Nowcasting for improving ^{222}Rn forecasting at LSC

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Abstract

The improvement of experiments at underground laboratories is closely linked to background reduction. The main source of background is the ^{222}Rn levels at this type of experiments i.e Argon Dark Matter 1-t located at the underground laboratory of Canfranc (LSC), Spain, aimed at the dark matter direct searches. One approach that can be done in order to get rid of this background consists of modeling and forecasting the signal for efficient planning activities at the experiment. In this work, we have analyzed five years of weekly ^{222}Rn levels using deep learning techniques such as Convolutional Neural Networks (CNN), Artificial Neural Networks (ANN) and Long-Short Term Memory Nets (LSTM). Taking into account several meteorological variables from cities around LSC such as Barcelona (BCN), Huesca (HSC), Pamplona (PMP) and Zaragoza (ZGZ). We study the variable importance in the forecasting of those variables through the Random Forest algorithm and we find that temperature is the one that would make significant improvements to the forecasting. Therefore, using temperature from each weather station and ^{222}Rn levels at LSC as input, we predict the Rn time series using a CNN, being N the number of future values of the series, the output. Finally, we estimate the maximum value of N where temperature doesn't improves the performance.

Keywords: Convolutional Neural Network · ^{222}Rn Measurements · Canfranc Underground Laboratory · Forecasting.

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1. Introduction

[1]

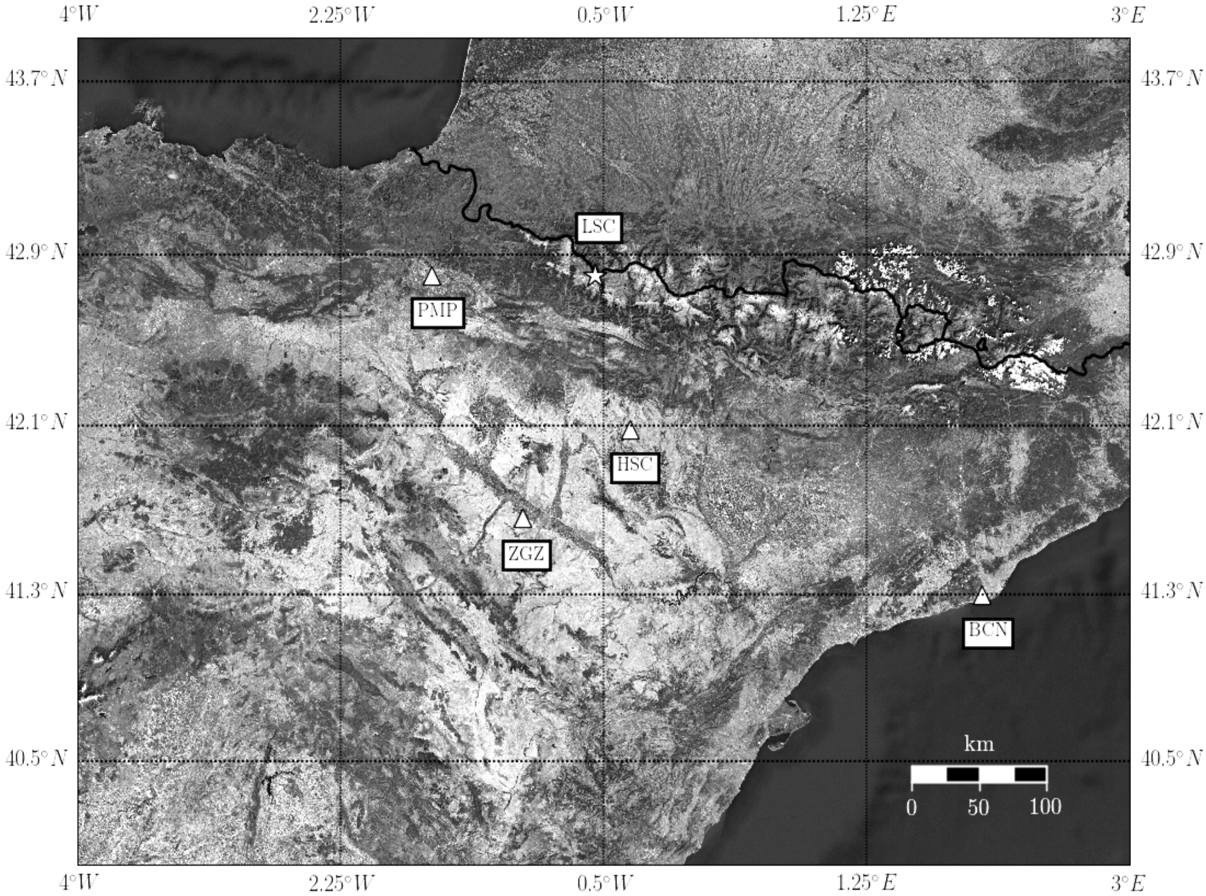

Figure 1: GPS map of the Spanish Peninsula area of interest. Triangles mark the location of the meteorological stations and the star marks the LSC station. Pamplona station is labeled as PMP, Barcelona station as BCN, Huesca station as HSC and Zaragoza station as ZGZ.

2. Methodology

2.1. Data preproccesing

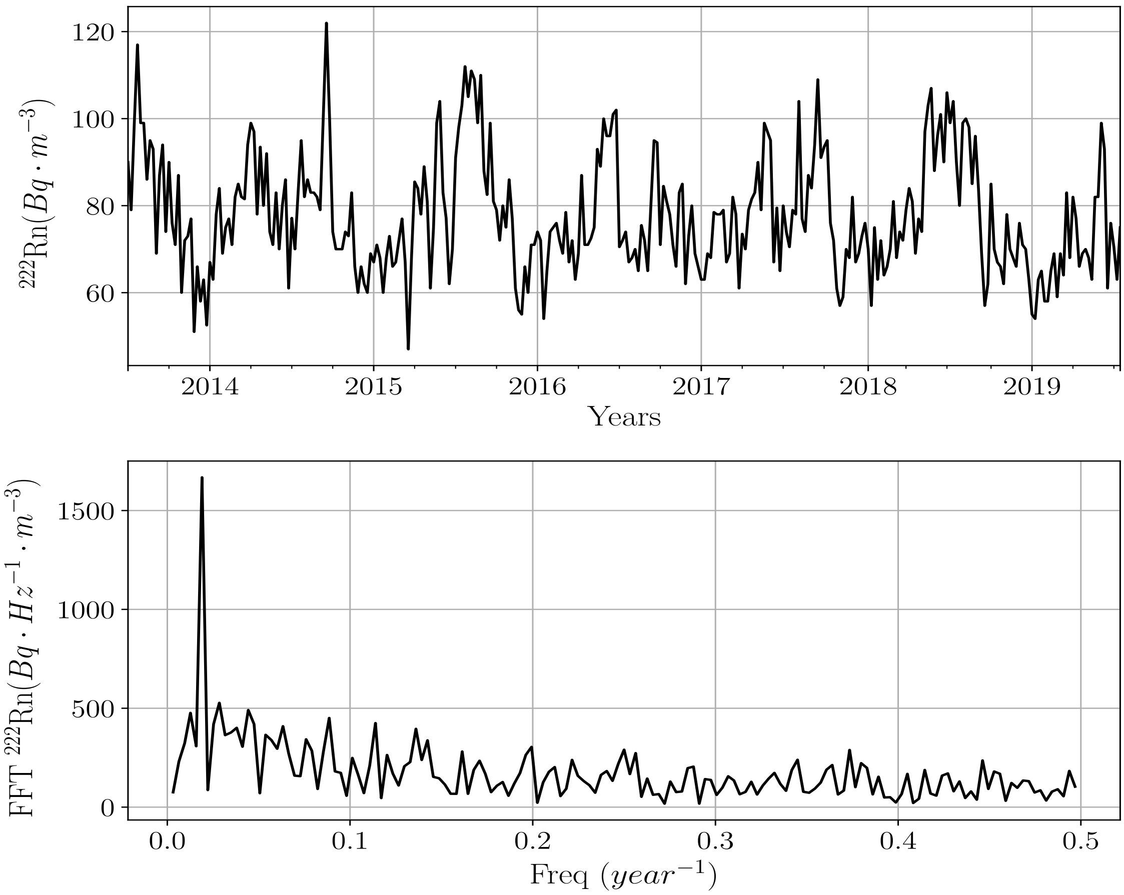

Figure 2: ^{222}Rn concentrations medians per week from July 2013 to July 2019 at Hall A of the LSC (upper) and its frequency domain obtained after applying a Fast Fourier Transform (FFT) (down).

2.2. Correlation with meteorological variables

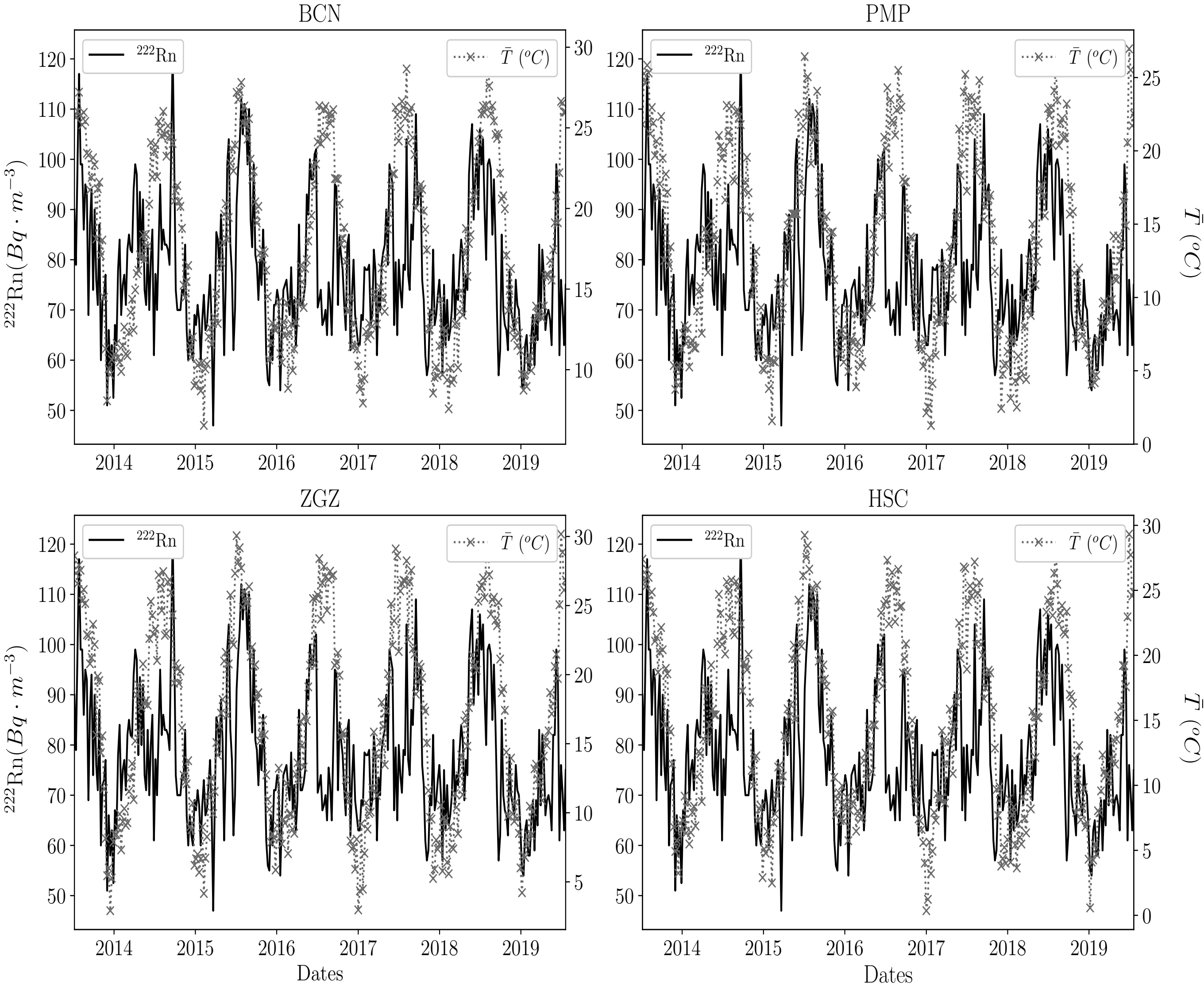

Figure 3: Weekly ^{222}Rn concentrations medians (solid black) and weekly average temperature in ^oC (dashed gray) from July 2013 to July 2019.

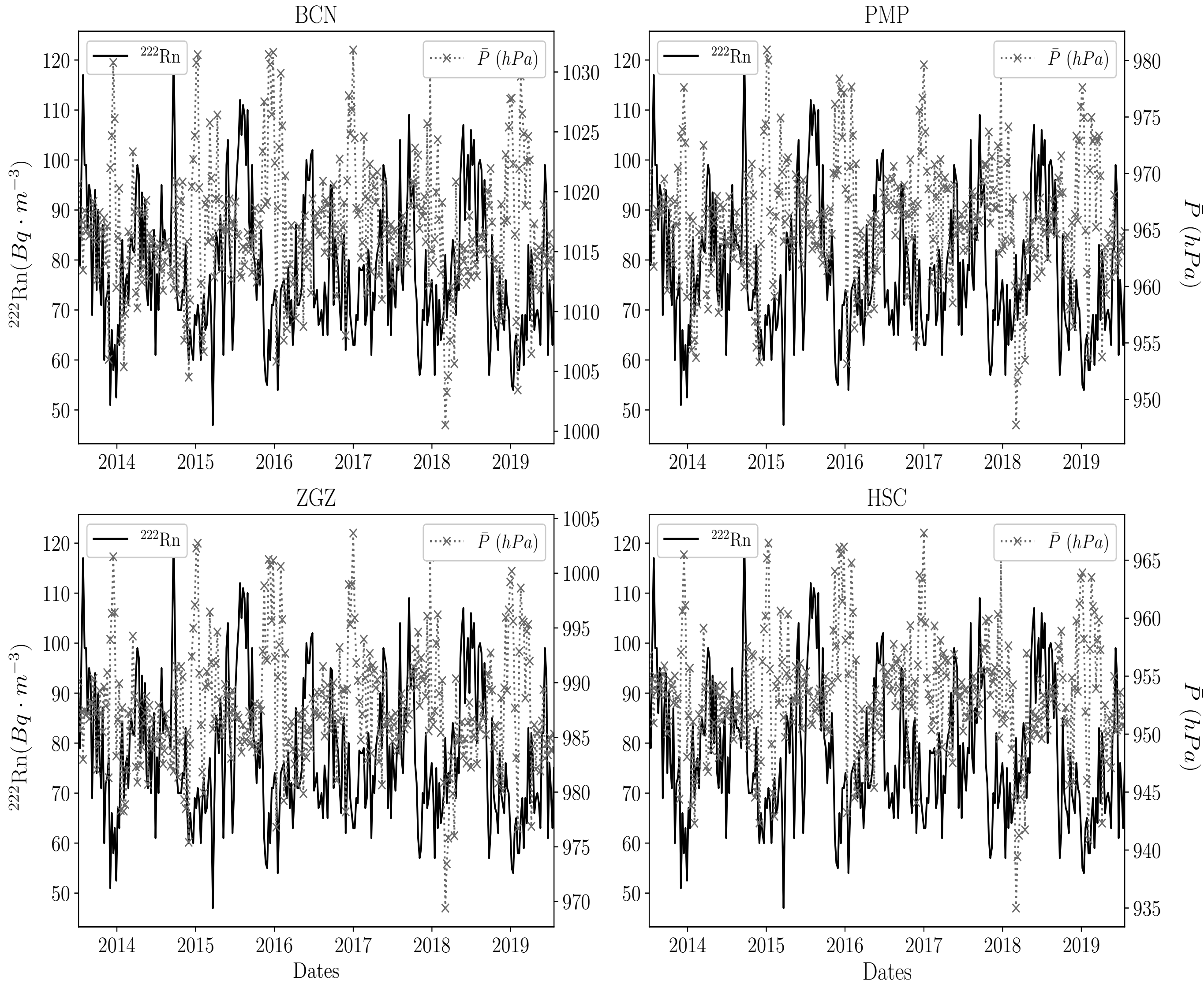

Figure 4: Weekly ^{222}Rn concentrations medians (solid black) and weekly average preassure in hPa (dashed gray) from July 2013 to July 2019.

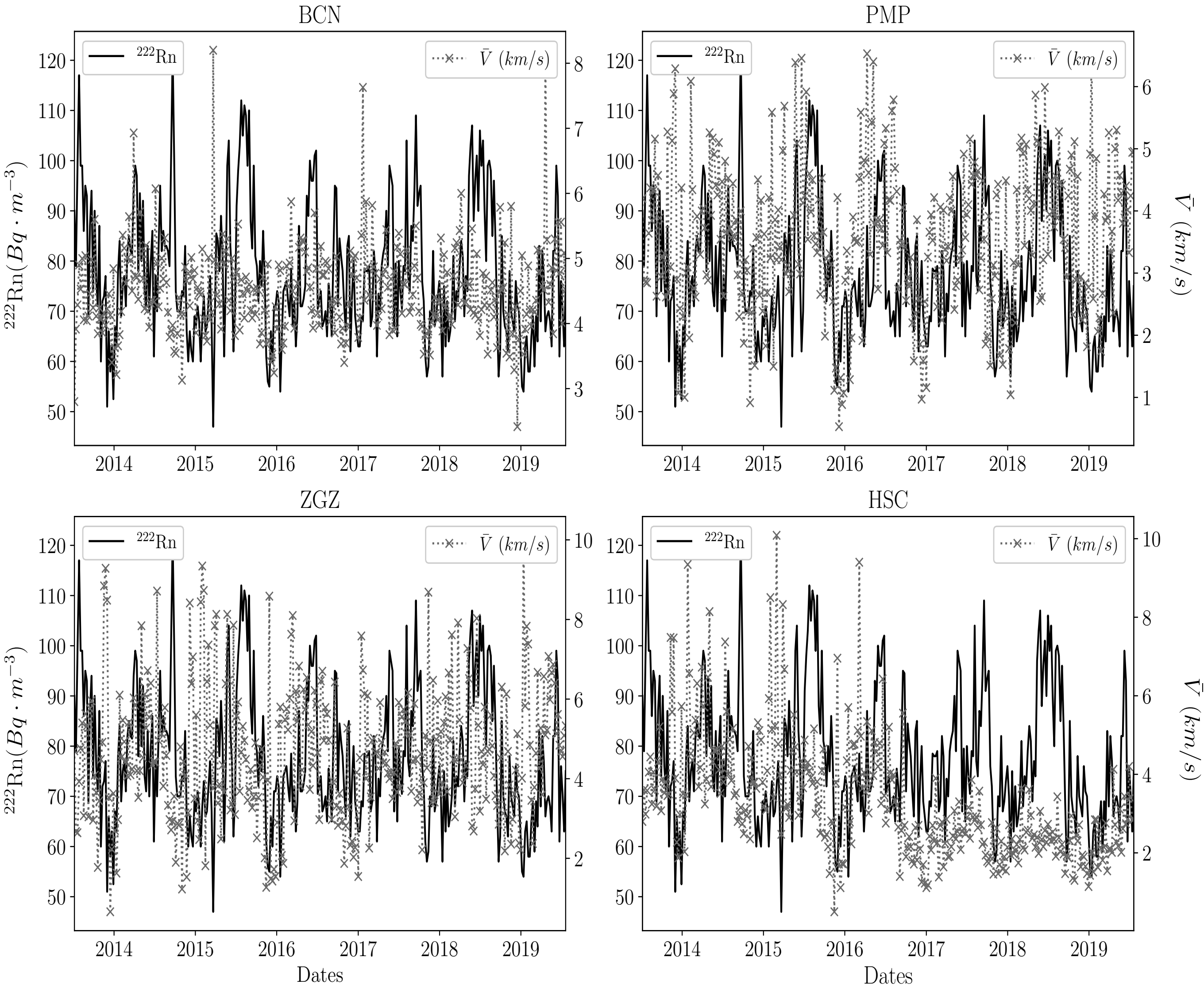

Figure 5: Weekly ^{222}Rn concentrations medians (solid black) and weekly average wind velocity in $km \cdot s^{-1}$ (dashed gray) from July 2013 to July 2019.

City	corr(Rn + T)	corr(Rn + P)	corr(Rn + V)
BCN	0.53	-0.21	0.06
PMP	0.52	-0.19	0.17
ZGZ	0.53	-0.27	0.10
HSC	0.52	-0.16	0.12

Table 1: Cross correlations of the weekly median ^{222}Rn levels at LSC and several meteorological variables: average preassure, average temperature and average wind velocity recorded at different stations (labeled with the city name).

2.3. Random Forest

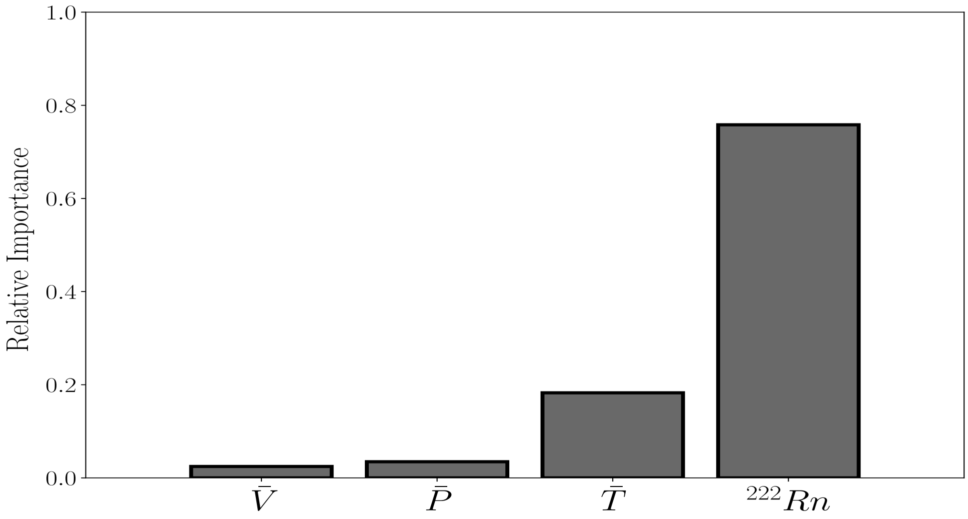

Figure 6: Variable importances to forecasting the signal obtained with Random Forest algorithm. Let i be $\{\bar{V}, \bar{P}, \bar{T}, {}^{222}\mathrm{Rn}\}$, the importances I_i satisfies the following condition: $\sum_i I_i = 1$.

2.4. Convolutional Neural Networks

3. Results

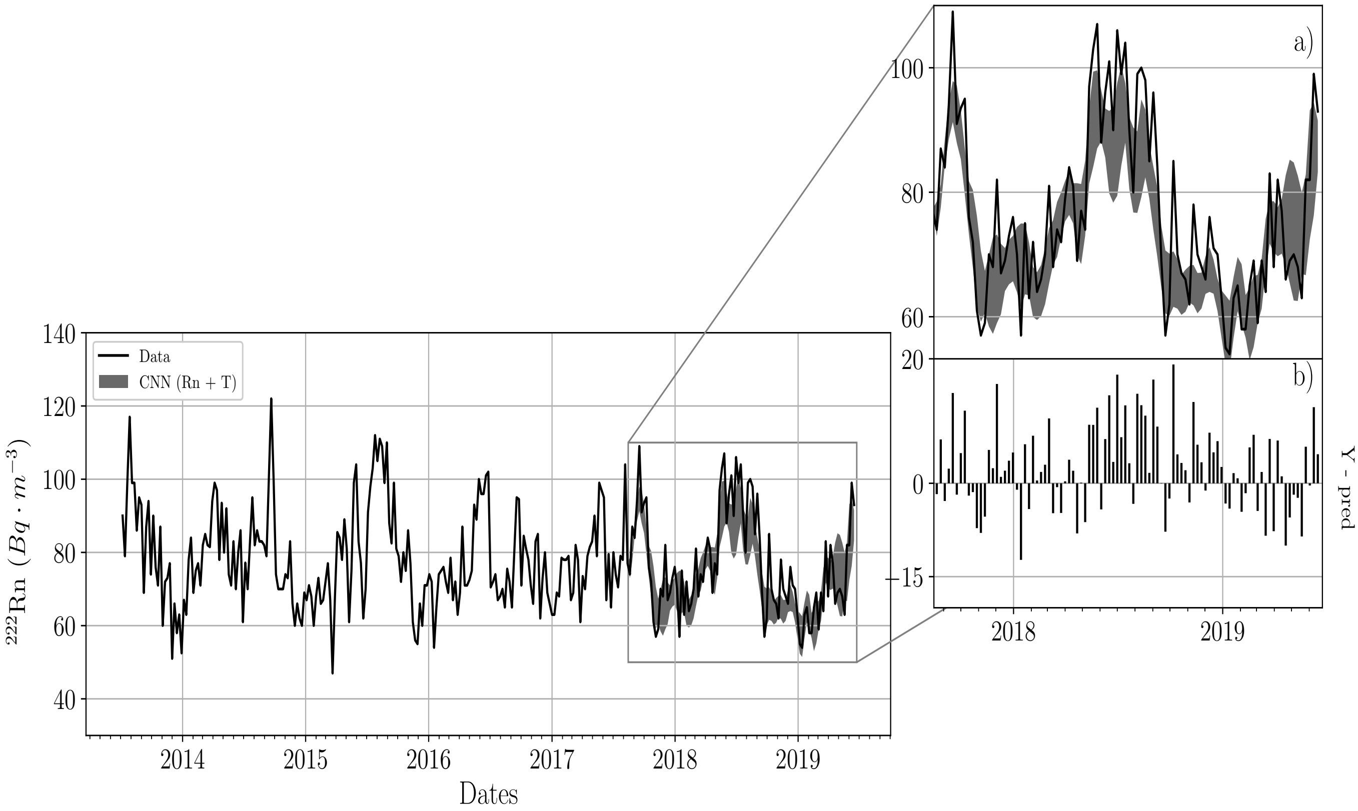

Figure 7: Weekly ^{222}Rn signal (solid black) and the CNN prediction on the test set (gray band). a) Zoomed plot of the prediction. b) Distances between data and average values of the prediction band.

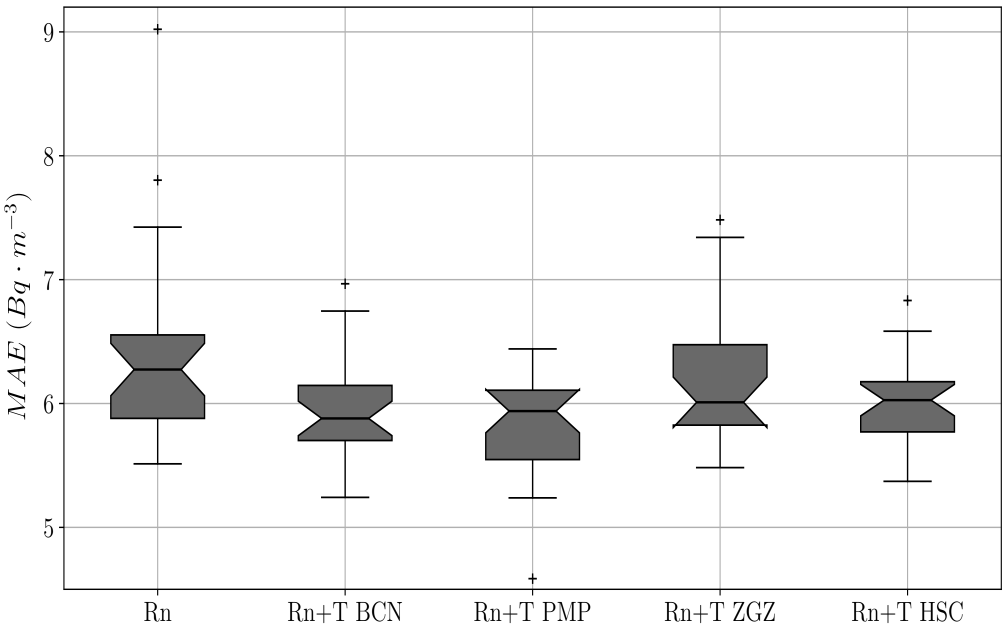

Figure 8: Mean Absolute Error Boxplots for $N = 3$ future values predicted in two cases: Rn as input of the CNN and Rn + Temperature as input for each city.

	^{222}Rn	$(\overline{\Delta y} \pm \sigma)_{BCN}$	$(\overline{\Delta y} \pm \sigma)_{PMP}$	$(\overline{\Delta y} \pm \sigma)_{ZGZ}$	$(\overline{\Delta y} \pm \sigma)_{HSC}$
3 Forward	6.42 ± 0.83	5.96 ± 0.42	5.84 ± 0.43	6.19 ± 0.57	6.01 ± 0.36
9 Forward	6.57 ± 0.95	6.80 ± 0.60	6.77 ± 0.54	6.68 ± 0.51	6.68 ± 0.66

Table 2: Mean and standard deviation (σ) of Mean Absolute Error ($\overline{\Delta y}$) for 25 independent runs for the test data test and for two different cases: Neural Network predicting 3 future values for each input window and predicting 9.

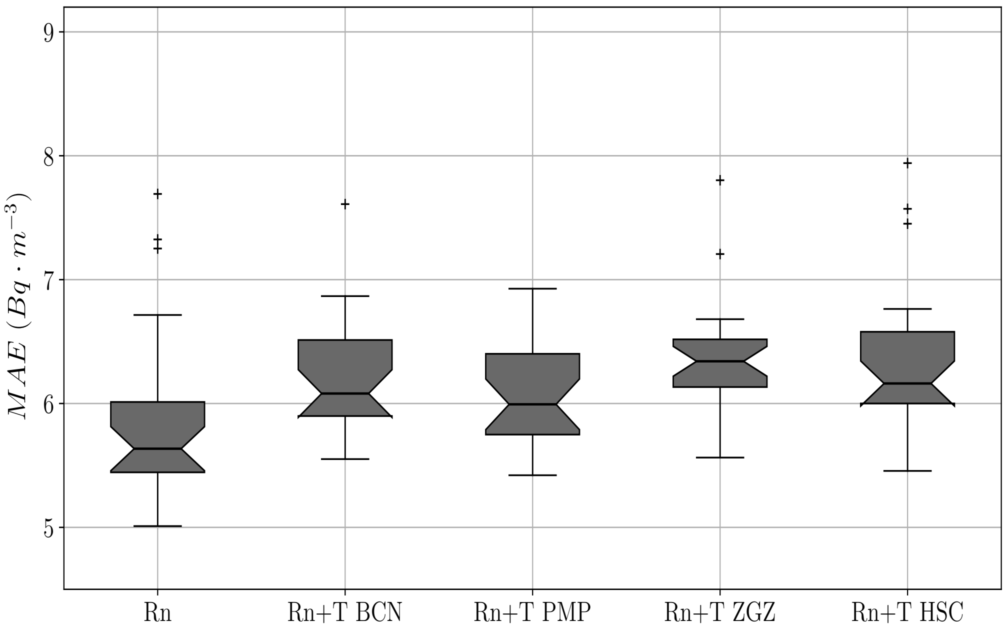

Figure 9: Mean Absolute Error Boxplots for $N = 9$ future values predicted in two cases: Rn as input of the CNN and Rn + Temperature as input for each city.

4. Conclusions

Appendix A. Section in Appendix

References

[1] A. Bettini, New underground laboratories: Europe, asia and the americas, Physics of the Dark Universe 4 (2014) 36 – 40, dARK TAUP2013. doi:https://doi.org/10.1016/j.dark.2014.05.006.
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