

# **MODELOS PREDITIVOS EM HOME OFFICE CONFORTO TÉRMICO E RADIACÃO NÃO IONIZANTE**

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# CONTEÚDO

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REVISÃO SISTEMÁTICA

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ANÁLISE PRELIMINAR

# INTRODUÇÃO

O conforto térmico pode afetar a produtividade, a saúde e a satisfação das pessoas (Jeong et al., 2022).

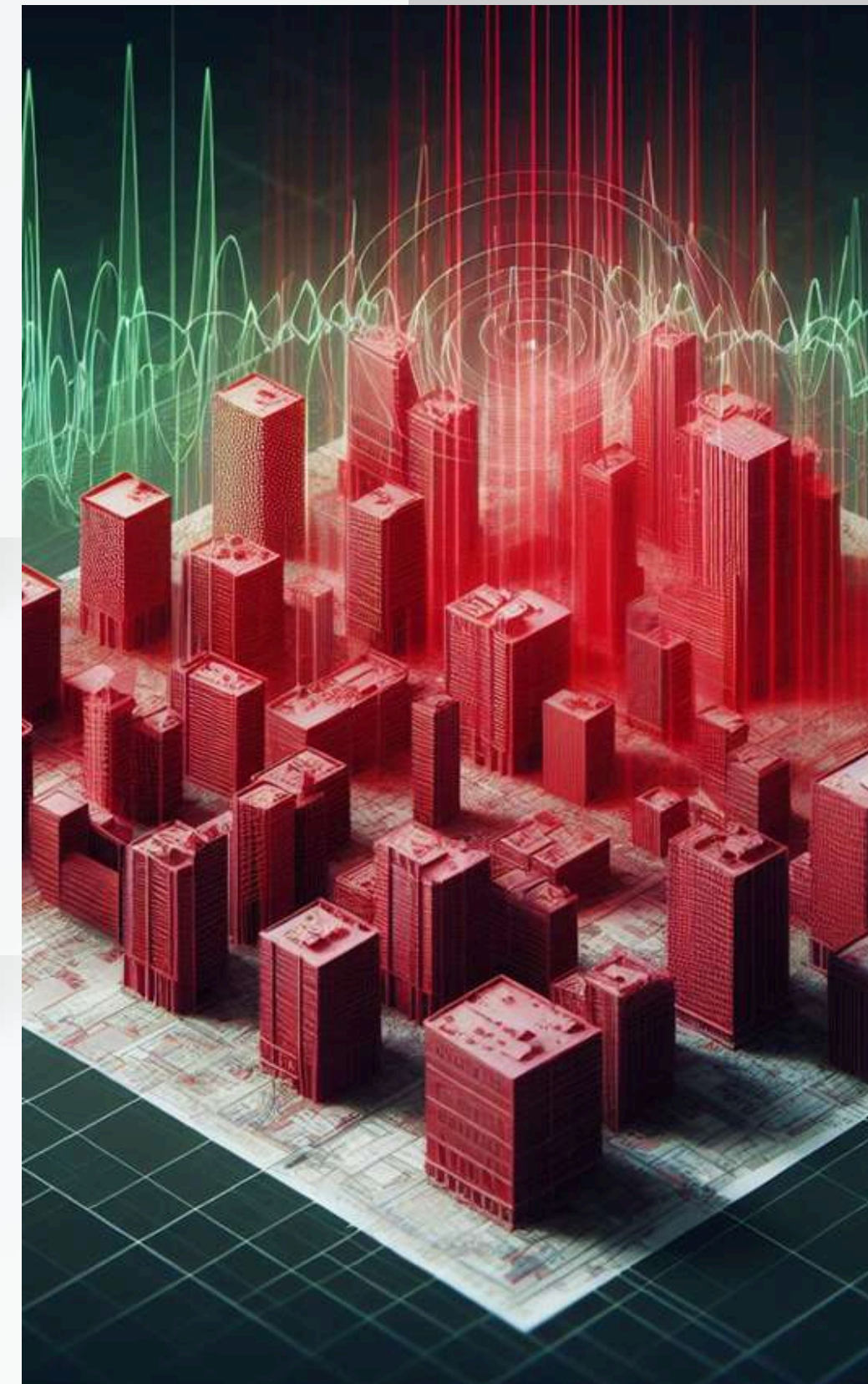
A saúde e o bem-estar podem ser seriamente comprometidos no caso de ambientes extremos de calor ou frio. Como evidenciado em muitos estudos, altas temperaturas externas e umidade também podem estar correlacionadas com o concentração de poluentes no ar (Pompei et al., 2024).



# INTRODUÇÃO

As preocupações pertinentes com a avaliação de campos eletromagnéticos e seus efeitos sobre a saúde tem refletido em estudos amplos em alguns países para monitoramentos urbanos (Dechamps e Dreambrogio DESCHAMPS & DEAMBROGIO, 2023).

A exposição a uma variedade de campos eletromagnéticos de baixa frequência (ELF) (principalmente em frequências extremamente baixas) se tornou inevitável e a investigação dos seus efeitos em sistemas biológicos tornou-se uma questão de interesse mundial e tem realizada em vários campos científicos (Hamedani et al., 2022).



# INTRODUÇÃO

## *Objetivo Geral*



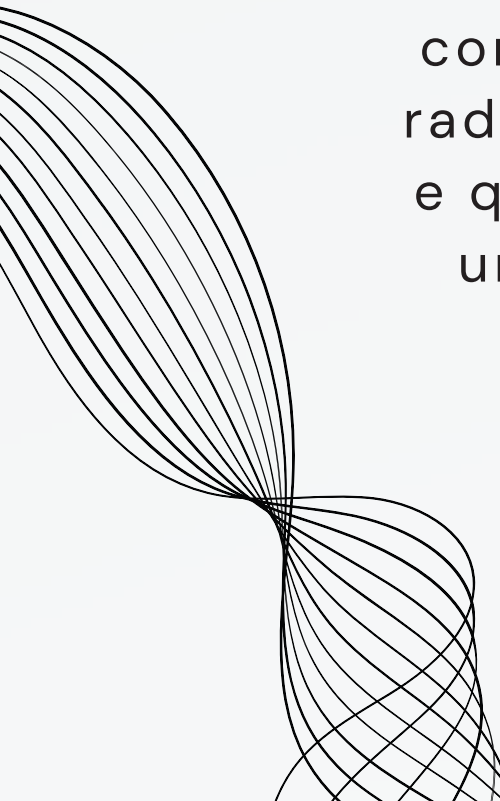
Obter modelos preditivos que permitam inferir sobre variáveis termoambientais, índices de conforto térmico e radiação não-ionizante em home offices considerandoos parâmetros de morfologia urbana para áreas do Nordeste Oriental do Brasil.



# INTRODUÇÃO

## Objetivos específicos

1



Caracterizar o ambiente dos home offices quanto às condições térmicas e radiação não ionizante e quanto a morfologia urbana no entorno.

2

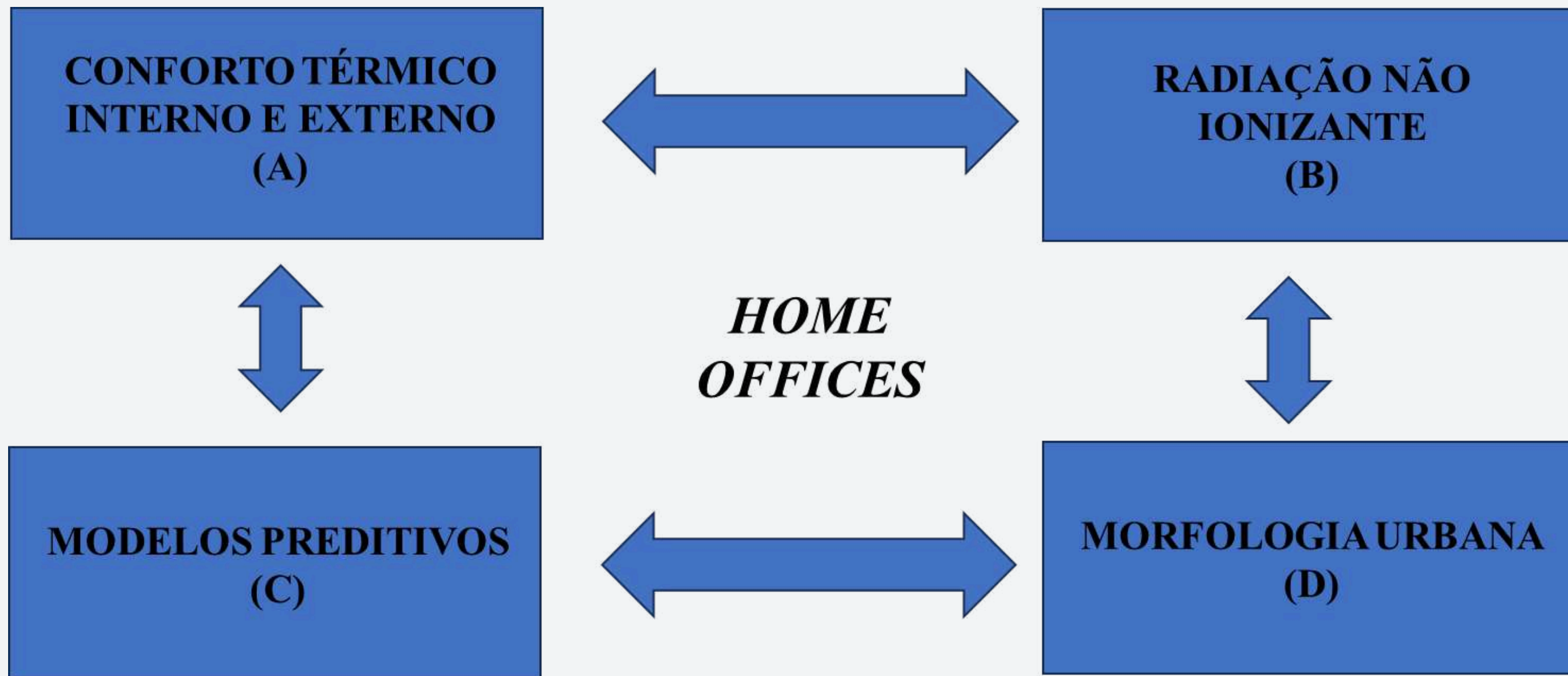
Aplicar e selecionar modelos matemáticos com as melhores capacidades de predição de indicadores das condições térmicas e de radiação não ionizante nos ambientes.

3

Apresentar diretrizes de planejamento do ambiente do entorno que contribuam na busca de medidas de mitigação e efeitos negativos das condições térmicas e de radiação não ionizante com base na formulação de cenários para home offices.

# REVISÃO SISTEMÁTICA

*INVESTIGAR TENDÊNCIAS NAS VARIÁVEIS TERMOAMBIENTAIS, ÍNDICES DE CONFORTO E DE RADIAÇÃO NÃO IONIZANTE EM AMBIENTES INTERNOS DE HOME OFFICE CONSIDERANDO O CONTEXTO EXTERNO NO QUAL SE INSEREM*



# REVISÃO SISTEMÁTICA

Tabela 1 – Descritores utilizados na busca

A	B	C	D
"indoor thermal comfort" "outdoor thermal comfort"	"non-ionizing radiation" "eletromagnetic*"	"predict* model*" "model*" "predict* algorithm*" "support vector machine" "deep learning" "machine learning" "time-series models" "regression" "random forest" "Neural Network"	"urban form*" "urban morphology"



## Tabela 2 – Resultado da busca

Bases	Palavras-chave	Número de artigos	2019-2024	Apenas artigos	Na Língua Inglesa	Sobre o tópico
Web of Science	A+C	328	250	233	233	74
	A+D	193	145	130	128	9
	B+C	43	23	15	14	5
	B+D	0	0	0	0	0
	A+B	0	0	0	0	0
	A+B+C+D	0	0	0	0	0
Scopus	A+C	368	261	213	210	-
	A+D	-	-	-	-	-
	B+C	76	46	27	23	-
	B+D	0	0	0	0	-
	A+B	0	0	0	0	-
	A+B+C+D	0	0	0	0	-
ProQuest	A+C	1459	1227	421	417	-
	A+D	777	627	619	616	-
	B+C	472	346	147	146	-
	B+D	2	2	1	1	-
	A+B	0	0	0	0	-
	A+B+C+D	0	0	0	0	-
Springer	A+C	885	716	219	219	-
	A+D	433	360	77	77	-
	B+C	956	597	160	159	-
	B+D	11	10	0	0	-
	A+B	0	0	0	0	-
	A+B+C+D	0	0	0	0	-
Wiley	A+C	54	32	27	27	-
	A+D	18	12	12	11	-
	B+C	336	105	105	84	-
	B+D	0	0	0	0	-
	A+B	0	0	0	0	-
	A+B+C+D	0	0	0	0	-

# REVISÃO SISTEMÁTICA

## Conforto térmico em ambientes externos

Urban Climate 42 (2022) 101134

Contents lists available at ScienceDirect

**Urban Climate**

journal homepage: [www.elsevier.com/locate/uclim](http://www.elsevier.com/locate/uclim)

Assessment of macroclimate and microclimate effects on outdoor thermal comfort via artificial neural network models

Jian Zhang<sup>a,b,e</sup>, Fan Zhang<sup>a,b,\*</sup>, Zhonghua Gou<sup>c</sup>, Jianlin Liu<sup>d</sup>



Sustainable Cities and Society 59 (2020) 102216

Contents lists available at ScienceDirect

**Sustainable Cities and Society**

journal homepage: [www.elsevier.com/locate/scs](http://www.elsevier.com/locate/scs)

A machine learning approach to predict outdoor thermal comfort using local skin temperatures

Kuixing Liu<sup>a</sup>, Ting Nie<sup>b</sup>, Wei Liu<sup>c</sup>, Yiqing Liu<sup>d</sup>, Dayi Lai<sup>e,\*</sup>

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<sup>d</sup> School of Built Environment, University of Reading, Reading, UK  
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Alexandria Engineering Journal (2022) 61, 10871–10896

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[www.sciencedirect.com](http://www.sciencedirect.com)

Urban physics and outdoor thermal comfort for sustainable street canyons using ANN models for composite climate

Rishika Shah<sup>\*</sup>, R.K. Pandit, M.K. Gaur



**buildings**

MDPI

Article

**Artificial Neural Network Modeling for Predicting and Evaluating the Mean Radiant Temperature around Buildings on Hot Summer Days**


Yuquan Xie<sup>1,2</sup>, Wen Hu<sup>2,\*</sup>, Xilin Zhou<sup>1</sup>, Shuting Yan<sup>3</sup> and Chuancheng Li<sup>1</sup>

# REVISÃO SISTEMÁTICA


## Conforto térmico em ambientes internos

Journal of Building Engineering 78 (2023) 107603

Contents lists available at ScienceDirect



 **Journal of Building Engineering** 

journal homepage: [www.elsevier.com/locate/jobe](http://www.elsevier.com/locate/jobe)

**Real-time indoor thermal comfort prediction in campus buildings driven by deep learning algorithms** 


Zherui Ma, Jiangjiang Wang<sup>\*</sup>, Shaoming Ye, Ruikun Wang, Fuxiang Dong, Yingsong Feng

Hebei Key Laboratory of Low Carbon and High Efficiency Power Generation Technology, North China Electric Power University, Baoding, 071003, Hebei, PR China

 **buildings** 

Article

**Analysis of Variables Affecting Indoor Thermal Comfort in Mediterranean Climates Using Machine Learning**

Pablo Aparicio-Ruiz<sup>\*</sup> , Elena Barbadilla-Martin, José Guadix and Julio Nevado

Energy & Buildings 277 (2022) 112547

Contents lists available at ScienceDirect

 **Energy & Buildings** 

journal homepage: [www.elsevier.com/locate/enb](http://www.elsevier.com/locate/enb)


**MyComfort: An integration of BIM-IoT-machine learning for optimizing indoor thermal comfort based on user experience** 

Khaoula Kanna, Kaltouma AIT Lachguer, Reda Yaagoubi<sup>\*</sup>


College of Geomatics and Surveying Engineering, IAV Hassan II, Rabat, Morocco

Building and Environment 202 (2021) 108026

Contents lists available at ScienceDirect

 **Building and Environment** 

journal homepage: [www.elsevier.com/locate/buildenv](http://www.elsevier.com/locate/buildenv)

**Study on an adaptive thermal comfort model with K-nearest-neighbors (KNN) algorithm** 

Lei Xiong, Ye Yao<sup>\*</sup>

Institute of Refrigeration and Cryogenics, School of Mechanical Engineering, Shanghai Jiao Tong University, 800 Dongchuan Rd., Shanghai, 200240, China


# REVISÃO SISTEMÁTICA

## Radiação não ionizante

IEEE CANADIAN JOURNAL OF ELECTRICAL AND COMPUTER ENGINEERING, VOL. 44, NO. 2, SPRING 2021

### Examining EMF Time Series Using Prediction Algorithms With R

### Examen des séries temporelles d'EMF à l'aide d'algorithmes de prédiction avec R

Zeydin Pala 

*Abstract*—In this study, electric field strength ( $E$ ) levels of high-voltage lines were measured monthly in Sütluce (38°N, 41°E), Muş, Turkey, between 2014 and 2018, and the obtained 60 monthly mean values were used as time series (TS) to forecast next 12 months by using conventional statistical and deep learning (DL) algorithms. In addition to the conventional statistical and DL algorithms developed for R, advanced algorithms, such as long short-term memory (LSTM) and recurrent neural network (RNN) derivative, were also used in the prediction process. We applied a cross-validation technique to the electromagnetic field (EMF) data set obtained in a period of 60 months. Thus, multiple algorithm performances were compared for the same data set. In addition, the electrical field values measured in the Sütluce neighborhood were found to exceed the International Commission on Non-Ionizing Radiation Protection (ICNIRP) values.


Environmental Science and Pollution Research (2023) 30:40445–40460

<https://doi.org/10.1007/s11356-023-25153-y>

RESEARCH ARTICLE



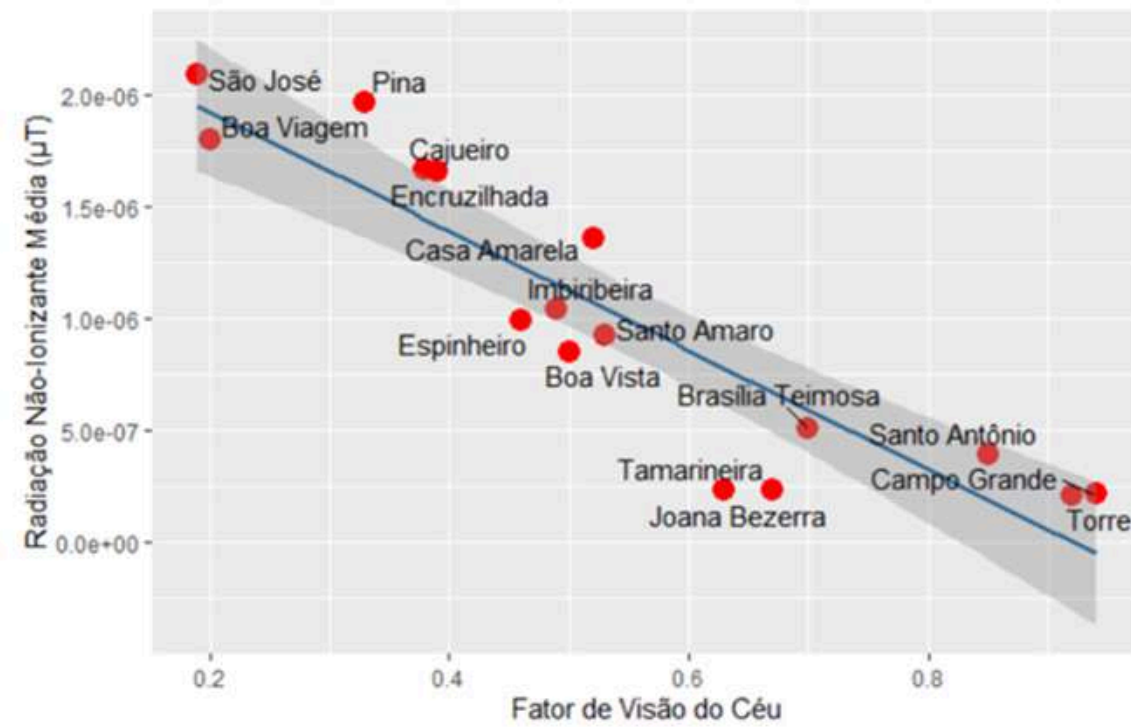
### Evaluation of Chinese populational exposure to environmental electromagnetic field based on stochastic dosimetry and parametric human modelling

Yuwei Jiang<sup>1</sup> · Hongkai Wang<sup>2</sup> · Xiaobang Sun<sup>2,3</sup> · Congsheng Li<sup>1</sup> · Tongning Wu<sup>1</sup> 

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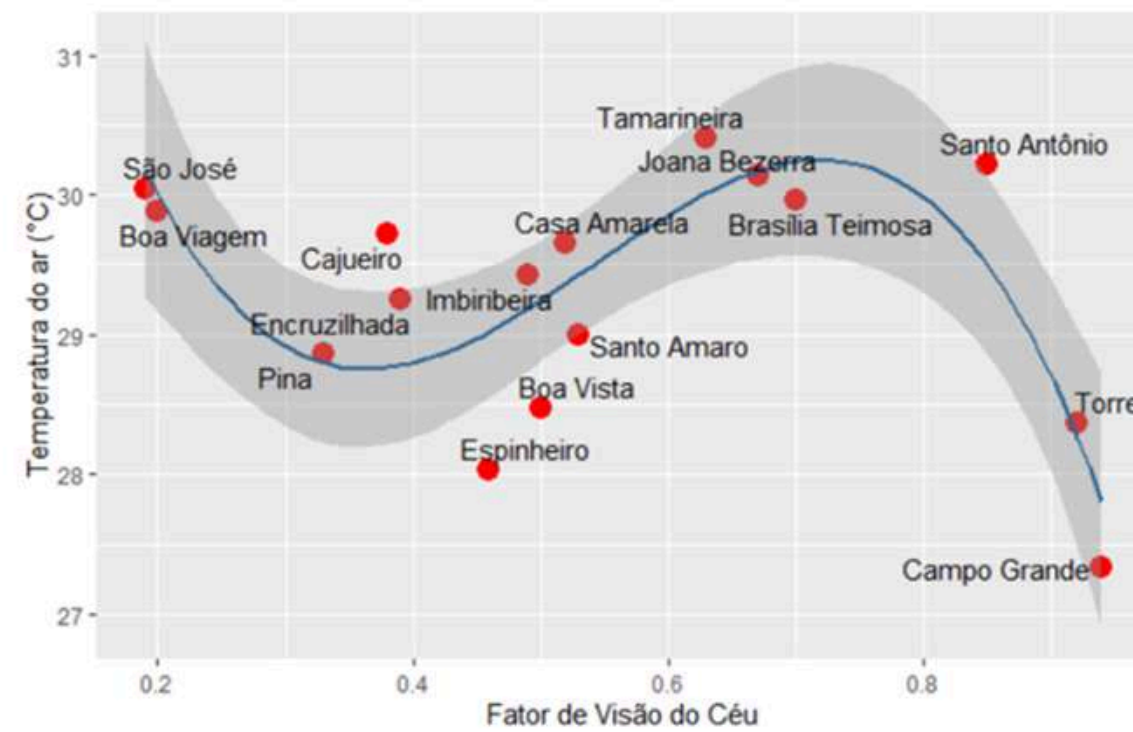
# ANÁLISE PRELIMINAR



Termo	Estimativa	t	Valor p
Intercepto	2,46	12,83	$3,95 \cdot 10^{-9}$
FVC	-2,66	-8,17	$1,06 \cdot 10^{-6}$

$$R^2 = 0,8268$$

$$\text{RNI} = 2,46 - 2,66 \cdot \text{FVC}$$



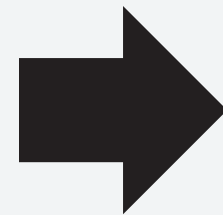
Termo	Estimativa	t	Valor p
Intercepto	36,67	18,92	$2,67 \cdot 10^{-10}$
FVC	-52,3	-4,04	0,001628
FVC <sup>2</sup>	108,17	4,21	0,001213
FVC <sup>3</sup>	-66,55	-4,34	0,000962

$$R^2 = 0,6522$$

$$\text{TBS} = 36,67 - 52,30 \cdot \text{FVC} + 108,17 \cdot \text{FVC}^2 - 66,55 \cdot \text{FVC}^3$$

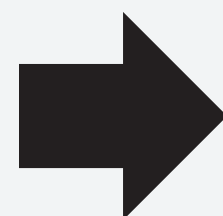
# ANÁLISE PRELIMINAR

**Radiação  
não ionizante**



Efeitos fixos			Efeitos aleatórios		
Termo	Estimativa	t	Termo	Variância	Percentual
Intercepto	$2,46 \cdot 10^{-6}$	12,827	Bairros	$8,41 \cdot 10^{-14}$	10,45%
FVC	$-2,66 \cdot 10^{-6}$	-8,17	Residual	$7,21 \cdot 10^{-13}$	89,55%
			Total	$8,05 \cdot 10^{-13}$	100,00%

**Temperatura de  
bulbo seco**



Efeitos Fixos			Efeitos aleatórios		
Termo	Estimativa	t	Termo	Variância	Percentual
Intercepto	36,67	18,92	Bairros	0,34	38,20%
FVC	-52,297	-4,044	Residual	0,55	61,80%
FVC2	108,17	4,21	Total	0,89	100,00%
FVC3	-66,55	-4,34			