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Use of a fuzzy qualitative model to reanalyze radon relationship with atmospheric variables in a coastal area near a NORM repository

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ABSTRACT

A soft computing methodology, PreFuRGe (Predictive Fuzzy Rules Generator), was applied to study atmospheric radon in relation to other meteorological variables. This algorithm is based on fuzzy clustering and generates a rule-based system that provides a qualitative model that describes the behavior of radon. Two one-year radon datasets were used to verify the consistency of the fuzzy methodology, by comparing the obtained models with published results obtained with statistical techniques. These datasets were collected in the city of Huelva, to the southwest of Europe, and were already studied in peer-reviewed publications. The proposed fuzzy methodology was able to provide results consistent with previous studies, identifying the main drivers in radon behavior, atmospheric stability and wind speed, together with a complete characterization of the daily cycle and its seasonality. PreFuRGe highlighted features that would otherwise require detailed examination combining a number of classical statistical techniques, proving to be a useful tool to characterize heterogeneous datasets.

1. Introduction

Fuzzy logic (FL) was developed by professor L.A. Zadeh, at Berkeley, University of California, using the idea of grade of membership as core concept (Zadeh, 1973, 1969, 1968, 1965). Due to its speed and computational efficiency, FL methods have been used in environmental sciences as a forecasting tool (Christian and Patel, 2014; Mishra and Goyal, 2016; Sardar Maran et al., 2020), risk analysis (Cai et al., 2021; Wang and Song, 2021) and to investigate existing relationships between pollution and meteorological variables (Dass et al., 2021; Vovchenko Natalia et al., 2019), among other purposes.

Considering the increasing interest and results that FL methods are achieving in the past years, it would be interesting to apply FL to study radon gas. Radon is a well-known gas in environmental sciences as it is a radioactive noble gas responsible for more than 42% of the dose from all source of radiation to the public (UNSCEAR, 2008). Radon is constantly generated in soils with significant radium content and can be accumulated insitu or transported long distances due to its long half-life (3.8 days). It has been studied extensively in the literature as a radiological risk to miners (Ahmad et al.,

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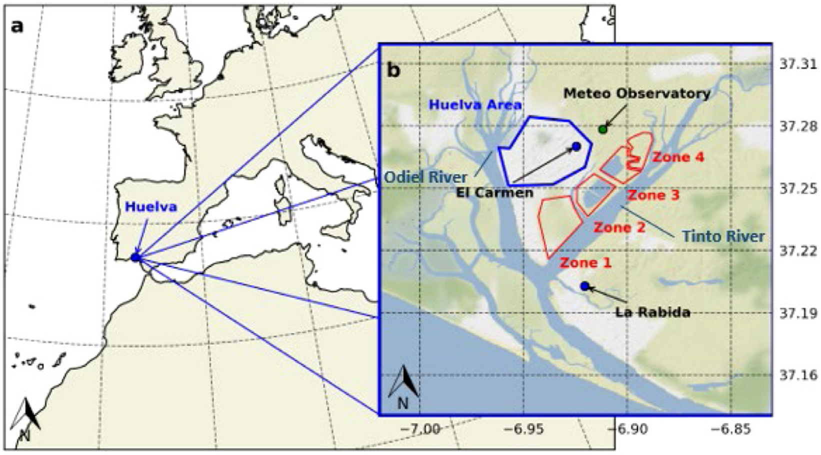

Fig. 1. Location of Huelva city in Europe (a). Huelva measurement stations (El Carmen and La Rabida), meteorological observatory (Meteo Observatory), Huelva city area (Huelva Area) and NORM repository zones (Zones 1, 2, 3 and 4) (b).

2019; Xie et al., 2014), due to its effects on residential dwellings (Burghele et al., 2021; López-Abente et al., 2018). It is also a useful tool as a tracer for atmospheric transport (Arnold et al., 2010; Burton and Stewart, 1960; Chambers et al., 2016; Polian et al., 2017; Wilkening, 1952) or as an indicator of the atmospheric mixing state (Chambers et al., 2015; Perrino et al., 2001; Sesana et al., 2006; Williams et al., 2016).

This paper presents a novel approach for the study of radon relationships with meteorological variables, oriented by the methodology proposed by PreFuRGe (Predictive Fuzzy Rules Generator) (Aroba, 2003), a soft computing tool based on fuzzy logic that have demonstrated its efficacy for modeling the qualitative behavior of complex systems in diverse contexts, like: software engineering (Aroba et al., 2008), systems identification in control (Gegúndez et al., 2008) or environmental systems (Grande et al., 2010a,b), where the obtained results were validated by experts, confirming the veracity and value of the generated qualitative information.

To the best of our knowledge, fuzzy logic techniques have not been applied yet to study atmospheric radon. For this reason, the main objective of this work is to perform a verification of the consistency of the fuzzy logic analysis applied to radon, ensuring that it can lead to reliable results. As a second objective, results provided by this FL tool were used to study radon and how different levels and combination of meteorological variables affect its behavior.

In order to achieve this objectives, PreFuRGe methodology was applied to atmospheric radon and other variables that could have an impact on its behavior, such as temperature, relative humidity, pressure, wind speed and direction and atmospheric boundary layer height (ABL), the hour of the day or the month. This information was measured in the city of Huelva, on the SW of Europe, during 2016 and 2018, from two measurement stations. Radon behavior in this area has been studied extensively in the past due to the existence of a phosphogypsum repository in the vicinity of Huelva City, a source of radon (Grossi et al., 2016; Gutiérrez-Álvarez et al., 2019; Hernández-Ceballos et al., 2015), which turns Huelva into an ideal location to carry out the proposed verification.

2. Experimental and methods

2.1. Area of study

Huelva city lies to the southwest of the Iberian Peninsula, near the coast of the Atlantic Ocean (Fig. 1a). It is located on the confluence of the Tinto and Odiel rivers. Despite being 75 km to the west of the Guadalquivir River mouth the city is influenced by the presence of the Guadalquivir valley. This valley is located to the south of the Iberian Peninsula extending 600 km with an orientation NE to SW.

Close to the urban area of Huelva, there is a NORM (Naturally Occurring Radioactive Materials) repository that holds significant amounts of Phosphogypsum (PG), with ^{226}Ra concentrations around 650 ± 50 Bq kg^{-1}. The repository is divided in four zones (Fig. 1b): zones 1 and 4 are topped with a layer of material, limiting radon transport to the atmosphere since their rehabilitation in 1992 and 1998. Zones 2 and 3 are still open to the atmosphere and contain 270 and 180 ha of PG, respectively. There is a number of previous studies that showed that the PG repository is a potential radon gas source to the atmosphere (Bolívar et al., 1996; Dueñas et al., 2007; López-Coto et al., 2014).

2.2. Wind regime

Before studying radon transport, it is important to address the wind regime, since it plays a critical role in radon behavior. In Huelva, it is characterized by a combination of SW synoptic winds from the Atlantic Ocean and mesoscale processes due to the proximity of the Atlantic Ocean to the coastline and the Guadalquivir Valley (Adame et al., 2010b). NW winds are frequent during the year, contributing 24 to 27% of the total wind distribution throughout the year, depending on the season. On one hand, winter season shows a major presence of NE winds (38%), being NW the second major direction (24%). On the other hand, in summer winds blowing from SW are the most common (38%), while NW stays roughly equal (25%). Autumn and spring are transitional seasons between summer and winter, with SW and NE direction being more proportionally similar. The SE direction is almost absent throughout the year, representing no more than 10% of the total (Adame et al., 2010a; Hernández-Ceballos, 2012).

An important characteristic of the wind regime of the city is the presence of sea–land breezes, generated by the proximity of the city to the coastline. Previous studies in the area showed two breeze patterns: pure and non-pure (Adame et al., 2010b). Pure-breezes presents a first phase in the afternoon (12:00–17:00 UTC) with wind speeds between 2 to 3 m s^{-1} and SW direction, which then rotates clockwise from SW to NE, maintaining NE direction and an average wind speed of 2.1 m s^{-1} during the night (03:00 to 08:00 UTC). Non-pure breezes show similar characteristics in the afternoon but have a counter-clockwise rotation after the afternoon to NW wind direction that is maintained during the night. Non-pure breeze is characterized by generally higher wind speeds than pure breezes.

2.3. Measurements and instrumentation

This study used two radon data series. The first one was taken from March 2015 to March 2016 with one measurement station located at 10 m above ground level on the flat roof of a building within El Carmen University Campus (Fig. 1b). This station is inside the urban area, roughly 1.5 km from the PG repository. The second data series was taken during 2018, using two measurements stations, the already mentioned El Carmen station, and a second one placed in La Rabida Campus, which is situated 7 km to the SE of the city, across the Tinto river (Fig. 1b). La Rabida is 5 km to the south of the PG piles. It is better defined as a rural station, as it is located in a small campus on the top of a hill, in an area surrounded by marshlands and farmlands. Raw data is uploaded for public access (https://doi.org/10.6084/m9.figshare.18480431.v1).

The radon measurement system employed in El Carmen and La Rabida was based on the Atmospheric Radon Monitor (ARMON), designed by INTE-UPC (Institut de Tècniques Energètiques - Universitat Politècnica de Catalunya) (Grossi et al., 2020, 2012; Vargas et al., 2015; Vargas and Ortega, 2006). This system uses a semiconductor detector inside a spherical detection volume of 20 L to detect α-particles generated by ^{218}Po ions decay. To collect these ions produced by radon decay, the moisture level is kept under 2000 ppmV and a potential difference of 8 kV is created between the inner layer of the sphere, covered with silver, and a PIPS (Passivated Implanted Planar Silicon) detector, electrically grounded and located at the top of the sphere. At the entrance of the sphere, a 1 μm filter traps all ^{222}Rn progeny generated before entering the sphere, ensuring that measured ^{218}Po ions are due to radon decay within the sphere. Both ARMON detectors were calibrated at the INTE-UPC ^{222}Rn chamber (Vargas et al., 2004). The minimum detection concentration was found to be 200 mBq m^{-3} over a period of 1 h. A detailed description of the ARMON device and its calibration can be found in Grossi et al. (2012), Vargas et al. (2015).

Meteorological data were collected in an observatory 1.5 km to the NE of the city, managed by the Spanish Agency of Meteorology (AEMET). The meteorological station measured at 16 m a.g.l., providing results every 10 min, which were hourly-averaged afterwards. Data provided include temperature, wind speed and direction, relative humidity and pressure. Finally, atmospheric boundary layer (ABL) height data was gathered from reanalysis models. For the first study, ABL data was download from ERA-Interim model (Dee et al., 2011), which provides one daily value at 12:00 UTC. The second study used the next generation of the ERA-Interim model, ERA5 data reanalysis (Hersbach et al., 2020), which provided data at 1-hour intervals. It is important to state that ABL height data used in the fuzzy logic analysis, which is described in detail in the next section, was extracted from the ERA5 data reanalysis.

2.4. Fuzzy logic

Fuzzy logic (Zadeh, 1965) works by using reasoning rules very near to the imprecise way of thinking of persons. In fuzzy logic a variable can be characterized without specifying a precise value, something which is not possible with classical logic. In fuzzy mathematics, fuzzy logic is a form of many-valued logic in which the true values of variables may be any real number between 0 and 1, both inclusive. It is employed to handle the concept of partial truth, where the true value may range between completely true and completely false (Novák et al., 1999).

Soft computing, term coined by Lofti Zadeh (Zadeh, 1992), can be defined as a group of computational techniques based on artificial intelligence that provides effective solutions to complex problems for which analytical formulations do not exist (Choudhury and Jha, 2016). The raise of soft computing has been determined by advances in machine learning, probabilistic reasoning, artificial neural networks, fuzzy logic and genetic algorithms (Jang and Sun, 1996).

2.4.1. Fuzzy clustering

In general terms, a clustering algorithm (Kaufman and Rousseeuw, 1990) groups similar objects in the same group (cluster). In classical clustering, each object is assigned to a cluster (rigid partition) where the membership grade of each object to a cluster is 0 (null membership) or 1 (whole membership). Conversely, in fuzzy clustering (Hathaway and Bezdek, 1993) the membership grade of each object to a cluster can take real values between 0 and 1 (partial membership grade), therefore, each object may belong (partially) to more than one cluster.

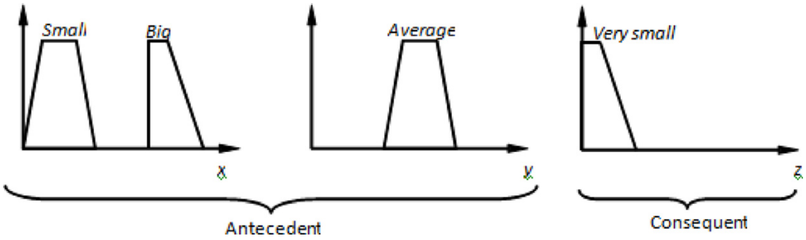

Fig. 2. Example of fuzzy rule representation.

2.4.2. Data mining: PREFURGE methodology

Data mining can be defined as the extraction of hidden information from a large data set. Algorithms based on data mining allow the extraction of tendencies and behaviors, and provide a more complete knowledge than the information obtained with classical statistical techniques (Glymour et al., 1996; Hand, 1998). PreFuRGe (Predictive Fuzzy Rules Generator) (Aroba, 2003) is a data mining computing tool based on fuzzy clustering, designed to be applied on multi-parametric quantitative databases to generate automatically a fuzzy rule-based system that provides a qualitative model of the processed data. The fuzzy clustering tool is based on the methodology described in Sugeno and Yasukawa (1993).

Before data processing, it is necessary to establish the interest parameters in the problem, i.e. variables to study its behavior. In the fuzzy rules that will be generated, the selected parameters will be the consequents, and the rest of the parameters will be the antecedents. Then, the consequent parameters are fuzzy clustered in an optimum number of fuzzy clusters as is described in Fukuyama (1989). One of the most used fuzzy clustering algorithms is the Fuzzy C-Means (FCM) (Bezdek, 1981), used in Sugeno and Yasukawa (1993). Once the consequent parameters have been clustered, each cluster is projected onto the antecedent space. As a result, the membership grade of the antecedents to each fuzzy cluster is determined. Finally, the fuzzy rules are built by considering the membership functions obtained in the fuzzy clustering and fuzzy projection stages, previously described. A more detailed description of the methodology is provided in Annex A, in the supplementary material.

As result of the data processing, a set of graphical fuzzy rules with the qualitative model of the system can be obtained. In Fig. 2 an example of fuzzy rule is represented, where the fuzzy sets assigned to each parameter (x, y, z) are represented by trapeziums, being x and y the antecedents and z the consequent. Note that, the parameter values are represented on the horizontal axis of each fuzzy set, and the value of membership grade to a cluster on the vertical axis. This fuzzy rule can be interpreted in natural language as: *IF* ***x*** *is small OR big AND* ***y*** *is average THEN* ***z*** *is very small.*

In the present work, PreFuRGe methodology was used to study hourly radon values. The consequents were hourly radon measurements and the antecedents were hourly meteorological variables. More specifically: temperature, relative humidity, pressure, wind speed and direction and ABL. The hour and month of the measurements were used as antecedents as well.

3. Results and discussion

3.1. First dataset: Radon at El Carmen station from March 2015 to march 2016

3.1.1. Previous results

Although El Carmen station is located near the Atlantic Ocean (Fig. 1a), it presents a radon concentration (Table SM1) more similar to stations found in continental areas (Tchorz-Trzeciakiewicz and Solecki, 2018; Vecchi et al., 2019). The radon daily curve found in Huelva can be seen in Figure SM1. The lowest radon concentration is usually reached in the afternoon (15:00 to 18:00 UTC) due to atmospheric instability caused by solar heating. After the sunset, soil starts to cool down, forming a stable nocturnal boundary layer that traps radon. This situation enhances radon accumulation, increasing its concentration throughout the night until sunrise (6:00 to 9:00 UTC), when radon reaches its maximum. After sunrise, soil warms up, generating vertical air movements that disperse radon, reducing its concentrations until the minimum is reached in the afternoon, starting the cycle again.

However, cluster analysis applied in a previous study (Gutiérrez-Álvarez et al., 2019) showed that 52% of the days radon remained under 10 Bq m^{-3} throughout the whole day with almost no radon increase during nighttime, which is a typical feature of coastal locations (Crawford et al., 2013; Kobayashi et al., 2015). Results of the cluster analysis are summarized in Figure SM2. Most days (52%) were associated with cluster 5, which represents an almost flat concentrations during the day. These low radon periods had wind speeds above 2–3 m s^{-1} throughout the day, especially during the nighttime, inhibiting accumulation by horizontal dispersion. The rest of the clusters follow the previously described daily cycle to a different degree. Cluster 1 showed that days with the highest radon peaks at sunrise were related to low wind speed in the nighttime but a rapid increase after sunrise. Cluster 2 shows a high peak, albeit slightly delayed with respect to Cluster 1, but lacks the radon purge in the afternoon seen in the rest of the clusters. This can be related to a lack of high wind

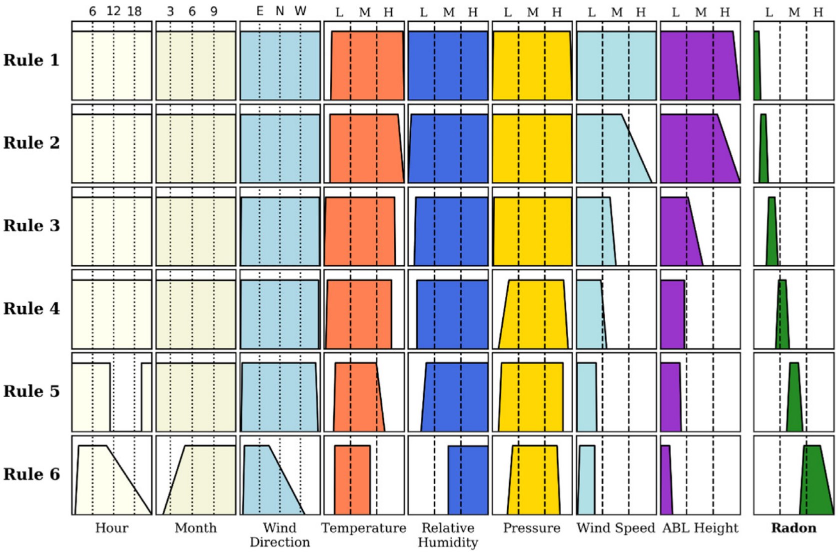

Fig. 3. Set of if–then rules obtained for El Carmen from March 2015 to March 2016. Each row represents one fuzzy logic rule or cluster and each column a variable. Non cyclic variables are divided in three value ranges: low values (L), medium values (M) and high values (H) (see Table SM2).

speeds in the afternoon and a generally low ABL height. Finally, clusters 3 and 4 represent intermediate stages between clusters 1 and 2 and cluster 5, respectively.

Radon has a strong seasonality. It presents higher average values in autumn than in the rest of the seasons, followed by winter (Table SM1). Winter is a complex season, because it includes the month with the highest radon average (December) together with low radon months (January and February). This could be caused by persistent high-pressure systems that result in lower daytime ABL heights, consistently low wind speeds over the whole day and higher relative humidity (Kikaj et al., 2019). This is the typical behavior observed for cluster 2, which is predominant in winter and autumn. On the other hand, summer and spring have lower radon values in general. This is quite noticeable when comparing the 50th, 75th and 95th percentiles, which are half of those found in autumn and spring. Cluster analysis reflect this seasonality, as high radon clusters (1 and 2) are more frequent in autumn and winter than in the rest of the seasons. Conversely, cluster 5 is predominant in spring and summer, with more than 61% of the days belonging to the lowest radon cluster (Gutiérrez-Álvarez et al., 2019).

3.1.2. Fuzzy logic analysis

The resulting if–then rules obtained after the application of the fuzzy logic algorithm can be found in Fig. 3. The non-cyclic antecedents (temperature, relative humidity, pressure, wind speed and ABL height) and radon are divided in three sections: low, medium and high. These segments are defined by dividing the range between the maximum and the minimum value for each variable into three equally spaced sections (see Table SM2).

Rules 1 to 3 are related to low radon; rules 4 and 5 shows medium values while rule 6 is the only case where high radon values are reached. Looking at the complete set of rules, it is noticeable the almost identical behavior for the wind speed and ABL height with respect to its effect on radon levels. The lower wind speed and ABL height, the higher the radon concentration. This is expected as both of these magnitudes have a direct impact on vertical and horizontal dispersion, which are the main factors contributing to radon accumulation in the lower layers of the atmosphere. The relation between these variables can be validated looking at the previous study, as can be seen in the low-wind nighttime hours of Clusters 1, 3, 4 and 5 and in the low ABL height present in cluster 2 (Figure SM2).

Temperature also shows a systematic absence of higher values as radon increases. This is associated to the daily cycle; as higher temperatures usually occur in the afternoon when radon reaches its lowest concentration, thus pointing to a common origin for both low temperature and low radon instead of the former causing the latter. The absence of low temperatures for Rules 5 and 6 could be caused by seasonality: winter has the lowest temperatures and lower radon concentrations on average. This is supported by the absence of winter months in Rule 6. Since the main wind direction in winter comes from continental areas (NE and NW), high wind speeds or reduced surface radon exhalation, produced by lower soil temperatures, could be causing this behavior. On the other hand, relative humidity is inversely proportional to temperature, so it follows the opposite effect.

Pressure shows an interesting behavior, as it does not show very high or very low values when radon is high. This absence of extreme values of pressure could indicate more stable conditions favorable for radon accumulation. Conversely, more extreme pressure values could indicate the presence of pressure gradients and higher turbulence. It is also possible that seasonal anti-cyclonic events generated stable conditions that would have increased both pressure and radon, as was pointed out by the characteristics of Cluster 2 in the previous study.

According to the fuzzy logic analysis: it is possible to observe lower radon concentrations even though both wind speeds and ABL are low, as in rules 1 to 3. It appears that dispersion is not the only mechanism capable of removing radon or inhibiting its accumulation in the area. One option to explain this is local soils having periods of lower exhalation rates that do not contribute as much to atmospheric radon concentrations. Periods with only low ABL but high wind speed, or vice versa, or transitional stages from low radon to high radon could also be responsible for this.

Low radon rules, 1 to 3, have no hourly or monthly distinction, showing that low radon can occur anytime during the year or the day. This is consistent with cluster 5 from the previous study, showing low radon throughout the whole day. Wind speed and ABL show a clear absence of high values as radon increases, as it was expected. Temperature, relative humidity and pressure present a wide range of values, albeit some absences at the extremes. These differences could be a consequence of the time of the day where radon is higher, which is usually in the first third of the day (00:00 to 08:00 UTC). During this period temperature is lower than during the rest of the day and relative humidity reaches higher values due to the lower temperatures.

Medium radon, as seen by rules 4 and 5, start to show a link to specific periods during the day as rule 5 has no presence in the afternoon hours and rule 6 decrease this probability from midday to midnight. This was expected as previous studies have shown that radon in Huelva follows a daily cycle where radon accumulates during the evening, peaking at dawn, and reducing during the day due to vertical and horizontal dispersion. This daily cycle is caused by the daily ABL evolution and is similar to those of temperature and relative humidity. Regarding ABL height and wind speed, they are restricted to low values, with no significant differences between rule 4 and 5. Wind start to show an absence from the S direction.

Finally, high radon (Rule 6) requires a very specific set of conditions. As expected, high radon measurements were observed exclusively with both low ABL height and wind speeds, i.e. atmospheric stagnant conditions, which only occurs during nighttime and early morning (02:00 to 10:00 UTC). This is coherent with the rules about temperature and relative humidity, as high temperature or low humidity are not observed during that time of the day. Wind direction also shows a restricted set of values for high radon, with a complete absence of high radon if wind blows from the S-SW, i.e. wind coming from the city to the PG repository, carrying radon away from the measurement station. This rule can be easily related to Clusters 1 and 2 from the previous study.

3.2. Second dataset: Radon at El Carmen and La Rabida in 2018

3.2.1. Previous results

The second dataset showed similar features as the previous one (Table SM3). In this case, a hierarchical clusterization technique was applied (Gutiérrez-Álvarez et al., 2021) This technique showed similar clusters (Figure SM3 and SM4) as those found in the previous dataset (Figure SM2). In general, low ABL height and wind speed were associated with high radon clusters, as it was expected, while higher wind speeds or ABL resulted in days with lower concentrations. However, some differences were found between El Carmen and La Rabida measurement stations. High radon days did not always coincide at both stations, being more frequent at El Carmen than La Rabida. This pointed out to some atmospheric process that prevent radon to accumulate or even reach La Rabida, while El Carmen was still able to develop radon growth. Conversely, La Rabida showed small subset of days where radon remain above 10 Bq m^{-3} throughout the day, while El Carmen still presented the classical radon removal during the afternoon.

The results provided by an atmospheric dispersion model suggested that the PG piles play a relevant role as a radon source. On one hand, La Rabida showed high concentrations only if radon was transported to the station, either directly or indirectly. On the other hand, El Carmen had the typical radon daily cycle even in situations when wind was blowing towards the repository, as long as wind speed and ABL height remained low enough. Being El Carmen closer to the PG piles, this pointed out to passive radon movement to El Carmen by either diffusion or turbulent motions, while El Carmen was far enough that direct or indirect transport from the piles was necessary to increase radon concentrations.

3.2.2. Classification according to fuzzy logic analysis

Fig. 4 shows the obtained results after applying the fuzzy logic algorithm to the second dataset. As explained in the previous subsection, radon and other non-cyclic variables were divided into three segments: low, medium and high, according to each variable's own data range (see Table SM2).

Rules 1, 2 and 3 have very low radon concentrations for both El Carmen and La Rabida. Rules 4 and 5 present situations with medium radon at least in El Carmen station. Rule 6 shows medium to high radon on El Carmen, with clearly higher radon levels in El Carmen than in La Rabida. Finally, rule 7 represents the higher radon concentrations for both stations, with slightly higher concentrations found in El Carmen. As observed in the previous case, the same trend for wind speed and ABL height is observed here: high radon concentration is only observed with atmospheric stagnant conditions. This can be seen in the general reduction of wind speed and ABL as radon increases. Once again, atmospheric stagnant conditions, i.e., the concurrence of thermal vertical stability (low vertical mixing) and scarce horizontal dispersion (low wind speed), appear to be the main factors that enhance radon accumulation in the lower atmospheric layers.

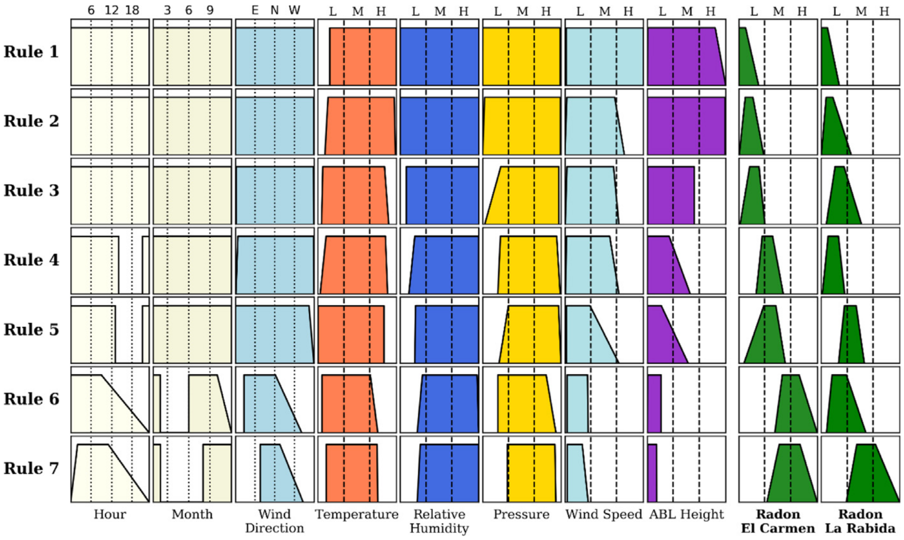

Fig. 4. Set of if–then rules obtained for El Carmen and La Rabida in 2018. Each row represents one fuzzy logic rule or cluster and each column a variable. Non cyclic variables are divided in three value ranges: low values (L), medium values (M) and high values (H) (see Table SM2).

Low radon rules (Rules 1, 2 and 3) are similar between them, except in relation to wind speed and ABL height. Very low radon (Rule 1) is the only case that features both high wind speed and ABL. Rule 2 shows slightly higher radon in both stations, albeit still in the low category, but has no presence of high wind speed. Although this sets a distinction between vertical and horizontal radon dispersion, making horizontal dispersion slightly more important than vertical stability, the concentration differences between Rules 1 and 2 are still minimal. In rule 3 both wind speed and ABL are restricted to low and middle values, and pressure and relative humidity have no presence of very low values. Very low temperature values have no presence in rule 1, but increase slightly for rules 2 and 3. For all low radon rules, there is no significant difference on wind direction, hour or month, showing that low radon can occur at any point during the day and any month of the year, regardless of where wind is blowing from.

On the opposite side, high radon rules (Rules 6 and 7) have distinct common features for most variables involved. Both 6 and 7 show the lowest values for wind speed and ABL height, reaffirming the fact that a stagnant atmosphere is the main cause of radon accumulation. High radon occurs when relative humidity and pressure are medium or high and temperature is low to medium and does not occur if wind blows from S or SW. This is easily explained since under this situation air would come directly from the Atlantic Ocean and transport radon from the PG repository to the NE direction, just between the two stations (Fig. 1). Both rules are also more common in the first half of the day, and do not appear on months from the end of winter to the beginning of summer (Feb to May, both included).

Nonetheless, these two rules (6 and 7) represent two clearly different radon situations, rule 6 has high radon in El Carmen but low in La Rabida, while rule 7 has high radon on both stations. This is important as differences in these two rulesets will define the conditions for high radon to appear in La Rabida. The main distinction appears to be the wind direction: high radon in El Carmen can occur if wind blows mainly from SE-E-NE-N, but high radon in La Rabida does not appear for winds from SE-E directions. This is coherent with the location of the stations since La Rabida is located to the SE from the PG piles, which means that if wind blows from east direction, radon will be transported away from the measurement station.

Rule 6 also shows that high radon in El Carmen but low in La Rabida can occur on June and July, as opposed to high radon on both stations, which is more restricted during the year. June and July are summer months, which is characterized by more presence of SW winds that come free of radon from the Atlantic Ocean. Summer is also a season characterized by periods of atmospheric stability, which can enhance radon accumulation during nighttime, exactly when Rule 6 takes place. The combination of these two characteristics provides the perfect situation to allow radon to rise in El Carmen, which in a previous study was found to be affected by radon movements from the piles by diffusion or turbulent motions (Gutiérrez-Álvarez et al., 2021), but not La Rabida, which was found to require direct transport from the PG piles.

Rules 4 and 5 have a similar relation than rules 6 and 7: 4 presents medium radon in El Carmen and low in La Rabida (as 6), while 5 shows medium radon values in both stations (as 7). Rules 4 and 5 appear throughout all year and during all day but the afternoon (14:00 to 21:00 UTC). Both rules show middle and high values for relative humidity and pressure, albeit slight differences for the low values. Temperature also has really similar features for both rulesets. The main differences are wind speed and ABL height, that show more inclination for lower values in 5 than in 4. This could imply that, for radon to accumulate to medium values in La Rabida, atmospheric conditions need to be more stable than to accumulate just in El Carmen. Furthermore, La Rabida is closer to the sea than El Carmen, which means that on equivalent stable nights with similar low wind speeds, the fetch region in La Rabida would include a larger proportion of water, which has a lower radon contribution, than in El Carmen.

It is important to note that there is no rule where La Rabida presents significantly higher values than El Carmen, which means that such situation does not happen in the dataset. Nonetheless, rules 3 and 5 have a slightly higher inclination for higher radon concentrations of La Rabida compared to El Carmen station. In the case of rule 3, the slope of La Rabida reaches well into the medium range of radon values. Rule 5 shows similar ranges on the medium-end, but El Carmen has higher disposition for low radon values.

4. Conclusions

The PreFuRGe methodology was able to accurately describe the general behavior of radon when it was compared to previous studies performed with complex classical techniques. It showed with clarity the relationship between radon and atmospheric dispersion, as higher radon rules were always associated with low wind and low ABL height. This is commonly reported in the literature, as it is a critical insight to understand radon behavior, and the graphs provided by the FL methodology easily revealed this relation.

Other relevant features of the dataset were identified as well. Radon seasonality was clearly confirmed; as high radon would not appear during certain months. A similar argument can be raised for the daily cycle, as afternoon hours showed a limited presence in rules with high radon. The influence of seasonality and the daily cycle could be deduced from temperature and relative humidity as well. High temperatures and low humidity were absent in high radon rules because they are more common in spring and summer than in autumn and winter. They were also absent due to the daily cycle of radon, that concentrates high radon during nighttime, where high temperatures and low humidity are harder to reach.

Furthermore, it also revealed the possible influence of the PG piles on each station in the second dataset by the differences in wind direction values in Rules 6 and 7. This is relevant as it shows that the methodology can be used with cyclic variables, a restriction that limits other techniques, such as classical clustering. In addition, its qualitative but complete characterization could allow its use as a forecasting tool. Finally, PreFuRGe identified that high radon was not occurring with high or low pressures. Future works will be carried out to investigate if this behavior was an artifact produced by pressure's seasonality or by the appearance of persistent high-pressure systems in the area.

In this work, a fuzzy logic technique was applied for the first time to study atmospheric radon. The PreFuRGe methodology was able to provide an accurate characterization of the two studied datasets, proving its consistency. It could be applied on cyclic variables and condensed the information into easily readable graphs where all known radon behavior features were easily identified. This tool provides a useful approach to explore other environmental datasets, allowing to quickly identify features that would require complex analysis combining several classical statistical techniques.

CRediT authorship contribution statement

I. Gutiérrez-Álvarez: Conceptualization, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **J. Aroba:** Conceptualization, Methodology, Software, Formal analysis, Investigation, Writing – review & editing. **J.E. Martín:** Conceptualization, Investigation, Resources, Data curation, Writing – review & editing. **J.A. Adame:** Conceptualization, Investigation, Resources, Validation, Writing – review & editing. **J.P. Bolívar:** Conceptualization, Writing – review & editing, Supervision, Project Administration, Funding acquisition.

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.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.eti.2022.102619.

References

Adame, J.A., Bolívar, J.P., de la Morena, B., Lammel, A., Gerhard, J., 2010a. Surface ozone measurements in the southwest of the Iberian Peninsula (Huelva, Spain). Environ. Sci. Pollut. Res. 17, 355–368. http://dx.doi.org/10.1007/s11356-008-0098-9.

Adame, J.A., Serrano, E., Bolívar, J.P., de la Morena, B.A., Adame, J.A., Serrano, E., Bolívar, J.P., Morena, B.A. de la, 2010b. On the tropospheric ozone variations in a coastal area of southwestern Europe under a mesoscale circulation. J. Appl. Meteorol. Climatol. 49, 748–759. http://dx.doi.org/10.1175/2009JAMC2097.1.

Ahmad, N., Nasir, T., ur Rehman, J., Ullah, H., Uddin, Z., 2019. Risk assessment of radon in soil collected from chromite mines of Khanozai and Muslim Bagh, Balochistan, Pakistan. Environ. Technol. Innov. 16, 100476. http://dx.doi.org/10.1016/J.ETI.2019.100476.

Arnold, D., Vargas, A., Vermeulen, A.T., Verheggen, B., Seibert, P., 2010. Analysis of radon origin by backward atmospheric transport modelling. Atmos. Environ. 44, 494–502. http://dx.doi.org/10.1016/j.atmosenv.2009.11.003.

Aroba, J., 2003. Advances in the Decision Making in Software Development Projects. University of Seville.

Aroba, J., Cuadrado-Gallego, J.J., Sicilia, M.Á., Ramos, I., García-Barriocanal, E., 2008. Segmented software cost estimation models based on fuzzy clustering. J. Syst. Softw. 81, 1944–1950. http://dx.doi.org/10.1016/j.jss.2008.01.016.

Bezdek, J.C., 1981. Pattern Recognition with Fuzzy Objective Function Algorithms. Springer US, http://dx.doi.org/10.1007/978-1-4757-0450-1.

Bolívar, J.P., García-Tenorio, R., García-León, M., 1996. Radioactive impact of some phosphogypsum piles in soils and salt marshes evaluated by γ-ray spectrometry. Appl. Radiat. Isot. 47, 1069–1075. http://dx.doi.org/10.1016/S0969-8043(96)00108-X.

Burghele, B.D., Botoş, M., Beldean-Galea, S., Cucoş, A., Catalina, T., Dicu, T., Dobrei, G., Florică Istrate, A., Lupulescu, A., Moldovan, M., Niţă, D., Papp, B., Pap, I., Szacsvai, K., Sainz, C., Tunyagi, A., Ţenter, A., 2021. Comprehensive survey on radon mitigation and indoor air quality in energy efficient buildings from Romania. Sci. Total Environ. 751, 141858. http://dx.doi.org/10.1016/j.scitotenv.2020.141858.

Burton, W.M., Stewart, N.G., 1960. Use of long-lived natural radioactivity as an atmospheric tracer. Nature 186, 584–589. http://dx.doi.org/10.1038/186584a0.

Cai, Y., Li, F., Zhang, J., Zhu, X., Li, Y., Fu, J., Chen, X., Liu, C., 2021. Toxic metals in size-fractionated road dust from typical industrial district: Seasonal distribution, bioaccessibility and stochastic-fuzzy health risk management. Environ. Technol. Innov. 23, 101643. http://dx.doi.org/10.1016/J.ETI.2021.101643.

Chambers, S.D., Wang, F., Williams, A.G., Xiaodong, D., Zhang, H., Lonati, G., Crawford, J., Griffiths, A.D., Ianniello, A., Allegrini, I., 2015. Quantifying the influences of atmospheric stability on air pollution in lanzhou, China, using a radon-based stability monitor. Atmos. Environ. 107, 233–243. http://dx.doi.org/10.1016/J.ATMOSENV.2015.02.016.

Chambers, S.D., Williams, A.G., Conen, F., Griffiths, A.D., Reimann, S., Steinbacher, M., Krummel, P.B., Steele, L.P., van der Schoot, M.v., Galbally, I.E., Molloy, S.B., Barnes, J.E., 2016. Towards a universal baseline characterisation of air masses for high-and low-altitude observing stations using Radon-222. Aerosol Air Qual. Res. 16, 885–899. http://dx.doi.org/10.4209/aaqr.2015.06.0391.

Choudhury, B., Jha, R.M., 2016. Soft Computing in Electromagnetics, Soft Computing in Electromagnetics. Cambridge University Press, http://dx.doi.org/10.1017/cbo9781316402924.

Christian, R.A., Patel, D.A., 2014. Potential of k-means clustering-based fuzzy logic for prediction of temperature in ambient atmosphere. Arab. J. Sci. Eng. 40, 227–234. http://dx.doi.org/10.1007/s13369-014-1495-7.

Crawford, J., Zahorowski, W., Cohen, D.D., Chambers, S., Stelcer, E., Werczynski, S., 2013. Estimating the near-surface daily fine aerosol load using hourly Radon-222 observations. Atmos. Pollut. Res. 4, 1–13. http://dx.doi.org/10.5094/APR.2013.001.

Dass, A., Srivastava, S., Chaudhary, G., 2021. Air pollution: A review and analysis using fuzzy techniques in Indian scenario. Environ. Technol. Innov. 22, 101441. http://dx.doi.org/10.1016/J.ETI.2021.101441.

Dee, D.P., Uppala, S.M., Simmons, A.J., Berrisford, P., Poli, P., Kobayashi, S., Andrae, U., Balmaseda, M.A., Balsamo, G., Bauer, P., Bechtold, P., Beljaars, A.C.M., van de Berg, L., Bidlot, J., Bormann, N., Delsol, C., Dragani, R., Fuentes, M., Geer, A.J., Haimberger, L., Healy, S.B., Hersbach, H., Hólm, E.V., Isaksen, L., Kållberg, P., Köhler, M., Matricardi, M., McNally, A.P., Monge-Sanz, B.M., Morcrette, J.-J., Park, B.-K., Peubey, C., de Rosnay, P., Tavolato, C., Thépaut, J.-N., Vitart, F., 2011. The ERA-Interim reanalysis: configuration and performance of the data assimilation system. Q. J. R. Meteorol. Soc. 137, 553–597. http://dx.doi.org/10.1002/qj.828.

Dueñas, C., Liger, E., Cañete, S., Pérez, M., Bolívar, J.P., 2007. Rn from phosphogypsum piles located at the Southwest of Spain. J. Environ. Radioact. 95, 63–74. http://dx.doi.org/10.1016/j.jenvrad.2007.01.012.

Fukuyama, Y., 1989. A new method of choosing the number of clusters for the fuzzy c-mean method. In: Proc. 5th Fuzzy Syst. Symp., vol. 1989. pp. 247–250.

Gegúndez, M.E., Aroba, J., Bravo, J.M., 2008. Identification of piecewise affine systems by means of fuzzy clustering and competitive learning. Eng. Appl. Artif. Intell. 21, 1321–1329. http://dx.doi.org/10.1016/j.engappai.2008.03.014.

Glymour, C., Madigan, D., Pregibon, D., Smyth, P., 1996. Statistical inference and data mining. Commun. ACM 39, 35–41. http://dx.doi.org/10.1145/240455.240466.

Grande, J.A., Andújar, J.M., Aroba, J., Beltrán, R., de la Torre, M.L., Cerón, J.C., Gómez, T., 2010a. Fuzzy modeling of the spatial evolution of the chemistry in the tinto river (SW Spain). Water Resourc. Manage. 24, 3219–3235. http://dx.doi.org/10.1007/s11269-010-9603-2.

Grande, J.A., Andújar, J.M., Aroba, J., de la Torre, M.L., 2010b. Presence of as in the fluvial network due to AMD processes in the riotinto mining area (SW Spain): A fuzzy logic qualitative model. J. Hard Mater. 176, 395–401. http://dx.doi.org/10.1016/j.jhazmat.2009.11.043.

Grossi, C., Àgueda, A., Vogel, F.R., Vargas, A., Zimnoch, M., Wach, P., Martín, J.E., López-Coto, I., Bolívar, J.P., Morguí, J.A., Rodó, X., 2016. Analysis of ground-based 222 rn measurements over Spain: Filling the gap in southwestern Europe. J. Geophys. Res.: Atmos. 121, 11021–11037. http://dx.doi.org/10.1002/2016JD025196.

Grossi, C., Arnold, D., Adame, J.A., López-Coto, I., Bolívar, J.P., De La Morena, B.A., Vargas, A., 2012. Atmospheric 222Rn concentration and source term at El Arenosillo 100 m meteorological tower in southwest Spain. Radiat. Meas. 47, 149–162. http://dx.doi.org/10.1016/j.radmeas.2011.11.006.

Grossi, C., Chambers, S.D., Llido, O., Vogel, F.R., Kazan, V., Capuana, A., Werczynski, S., Curcoll, R., Delmotte, M., Vargas, A., Morguí, J.A., Levin, I., Ramonet, M., 2020. Intercomparison study of atmospheric 222Rn and 222Rn progeny monitors. Atmos. Meas. Tech. 13, 2241–2255. http://dx.doi.org/10.5194/AMT-13-2241-2020.

Gutiérrez-Álvarez, I., Guerrero, J.L., Martín, J.E., Adame, J.A., Vargas, A., Bolívar, J.P., 2019. Radon behavior investigation based on cluster analysis and atmospheric modelling. Atmos. Environ. 201, 50–61. http://dx.doi.org/10.1016/j.atmosenv.2018.12.010.

Gutiérrez-Álvarez, I., Guerrero, J.L., Martín, J.E., Adame, J.A., Vargas, A., Bolívar, J.P., 2021. Radon transport events associated with the impact of a NORM repository in the SW of Europe. Environ. Pollut. 289, 117963. http://dx.doi.org/10.1016/J.ENVPOL.2021.117963.

Hand, D.J., 1998. Data mining: Statistics and more? Amer. Statist. 52, 112–118. http://dx.doi.org/10.1080/00031305.1998.10480549.

Hathaway, R.J., Bezdek, J.C., 1993. Switching regression models and fuzzy clustering. IEEE Trans. Fuzzy Syst. 1, 195–204. http://dx.doi.org/10.1109/91.236552.

Hernández-Ceballos, M.A., 2012. Caracterización meteorológica y modelización de Andalucía occidental. University of Huelva.

Hernández-Ceballos, M.A., Vargas, A., Arnold, D., Bolívar, J.P., 2015. The role of mesoscale meteorology in modulating the^{222}Rn concentrations in Huelva (Spain) - impact of phosphogypsum piles. J. Environ. Radioact. 145, 1–9. http://dx.doi.org/10.1016/j.jenvrad.2015.03.023.

Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz Sabater, J., Nicolas, J., Peubey, C., Radu, R., Schepers, D., Simmons, A., Soci, C., Abdalla, S., Abellan, X., Balsamo, G., Bechtold, P., Biavati, G., Bidlot, J., Bonavita, M., De Chiara, G., Dahlgren, P., Dee, D., Diamantakis, M., Dragani, R., Flemming, J., Forbes, R., Fuentes, M., Geer, A., Haimberger, L., Healy, S., Hogan, R.J., Hólm, E., Janisková, M., Keeley, S., Laloyaux, P., Lopez, P., Lupu, C., Radnoti, G., de Rosnay, P., Rozum, I., Vamborg, F., Villaume, S., Thépaut, J.N., 2020. The ERA5 global reanalysis. Q. J. R. Meteorol. Soc. 146, 1999–2049. http://dx.doi.org/10.1002/qj.3803.

Jang, Jyh-Shing Roger, Sun, C.-T., 1996. Neuro-Fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence. Prentice-Hall, Inc., River, http://dx.doi.org/10.5555/248321.

Kaufman, L., Rousseeuw, P.J., 1990. Finding Groups in Data, Wiley Series in Probability and Statistics. John Wiley & Sons, Inc. Hoboken, NJ, USA, http://dx.doi.org/10.1002/9780470316801.

Kikaj, D., Vaupotič, J., Chambers, S.D., 2019. Identifying persistent temperature inversion events in a subalpine basin using radon-222. Atmos. Meas. Tech. 12, 4455–4477. http://dx.doi.org/10.5194/AMT-12-4455-2019.

Kobayashi, Y., Yasuoka, Y., Omori, Y., Nagahama, H., Sanada, T., Muto, J., Suzuki, T., Homma, Y., Ihara, H., Kubota, K., Mukai, T., 2015. Annual variation in the atmospheric radon concentration in Japan. J. Environ. Radioact. 146, 110–118. http://dx.doi.org/10.1016/J.JENVRAD.2015.04.007.

López-Abente, G., Núñez, O., Fernández-Navarro, P., Barros-Dios, J.M., Martín-Méndez, I., Bel-Lan, A., Locutura, J., Quindós, L., Sainz, C., Ruano-Ravina, A., 2018. Residential radon and cancer mortality in Galicia, Spain. Sci. Total Environ. (1125), 610–611–1132. http://dx.doi.org/10.1016/j.scitotenv.2017.08.144.

López-Coto, I., Mas, J.L., Vargas, A., Bolívar, J.P., 2014. Studying radon exhalation rates variability from phosphogypsum piles in the SW of Spain. J. Hard Mater. 280, 464–471. http://dx.doi.org/10.1016/j.jhazmat.2014.07.025.

Mishra, D., Goyal, P., 2016. Neuro-fuzzy approach to forecasting ozone episodes over the urban area of Delhi, India. Environ. Technol. Innov. 5, 83–94. http://dx.doi.org/10.1016/J.ETI.2016.01.001.

Novák, V., Perfilieva, I., Močkoř, J., 1999. Mathematical Principles of Fuzzy Logic. Springer US, http://dx.doi.org/10.1007/978-1-4615-5217-8.

Perrino, C., Pietrodangelo, A., Febo, A., 2001. An atmospheric stability index based on radon progeny measurements for the evaluation of primary urban pollution. Atmos. Environ. 35, 5235–5244. http://dx.doi.org/10.1016/S1352-2310(01)00349-1.

Polian, G., Lambert, G., Ardouin, B., Jegou, A., 2017. Long-range transport of continental radon in subantarctic and antarctic areas. Tellus B 38, 178–189. http://dx.doi.org/10.3402/tellusb.v38i3-4.15126.

Sardar Maran, P., Ashok Kumar, K., Refonaa, J., Shabu, J., Jesudoss, A., Lakshmanan, L., 2020. Prediction of extreme atmospheric temperature with meteorological tower observations using fuzzy logic technique. J. Comput. Theor. Nanosci. 17, 3408–3411. http://dx.doi.org/10.1166/jctn.2020.9195.

Sesana, L., Ottobrini, B., Polla, G., Facchini, U., 2006. 222Rn as indicator of atmospheric turbulence: measurements at Lake Maggiore and on the pre-Alps. J. Environ. Radioact. 86, 271–288. http://dx.doi.org/10.1016/J.JENVRAD.2005.09.005.

Sugeno, M., Yasukawa, T., 1993. A fuzzy-logic-based approach to qualitative modeling. IEEE Trans. Fuzzy Syst. 1, 7–31. http://dx.doi.org/10.1109/TFUZZ.1993.390281.

Tchorz-Trzeciakiewicz, D.E., Solecki, A.T., 2018. Variations of radon concentration in the atmosphere. Gamma dose rate. Atmos. Environ. 174, 54–65. http://dx.doi.org/10.1016/J.ATMOSENV.2017.11.033.

UNSCEAR, 2008. Sources, Effects and Risks of Ionizing Radiation Vol. I, Radiation Research. http://dx.doi.org/10.2307/3577647.

Vargas, A., Arnold, D., Adame, J.A., Grossi, C., Hernández-Ceballos, M.A., Bolívar, J.P., 2015. Analysis of the vertical radon structure at the spanish El arenosillo tower station. J. Environ. Radioact. 139, 1–17. http://dx.doi.org/10.1016/j.jenvrad.2014.09.018.

Vargas, A., Ortega, X., 2006. Influence of environmental changes on continuous radon monitors. Results of a Spanish intercomparison exercise. Radiat. Prot. Dosim. 121, 303–309. http://dx.doi.org/10.1093/rpd/ncl036.

Vargas, A., Ortega, X., Matarranz, J.L.M., 2004. Traceability of radon-222 activity concentration in the radon chamber at the technical university of catalonia (Spain). Nucl. Instrum. Methods Phys. Res.A 526, 501–509. http://dx.doi.org/10.1016/j.nima.2004.02.022.

Vecchi, R., Piziali, F.A., Valli, G., Favaron, M., Bernardoni, V., 2019. Radon-based estimates of equivalent mixing layer heights: A long-term assessment. Atmos. Environ. 197, 150–158. http://dx.doi.org/10.1016/J.ATMOSENV.2018.10.020.

Vovchenko Natalia, G., Stryukov Michael, B., Sakharova Lyudmila, V., Domakur Olga, V., 2019. Fuzzy-logic analysis of the state of the atmosphere in large cities of the industrial region on the example of rostov region. In: Advances in Intelligent Systems and Computing. Springer Verlag, pp. 709–715. http://dx.doi.org/10.1007/978-3-030-04164-9_93.

Wang, S. sha, Song, B. lai, 2021. Application of fuzzy analytic hierarchy process in sandstone aquifer water yield property evaluation. Environ. Technol. Innov. 22, 101488. http://dx.doi.org/10.1016/J.ETI.2021.101488.

Wilkening, M.H., 1952. Natural radioactivity as a tracer in the sorting of aerosols according to mobility. Rev. Sci. Instrum. 23, 13–16. http://dx.doi.org/10.1063/1.1746056.

Williams, A.G., Chambers, S.D., Conen, F., Reimann, S., Hill, M., Griffiths, A.D., Crawford, J., 2016. Radon as a tracer of atmospheric influences on traffic-related air pollution in a small inland city. Tellus B 68 (30967), http://dx.doi.org/10.3402/tellusb.v68.30967.

Xie, D., Wang, H., Kearfott, K.J., Liu, Z., Mo, S., 2014. Radon dispersion modeling and dose assessment for uranium mine ventilation shaft exhausts under neutral atmospheric stability. J. Environ. Radioact. 129, 57–62. http://dx.doi.org/10.1016/j.jenvrad.2013.12.003.

Zadeh, L.A., 1965. Fuzzy sets. Inf. Control 8, 338–353. http://dx.doi.org/10.1016/S0019-9958(65)90241-X.

Zadeh, L.A., 1968. Probability measures of fuzzy events. J. Math. Anal. Appl. 23, 421–427. http://dx.doi.org/10.1016/0022-247X(68)90078-4.

Zadeh, L.A., 1969. Towards a Theory of Fuzzy Systems. NASA Contractor Reports, http://dx.doi.org/10.1142/9789814261302_0007.

Zadeh, L.A., 1973. Outline of a new approach to the analysis of complex systems and decision processes. IEEE Trans. Syst. Man Cybern. 3, 28–44. http://dx.doi.org/10.1109/TSMC.1973.5408575.

Zadeh, L.A., 1992. Fuzzy Logic, Neural Networks and Soft Computing. One-Page Course Announcement of CS 294–4. The University of California at Berkeley.