista Brasileira de Ciência do Solo 2013;37:596–603.
[20] Bergamin AC, Vitorino ACT, Prado EAF do, Souza FR de, Mauad M, Souza LCF de. Structural Quality of a Latosol Cultivated with Oilseed in Succession to Corn. Ciencia e Investigación Agraria, 2018,(45):169–180
[21] Inema. CBH Grande. Available in: <http://www.inema.ba.gov.br/gestao-2/comites-de-bacias/comites/cbh-grande/>. Accessed on: 08/10/2020.
[22] SDE. Secretária de Desenvolvimento Econômico da Bahia. Meio Ambiente na Bahia. Available in: <http://www.cbpm.ba.gov.br/modules/conteudo/conteudo.php?conteudo=22>. Accessed on: 22/01/2020.
[23] Embrapa. Empresa Brasileira de Pesquisa Agropecuária. Grupo de inteligência Territorial Estratégica Available in: < https://www.embrapa.br/gite/projetos/matopiba/matopiba.html>. Accessed on: 05/10/2019
[24] USGS. United State Geological Survey. Landsat missions. Available in: <https://earthexplorer.usgs.gov/>. Accessed on: 18/07/2019
[25] NASA. National Aeronautics and Space Administration. Landsat Science. Available in: <https://landsat.gsfc.nasa.gov/landsat-8/landsat-8-bands/>. Accessed on: 05/12/2019
[26] Embrapa. Empresa Brasileira de Pesquisa e Agropecuária. Sistema Brasileiro de Classificação de Solos. 5th ed. Brasília: Embrapa, 2018.

[27] Tarboton D. TauDEM hydrology Research Group. Available in: <http://hydrology.usu.edu/taudem/taudem5/>. Accessed on: 18/07/2019.
[28] NASA. National Aeronautics and Space Administration. Earth Data - Soil Moisture Passive-Active. Available in: <https://earthdata.nasa.gov/search?q=soil+moisture>. Accessed on: 05/07/2019
[29] Joseph M, Oakley M, Schira Z (NA). SMAPR: Acquisition and processing of NASA Soil Moisture Active-Passive (SMAP) Data. R package version 0.2.0. Available in: <https://github.com/ropensci/smapr>. Accessed on: 18/09/2019.
[30] Pedesma EJ, Bivand RS. Classes and methods for spatial data in R. R News 2005;5:9–13.
[31] Hijmans RJ. Raster: Geographic data analysis and modeling. Package version 2.6.7. Available in: <https://CRAN.R-project.org/package=raster>. Accessed on: 23/01/2020.
[32] Nascimento OS, Morais RCS, Souza IRM, Lima TP. Análise espaço-temporal do uso e cobertura da terra da bacia hidrográfica do Alto Paraim – Piauí. Revista Geoambiente 2018;32:210–30.
[33] Medeiros AR, Câmara Júnior CL, Pereira JO, Oliveira FA, Amaro FJ. Avaliação da compactação do solo por meio de um ensaio oedometrico. Revista Verde de Agroecologia e Desenvolvimento Sustentável 2015;10:9–22.
[34] Drescher MS, Eltz FLF, Denardin JE, Faganello A. Persistência do efeito de intervenções mecânicas para a descompactação de solos sob plantio direto. Revista Brasileira de Ciência do Solo 2011;35:1713–22.
[35] Vischi Filho OJ, Souza ZM, Silva RB, Lima CC, Pereira DMG, Lima ME, et al. Capacidade de suporte de carga de Latossolo Vermelho cultivado com cana-de açúcar e efeitos da mecanização no solo. Pesquisa Agropecuária Brasileira 2015;50:322–32.
[36] Araújo Júnior CF, Dias Júnior MS, Guimarães PTG, Alcântara EN. Capacidade de suporte de carga e umidade crítica de um latossolo induzida por diferentes manejos. Revista Brasileira de Ciência do Solo 2011;35:115–31.
[37] Parente HN, Maia MO. Impacto do pastejo sobre a compactação dos solos com ênfase no semiárido. Revista Trópica - Ciências Agrárias e Biológicas 2011;5:3–15.
[38] Bias ES, Pivelo L, Guides SC, Rocha KC. Análise da eficiência da vegetação no controle do escoamento superficial: uma aplicação na bacia hidrográfica do Rio São Bartolomeu. DF. Revista Geociências 2012;31:411–29.
[39] Iori P, Dias Júnior MS, Ajayi AE, Guimarães PTG, Abreu Júnior AA. Influence of field slope and coffee plantation age on the physical properties of a Red-Yellow Latosol. Revista Brasileira de Ciência do Solo 2014;38:107–17.