

**TEXT MINING TO ASSESS CLIMATE RISK DISCLOSURES  
OF FIRMS LISTED IN PSX**

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**ABSTRACT**

Climate change have countless consequences not only on environment but also to sustainable Economic development & financial markets. Climate risks i.e. Physical and transition risk required to be assessed for efficient capital allocation and optimal investment decisions. The current study is an attempt to assess and analyze firm's strategies and concerns to address climate risks from their disclosures in sustainability reports and corporate publications related to climate change risk. For the analysis of objective, the most vulnerable sector to climate risk i.e. energy sector firms listed in Pakistan Stock Exchange were selected. The firms' data of climate related texts from 2016 to 2021 was analyzed to assess their concerns on climate risk by using NLP of Machine Learning approach. The results of study revealed that firms have reported their concerns for climate risk and have opted strategies to address or reduce the climate risk instead of mere transfer and avoiding these risks. Their concerns to overcome climate risk and to address environmental hazards also reported via score obtained through sentiment analysis using commitments to opt for Green practices to save environment. The results of the study are useful for fund managers, regulatory bodies and investment Managers for the identification of green practices companies and construction of portfolios.

**KEYWORDS**

Climate Change Risk, Machine Learning, Corporate disclosure, Supervised Learning, Unsupervised Learning, sustainable investment practices.

**INTRODUCTION**

Climate change has impacted global economy through posing complex risk and expected to have increase impact in future due to its nature. Global regulatory and standard setting bodies are striving to implement consistent and reliable measure to capture climate risk and to establish disclosure in financial reporting. It is well agreed fact that the increase in business activities leads towards the social and environmental issues (Ansu-Mensah, Marfo, Awuah, & Amoako, 2021). One of the causes of the devastating impact on both the economy and human lives has been the growth of climate changes resulting in more frequent natural disasters. Due to this, an increasing number of nations and financial sectors

are implementing environmentally friendly economic policies through Green Business practices. The world Economic Forum Global Risk Report (2018) has reported that most critical risk faced by global investors, governments organizations and industry experts are the climate risk. Due to this fact increase climate change regulations has been witnessed from the last two decades and since 1997 the number of legislations / laws get doubled in every five years (GRICCE, 2015). In order to address the climate change issues the corporate need to refine their role to take responsible actions and to reduce negative environmental activities (Abbas & Sağsan, 2019).

The goal is to create and maintain corporate practices and services that reduce their harmful environmental impacts and increase the economy's resilience to climate change which is required Instilling environmental consciousness in organizational culture and the adaption of sustainability practices.

The climate risk can be divided in two types i.e. Physical Climate Risk and Transition Climate Risk. Physical climate risk or direct climate risk refers to the possibility of both material losses and harm as a result of a corporate increased exposure to climate change risk. The direct impact of climate change related to the weather-change conditions caused damage through, flood, drought etc. The indirect climate risk is related to the regulations which resulted increase in cost due to the carbon emission activities.

Pakistan has ranked in the top 10 countries in the Climate Risk Index from the last 20 years and due to 173 extreme weather events, the country has suffered financial losses of approximately \$4billion. (Siddiqui, 2022). Further, in the light of the projection of ADB that the expected average rise in Pakistan temperature is between 3<sup>o</sup>C & 5<sup>o</sup> by the end of this century (Chaudhry, 2017), which is higher than the global average and in contrary to Paris COP21 Agreement where the 195 countries made commitment to limit global warming upto 2<sup>o</sup>C. The expected rise in temperature makes Pakistan vulnerable to climate risk and requires to initiate measures and to opt for pro climate policies. Such climate changes forecasted to have impacts on all spheres of economy and may leads to reduction in agriculture produce, water reservoirs, erosion of coastal and exposure to climatic events (GOP, 2019-2020). The sustainability profile of the corporate can be achieved through reduction of climate related issues (Khandokar & Andrew Price, 2009). It is the need of the hour to take initiative to assess, measures, and develop monitoring systems that align industrial processes that can positively impact on society's social, economic, and environmental well-being.

The data availability is the chronic issue in emerging economies to measure and assess climate risk. To address climate issue there is scarcity of quality, reliability, consistency of data (Li, 2023). The objective of current study is to assess the extent to which firms listed in Pakistan Stock Exchange are disclosing their concerns and strategies related to climate change risk in their sustainability reports and corporate publications to address the climate risk issues by using text mining a machine learning approach. It is the process of extracting useful information in an efficient and fool proof way from text data. This approach has reported superiority to analyze big data through structuring and analyzing with an essence of objectivity and accuracy (Bhanot, Singh, Sharma, Jain, & Jain, 2019). The firms who report their concerns and report to adopt green practices have more potential to contribute towards sustainable development. The current study explores and analyze the large volume

of published data of disclosures of companies through text mining and sentiment analysis to assess the corporate concerns to climate risk.

Climate change risk has captured attention of financial institutions and most of the studies have been performed in developed economies for the management of assets. It has been reported that the climate changes have impact on investment returns in two ways i.e. direct & indirect (Fang, Tan, & Wirjanto, 2019). The climate risk assessment is required to be assessed to achieve corporate goal of shareholders wealth maximization. In emerging economy like Pakistan no study has so far initiated to assess corporate climate concerns. The current study will contribute in literature to assess environmental concerns of company and through performing sentiment analysis through analyzing published source of companies. Climate-related disclosures that could encourage more knowledgeable credit, insurance, and investment decisions, enabling stakeholders to better comprehend the financial system's exposure to risks related to climate change.

The remainder of this study is arranged as follows: In section 2 the brief overview of relevant literature of climate risk, firms disclosures and techniques to assess climate risk is presented. In section 3 the data, summary statistics methodology of the research is presented. In section 4 and 5 the empirical results of data are reported and conclusion of the study is presented respectively.

## **LITERATURE REVIEW**

Climate change risk have consequences on humans, economic, social, infrastructure, financial systems and capital markets. For corporate sector it may be defined as the exposure to climate related impact both direct (physical climate factor) and indirect (transitional risk) that have consequences on financial performance of firms (Fang, Tan, & Wirjanto, 2019). The repercussions of climate change may range from simple loss of asset to complete loss. The extreme weather events have caused economic loss of USD 329 billion in year 2021 such losses are expected to increase in intensity and frequency, the loss of 45% in 2019 is higher than the historical average of 21<sup>st</sup> century (Aon report). McKinsey (Company) a global Management consulting firm reported through analysis of 105 countries (90% of the world's population & GDP) "all are expected to experience an increase in at least one major type of impact on their stock of human, physical, and natural capital by 2030.

The extreme weather events and the climate risk put millions of life at stake along with trillions dollar of economic activities and assets and the stock of world's natural capital. This area of Climate finance captured global attention since the 2015 United Nations Climate Change Conference. The Financial Stability Board (FSB) has implemented Task Force for Financial Disclosure who in 2017 made its recommendation to incorporate Financial Disclosures which enables the stakeholders to make informed decisions keeping in view of Climate risk of Corporates. The TCFD identified and broadly divide climate risk faced by companies in two categories as acute risk (climate shock) & chronic risk (climate stress) most of the risks can't be reversed due to their escalation nature. The "Climate Scenario" tool is used to assess the climate related risk assessment through evaluation of firms under different scenarios of climate impact on business activities. These techniques have advantage to assess climate risk under multiple scenarios faced by corporates and enables organizations to take timely initiate strategies to mitigate risks. Over the last decade

the research on topic of climate change and financial performance has accelerated to explore the relationship between climate change which leads to economic risk and have an impact on financial performance. Much research has been done on the link between climate change and economic growth (Bingler, Senni, & Monnin, 2021) has developed model named "Climate BERT" to assess the corporates compliance of TCFD and reported the disclosures as non-material. Earlier studies have analyzed the number of mentions of climate-related disclosures, however, the quality and materiality of the disclosures remains largely unclear. In 2020 (Krueger, Sautner, & Starks, 2019) through Machine Learning of rule based approach has assessed from conference calls of firms to assess CRO related language.

To analyze unstructured data set text mining technique is used with the help of algorithm of machine learning which enables the transformation of data from text to numeric to perform statistical analysis (Miner, et al., 2012) . The NLP is widely used in social media post analysis, in business health and politics (Velasco, Agheneza, Denecke, Kirchner, & Eckmanns, 2014) (Miner, et al., 2012). Natural language processing technique (NLP) is used in text mining. This technique is widely used for classification and clustering of documents, retrieval of information and for web mining (Miner, et al., 2012).

The issues associated with text mining is not the scarcity of information but the "information overload" (Sarkar, 2016). To assess climate risk (Luccioni, 2019) has developed a question answering approach to identify passages in climate disclosures to answer 14 TCFD recommendations they have made their model accessible to ascertain sustainability. (Bingler, et al., 2022) has developed "ClimateBERT" to analyze compliance with TCFD recommendations in a variety of corporate reporting globally, and find mostly disclosure of non-material TCFD categories. (Kolbel, 2020) were able to identify an increase in disclosure of transition risks in 10-K reports that outpaced those of physical risks, based on their measure of climate disclosure using a fine-tuned BERT model. Finally, (Sautner, Lent, Vilkov, & Zhang, 2020) has used a rule-based approach for identifying CRO-related language in corporate conference calls. They use machine learning (ML) for expanding their set of keywords, which was also proposed by (Luccioni, 2019).

Text mining techniques that are widely used are the (a). Topic Modeling and (b) sentiment analysis. By examining the word co-occurrence in these documents and finding major topics in the corpus and prominent terms in each topic, a range of unsupervised machine learning techniques known as "topic modelling" can discover themes in a corpus of documents or a collection of documents. (Törnberg & Törnberg, 2016). It uses a variety of NLP techniques to convert textual data, which is by nature unstructured, into a structured, quantifiable form that can be used for statistical analysis (Lane, Howard, & Hapke, 2019). The absence of any type of pre-classification or human annotation of the materials is a critical feature of topic modelling. While such annotation is impractical, it has been used to evaluate high-volume data sources such as social media data, genetic sequences, and digital library collections. Research on healthcare has also made use of topic modelling (Zakkar & Lizotte, 2021).

The Latent Dirichlet Allocation (LDA) is widely used topic Modelling method in text mining. This approach makes the assumption that a corpus of text contains a number of subjects, each of which is a distribution of words with a probability for each word within it. With variable probabilities, any document in the corpus can be connected to any of the

themes in the set. LDA has been used to examine people's experiences and views regarding the effects of smoking and quitting using social media posts that were related to smoking (Chen, Zhu, & Conway, 2015). LDA was also used to examine how Muslim immigrants are represented on social media by analyzing millions of posts on a Swedish social media platform (Törnberg & Törnberg, 2016).

A text mining approach called sentiment analysis can be used to examine the polarity or valence of textual material (Pang & Lee, 2008). The comments of an online product review expresses how satisfied the reviewer or consumer is with the product (Kietzmann & Canhoto, 2013) (AnoopV. & Asharaf, 2018). In e-business it is important to get customer reviews analysis. Several methods and approaches are available to perform sentiment analysis. Models created by machine learning techniques can be trained to categorize documents according to their sentiment (Pirayani, Gupta, & Ghose, 2017). The lexicon-based techniques make use of a dictionary that has a collection of terms with certain connotations. Depending on whether a term conveys a positive or negative sentiment, it is given a positive or negative sentiment score. The sentiment score of a document, which offers an estimation of its overall sentiment, can be calculated by analyzing the sentiment scores of the words in the text. Sentiment analysis has been used by researchers to examine social media posts, polls, and online product reviews. In current study we used nltk built in sentiment analyzer to measure polarity score.

The goal of climate risk governance can be achieved with improved disclosures. the better the firms will manage financial risk and opportunities emerged due to existence of climate risk the better they will be in position to make efficient allocation of resources. The research by (Thomä, Murray, Jerosch-Herold, & Magdanz, 2021) found that 40% of companies who were informed about their level of alignment with the Paris Agreement subsequently chose to implement climate strategies into their investment processes. By undertaking CRDs, firms gain legitimacy, reduce risk and uncertainty, enhance brand value, gain competitive advantages, and achieve financial gain (De. Grosbois & Fennell, 2022). (Ameli, Drummond, Bisaro, Grubb, & Chenet, 2020) suggests assumptions that disclosure results in shifts of finance from risky to less risky is an “efficient market hypothesis” (EMH) whereby market participants are all rational actors. However, Ameli et al, (2020) further argues that the EMH is inherently flawed and transparency alone is not effective for reducing the impact of firms on climate change. (Baker, 2018) suggests that mandatory disclosure standards are required for reports to be sufficiently detailed and thus more useful and influential.

## METHODOLOGY

The analysis was started by first identification of most vulnerable sector to climate risk. The sector as defined by GIGS (Global Industry Classification Standard), the Energy Sector has been classified as the most carbon intensive sector as about 80% of the world's energy is caused by fossil fuels. This sector is more exposed to climate risk as due to shift in energy sources have an impact on business activities of these sectors listed firms. Therefore, energy sector is more vulnerable to climate risk. In current study all the Energy Sector listed firms with ticker symbol MARI, OGDC, PPL, POL of PSX was selected for the assessment of climate risk disclosures. The text data of climate related opinion and views of the selected firms were extracted from their sustainability reports, Annual

Financial report w.e.f. 2016 to 2021 in phases. In first step all the firms listed in the energy sectors financial reports and sustainability reports were extracted from PSX website of study period i.e. 2016 to 2021. The meta-data was labelled as per the name of the company and the number of years. The text preprocessing of all the companies data was performed through nltk using python library. The workflow chart presented in Figure 1.

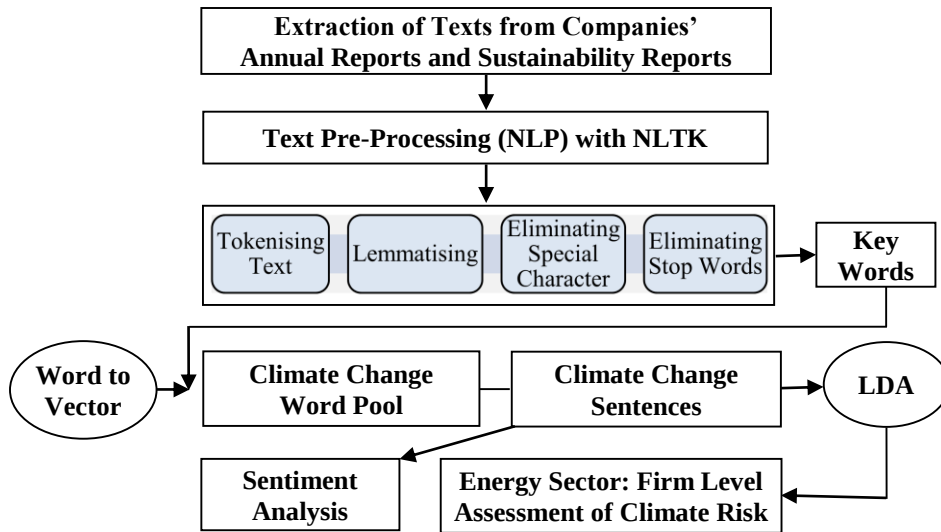
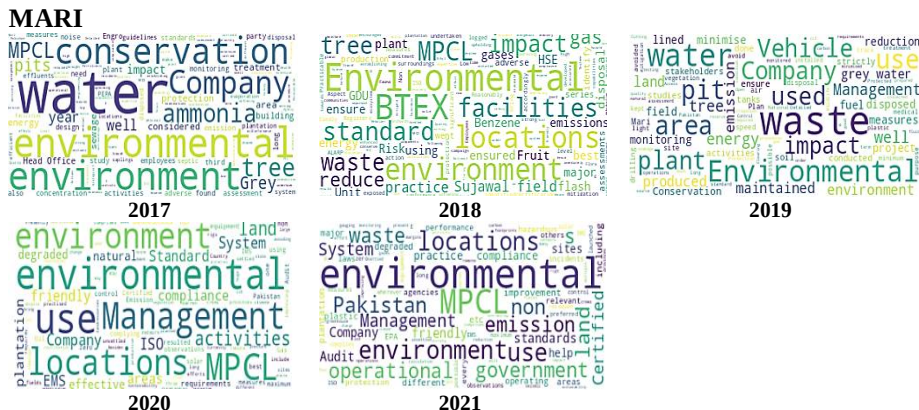


Figure 1: Text Mining Workflow

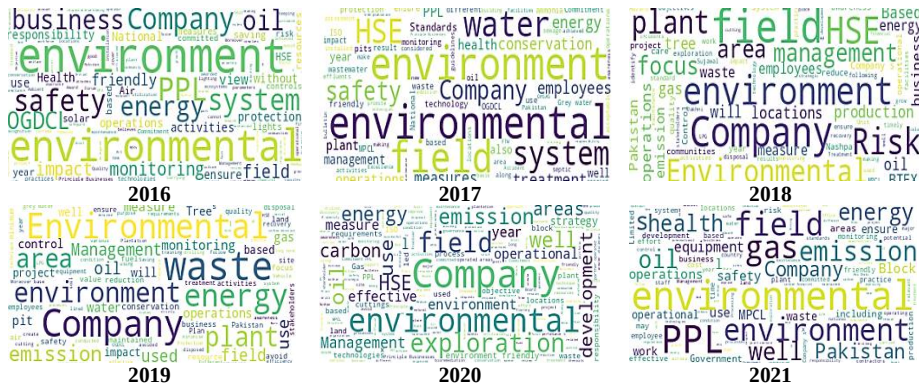
For the purpose of the analysis of text mining and processing of data multiple python libraries were used i.e. NLTK, Spacy, VADER (Valence Aware Dictionary and sentiment reasoner), Matplotlib and seaborn for visualization of data. VADER is built in in NLTK sentiment analyzer which has an ability to quickly process the word cloud of extracted texts from the reports of firms presented in Figure 2.





**Figure 2: Word Cloud of Energy Sector Listed Firms**

Form the procedure the word cloud highlighted the key word-cloud which the most highlighted word is environment. The energy sector overall trend assessed from Figure 3.



**Figure 3: Trend Analysis of Environments Concerns All Companies**

The Figure 3 highlighted that the energy sector has reporting their concerns towards environment as the most highlighted key word over the years is environment. The other words are energy, emission, risk, safety, carbon, waste management, business, operations development etc.

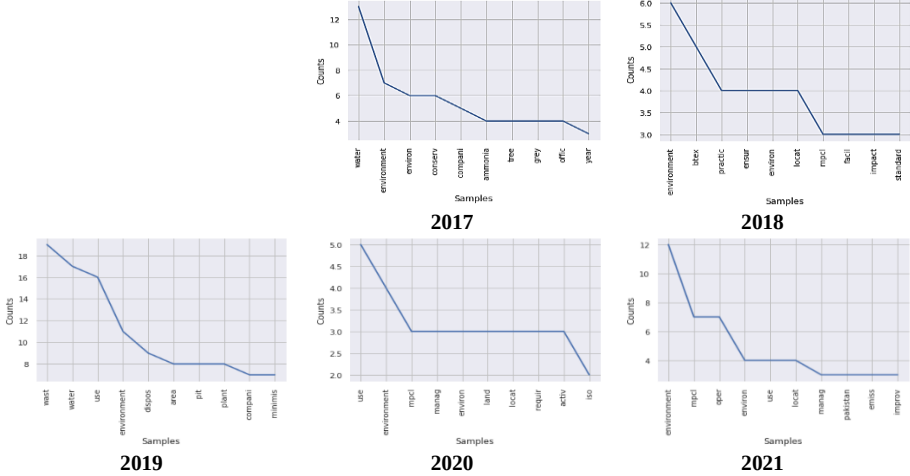
In order to clarify the key words the processing of the texts were performed using python libraries. The Table 1 reports the statistics of text processing.

**Table 1**  
**Statistics of Extracted Words**

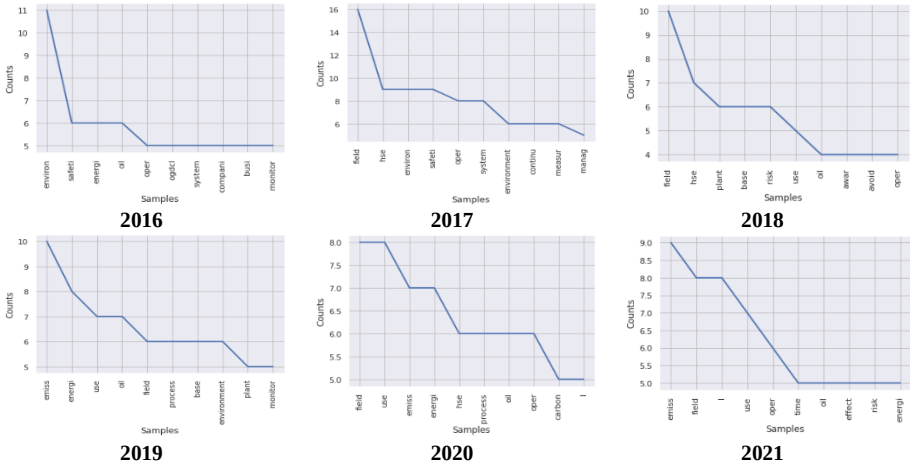
| Company /<br>Ticker Symbol | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 |
|----------------------------|------|------|------|------|------|------|
| <b>MARI</b>                | NA   | 3992 | 2384 | 7370 | 1614 | 2858 |
| <b>OGDC</b>                | 3984 | 5966 | 3903 | 5247 | 4743 | 4387 |
| <b>POL</b>                 | 917  | 659  | 1871 | 1246 | 840  | 1742 |
| <b>PPL</b>                 | 998  | 999  | 1721 | 2042 | 3385 | 6445 |

After extracting key words the frequency distribution of top 10 key words were made the results presented in Figure 4.

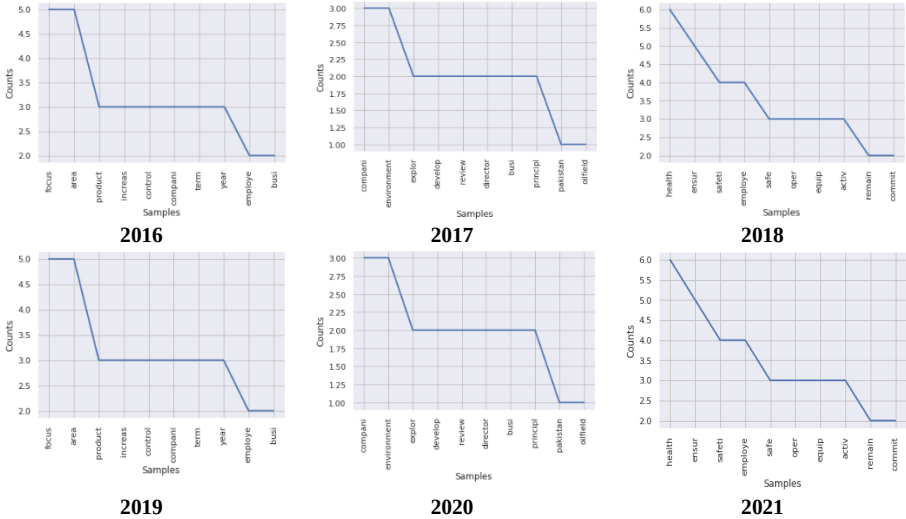
MARI



OGDC



POL



PPL

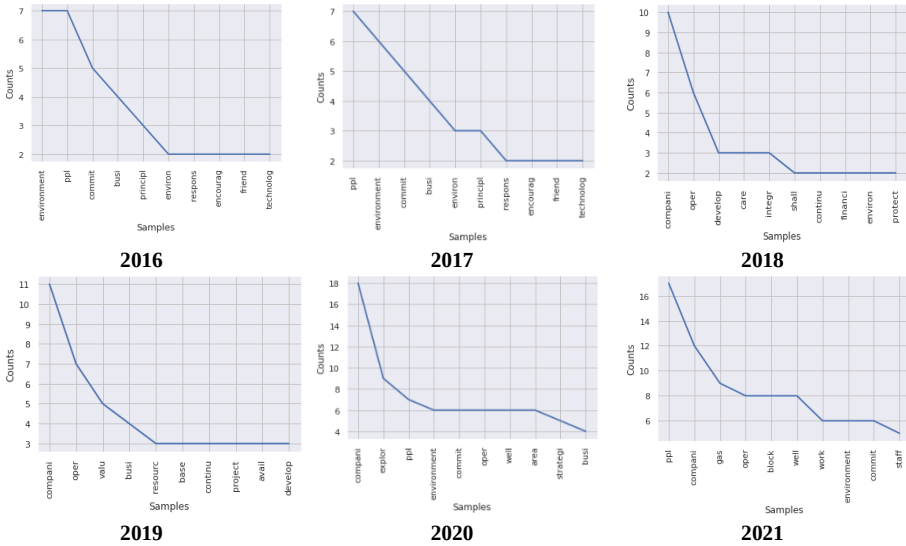
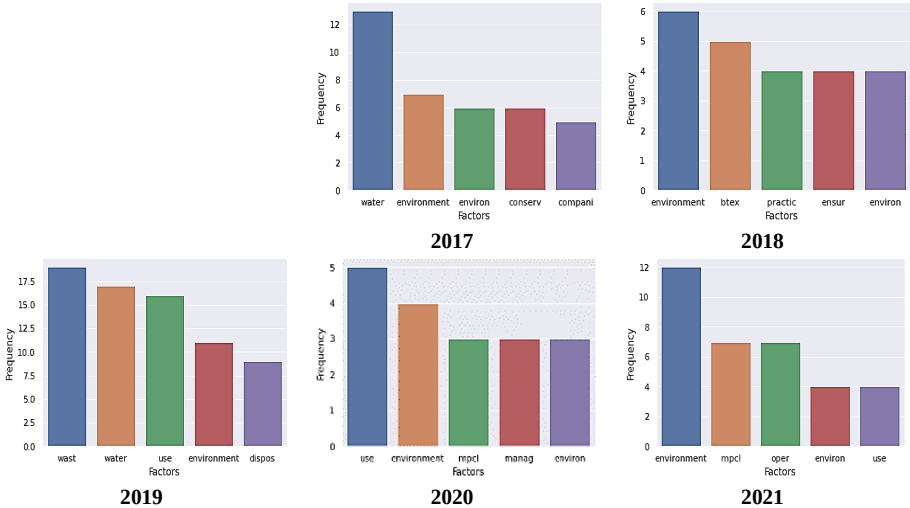


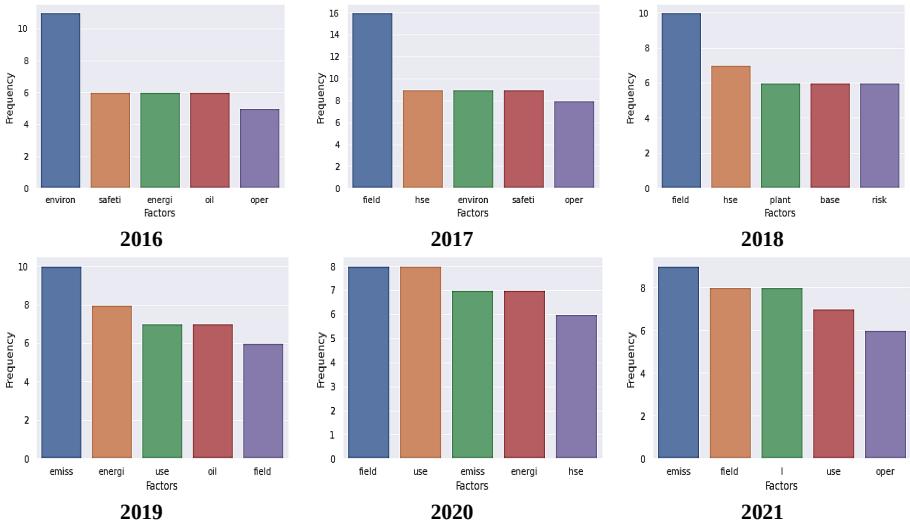
Figure 4: Frequency Distribution of Topic Key Words

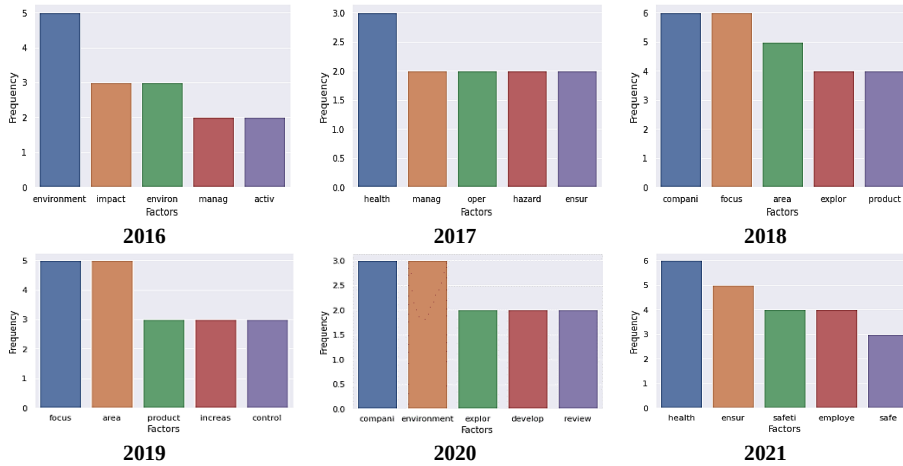
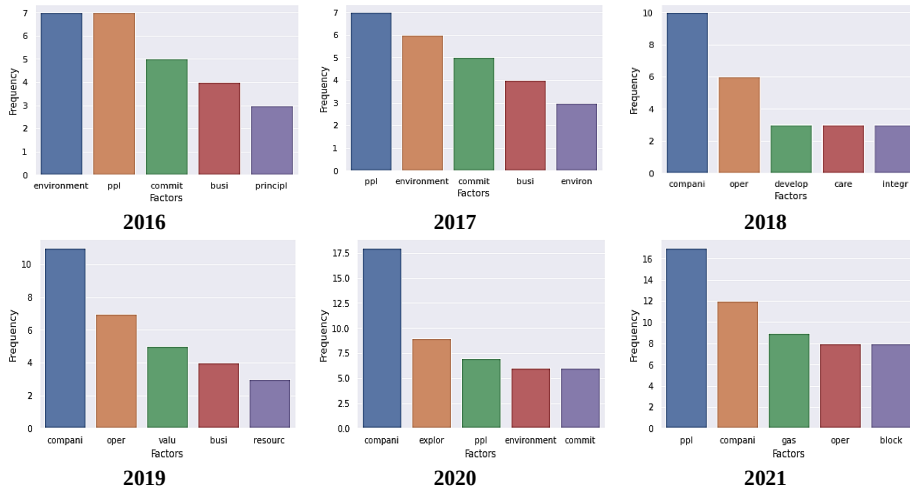
From the frequency distribution it is depicted that the most repeated word is environment in all firms' cases. The case may be further clarified through narrowing the key words the Figure 5 indicate the bar plot of 5 key words.

MARI



OGDC



**POL****PPL****Figure 5: Bar Graph of Climate Topic**

From Figure 5 the top five topics are environment, operations, emission, waste water, risk these topics are from both direct and transitional climate risks, moreover the text mining of energy firms also indicates the firms have shown their concerns towards the environment. Since the texts are related to the corporate sustainability and management performance reports so the sentiments are clear in the text data that can be positive or negative. The sentiment analysis score is presented in Table 2. The Lexicon based methodology were utilized for sentiment analysis. This method has reported superiority of accuracy on other methods in Machine learning in case of semi supervised and supervised

corpus of text and results reliability (Zakkar & Lizotte, 2021). The polarity score obtained through VADER, NLTK sentiment analyzer is presented in Table 3.

**Table 3**  
**Firm Level Sentiment Analysis**

| <b>Company /<br/>Ticker Symbol</b> | <b>Year</b> | <b>Negative</b> | <b>Neutral</b> | <b>Positive</b> | <b>Compound</b> |
|------------------------------------|-------------|-----------------|----------------|-----------------|-----------------|
| <b>MARI</b>                        | 2017        | 0.034           | 0.871          | 0.095           | 0.9842          |
|                                    | 2018        | 0.046           | 0.82           | 0.134           | 0.9857          |
|                                    | 2019        | 0.074           | 0.82           | 0.107           | 0.9826          |
|                                    | 2020        | 0.057           | 0.827          | 0.116           | 0.9456          |
|                                    | 2021        | 0.07            | 0.801          | 0.129           | 0.9771          |
| <b>OGDC</b>                        | 2016        | 0.059           | 0.768          | 0.173           | 0.9974          |
|                                    | 2017        | 0.057           | 0.773          | 0.17            | 0.9986          |
|                                    | 2018        | 0.06            | 0.833          | 0.106           | 0.9789          |
|                                    | 2019        | 0.054           | 0.81           | 0.136           | 0.9958          |
|                                    | 2020        | 0.042           | 0.816          | 0.142           | 0.9969          |
|                                    | 2021        | 0.047           | 0.818          | 0.135           | 0.9956          |
| <b>POL</b>                         | 2016        | 0.0             | 0.808          | 0.192           | 0.9733          |
|                                    | 2017        | 0.049           | 0.867          | 0.084           | 0.5106          |
|                                    | 2018        | 0.011           | 0.85           | 0.139           | 0.9873          |
|                                    | 2019        | 0.007           | 0.858          | 0.135           | 0.974           |
|                                    | 2020        | 0.015           | 0.781          | 0.204           | 0.967           |
|                                    | 2021        | 0.059           | 0.717          | 0.225           | 0.9903          |
| <b>PPL</b>                         | 2016        | 0.0             | 0.696          | 0.304           | 0.9906          |
|                                    | 2017        | 0.0             | 0.696          | 0.304           | 0.9906          |
|                                    | 2018        | 0.006           | 0.8            | 0.194           | 0.9935          |
|                                    | 2019        | 0.0             | 0.757          | 0.243           | 0.9971          |
|                                    | 2020        | 0.026           | 0.749          | 0.225           | 0.9984          |
|                                    | 2021        | 0.053           | 0.77           | 0.178           | 0.999           |

The results indicates that in almost all cases the higher weightage are on neutral results this is due to the non-availability of standardized disclosure standard related to climate risk moreover in comparison to negative sentiment the higher weightage is on positive sentiments the minimum score of negative sentiment is zero.

## CONCLUSION

The Climate Change risks has an impact on all spheres of economy it also have an impact on companies, Financial Institutions, humans etc., which will material consequences on assets and their values. So this is the need of the hour to report these risks to initiate strategies and timely action. The study found that the energy sector firms listed in Pakistan Stock Exchange have reported their concerns for climate risk and have opted for strategies to address these risks, indicating a potential for positive impact on sustainability practices in the sector. The goal of low carbon economy and sustainability is achieved through properly aligning and addressing issues causing change in global environment. (Christophers, 2017) agrees, suggesting that disclosure alone will not protect the financial system and regulatory directives are critical.

The limitations of the study are this study has analyzed the climate risk disclosure of firms of energy sector through analyzing their published annual reports and sustainability report, in the absence of any legal and mandatory requirement of climate disclosures of PSX listed firms the sentiment analysis was performed and polarity scores were obtained through nltk built in method VADER, the other techniques and approaches will be utilized in future to get results.

The recommendations of TCFD are the basis and the most effective framework to disclose climate related risk. The four pillar framework i.e. “Governance, Strategy, Risk Management & Metrics” served as a basis of climate related disclosure requirement. So, in absence of any standard disclosures of climate related risks and corporate practices, limit the generalizability of the findings and call for further research in the topic.

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