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Artificial neural network for assessment of impacts of rural anthropization in a tropical climate region

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A B S T R A C T

This research evaluated the environmental conditions that represent diverse types of occupation in an urbanized rural area, compared microclimates, and described their characteristics in a computational algorithm that assigned a classification for indicates the environmental quality of these areas. The experimental part was carried out in the city of Dourados - MS, at the Federal University of Grande Dourados, between the summer of 2020 and the winter of 2021. Temperature and relative air humidity were collected to calculate the temperature and humidity index (THI) during 40 days of winter (cold) and 40 days of summer (heat), using a Datalogger Wireless data acquisition system in 9 microenvironments and INMET information. The second part of the study consisted of developing a logical-mathematical model involving an Artificial Neural Network of the evaluated scenario to classify the environment according to the THI and human well-being index (HWBI). The proposed neural network has an input layer with twelve neurons, a hidden layer with eighteen, and an output layer with five neurons. The system proved efficient, with approximately 90% accuracy in its training and 80% in the test phases. As it is the first complex architecture built for multiclass indication of local environmental comfort, it can conclude that the algorithm well reflected the studied environments involving the interaction of natural resources and built spaces.

Keywords: environmental comfort, agrarian occupation, semantic segmentation.

Rede neural artificial para avaliação de impactos da antropização rural em uma região de clima tropical

R E S U M O

Esta pesquisa avaliou as condições ambientais que representam diferentes tipos de ocupação em uma área rural urbanizada, comparou microclimas e descreveu suas características em um algoritmo computacional que atribuiu classificação para indicar a qualidade ambiental desse local. A parte experimental foi realizada na cidade de Dourados - MS, Universidade Federal da Grande Dourados, entre o verão de 2020 e o inverno de 2021. Foram coletadas temperatura e umidade relativa do ar para cálculo do índice de temperatura e umidade (ITU) durante 40 dias de inverno (frio) e 40 dias de verão (calor), utilizando sistema de aquisição de dados *Datalogger Wireless* em 9 microambientes e as informações do Instituto Nacional de Meteorologia (INMET). A segunda parte do estudo consistiu no desenvolvimento

de um modelo lógico-matemático envolvendo uma Rede Neural Artificial do cenário avaliado para classificar os ambientes de acordo com o ITU e o índice de bem-estar humano (IBEH). A rede neural proposta possuiu uma camada de entrada com doze neurônios, uma camada oculta com dezoito e uma camada de saída com cinco neurônios. O sistema se mostrou eficiente, com aproximadamente 90% de precisão no treinamento e 80% nas fases de teste. Por ser a primeira arquitetura complexa construída para indicação multiclasse de conforto ambiental local, pode-se concluir que o algoritmo refletiu bem os ambientes estudados envolvendo a interação de recursos naturais e espaços construídos.
Palavras-chave: conforto ambiental, ocupação agrária, segmentação semântica.

Introduction

The growth of a region is directly linked to local economic development. In this context, the population increases in rural areas occurs, expanding the urban occupation of large cities, and transforming some surrounding territories into anthropized spaces (Cattivelli, 2021).

With alarmingly rapid urbanization towards rural areas, comprehending irreversible environmental and climatic consequences becomes an absolute necessity. Urban sprawl contributes to degradation of natural resources, native vegetation vanishing, and emergence of heat islands (Iamtrakul et al., 2024). This complex dynamic necessitates a holistic approach to assess the impacts of rural anthropization, especially in regions characterized by significant temperature variations.

In tropical regions where elevated temperatures persist during summers and harsh winters are experienced, concerns about environmental disruption have intensified due to these climatic variations. The substantial fluctuations in temperature and humidity present specific challenges for sustainable management resulting from rural anthropization (Radic-Schilling et al., 2024). The imperative need for innovative research to gain a deeper understanding of these phenomena underscores tropical climate regions (e.g., Brazil), contributing to the expansion of scientific knowledge and proposing context-specific solutions that promote environmental sustainability.

Allied to rural development is the degradation of natural resources to construct buildings that meet human needs. During this process, vegetation decrease is also noticeable, as the coating of the soil surface with impermeable materials. The resulting volume of buildings generated in the urbanization process of rural areas causes a considerable increase in temperatures and a decrease in air humidity (Lovatto et al., 2020). According to Lima et al. (2023), human actions are the leading accelerators of this process, causing multiple disorders in the landscapes.

When analyzing unplanned rural occupations, a crucial aspect lies in dissecting their direct impact on heat island formations. This disorderly settlement pattern acts as a heat magnet, trapping warmth and reducing air humidity, compromising production, thermal comfort, and health of inhabitants. (Su et al., 2023; Li et al., 2024). Hence, innovative solutions should be explored to mitigate the adverse consequences of rural anthropization.

Prolonged exposure to extreme thermal conditions can result in adverse health effects, in addition to affecting workers' productivity and well-being (Taggart et al., 2023). In tropical regions, where climatic variations are more pronounced, understanding and addressing these issues become even more relevant (Silva et al., 2020; Espinoza et al., 2023). Therefore, a comprehensive study of spatial occupation is essential to minimize the risks associated with thermal stress and ensure healthier and more resilient urban environments.

It is already well documented that the heat island effect is a challenge towards maintaining adequate levels of thermal comfort in changed microclimates resulting from unplanned agrarian occupation. With the rise of challenges like climate change or global warming, an increase in interest and involvement of researchers, engineers, and policymakers looking for solutions to deal with this effects (Shah et al., 2022).

In recent years, tropical regions, where environmental demands are particularly acute, have seen a rise in innovative strategies to mitigate the impacts of anthropization. Beyond sustainable urban planning practices and eco-efficient technologies in civil construction, the integration of new computational tools like machine learning and neural networks is emerging as a promising approach (Sari et al., 2023; Noor et al., 2024). These advancements highlight the crucial role of integrated and innovative strategies in pursuing sustainable solutions for new area development.

Integrating technological advances into regional development, particularly through simulations based on mathematical modeling, has demonstrably reduced the uncertainty associated with climate change. Studies by Tehrani et al.

(2024) demonstrated how applying artificial neural networks (ANNs) to urban planning facilitates strategic development by considering minimal project information, thereby contributing to decision-making processes and mitigating climate change's impact on sustainability. This innovative approach aligns with the growing demand for precise solutions to contemporary challenges related to this theme.

The inherent uncertainty of climate change complicates planning and decision-making regarding the use and occupation of environmentally sensitive areas. Botín-Sanabria et al. (2022) suggest that combining existing technological advances with simulation techniques has proven most effective, enabling the development of diverse models tailored to specific problems.

In recent years there has been significant growth in agro-industrial processes, where the development of technologies that guide quality assurance has become a decisive factor for the insertion and maintenance of products or services in the market. In this sense, Xu et al. (2024) used Long Short-Term Memory (LSTM) deep learning time series to assess land use and stated that mathematical modeling for scenario simulation deserves special attention, given the multiple purposes for which it is intended.

The theory of Artificial Neural Networks (ANNs) holds promise as a solution to the complex challenges posed by rural anthropization. Onyelowe et al. (2023) emphasize the growing computational significance of this approach, concluding that ANNs are robust, nonlinear models capable of addressing complex engineering problems, providing a viable alternative to deterministic or experimental methods. Thus, comprehending the neural structure that processes information within ANNs enables more flexible modeling of the dynamic scenarios arising from the interaction between natural and built environments.

The accelerated urban expansion, often without proper planning, has resulted in microclimatic changes and the formation of heat islands, impacting thermal comfort, productivity, and health. The issues stemming from the interactions between natural and built elements remain evident, especially in tropical climate regions like Brazil. This underscores the importance of studies aimed at developing tools that contribute to a better understanding and resolution of problems arising from the relationship between environmental and climatic variables and area occupancy.

Given that the anthropization of rural environments through unplanned urban expansion contributes to the degradation of natural resources and the acceleration of disorder-causing processes in landscapes, and considering the promise of Artificial Neural Networks (ANNs) in addressing the complex challenges of rural anthropization, the hypothesis of this investigation was that a properly trained ANN, utilizing microclimatic parameters and environmental elements, can accurately represent different environments and their climatic interactions. This, in turn, can be utilized to support scenario assessment strategies aimed at achieving more sustainable urban development.

Duarte et al. (2022) evaluated the performance of four machine learning models, including artificial neural networks (ANN). The results showed a more significant prediction potential of ANN compared to a linear regression model for solving complex problems involving natural resources and environmental comfort. This innovative approach overcame the predictive limitations of traditional methods and also opened new perspectives to improve decision making, providing a solid basis for sustainable environmental management strategies.

Thus, this study aimed to evaluate different occupation types in an urbanized rural area, comparing microclimates and representing characteristics that return from the interaction between natural and built environments in a computational ANN algorithm. Another objective was to compare several types of occupancy to identify the most sustainable form of environmental intervention for expanding agribusiness or urbanization in rural areas.

Material and methods

This research consisted of 3 stages, the first being a Field Experiment, tabulation of information, and calculation of the temperature and humidity index (THI); the second was the Semantic Segmentation with a percentile of elements of the authentic RGB images of the points collected, decomposed in Ground Truth annotations; and finally, the third, which consisted in the construction of a Deep Artificial Neural Network (ANN) to automatically classify the images into environmental comfort classes.

Stage 1 – Field Experiment - It was carried out at the Federal University of Grande Dourados – Unit II, located at the geographic coordinates 22° 11' S and 54° 56' W, average altitude of 464 m (Figure 1), with a climate classification according to Köppen-Geiger type Am (monsoon climate) with dry winters and hot summers. The average annual precipitation is 1500 mm year-1, and the average temperature is 22 ºC year-1 (Alvares et al., 2013).

We collected 40 days of summer data (heat) between 12/01/2020 to 03/01/2021 and 40 winter days (cold) between 06/01/2021 to 08/10/2021. The database consisted of hourly averages of temperature (T) and relative humidity (RH), from 6 am to 6 pm, local time, at 9 points of interest, in addition to INMET data (witness).

Local T and RH data were collected using wireless automatic datalogger equipment calibrated by INMETRO. The equipment was programmed to record data every 5 minutes and calculate hourly averages. It consisted of RHT sensors (model RHT-AIR WM - Novus 8804400110) and a FieldLogger module (model S/IHM ETH, USB, X512K LOGS, 2XRS485, 24V - Novus 8812120004). Each sensor was strategically placed at a height of 1.5 meters in locations shielded from direct sunlight and rain. These locations were carefully selected to ensure the representativeness of the microenvironments under study. The RHT sensors have a response time of 30 seconds and an accuracy of ±0.4°C for temperature and ±3% for relative humidity. The FieldLogger performed data reading and storage and was situated in the central region of the experimental area, housed in a protected environment, ensuring precise and reliable collection of environmental parameters.

The data obtained during collection were organized and tabulated in electronic spreadsheets using Excel® software.

The collection points evaluated are shown in Figure 1, representative of the microenvironments that highlight the characteristics: 1A- tree cover with asphalt floor; 2A- without shading with concrete floor; 3A- tree cover with grassy floor; 1B- between buildings with concrete floor; 2B- tree cover with concrete floor; 3B- without shading with grass floor; 1C- between buildings with grassy floor; 2C- without shading and dirt floor (bare ground); and 3C - without shading with asphalt floor.

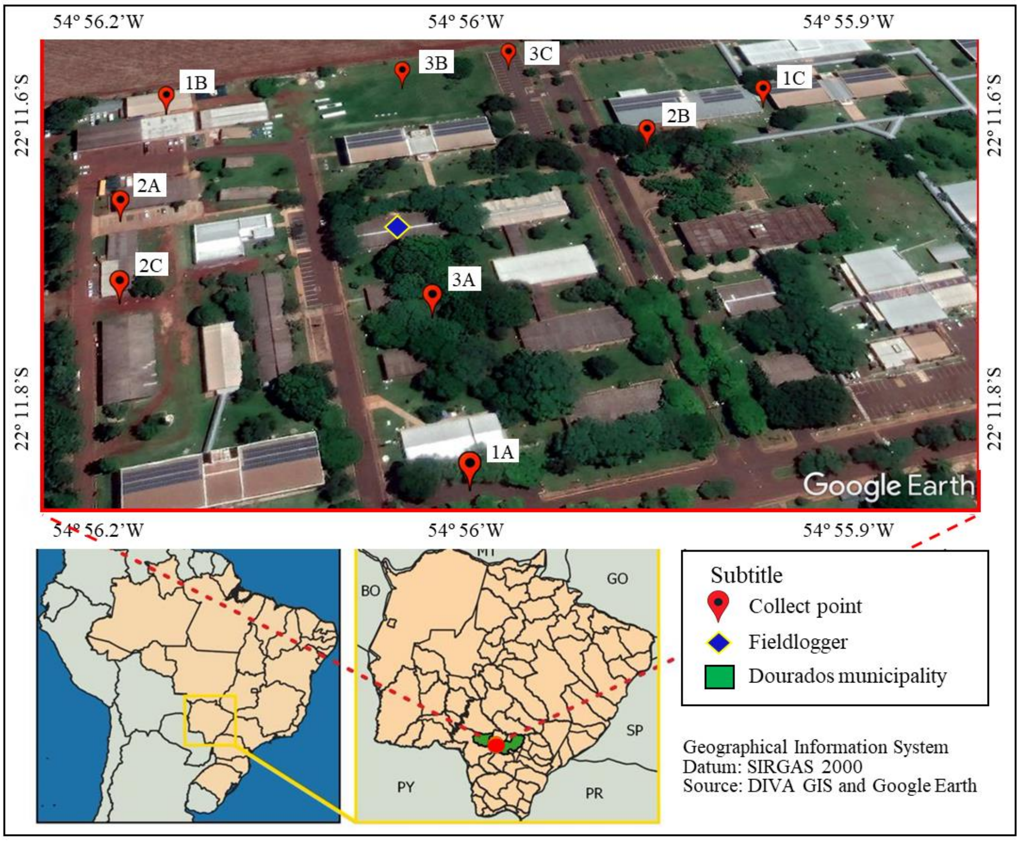

Figure 1. Geographic location and experimental area.

While a single environment can exhibit significant heterogeneity in building materials (roof, asphalt, concrete, grassland, and trees), each with distinct albedos and thermophysical properties (Mahapatra et al., 2024), this research focuses on comparing the impact of these key materials commonly used in urbanization.

With the T and RH values, was calculated the Temperature and Humidity Index (THI), proposed by Thom (1959) and used by Cesca et al. (2021) and Oliveira et al. (2024) for environmental assessment, according to Equation 1.

$$\text{THI} = AT_m - (0.55 - 0.0055 . RH_m) \cdot (AT_m - 14.5) \quad (1)$$

Where:

THI - Temperature and Humidity Index, adm;

AT_m - mean ambient temperature, (°C);

RH_m - mean relative humidity, (%).

Based on the data obtained and the evaluation of the information, it was possible to classify the environments according to the ranges related to the situations of environmental thermal comfort established in Table 1.

Table 1. Comfort rating scale and output classes conversion

Tracks	THI interval	Features
1	< 5.9	Very-high cooling
2	6.0 to 8.9	High cooling
3	9.0 to 11.9	Cold
4	12.0 to 14.9	Cold discomfort
5	15.0 to 17.9	Take discomfort to the cold
6	18.0 to 26.9	Comfort zone
7	27.0 to 29.9	Take discomfort to heat
8	30.0 to 32.9	Heat discomfort
9	> 33	High heating

Source: Wang et al. (2022) adapted

Another index used in the research was the Human Well-Being Index (HWBI) described by Yanagi et al. (2012) and represented in Figure 2, which allowed the classification of environments, taking into account the level of well-being experienced by its users.

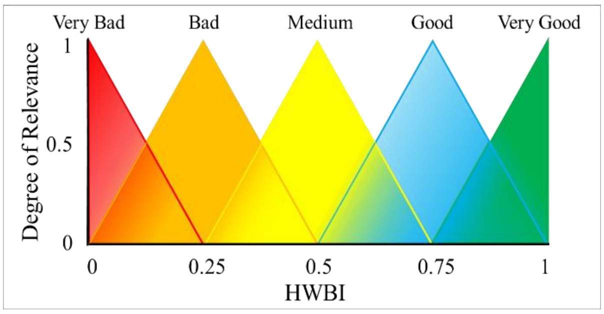

Figure 2. Variations in the Human Well-Being Index (HWBI).

The THI averages were submitted for analysis of variance and regression to compare the different microenvironments and seasons, verifying the levels of possible discomfort resulting from the points and considering the distinct characteristics of the surfaces.

The experiment was set up in subdivided plots, with a 10 x 2 factorial scheme in the plots (10 microenvironments and two seasons), and in the subplots the observation schedules (13 schedules). Analysis of Variance (ANOVA) was used to evaluate significant differences between the means of the Temperature and Humidity Index (THI) in relation to microenvironments and seasons. The null hypothesis tested by ANOVA was that there are no significant differences between the treatment means.

We employed a Randomized Block Design (RBD) with 40 repetitions (experimental days) to control unwanted variability by dividing the experiment into homogeneous sets. In this study, the blocks can represent factors such as climate variations or other sources of variation unrelated to the treatments under investigation. Following the ANOVA, we conducted a post-hoc analysis using the Scott Knott test at a 5% probability level. This nonparametric test helped identify which treatments exhibited statistically significant differences from one another.

Stage 2 – Semantic segmentation with the percentile of landscape elements. Labeling RGB images of the environments studied were conducted to extract mathematical characteristics considered relevant for the microclimate of the scenarios observed in the field.

The colors used to classify the manual segmentation masks were based on the classes used by Sambaturu et al. (2022). They addressed 30 (thirty) different categories of elements and decomposed them into scenes of interaction between natural resources and built spaces. The segmentation mask of the images was performed using Adobe Photoshop CC ® 2023 Software (Adobe, 2023), and the shadows were considered the continuation of their origin.

With the semantic segmentation and its decomposition in Ground Truth annotations, the percentages of the referring colors in each class were extracted. This calculation was made possible by an open-source PHP script (Personal Home Page, 2022) inserted in HyperText Markup Language (HMTL).

Stage 3 - Deep Artificial Neural Network - To represent the interaction of the anthropized environment and the best conditions of thermal comfort observed, a model of neural networks with multilayers was built using the aid of Python® Software (2020). As seen in the architecture represented by Figure 3, we have a three-layer including the input layer, a hidden layer and output layer. The complex part of this architectural ANN is hidden layer.

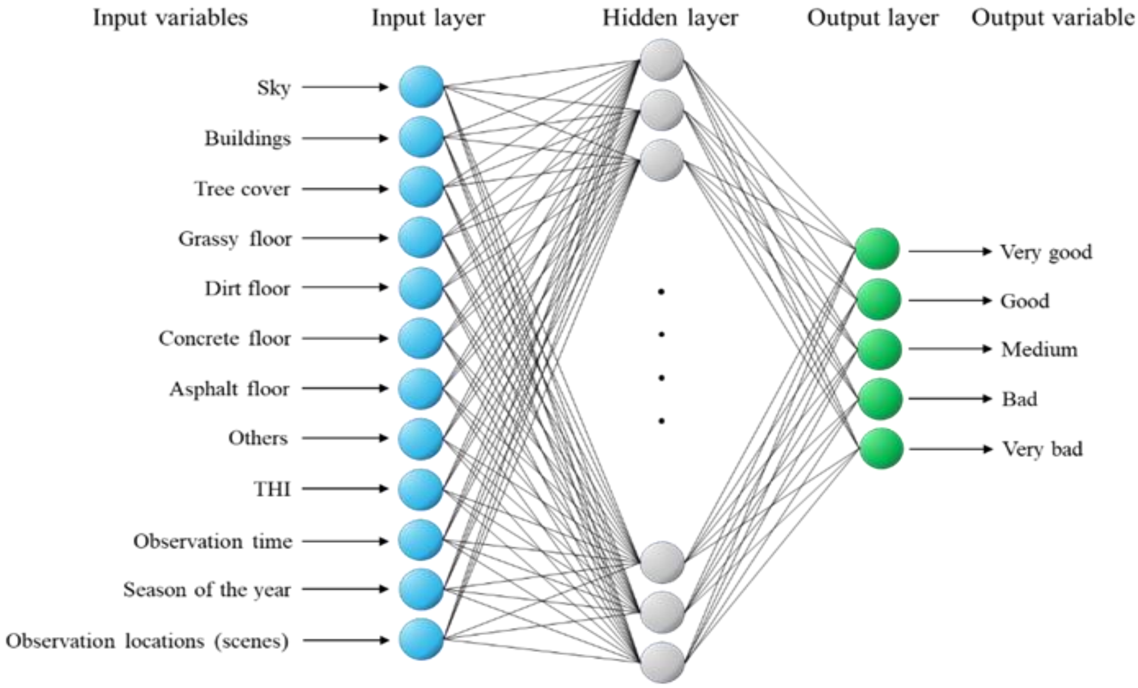

Figure 3. Multilayer neural network architecture.

The selected architecture model was Feed Forward (FF) with supervised machine learning, which fed and trained the system in the Feedforward and FeedBackward stages. In the model, a configuration was sought that was learned from a database formed by 234 inputs derived from 9 environments, 13 observation times, and 2 (two) stations.

In the built scenario, 12 neurons were established in the input layer, composed of the THI of the 9 locations, observation time, the season of the year, and the percentages of the composition of each scene, added to another eight neurons, referring to the presence of soil, grass, concrete, asphalt, tree, building, sky and others. In the hidden layer, 18 neurons were determined because the amount returned the smallest error. Five neurons were considered the five comfort classes of the Human Well-being Index (HWBI) for the output layer.

The number of epochs was stipulated in 2000, and the number of mini-lots in 10. The ReLu function was used in all layers to activate the neurons of the network. The first procedure performed on the network was training with 80% of the data and then the test with the other 20%.

According to Da Silva et al. (2021), even knowing the characteristics of the classification algorithms and the nature of the data studied, it is still very difficult for an ANN designer to predict which will be the best model and configurations, suggesting the use of tests with trial and error to fit the model. Quantifying different types of uncertainty in an ANN model improves the accuracy and reliability of the simulator (Gawlikowski et al., 2023). Thus, the proposed network architecture and the parameters considered similar studies, expert knowledge, and intense empirical tests to fit the model.

After all, stages were completed, it was possible to analyze the interaction between environmental comfort, observed natural resources, and built spaces, in addition to performing simulations with the model and adjusting aiming at greater precision and lesser error of the intelligent system in the complex scenario studied.

Results and discussion

With the data collected in the field and the temperature and humidity index (THI) calculated, it was possible to construct Figures 4 and 5, highlighting the upper and lower comfort limits. In Figure 4, environments 3C (area without shading and asphalt floor) and 2A (area without shading and concrete floor) are the most uncomfortable. These results are justified by research by Kumar et al. (2024), who concluded that asphalt and concrete represent materials with high values of absorptivity and emissivity, reaching temperatures of 45°C during daylight hours with a heating rate of 5.26°C/h. These properties contribute to air heating and the formation of heat islands, especially on a microscale, and should be avoided whenever possible in the rural occupation process.

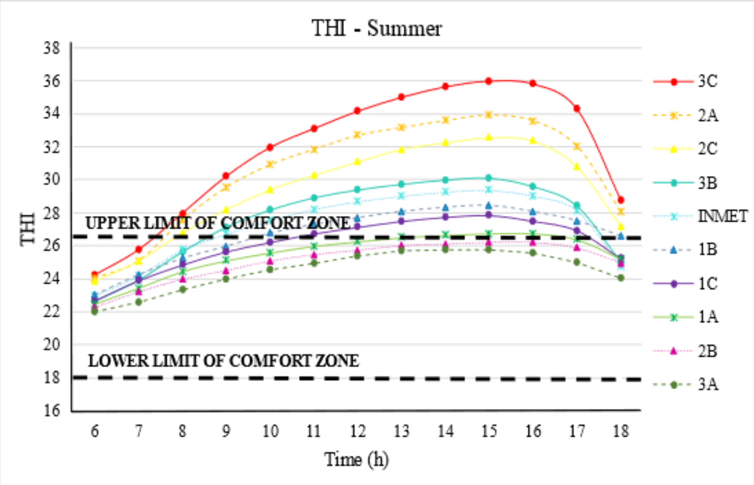

Figure 4. Average THIs of the environments as a function of time – Summer

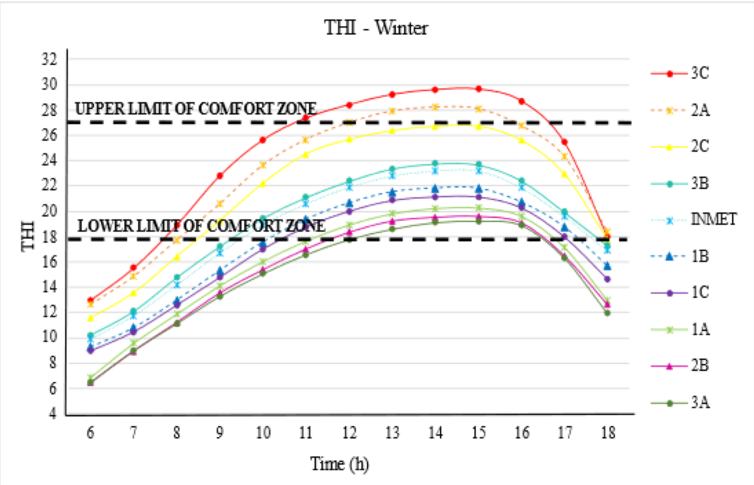

Figure 5. Average THIs of the environments as a function of time – Winter

In Figure 5, it is observed that all environments were uncomfortable due to the cold in the early morning hours. The warmest microenvironments in the summer period (3C and 2A) were also outside the upper comfort limit in the cold season, in the afternoon, because, according to Pan et al. (2022), they have low thermal inertia and fluctuate a lot in temperature between night cooling and heating caused by exposure to daytime heat.

Summaries of the analysis of variance for the microenvironments evaluated in the summer and winter seasons can be seen in Tables 2 and 3. It is possible to observe that F > Fcritical, which in turn is less than 1%, meaning that there were significant differences between the microenvironments in both seasons. This way, the analysis was unfolded to verify where the minimum significant differences exist, as shown in Tables 4 and 5 for summer and winter, respectively.

Table 2. Analysis of variance for the evaluation of microenvironments - Summer

Source of Variation	DF	SS	MS	F	Fcritical
Microenvironments	9	25806.00	2867.35	256.82**	2.20E-16
Residue	5190	57945.00	11.16		
Total	5199	83751.00			

DF = Degrees of freedom, SS = Sum of squares, MS = Medium square, F = Test F

** Significant at 1% level

Table 3. Analysis of variance for the evaluation of microenvironments - Winter

Source of Variation	DF	SS	MS	F	Fcritical
Microenvironments	9	48968.00	5440.90	207.65	2.20E-16
Residue	5190	135987.00	26.20		
Total	5199	184955.00			

DF = Degrees of freedom, SS = Sum of squares, MS = Medium square, F = Test F
** Significant at 1% level

The unfolding carried out for the summer season (Table 4) evidence the importance of shading, mainly arboreal, for the studied microenvironments, even though they have the presence of artificial surfaces. Ribeiro et al. (2021) analyzed the influence of tree vegetation on the thermal behavior of soil coverings. Their results showed that waterproofed floors under the treetops had better thermal performance than any others exposed to the sun.

In Table 5, when analyzing the winter season, it is evident that the most comfortable environments in the summer are the most uncomfortable in the winter, at the beginning and end of the day, which is justified by the presence of afforestation, which hinders the incidence of solar radiation, responsible for local heating. According to Sales et al. (2022) who studied energy balance and heat islands resulting from urbanization, the types of land use and cover directly influence the intensity of local heat, with vegetation generally intensifying the cooling effect, which varies directly with the hours of the day.

Table 4. THI averages for the summer

Microenvironments	**THI**
3C	29.99 a
2A	28.04 b
INMET	26.94 c
3B	26.89 c
1B	25.65 d
1C	25.14 e
2C	24.62 f
1A	23.37 g
2B	22.90 h
3A	22.87 h

Means followed by lowercase letters differ from each other by the Scott Knott test ($p \leq 0.05$)

Table 5. THI averages for the winter

Microenvironments	**THI**
3C	24.04 a
2A	22.78 b
2C	21.49 c
3B	19.09 d
INMET	18.60 d
1B	17.44 e
1C	16.83 e
1A	15.79 f
2B	15.20 g
3A	14.77 g

Means followed by lowercase letters differ from each other by the Scott Knott test ($p \leq 0.05$)

With the data obtained in the field study, it was possible to carry out the artificial neural network training process. As seen in Figure 6, there was a direct evolution of precision, originating between 10% (0.1) and 39% (0.39) at the starting point, which continued to evolve steadily until 90% (0.9) at the end of training. As opposed to precision, the error started close to 20% (0.2) and tended to 0% (0.0001). Han and Kang (2022) studied dynamics for neural network training. They stated that the diversification of layers makes the neural network more robust to inaccuracies, being excellent training with errors that tend to 0 and precision present constant growth.

This result reflects the importance of modeling when considering that the neural network was proposed for the specific problem of classifying scenes of environments composed of natural resources and buildings that reflect the comfort classes, according to Lu et al. (2024) are uncertain variables and challenging to qualify.

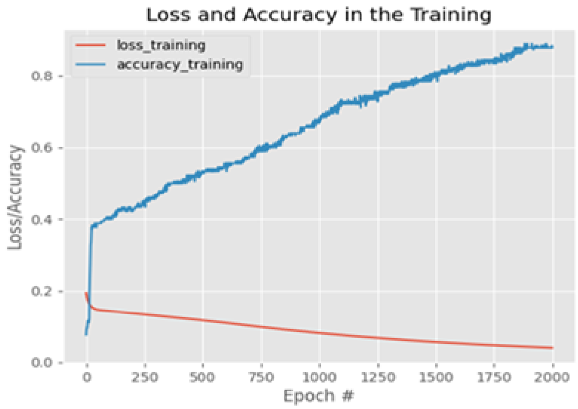

Figure 6. Loss and network accuracy in the training phase

Then, the test phase was carried out to verify the ability of generalization of the network, as seen in Figure 7, where the precision was stabilized at 80% (0.8), hitting 40 out of 50 confronted classes.

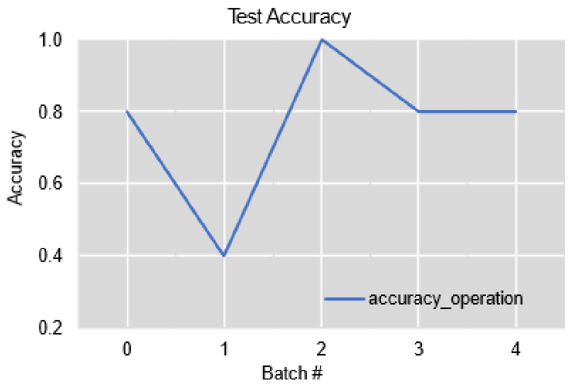

Figure 7. Network accuracy in the test phase

Qiu et al. (2019) proposed a model capable of representing different environmental characteristics and different occupations of areas based on image segmentation and neural network. At the end of the research, the model presented accuracy between 76% and 81%, and the authors concluded that this result is ideal when reproducing maps with different land cover, serving as a support tool in making decisions about the occupation of areas and carrying out analyzes involving climatic variables.

Determination of the number of layers in an ANN model is one of the most crucial tasks in construction design. According to Cheraghi et al. (2023) and Chang et al. (2024), adding more hidden layers can improve the model accuracy, but it also adds to complexity of the network training process, which may negatively reflect in the error.

Another critical factor of the network to be analyzed is how it hits the desired output classes (HWBI). When testing environments with complex landscape composition, where thermal extremes occur, exploring the error values of the algorithm's cross-entropy output, it was possible to observe how the network returns the interaction between input elements, hidden layer, and their outputs (Table 6).

When analyzing scenes 3B and 2A in Table 6, it is possible to observe that these were the ones that returned the lowest error between the expected and observed output classes in the network. The extreme thermal environment of the 2A scene features more elements in its composition, as seen in its Ground Truth image. It translates into a more complex environment with a greater propensity for entropy error. For Althnian et al. (2021), the dataset size that composes an image is considered a critical property in determining the performance of neural network learning.

Table 6. Classes expected and returned by the Neural Network in the test phase

Inputs		**Hidden**	**Outputs**		**Error**
Locations and features / RGB and Segmented Image	Compositions		Expected Class of HWBI	Returned Class of HWBI	
3B THI = 10.2 Time = 6h Season = Winter  	Gram = 42.07% Sky = 40.18% Buildings = 9.47% Trees = 5.81% Asphalt floor = 0.97% Concrete floor = 0.0% Ground = 0.0% Others = 1.23%	Very bad = - 10.99 Bad = 1.58 Medium = - 11.11 Good = - 45.65 Very good = - 7.53	Bad	Bad	0.0001
2A THI = 33.6 Time = 14h Season = Summer  	Concrete floor = 28.72% Buildings = 24.20% Sky = 22.61% Trees = 19.42% Gram = 4.15% Asphalt floor = 0.0% Ground = 0.0% Others = 0.51%	Very bad = 1.77 Bad = 0.94 Medium = 1.15 Good = - 0.95 Very good = - 5.41	Very Bad	Very Bad	0.0013
1A THI = 20.9 Time = 14h Season = Winter  	Trees = 71.24% Asphalt floor = 18.31% Buildings = 5.44% Sky = 3.24% Concrete floor = 0.70% Gram = 0.70% Ground = 0.0% Others = 0.37%	Very bad = - 5.52 Bad = 0.09 Medium = - 0.18 Good = - 12.84 Very good = - 4.74	Very Good	Bad	0.8459
3A THI = 21.9 Time = 6h Season = Summer  	Trees = 90.02% Gram = 3.63% Buildings = 4.14% Concrete floor = 0.68% Sky = 0.26% Asphalt floor = 0.0% Ground = 0.0% Others = 1.27%	Very bad = - 4.94 Bad = 0.29 Medium = - 0.12 Good = - 3.57 Very good = - 0.99	Very Good	Bad	1.9557

When comparing environments that include tree cover, in scenes 1A and 3A of Table 6, there is an increase in the error, which is much more significant in the more wooded environment, so that the expected and returned outputs are not of the same class. Martins et al. (2021) used deep neural networks to evaluate their performance in identifying different tree species, comparing 1394 aerial images of crowns. This study concluded that wooded environments result in a high error since the images are directed to binary classification involving shades of the same color.

A research with ANN was developed and tested by Shah et al. (2022), to the estimation of thermal comfort in outdoor spaces using a case study with a composite climate and models categorized for the summer and winter seasons. In the end they concluded since in many cases that it is not easy to gather all the variables for a particular site, and the mean cross-entropy error was smaller for winter (0.09) than for summer (0.47).

Rhoden et al. (2022) analyzed land use change in an Environmental Protection Area (EPA) and its impact on the region's economic dynamics. In the end, they concluded that it is necessary to develop tools that stimulate the conservation of ecosystems and sustainable agricultural exploitation. Thus, the neural network proposed here meets the description put forward by these researchers.

Conclusions

The algorithm model obtained resulted in an accuracy of 80% in the test phase, considered satisfactory, given the complexity of the variables, making it possible to obtain a multiclass model for the classification of environmental comfort.

The input variables in a decision-making support model based on an artificial neural network need to be deepened to enable the correct assessment of impacts resulting from rural anthropization.

When evaluating the distinct types of occupation, it is possible to affirm that the most sustainable interference for the expansion of agribusiness or urbanization in rural areas must maintain the trees and avoid open areas even if grassy, and whenever possible, to cover asphalt or concrete floors with the shading of trees.

Modeling involving a neural network to represent wooded environments must be carefully constructed and tested since the tones of the same color reflect a high entropy error.

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