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Risk Assessment of Dust Extremes and Mud Deposition on Human Activity in the Southwest of Iran

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ABSTRACT

Climate changes have a significant effect on dust extremes. Dust extremes in humid ambient air can simultaneously or successively form wet mud deposition on the surface of urban areas. The mud deposition on the power network systems and devices causes irreversible damage and significantly influences system performance and efficiency in southwest Iran. This often results in blackouts that cause problems in the operation of urban infrastructure and people's daily activities for up to several days. Khuzestan province was chosen as the case study in this study, and the climatic conditions and risk assessment of mud formation in this area were investigated. Data on a diurnal and monthly timescale of dust and humidity level was used for assessing extreme dust and wet conditions. The data was taken from Khuzestan synoptic station 8 over 11 years (2009-2019). The multivariate copula-based framework is used to calculate univariate and bivariate return periods of mud deposition hazard. The results imply that dust anomalies increase the probability of dust extreme coincidence with wet extreme and occurrence of wet mud hazards in the cold seasons of the year. In addition, limited adaptive capacity, shortage of information, and poor coordination and cooperation by the authorities caused the large-scale impact of the wet mud hazard in Khuzestan. Considering only relative humidity data, the return period of 2017 Khuzestan mud adhesion hazard is approximately 12 to 43 years. If we consider only dust, the return period of 2017 Khuzestan mud adhesion hazard is estimated at 80 to 700 years. However, for both dust and relative humidity extremes, the joint return periods for TDR (Dust and Relative humidity) and T'DR (Dust or Relative humidity) are respectively estimated greater than 200 and lower than 20 years.

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1. Introduction

Compound extreme events are the concurrent occurrence of extreme values for multiple variables (Whitney *et al*. 2021; Zhang *et al*. 2021). Recently, the risk of compound extremes has become challenging in urban areas (Birkmann *et al*. 2016). Dust storm is one of the most typical climate extremes in the Middle East, especially southwest of Iran (Rashki *et al*. 2021). Over the past decades, cycles of dust storms and dust settlement on surfaces have been severe and frequent under the influence of climate change (Adukwu *et al*. 2020).

In February 2017, many cities in the southwest of Iran were struck by dust storms and unprecedented major blackouts. During the power blackout, all critical infrastructures such as water, information technology, telecommunications (fixed-network, mobile phones and the Internet), transport and education sectors were out of action for several days (KZREC, 2017).

In dust storms, dust particles settle on surfaces (Sarver *et al*. 2013), and these particles absorb water vapor in humid air environments and form mud on the covers (Hassan *et al*. 2016). Additionally, it seems that precipitation, fog, and drizzle could be aggravating the situation. The formation of wet mud deposition leaves one of the most adverse effects on all aspects of urban life (Yilbas *et al*. 2016; Lyu *et al*. 2017), especially power network systems.

Power networks have become highly complicated (Bialek, 2010). Faults in electric power systems, such as short circuits, can lead to disasters (Esen *et al*. 2015). This reflects the dependence of modern life on electricity (Petermann *et al*. 2011). The formation of wet mud deposition on components of a power system was one of the practical culprits in reducing the reliability of system operation in the southwest cities of Iran (KZREC, 2017).

Therefore, it is essential to assess the risk of such events properly (AghaKouchak *et al*. 2014). Risk assessment provides basic information for decision-makers to decrease losses and seize opportunities (Salvadori *et al*. 2016).

Substantial evidence shows traditional risk assessment methods poorly represented extreme event dependence structure (Zscheischler & Seneviratne, 2017). It can lead to underestimating or overestimating risk assessment and decision-making about compound extreme events (Cardona *et al*. 2012). Traditional risk assessment methods only consider one variant at a time, while compound extreme events often interact and are interdependent (Zscheischler *et al*. 2018).

Consequently, in this study Copula functions were employed to estimate the probability of occurrence and return periods of mud deposition. A copula is a set of mathematical tools that can connect two or more time-independent variables (Nelson, 2003). A copula function is defined from $I^2(F, G)$ to $I(H)$ such that $[F(x), G(y), H(x, y)]$ is a point in I^3 with $I \in [0, 1]$, and X, Y are continuous random variables with distribution functions $F(x) = P(X \leq x)$ and $G(y) = P(Y \leq y)$, and $H(x,y) = P(X \leq x, Y \leq y)$ is a function of joint distribution. R software was used to calculate the copula function. There is a surge of interest in the copula functions in compound events research (Kim *et al*. 2018; Gimeno-Sotelo & Gimeno, 2022) because they can combine different marginal distributions (Silva and Lopes 2008). Copulas are widely used to estimate the return period of dependent variables and risk assessment (Mesbahzadeh *et al*. 2019; Tavakol *et al*. 2020). Pabaghi *et al*. (2023) analyzed extreme precipitation events in arid and semi-arid regions of Iran. They applied copula functions to compute the joint return periods of extreme events, and univariate and bivariate distributions were used to determine risk.

In Klang, Malaysia, Sabri Smail & Masseran (2024) evaluated extreme air pollution events using vine copula modeling. Results of the return period measures indicate that extreme air pollution events have long waiting periods.

Numerous studies have focused on mud deposition hazards and their effects on energy. Hassan *et al*. (2016) characterized dust particles and dryness that affect PV panels. They demonstrated dust particles containing alkaline form an alkaline mud solution that can reduce the optical transmittance of PV panel glasses. Hasan *et al*. (2021) reported that environmental factors such as dust, wind, humidity, and temperature significantly affect the performance of PV modules. Yilbas *et al*. (2015) investigated the impact of dust and mud on the optical, chemical, and mechanical properties of PV protective glass.

2. Materials and Methods

2.1. Study area

Khuzestan province is one of the most important economic and industrial centers in Iran (Fig. 1). It lies between 47°42'- 50°39' E longitudes and 29°58'-32°58' N latitudes. Annual precipitation (226 mm) mainly occurs in winter, and the mean annual temperature is 31 to 50°C. The warm season is an extremely effective period for dust storm activity in Khuzestan. This province is surrounded by a huge source of gas and oil. The presence of big industrial factories, the National Iranian South Oil Fields Company, and the National Iranian Drilling Company has turned this province into a central hub of power generation in Iran.

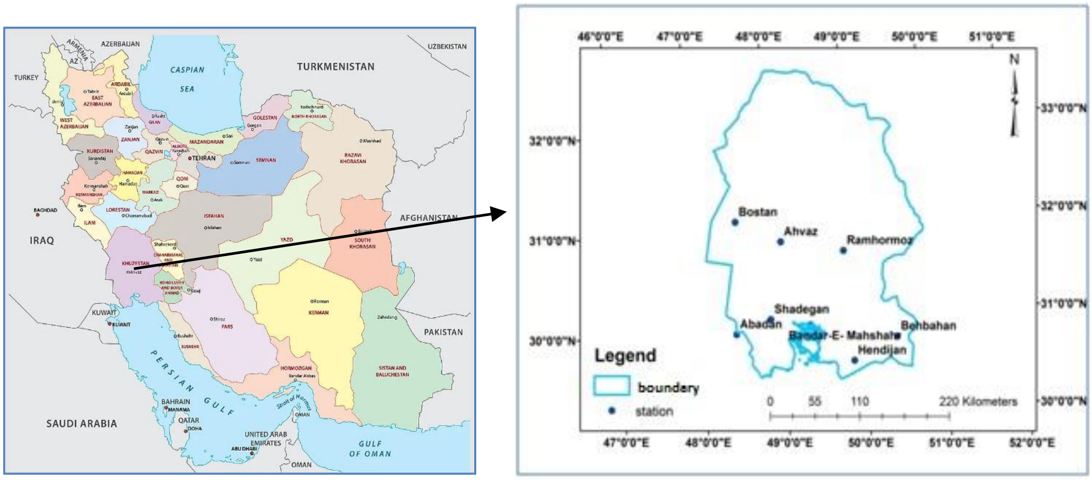

Fig 1. Location of Khuzestan province and synoptic stations used in this study

2.2. Data collection

To investigate the wet mud deposition in Khuzestan, a 3-hourly and daily time-step was obtained from the number of dusty days and relative humidity. Data was acquired from the Iran Meteorological Organization (IMO) (https://irimo.ir/far/index.php) from the 8 meteorological stations distributed in the study areas spanning 2009 to 2019.

2.3. Methods

2.3.1. Copula function overview

Here is a brief overview of the essential aspects of copula function. We consider (U, V) a random pair with U and V, while univariate marginal distributions are uniform on the interval (0, 1).

By Sklar theorem, a copula C is defined as a joint distribution function, more precisely,

$$C\,(u, v) = P\,(U \leq u, V \leq v),\ u, v \in (0, 1) \qquad (1)$$

If (Y1... Yd) ∈ $\mathbb{R}^d$ has a continuous multivariate distribution with F (y1,…, y_d) = Pr (Y1 ≤ y1, . . . , $Y_d \leq y_d$), there is a function of copula C : $[0, 1]^d \rightarrow [0, 1]$ of F

F (y1,…, y_d) = C (F1(y1), . . . , $F_d(y_d)$) (2)

2.3.2. Fitting the copula

This study employed the copula models belonging to the Elliptical and Archimedean families. Copula functions with different structures are used to fit the data. In the first step, random variables transform to uniformly marginal distributions [0, 1], thus allowing us to model the joint probability distribution.

By using Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), statistics from several copulas, i.e. Frank (Archimedean families), Gaussian, and Student-t (Elliptical families) copula functions, were selected. The Akaike information criterion (AIC) is an estimator of prediction error and thereby the relative quality of statistical models for a given set of data. Given a collection of models for the data, AIC estimates the quality of each model, relative to each of the other models. Thus, AIC provides a means for model selection. Bayesian Information Criterion (BIC) is an estimate of a function of the posterior probability of a model being true, under a certain Bayesian setup. Table 1 shows the expressions of the copula models used in this content.

Table 1. Archimedean and Elliptical expressions of copulas

Model	C(u,v)	$\alpha \in$
Frank	$(u, v \mid \theta) = -\frac{1}{\theta}\log(1 + \frac{(\exp(-\theta u) - 1)(\exp(-\theta v) - 1}{\exp(-\theta) - 1)}$	For $\theta \in \mathbb{R} \setminus \{0\}$
Gaussian	$C(u, v \mid \theta) = \int_{-\infty}^{\Phi-1(u)} \int_{-\infty}^{\Phi-1(v)} \frac{1}{2\pi\sqrt{1-\theta^2}} \exp\{\frac{2\theta st - s^2 - t^2}{2(1-\theta^2)}\} dsdt$	u,v ϵ (0, 1)
Student-*t*	$C(u, v \mid \theta) = \int_{-\infty}^{T_v^{1-(u)}} \int_{-\infty}^{T_v^{-1}(v)} \frac{\Gamma(\frac{(v+2)}{2})}{\Gamma\left(\frac{v}{2}\right) v\pi\sqrt{1-\theta^2}} \left(1 + \frac{s^2 + t^2 - 2\theta st}{v(1-\theta^2}\right) dsdt$	u,v ϵ (0, 1)

2.3.3. Parameter estimation

Frank, Gaussian, and Student-t copulas are described by parameter (θ). This study also employed Kendall's rank correlation coefficient, Pearson's correlation, and Spearman's rank correlation to estimate the copula parameter, θ.

2.3.4. Return periods

The average time interval of an occasion over time E (L) can calculate as follows:

$$E(L) = {}^{N}/_{n} \quad (3)$$

Where L is the time interval between events, n is the number of occasions, and N is the length of time of an experience. In this study, wet mud deposition risk assessment was estimated by considering the univariate and bivariate return period viewpoint.

The return period of the bivariate compound extreme events can also be considered a joint return period. Based on Shiau's (2006) proposed methodology, the bivariate return period of wet mud deposition (dust and wet extreme) can be categorized into two cases as follow:

For the two random variables D (e.g., dust) and R (e.g., relative humidity), the joint return period with cumulative distribution can be described as D ≥ r and R ≥ d (T_{DR}) and the return period for D ≥ r or R ≥ d (T'_{DR}). T_{DR} and T'_{DR} are joint return periods in that the specified threshold dust (d) and/or relative humidity (r) are invaded by the respective random variables D and R.

$$T^{and}{}_{D,R} = \frac{E(L)}{P(D>d \ and \ R>r)} = \frac{E(L)}{1-F_D(d)-F_R(r)+F_{D,R}(d,r)} = \frac{E(L)}{1-F_D(d)-F_R(r)+C\left(F_D(d),F_R(r)\right)} \quad (4)$$

$$T^{or}{}_{D,R} = \frac{E(L)}{P(D>d \ or \ R>r)} = \frac{E(L)}{1-C(F_D(d),F_R(r))} \quad (5)$$

The univariate return period of dust and wet extreme can be written as follows:

$$T_D = \frac{E(L)}{P(D>d)} = \frac{E(L)}{1-FD(d)} \quad (6)$$

$$T_R = \frac{E(L)}{P(R\geq r)} = \frac{E(L)}{1-FR(r)} \quad (7)$$

3. Results and discussion

3.1. Interdependence of variables

In this section, Pearson, Spearman, and Kendall correlation methods were used to recognize the correlation influence of dust and wet extreme on the probability of wet mud deposition events. Results are summarized in Table 2 and indicate the negative correlation between variables. Kendall correlation values calculated demonstrate a strong association between dust and relative humidity (*P-value* -0.212).

Table 2. Correlation coefficient tests result between dust and relative humidity

Correlation test	Statics	*p*-value
Mann-Kendall	z = -17.377	-0.212
Pearson	t = -16.091	-0.246
Spearman	S = 1.3759e+10	-0.273

3.2. Copula function selection and Return periods

3.2.1. Bivariate Return periods

Based on the lowest AIC, BIC, and the greatest log-likelihood (Table 3), Frank, Gaussian, and Student-t were selected as the candidate's copula for modeling the association structure between dust and humidity extreme variables. The Gaussian copula was the best-fitted copula (Table 3) and was used to estimate the bivariate return period of a wet mud deposition event (WMD).

Table 3. AIC and BIC values of the three selected copula functions

Family	Logic	AIC	BIC
Gaussian copula	161.51	-321.03	-314.73
t copula	152.39	-300.78	-288.19
Frank copula	150.56	-299.13	-292.83

Figure 2 shows the density function (a) and distribution function (b) of the Gaussian copula.

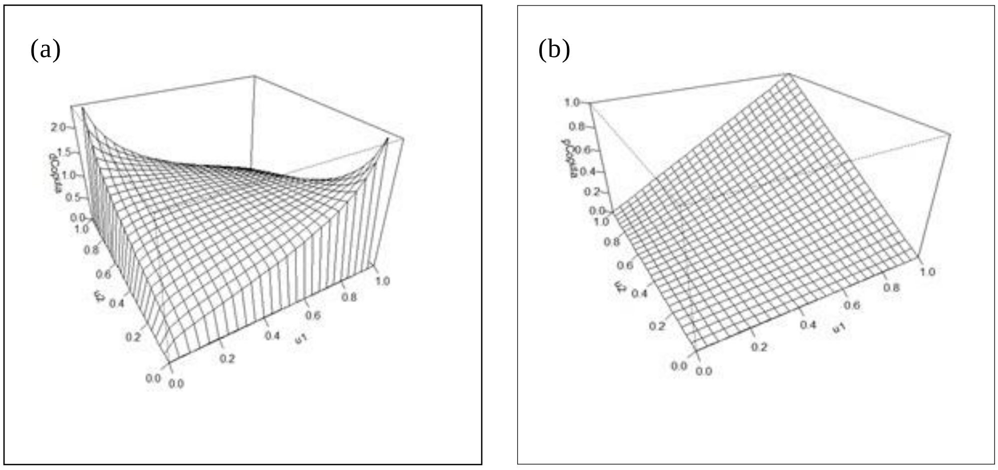

Fig. 2. Density function (a) and distribution function (b) of the best-fitted copula

Figure 3 also shows the contour plots of the bivariate return periods of wet mud deposition based on the Gaussian copula function.

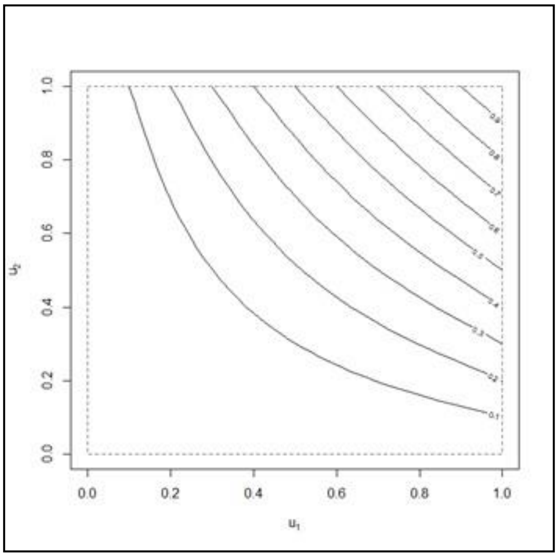

Fig. 3. The contour plots of the bivariate return periods of wet mud deposition based on the Gaussian copula function

To assess the bivariate return periods (T_{DR} and T'_{DR}), the joint distribution of dust and relative humidity was applied to the Gaussian copula function using expressions (4) and (5). The joint return period for T_{DR} results is summarized in table 4. The wet mud deposition joint return period, in general, for different levels of dust (6, 4, and 2-hourly) and humidity (79, 72, and 65 %) are estimated to be greater than 200 years.

As shown in Table 5, the calculated joint return period for T'_{DR} for different dust levels (6, 4, and 2-hourly) and humidity (79, 72, and 65 %) is lower than 20 years. We argue that joint return period T'_{DR} to determine the bivariate return period has higher accuracy.

Table 4. The joint return period for T_{DR} of wet mud deposition

Minimum relative humidity (%)	Minimum dust (Hour)	The turning point period (Year)
79	6	7145.6
72	4	940.16
79	4	1268.26
72	2	518.94
65	2	291.95

Table 5. The joint return period for T'DR of wet mud deposition

Minimum relative humidity (%)	Minimum dust (Hour)	The turning point period (Year)
79	6	20.16
72	4	10.11
79	4	13.4
72	2	8.13
65	2	6.82

3.2.2. Univariate Return periods

The univariate return periods were calculated based on relative humidity (T_{RH}) and dust (T_D) associated with the selected return levels, and the results are summarized in table 6.

Several marginal distributions were fitted to the relative humidity and dust. Regarding relative humidity data, Gamma distribution was selected based on the smallest AIC and BIC. Results are presented in Table 6.

Table 6. AIC and BIC values of the different fitted marginal distributions to relative humidity

Goodness-of-fit criteria	Exponential	Normal	log-Normal	Weibull	Gamma
AIC	38007.14	35441.45	34926.24	34960.59	34815.74
BIC	38013.44	35454.05	34938.84	34973.19	34828.34

The univariate return period is estimated based on relative humidity associated with the selected return levels (90, 80, and 70 %) using expressions (6). Results are summarized in Table 7.

Table 7 The univariate return periods based on different levels of relative humidity

Relative humidity (%)	Return period (Year)
90	43.2
80	20.4
70	12.2

Considering several marginal distributions were fitted to the dust, the Exponential distribution was sorted out based on the smallest AIC and BIC. Results are presented in Table

8. Exponential distribution was selected based on the smallest AIC and BIC.

Table 8. AIC and BIC values of the different fitted marginal distributions to dust

Goodness-of-fit criteria	Poisson	Normal	Exponential	Nbinom
AIC	14749.23	16940.60	7224.347	8829.024
BIC	14755.52	16953.19	7230.645	8841.620

Correspondingly, analyses related to univariate return periods based on dust associated with the selected return levels (4, 5, and 6 hours) using expressions 7. Results are summarized in Table 10

Table 9. The univariate return periods based on different levels of dust

Dust (hourly)	Return period (Year)
4	84
5	253
6	763

3.3 Dominant climatic conditions

3.3.1. Investigating the trend of changes

Figure 4 (a) and (b) show the annual trend of the frequency of days with dust and relative humidity in Khuzestan stations. The annual trend of dust increases during spring and summer and decreases in the fall and winter. The maximum and minimum dust levels are recorded in June and November, respectively.

In addition, the analysis of relative humidity annual trend revealed that the highest rate of humidity occurs in December, January, and February (cold period), and the lowest rate of humidity occurs in May, June, and July (warm period). Therefore, we can argue dust and relative humidity have an opposite trend through the year. The analysis of the monthly trend in 2017 (Figure 4 (c) and (d)) demonstrates that the trends of the frequency of dust days and relative humidity follow the same pattern as long-term annual trends.

We argue that dust extreme occurs in just some rare cases in fall and winter, but it has been hypothesized that climate changes can change the patterns of dust occurrence. From October to March 2017, there was a notable ascending trend in the frequency of dust days in February. We argue that the peak of dust extreme frequency in February, considering the humid air conditions, is the main reason for mud deposition on the surface of Khuzestan urban areas.

4. Conclusion

Southwest Iran has been identified as one of the region’s most vulnerable to the impacts of dust extremes associated with urban systems. Under the influence of the sedimentation of wet mud on the power systems, Khuzestan citizens experienced the strong impact of blackouts causing great pressure on the urban infrastructure and people's daily activities. These consequences include a lack of health facilities, defects in communication and social networks, a reduction in water supply, and food production losses. Sedimentation of wet mud on the power systems in Khuzestan province could be viewed as too rare and there aren't many cases of such event through the history of the province. However, many research studies have been performed on dust accumulation on PV and solar thermal surfaces particularly in the

Persian Gulf region which has similar weather conditions as Khuzestan.

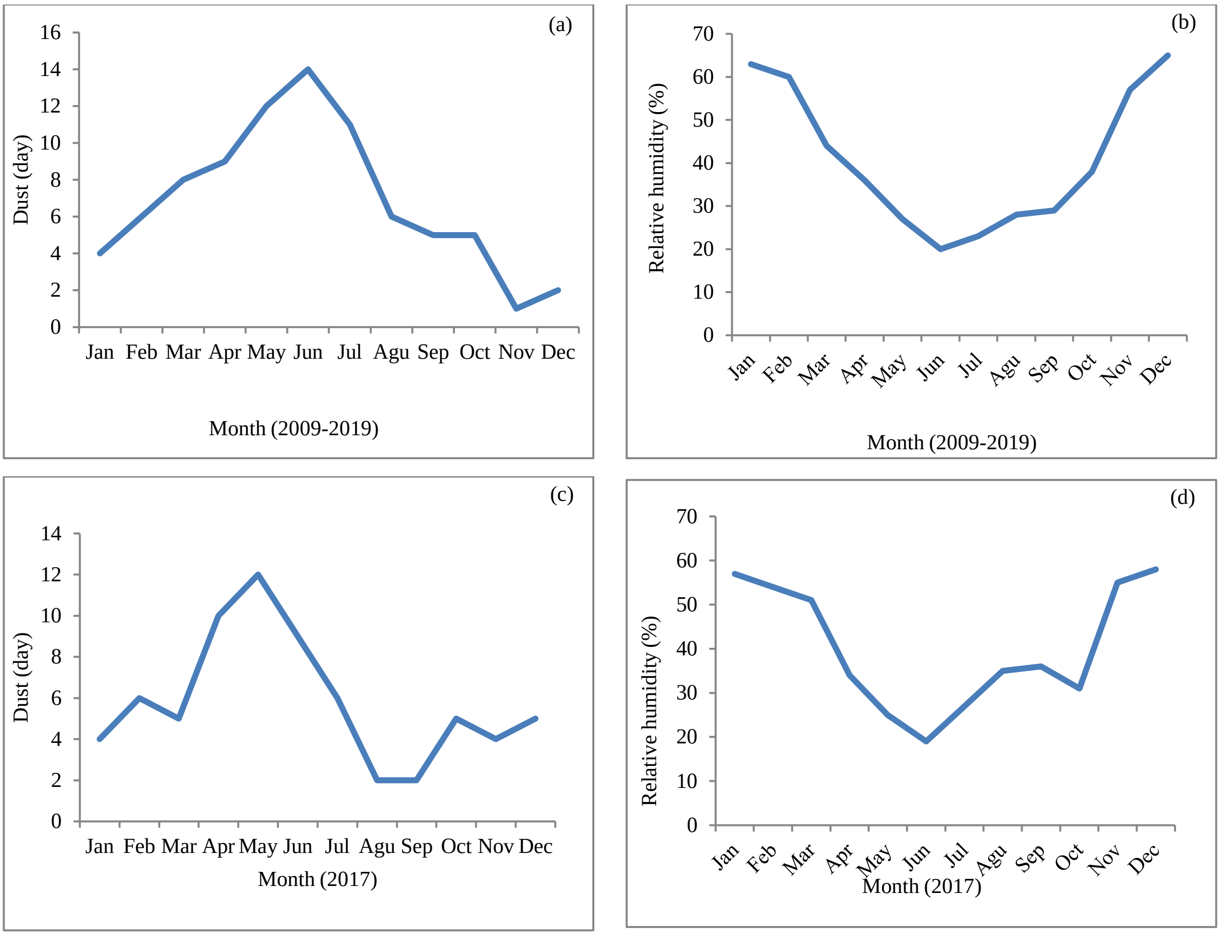

Fig. 4. (a) and (b) Annual trends of dust and relative humidity period 2009-2019, (c) and (d) Monthly trend of relative humidity in Khuzestan synoptic stations in 2017

Isaifan *et al*. (2018) evaluate the adhesion forces between dust particles and solar panels in Qatar. They showed that under high relative humidity, the adhesion mechanism between dust particles and PV module surfaces is dominated by capillary force.

Adukwu *et al.* (2020) investigated the adhesion of environmental dust by hydrofluoric acid solution treated on photovoltaic panel surfaces in the local area of Dammam in Saudi Arabia.

Caron & Littmann (2013) introduced a practical method for measuring the soiling rate to full recovery of module performance in the United States.

Our findings revealed that dust extremes follow specific seasonal patterns (figure 4 a and b), but in recent years, have shown anomalies in the cold seasons due to climate changes and the adverse effects associated with human intervention such as land degradation and desertification. These anomalies increase the probability of dust extreme coincidence with wet extreme. Therefore, the likelihood of the occurrence of wet mud hazards is expected to be high in the cold seasons of the year.

Here, we used the return period and risk assessment as critical solutions for adaptation and mitigation to combat and amplify the impacts of wet mud deposition. It is seen that traditional empirical methods seem insufficient; therefore, copula families were used to analyze univariate and joint return periods of compound dust and wet extremes in this study.

It should be noted that the estimated joint return period for T_{DR} compared to the joint return period for T'_{DR} return periods for various levels of minimum relative humidity and dust hours are rather unrealistic and, their uncertainties are pretty large. The joint return period for T_{DR} is estimated to be greater than 200 years and the joint return period for T'_{DR} is to be lower than 20 years. By considering only relative humidity data (different levels are 79, 72, and 65 %), the return period of mud adhesion hazard in Khuzestan in 2017 is approximately 12 to 43 years. If we merely consider dust (different levels are 6, 4, and 2 hourly), the return period of mud adhesion hazard in Khuzestan in 2017 is estimated at 80 to 700 years.

Based on the results, we suggest developing strategies for adaptation to wet mud deposition hazards considering the examination of the vulnerability of the power systems in terms of system operation and components. Khuzestan mud adhesion hazard was such a rare and unusual cooccurrence of dust extremes and humid ambient air, which makes it difficult to foresee, mainly because there were no observed historical analogs. In fact, an increase in the number of extreme dust events and limited adaptive capacity to wet mud deposition hazards have put the lives of people in the urban areas of Khuzestan province at risk.

Therefore, this study tried to prepare a historical record of this event to provide information on how it may occur in future. Particularly, strategies should be defined to reduce the degree of the vulnerability of Khuzestan power networks to dust extreme impacts and empower the authorities to handle this issue. In this case, the use of adaptation approaches could be assisted.

However, although in this study dust and relative humidity have been considered the most limiting variables which control the occurrence of wet mud deposition, other variables such as temperature, sea surface temperature, precipitation, and wind speed should be considered in future studies.

Author Contributions

Conceptualization, Mohammad Rahimi and Maede Nasry; methodology, Saeed Zalzadeh; software, Maede Nasry and Saeed Zalzadeh; validation, Maede Nasry and Saeed Zalzadeh. and; formal analysis, Maede Nasry and Saeed Zalzadeh.; investigation, Mohammad Rahimi, Maede Nasry and Saeed Zalzadeh; resources, Maede Nasry; data Mohammad Rahimi, Maede Nasry and Saeed Zalzadeh; writing—original draft preparation, Maede Nasry; writing—review and editing, Mohammad Rahimi; visualization, Maede Nasry

All authors contributed equally to the conceptualization of the article and writing of the original and subsequent drafts.

Data Availability Statement

“Not applicable”

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Ethical considerations

The authors avoided from data fabrication and falsification.

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Conflict of interest

“The authors declare no conflict of interest.”

References

Adukwu, JE., Yilbas, BS., Jalilov, AS. (2020). Adhesion characteristics of solution-treated environmental dust. *Scientific Reports*, 10(13812). https://doi.org/10.1038/s41598-020-70858-6

AghaKouchak, A., Cheng, L., Mazdiyasni, O., Farahmand, A. (2014). Global warming and changes in risk of concurrent climate extremes: Insights from the 2014 California drought. *Geophysical Research Letters*, 41, 8847–8852. https://doi.org/10.1002/2014GL062308

Bialek, JW. (2010). *Critical interrelations between ICT and electricity system. in Securing electricity supply in the cyber age: exploring the risks of Information and communication technology in tomorrow's electricity infrastructure*. Springer Press.

Birkmann, J., Wenzel, F., Greiving, S., Garschagen, M., Vallée, D. (2017). Extreme Events, Critical Infrastructures, Human Vulnerability and Strategic Planning: Emerging Research Issues. *Journal of Extreme Events*. 03. 1650017. https://doi.org/10.1142/S2345737616500172

Cardona, OD *et al*. (2012). In Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation.65–108 (IPCC, Cambridge Univ. Press, 2012). Esen V, Oral B, Akinci TC (2015) the determination of short circuits and ground faults in electric power systems using time-frequency analysis. *Journal of Energy in Southern Africa*, 26(2), 123-132. https://doi.org/10.17159/2413-3051/2015/v26i2a2206

Caron, J.R., Littmann, B. (2013). Direct monitoring of energy lost due to soiling on first PV modules in California. IEEE J. Photovoltaic’s Press. 3, (1), pp. 336–340.

Gimeno-Sotelo, L., Gimeno, L. (2022). Concurrent extreme events of atmospheric moisture transport and continental precipitation: The role of landfalling atmospheric rivers. *Atmospheric Research*. 278. 106356. https://doi.org/10.1016/j.atmosres.2022.106356

Hassan, G., Yilbas, BS., Said, S.A., Al-Aqeeli, N., Matin, A. (2016). Chemo-mechanical characteristics of mud formed from environmental dust particles in humid ambient air. *Scientific Report*. 6, 1–14. https://doi.org/10.1038/srep30253.

Hasan, K., Yousuf, S., Tushar M, Das, B., Das, P., Islam, Md. (2021). Effects of different environmental and operational factors on the PV performance: A comprehensive review. *Energy Science & Engineering*. 2(21). https://doi.org/10. 10.1002/ese3.1043

Isaifan, R., Johnson, D., Ackermann, L., Figgis, B., Ayoub, M. (2018). Evaluation of the adhesion forces between dust particles and photovoltaic module surfaces. *Solar Energy Materials and Solar Cells*. 191, 413-421.

Kim, J., So, B., Kwon, H., Kim, T., Lee, JH. (2018). Estimation of return period and its uncertainty for the recent 2013–2015 drought in the Han River watershed in South Korea. *Hydrology Research*. https://doi.org/49. 10.2166/nh.2018.146

Lyu, Y. (2017). Characterization of dust falls in rural and urban sites during three dust storms in northern China. *Aeolian Reserch*. 28, 29–37. https://doi.org/10.1016/j.aeolia.2017.06.004

Mesbahzadeh, T., Mirakbari, M., Saravi, M., Sardoo, F., Miglietta, M. (2019). Meteorological drought analysis using copula theory and drought indicators under climate change scenarios (RCP). *Meteorological Applications*. 27 (7). https://doi.org/10.1002/met.1856

Bradke, T., Lüllmann, H., Poetzsch, A., Riehm, M. (2011). What happens during a blackout: Consequences of a prolonged and wide-ranging power outage SE. *Technology Assessment Studies Series*. 2 (14).

Pabaghi, Z., Bazrafshan, O., Zamani, H., Shekari, M., Singh, V.P. (2023). Bivariate analysis of extreme precipitation using copula functions in arid and semi-arid regions. *Atmosphere Journal*, 14(2), 275.

Rashki, A., Middleton, N.J., Goudie, A.S. (2021). Dust storms in Iran-Distribution, causes, frequencies and impacts. Aeolian Research Journal. 48(100655). https://doi.org/10.1016/j.aeolia.2020.100655.

Raymond, C., Horton, R.M., Zscheischler, J., Martius, O., AghaKouchak, A., Balch, J., (2020). Understanding and Managing Connected Extreme Events. Nat. Clim. Chang. 10, 611–621. https://doi.org/10.1038/s41558-020-0790-4.

Sabri Ismail, M and Masseran, N. (2024). Risk assessment for extreme air pollution events using vine copula. Stochastic. Environmental Research and Risk Assessment, 38(2331-2358).

Salvadori, G., Durante, F., De Michele, C., Bernardi, M., Petrella, L. (2016) A multivariate copula-based framework for dealing with hazard scenarios and failure probabilities, Water Resource Reserch. 52 (3701–3721). https://doi.org/10.1002/2015WR017225

Sarver, T., Al-Qaraghuli, A., Kazmerski, L.L. (2013). A comprehensive review of the impact of dust on the use of solar energy: history, investigations, results, literature, and mitigation approaches. Renew. Sustainable Energy Reviews. 22(698–733). https://doi.org/10.1016/j.rser.2012.12.065.

Seneviratne, SI. (2012). In Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation (eds Field, C. B. *et al*.) 109–230 (IPCC, Cambridge Univ. Press, 2012).

Silva, R.d and Lopes HF. (2008). Copula, marginal distributions and model selection: a Bayesian note. *Springer Nature*, 18, 313–320. https://doi.org/10.1007/s11222-008-9058-y.

Shiau, JT. (2006). Fitting drought duration and severity with two-dimensional copulas. *Water Resources Management*, 20 (5), 795–815. https://doi.org/10.1007/s11269-005-9008-9

Sklar, M. (1959). Functions de répartition à n dimensions et leurs marges. Université Paris 8, Paris, France.

Tavakol, A., Rahmani, V., John Harrington, J. (2020). Probability of compound climate extremes in a changing climate: A copula-based study of hot, dry, and windy events in the central United States. *Environmental Research Letters*, 15. https://doi.org/10.1088/1748-9326/abb1ef

Whitney, K.H., Adam, H.M., Francis, W.Z. (2021). Estimating concurrent climate extremes: A conditional approach. *Weather and Climate Extremes*, 33 (44). https://doi.org/10.1016/j.wace.2021.100332

Yilbas, B., Ali H, Khaled, M. (2015). Influence of dust and mud on the optical, chemical and mechanical properties of a pv protective glass. *Scientific Reports.* 5 (15833). https://doi.org/10.1038/srep15833

Zhang, W., Murakami, H., Khouakhi, A., Luo, M. (2021). Editorial: Compound Climate Extremes in the Present and Future Climates: Machine Learning, Statistical Methods and Dynamical Modelling. Front. *Atmospheric Science.* 9:807224. https://doi.org/10.3389/feart.2021.807224.

Zscheischler J, Seneviratne SI (2017) Dependence of drivers affects risks associated with compound events. Science Adviser. 3 (25). https://doi.org/10.1126/sciadv.1700263

Zscheischler, J., Westra, S., Van Den Hurk, BJ., Seneviratne, SI., Ward, PJ., Pitman, A. (2018). Future climate risk from compound events. Nature Climate Change. 8, 469–477. https://doi.org/10.1038/s41558-018-0156-3.