Sentiment Polarity Analysis of Amharic Climate Change Discourse Using Large Language Models

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Abstract

Climate change refers to variations in temperature and weather conditions due to various climate-related factors on earth.These factors vary across regions, and people's perceptions of climate change. Analyzing public opinion on climate change at a regional level is crucial for developing targeted solutions. However, manually analyzing large volumes of data is challenging for informed dissension. Applying emerging pre-trained Large Language Models offers a promising solution for efficiently analyzing large datasets and understanding public perspectives on climate change. Amharic is one of the widely spoken African languages. Many speakers of the language are actively discussing and expressing their opinions on various topics, including climate change, on social media. Given the increasing discussions about climate change, this study focuses on the sentiment analysis of Amharic climate texts. We collected 6013 sentences from social media and news sources. The data is annotated manually by native speakers to its target polarity. We conducted experiments using the LLM that supports African languages during pre-training. In this study, MultilingualBert and AfriBERTa models were employed with hyperparameter tuning to perform sentiment polarity analysis on Amharic climate text. The experimental results shows that MultilingualBert outperforms AfriBERTa, achieving an accuracy of 69%. This performance is attributed to MultilingualBert's enhanced capability to capture token-level semantics by giving a variety of attention across tokens, thereby improving its contextual understanding in downstream sentiment classification tasks.

Keywords: Climate NLP, Sentiment, LLM, mBERT, AfriBERTa, Climate Sentiment

1. Introduction

Climate change can occur naturally due to factors such as solar activity, large-scale volcanic eruptions or human activities. In the last few decades, industrial and human activities have led to gradually accelerating this climate changes, including an annually incremental change in the average surface temperature and carbon emission Santos and Bakhshoodeh (2021). This global temperate change affects human health and the melting of ice, as well as the rising of sea levels Bolan et al. (2022). These changes contribute to extreme weather events, such as hurricanes, floods, and droughts, which disrupt ecosystems and human settlements.

Over the past few decades, public concern about climate change has increased globally, with many people recognizing its severity Center (2022). Therefore public opinion have important contribution for achieving significant reductions in greenhouse gas emissions, low-carbon emission, and implementing effective adaptation Capstick et al. (2015). According to the Public Support for Climate Change Mitigation Policies Cross Country Survey Fund (2023), building public support for climate mitigation is an important factor for meaningful change toward decarbonization and net-zero emissions. Social media has becomes a prominent platform for individuals to express their views, concerns, and opinions on various topics Ausat (2023).

This widespread engagement has resulted in the generation of vast amounts of unstructured and dynamic data. The collection and analysis of such data are essential for understanding public perceptions Anoop and Sreelakshmi (2023), enabling data-driven insights into prevailing trends. Sentiment analysis is the process of gathering and analyzing people's opinion regarding to specific topics which can be used for informed decisions Wankhade et al. (2022). Therefore sentiment analysis using LLM helps for a better understanding of public attitudes towards climate change.

Amharic is a morphologically rich language from the Semitic family Seyoum et al. (2020), extensively used in public communication, including the dissemination of climate-related news and opinions. Given its widespread use, analyzing sentiment polarity in Amharic text is critical for understanding public attitudes toward climate change, particularly in regions that are highly vulnerable to climate-change. Despite the relevance of such analysis, less attention was given to sentiment detection in climate-related Amharic discourse Santos and Bakhshoodeh (2021). Therefore in this study we have analyzed the sentiment polarity of Amharic climate-change public opinions using LLM. The findings aim to contribute to climate change mitigation by supporting informed decision-making for policymakers, environmental organizations, and media outlets.

2. Related work

Automatic sentiment analysis in large texts data has become an important task in recent years due to the exponential growth of opinions and news contents on products and services. This represents a valuable opportunity for industries and organizations to give emphasis for customers sentiment for refine their service accordingly Gupta et al. (2021). The concern of sentiment analysis is to identify the polarity of individuals' thought as positive, negative or neutral Li and Zong (2010). Machine learning methods have been applied to improve sentiment detection tasks in various domains Bhavitha et al. (2017). Both classical machine learning algorithms Liao (2023) and deep learning models Jia and SungChu (2020) have been used for sentiment classification. With the increasing presence of climate change-related content on social media, studies have explored the use of deep learning and pre-trained models for analyzing sentiment polarity.

Sham and Mohamed, proposed a hybrid approach that combines Bag-of-Words and TF–IDF feature extraction with lexicon-based and machine learning techniques for climate sentiment analysis Sham and Mohamed (2022). Their approach showed improved performance in classifying sentiment related to climate change. In addition, transformer-based models have been used to analyze climate change discourse using tweet data collected over a one-year period, helping to identify sentiment trends and associated entities Anoop et al. (2024).

Taufek et al. develops a corpus-driven sentiment analysis approach to classify the polarity of Malaysian public perceptionsTaufek et al. (2021). They have used news articles associated with climate change. According to their analysis, the majority of public sentiments were predominantly negative.

Discussions about climate change on social media platforms have increased significantly in recent years Bruno et al. (2023). Key drivers of these discussions include seasonal events such as extreme summer heat, often associated with negative sentiment, and the implementation of public policies promoting renewable energy and sustainable development, which tend to elicit positive sentiment. Linguistic patterns and word usage are critical in understanding the socio-cultural framing of climate changes Wuraola et al. (2023). Given the disproportionate impact of climate change on developing countries, this study further explores the cultural differences in climate-related discourse between developing and developed nations Mirza et al. (2023).

While extensive research has been conducted on sentiment analysis for high-resourced languages across various domains including climate change discourse Alshamsi et al. (2020); de Bruin (2022), studies focusing on low-resource languages remain limited. To address this gap, recent work has emphasized the importance of large-scale sentiment analysis in low-resource languages Santos and Bakhshoodeh (2021). In response, this study fine-tune LLMs for sentiment polarity classification in Amharic, a morphologically rich and underrepresented language.

3. Climate Change Dataset

The climate change dataset used in this study was compiled from Facebook, news articles and Twitter. These platforms have recently emerged as significant sources of public discourse on climate change Mi and Zhan (2023), Sham and Mohamed (2022), As evidenced by numerous news articles and social media posts, key discussions and reports on climate action such as those from COP28 and COP29 are extensively disseminated across various platforms and in multiple languages, including Amharic UNFCCC (2023), on Climate Change (2024). Media outlets such as Al-Ain Amharic, DW Amharic, and others are actively reporting platforms on climate change were considered during the data collection process. A total of 6013 Amharic sentences, published between 2011 and 2025, were collected for this study.

3.1. Public Perceptions

Public perceptions of climate change are influenced by a range of factors that vary across geographical regions, including cultural, social, economic, and political contexts Wuraola et al. (2023). These perceptions play a critical role in shaping how communities and individuals respond to climate-related challenges. Economic factors such as dependence on fossil fuels Valavanidis (2025) and the anticipated impacts of climate policies can also significantly influence how individuals perceive and engage with climate change. Public opinions on climate change in Ethiopia are diverse, with negative sentiments largely related to the increasing frequency of droughts, widespread of deforestation, and economic losses in the agricultural sector. On the other hand, positive sentiments are associated with the promotion of renewable energy solutions and international support for climate change mitigation efforts, which offer hope for a sustainable future. In addition, some opinions remain neutral, reflecting neither strong support nor opposition when discussing the general concepts of climate change.

3.2. Sentiment Annotation

The predominant rule for sentiment annotation is to label instances as positive, negative or neutral, the decision is based on the word that is associated with the sentiment Mohammad (2020). Human annotators categorized the dataset into three main sentiment classes. The positive category includes opinions that express support for climate action and mitigation efforts. The negative category comprises statements that reflect concerns about the impacts of climate change, such as droughts, deforestation, floods, and agricultural losses. The neutral category consists of sentences that neither support nor oppose the positive or negative consequences of climate change instead, they present factual information or express uncertainty regarding the issue.Table 1 summarizes the annotation agreement evaluation process, to assess the annotation quality of the data, we used a lightweight annotation tool trained on a pre-curated dataset. For this evaluation, a total of 2,555 human-annotated samples were used out of these, 1,294 annotations agreed with the tool, while 1,261 showed disagreement. After reviewing both cases, 2,303 annotations were finalized as the curated gold standard by a human curator and used for model training from these sample data.

Table 1: Inter-Annotation Agreement Evaluation Using Sampled Data

Description	**Result**
Sampled Data for Eval	2,555
Inter-Annotation Agre.	1,294
Inter-Annotation Disagre.	1,261
Curated Annotations	2,303

3.3. Text Preprocessing

Amharic is a morphologically rich and complex language, which needs accurate data preprocessing for climate change sentiment polarity detection Nigusie and Tesfa (2022). Tokenization was used as the primary preprocessing step to segment the text into individual words and at this stage, Amharic stop words commonly found across all opinion classes and special characters were removed. Punctuation marks such as ፤, ፣, and ።, as well as stop words like **ስለዚህ** (because), **እና** (and), and **ወደ** (to), among others, were excluded from the dataset to reduce noise and enhance model performance. The next preprocessing step for the Amharic climate change dataset involved text normalization, which reduces variations in word representations Yimam et al. (2021). Words with similar meanings but different orthographic forms, such as **ሀ** (he), **ሃ** (ha), and **ሐ** (he), were normalized to a common form, **ሃ** (ha), to improve semantic consistency.

4. Model Architecture

The architecture used in this study is based on the Transformer model, introduced by Vaswani et al. Vaswani et al. (2017). This architecture relies heavily on self-attention mechanisms to capture relationships between words in a sentence, regardless of their position. It is particularly effective for understanding context in morphologically rich and structurally complex languages like Amharic. For the Amharic climate sentiment classification task, we fine-tuned two pre-trained multilingual models, mBert Libovický et al. (2020) and AfriBERTa Ogueji et al. (2021) both of which demonstrated strong performance and multilingual understanding capabilities for downstream tasks.

4.1. mBERT

mBERT is pre-trained on multiple languages Libovický et al. (2020), including Amharic, and can be adapted for sentiment classification. The architecture follows the BERT base model, which consists of 12 transformer encoder layers, each incorporating multi-head self-attention mechanisms. Given the complex structure of Amharic data, the use of all 12 attention heads allows us for detailed semantic analysis of the sentiments by attending to both the left and right contexts Clark et al. (2019). For the final classification, we added a classification head to the output layer of the attention mechanism.

4.2. AfriBERTa

AfriBERTa is a multilingual transformer model specifically trained for African languages, and it will be fine-tuned for sentiment polarity classification, particularly for low-resource languages like Amharic. Designed to handle the linguistic diversity and unique characteristics of African languages Ogueji et al. (2021), its specialized training for low-resource and morphologically rich languages enhances its performance for our task. This model features a reduced attention size compared to mBERT, making it more suitable for shorter sentences, while our dataset includes mixed-length sentences, still, it shows acceptable result.

4.3. Amharic Pretrained Tokenizer

In this study, we have utilized the pretrained models tokenizer to segment the pre-processed Amharic climate change data into words. However, we encountered issues with unusual tokens during sub-word tokenization for some domain-specific terms related to climate change, which were not sufficiently represented in the models' pre-training data. This resulted in semantic inconsistencies, causing the attention process of the model to be negatively impacted Nayak et al. (2020).

In our analysis, we observed notable inconsistencies in subword tokenization when applying AfriBERTa and AmharicBERT to domain-specific Amharic vocabulary. For instance, the word **ተጠናከረው** (to be strengthened) was tokenized differently by the two models despite having a semantically unified form.

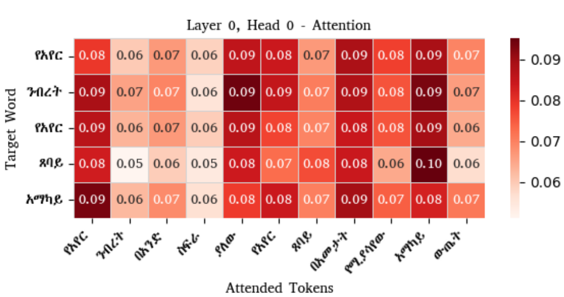
Specifically, AmharicBERT segmented it into subwords as **ተጠ, ና, ክረው**, while AfriBERTa produced **ተጠና, ##ክረው**. These discrepancies in subword segmentation highlight the limitations of general-purpose tokenizers in handling for specialized domains such as Amharic climate change data. To address these issues, we developed a domain-specific tokenizer with a vocabulary of Amharic climate change discourse. The custom vocabulary comprises 32,000 unique Amharic terms extracted from our annotated climate change data. When we evaluate the overall performance of these three tokenizers using sample sentence **መግለጫወች ተጠናክረው ለመቀጠላቸው በመላው አለም የታዩ ክስተቶች ማሳያ መሆናቸውን የአየር ንብረት ተመራማሪወች የሚገልጹት** (Climate scientists are broadcasting a display of events happening around the world to continue to strengthen the statements) AmharicBERT and AfriBERTa pre-trained tokenizers produced unusual sub-tokens. In contrast, our proposed tokenizer accurately generated valid tokens for the entire sentence, resulting in zero unusual tokens. This outcome demonstrates the effectiveness of a task-specific tokenizer in improving tokenization quality for downstream tasks for Amharic text. To assess the validity of the pre-trained tokenizers and new proposed one on Amharic climate-related text, we computed vocabulary tokenization statistics summary of the above sentence which is tokenized using three models: AmharicBERT, AfriBERTa, and our proposed Amharic Climate Tokenizer. We focused on the unusual vocabulary size as depicted in Table 2 , which we define as the number of tokens that are either rare, fragmented, or subword units not semantically meaningful in Amharic.

Table 2: Performance Analysis of Pretrained and Custom Tokenizers

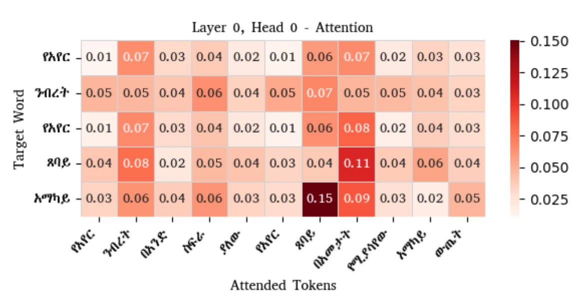
Tokenizer	**Unusual Vocab**
AmharicBERT (pre-trained)	7
AfriBERTa (pre-trained)	8
Amharic Climate Tokenizer (ours)	**0**

4.4. Attention-Based Analysis of Amharic Climate Data

Self-attention is key mechanism for LLM to capture the relationships between words, enabling the model to recognize which terms are most relevant to the other, regardless of their position in the sentence. We have used the sentence **የአየር ንብረት በአንድ ስፍራ ያለው የአየር ጸባይ በአመታት የሚያሳየው አማካይ ውጤት** (Climate is the weather pattern of a place over a period of years), where we focus on key target words like **የአየር** (Weather), **ንብረት** (conditions), **ጸባይ** (nature), **አማካይ** (average) for evaluating the attention result of the two large language models we have used. As shown in Figure 1(*a*) (mBERT) and Figure 1(*b*) (AfriBERTa), the attention scores are evenly distributed across the tokens, highlighting a more or less uniform attention distribution in the first layer of the models. This suggests that the model is treating all words with balanced importance, ensuring no single word is overly emphasized in the very beginning of the attention process.



(*a*) mBERT first layer self-attention result

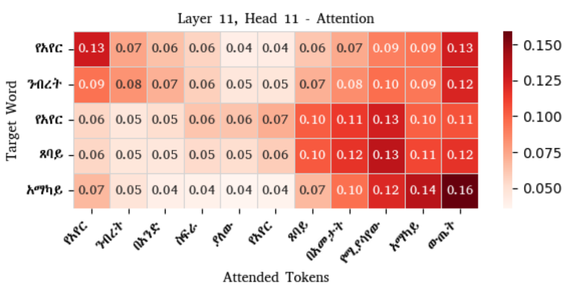


(*b*) AfriBERTa first layer self-attention result

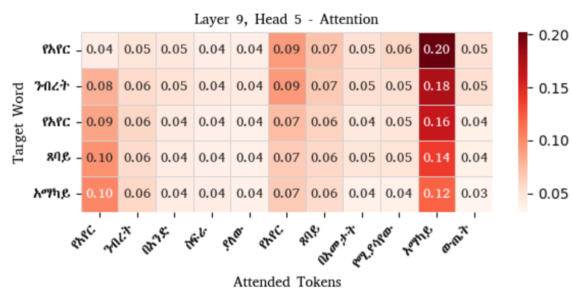
Figure 1: Comparison of first layer self-attention results for mBERT and AfriBERTa.).

While we evaluate the result of the intermediate layers, the attention distribution is noticeably less uniform. For each single target word, there are a few tokens that receive significantly higher attention scores, indicating a greater degree of focus on the semantical relationship between words in our sample sentence both models gives more attention for the diagonal terms. The words **አማካይ** (average) attended to **ውጤት** (result) with score of 0.31 which have high atention value in mBert and for the AfriBerta **የአየር** (climate) is give more attention to **ንብረት** (conditions) with attention result of 0.91. Here the result indicates that the models give emphasis for the compound nature of the words.

In analyzing the final layer attention distributions of the models, we observe a strong focus on key semantic relationships within the sentences. Specifically, target words frequently exhibit significant self-attention as well as strong mutual attention with semantically related terms. In the case of mBERT, the attention weight from the word **አማካይ** (average) to **ውጤት** (result) at the 12th (final) attention layer is score a result of 0.16, highlighting a moderate semantic linkage. In contrast, AfriBERTa demonstrates a higher attention weight of 0.20 from **የአየር** (climate) to **አማካይ** (average). It is noteworthy that AfriBERTa, despite being pre-trained with only 10 attention layers fewer than those in standard large language models exhibits competitive attention dynamics. Figure 2(a) and Figure 2(b) presents a comparative visualization of the final layer attention results of mBERT and AfriBERTa models respectively, applied to Amharic climate change sentiment data.



(a) mBERT last layer self-attention result

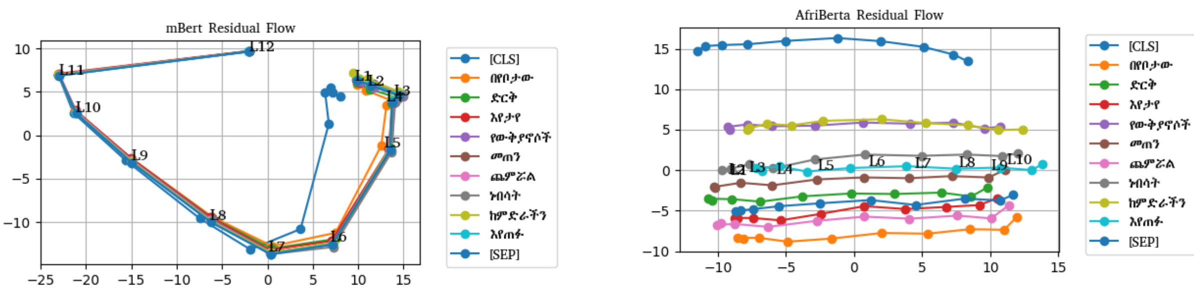


(b) AfriBERTa last layer self-attention result

Figure 2: Comparison of last layer self-attention results for mBERT and AfriBERTa).

4.5. Residual Connection Between Layers

To understand how contextual representations evolve, we analyzed the residual flow across all layers in two fine-tuned LLMs using the sample sentence **በየቦታው ድርቅ እየታየ የውቅያኖሶች መጠን ጨምሯል ነብሳት ከምድራችን እየጠፉ** (droughts are occurring everywhere, the oceans are shrinking, and insects are being washed away from our land). The layer-wise embedding transitions reveal that early layers encode surface-level and structural patterns of Amharic data. As shown in Figure 3(a), the mBert middle layers, specifically from layer 6 to 8, exhibit significant representational shifts of the model which contextualizing the tokens. Interestingly, token embeddings from the initial and final layers often converge indicating the stabilization of semantic content toward the final layers. On the other hand Figure 3(b) illustrated that AfriBerta appears to capture nearly uniform contextual representations across layers, as indicated by minimal attention variation among tokens. This limited diversity in token-level attention likely contributed to the model's lack of significant improvement during training.



(*a*) Residual flow of tokens across mBERT layers

(*b*) Residual flow of tokens across AfriBERTa layers

Figure 3: Comparison of residual token flow across mBERT and AfriBERTa layers.

4.6. Training

We have collected 6013 Amharic climate-change sentiment dataset and we fine-tuned mBERT and AfriBERTa large languaguage models, with mBERT having 12 layers Devlin et al. (2019) and 768 hidden units, and AfriBERTa-large having 10 layers. The token embedding and attention masking for both models were tokenized using new tokenizer that we have built using the vocabularies extracted from the collected climate based dataset. We have conducted the training using Colab with minimal bach size(32) and a learning rate of 0.00003 for 7 epochs of iteration. Training logs showed that mBERT shows reasonable convergence with stable progress. Class imbalance, noisy labels, and resource for efficiently train the models are some of the challenges we have experienced during training.

5. Experimental Results and Discussion

In this study, we have conducted an experiment on transformer-based pretrained models which are trained on a large and multilingual dataset and fine-tuned to analyze the sentiment polarity of Amharic societal opinions on climate change. A total dataset of 6013 was split into 80% for training, 10% for validation, and 10% for testing. To improve word tokenization, we developed a new Amharic climate data tokenizer with a vocabulary size of 32,000 tokens. This tokenizer addresses the issue of uncommon subword generation commonly encountered with pretrained models. To evaluate the model's sentiment detection performance, we tested them on 602 unseen sentences. The mBERT model achieved an accuracy of 69%, outperforming the AfriBERTa model, which reached 63%. The confusion matrix provided detailed information on the classification distribution in the three sentiment categories: 135 sentences were correctly classified as positive, 157 as negative, and 124 as neutral. Despite this, the misclassification patterns reveal considerable overlap among sentiment categories. Notably, negative sentences were frequently misclassified as positive (40 instances). Likewise, 38 negative sentences were misclassified as neutral. It is also important to note that the models were trained under resource-constrained conditions and with a limited number of training epochs.

6. Conclusion and Future Work

Climate change has become a significant global challenge, prompting continuous research efforts and international discussions to find solutions. Recently, natural language processing techniques have emerged as a powerful tool for analyzing public opinion and news, providing insights into societal perspectives on climate change. These insights enable policymakers to take informed actions based on the generalization of the model's findings and foster more inclusive, data-driven climate strategies. Analyzing sentiment polarity at the country level is particularly important, as climate change mitigation strategies vary by region. For instance, in Sub-Saharan African countries, afforestation is a key approach to address the climate change issue, whereas in developed nations, reducing industrial carbon emissions remains a primary focus. By leveraging NLP techniques, we can better understand regional attitudes toward climate change and develop targeted solutions that align with the specific needs and priorities of each region. In this paper we have developed sentiment polarity analysis model for Amharic climate change discourse using large language models. For the experiment, we collected a total of 6013 sentences, and the data was annotated into three sentiment classes: negative, positive, and neutral. The experiment was conducted using pre-trained transformer-based models mBERT and AfriBERTa, based on final result analysis using model performance evaluation metrics, mBERT demonstrated better sentiment polarity detection with an accuracy of 69%. The main contributions of this study are the collection and availability of a low-resourced climate change dataset and the analysis of people's perspectives on climate change to identify appropriate mitigation strategies based on regions which helps to advance sentiment analysis in underrepresented languages like Amharic and illustrate how NLP can contribute to localized climate action. Training the models using optimized resources and considering other sources beyond social media for topic diversity as well as to expand the dataset are the future directions of this study.

References

R. Alshamsi, S. Bayari, and S. Salloum. Sentiment analysis in english texts. *Advances in Science, Technology and Engineering Systems Journal*, 5(6):1683–1689, December 2020.

V. S. Anoop and S. Sreelakshmi. Public discourse and sentiment during the mpox outbreak: An analysis using natural language processing. *Public Health*, 28:114–120, 2023. doi: 10.1016/j.puhe.2023.100123.

V. S. Anoop, T. K. Ajay Krishnan, Ali Daud, Ameen Banjar, and Amal Bukhari. Climate change sentiment analysis using domain specific bidirectional encoder representations from transformers. *IEEE Access*, 11: 1–11, 2024. doi: 10.1109/ACCESS.2024.3441310.

Abu Muna Almaududi Ausat. The role of social media in shaping public opinion and its influence on economic decisions. *Technology and Society Perspectives (TACIT)*, 1(1):35–44, 2023.

B. Bhavitha, Anisha P. Rodrigues, and Niranjan N. Chiplunkar. Comparative study of machine learning techniques in sentimental analysis. In *Proceedings of the International Conference on Computing, Communication, Control, and Automation (IC4A)*, pages 1–6, 2017. doi: 10.1109/IC4A.2017.7975191.

Shiv S. Bolan, Lokesh P. Padhye, and Hongyu Wang. Impacts of climate change on the fate of contaminants through extreme weather events. *Environmental Science and Pollution Research*, 29(28):42539–42559, 2022. doi: 10.1007/s11356-022-19718-6.

Mauro Bruno, Monica Scannapieco, Elena Catanese, and Luca Valentino. Italian sentiment analysis on climate change: Emerging patterns from 2016 to today. *Statistical Journal of the IAOS*, 39:189–202, 2023. doi: 10.3233/SJI-220064.

Stuart Capstick, Lorraine Whitmarsh, Wouter Poortinga, Nick Pidgeon, and Paul Upham. International trends in public perceptions of climate change over the past quarter century. *WIREs Climate Change*, 6(1):35–61, 2015. doi: 10.1002/wcc.321.

Pew Research Center. Climate change remains top global threat across 19-country survey. *Pew Research Center*, 2022.

Kevin Clark, Urvashi Khandelwal, Omer Levy, and Christopher D. Manning. What does bert look at? an analysis of bert's attention. In *Proceedings of the ACL Workshop on BlackboxNLP: Analyzing and Interpreting Neural Networks for NLP*, pages 276–286. Association for Computational Linguistics, 2019.

Wändi Bruine de Bruin. Public opinion about climate policies: A review and call for more studies of what people want. *PLOS Climate*, 1(6):1–14, 2022.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of NAACL-HLT 2019*, pages 4171–4186, Minneapolis, Minnesota, June 2 - June 7, 2019, 2019. Association for Computational Linguistics.

International Monetary Fund. Public support for climate change mitigation policies: A cross-country survey. *International Monetary Fund*, 2023.

Bhavika Gupta, Devinder Kaur, and Gaurav Gupta. A review on text sentiment analysis with machine learning and deep learning techniques. *Applied Computational Intelligence and Soft Computing*, 2021:1–20, 2021. doi: 10.1155/2021/7782243.

Yanan Jia and Sony SungChu. A deep learning system for sentiment analysis of service calls. In *Proceedings of the 3rd Workshop on e-Commerce and NLP (ECNLP 3)*, pages 24–34, Seattle, WA, USA, July 2020. Association for Computational Linguistics. doi: 10.18653/v1/2020.ecnlp-1.4.

Shoushan Li and Chengqing Zong. Sentiment classification and polarity shifting. In *Proceedings of the 23rd International Conference on Computational Linguistics (COLING 2010)*, pages 635–643, Beijing, China, August 2010.

Xinya Liao. Sentiment analysis based on machine learning models. *EWA Direct Proceedings*, 1(1):1–6, 2023.

Jindřich Libovický, Rudolf Rosa, and Alexander Fraser. How language-neutral is multilingual bert? In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 1663–1674. Association for Computational Linguistics, 2020. doi: 10.18653/v1/2020.acl-main.151.

Zhewei Mi and Hongwei Zhan. Text mining attitudes toward climate change: Emotion and sentiment analysis of the twitter corpus. *Weather, Climate, and Society*, 15(2):277–292, 2023. doi: 10.1175/WCAS-D-22-0123.1.

Misha Mirza, Stephan G. Lukosch, and Heide K. Lukosch. Twitter sentiment analysis of cross-cultural perspectives on climate change. In *Human-Computer Interaction. Interaction Techniques and Novel Applications*, pages 392–406. Springer, 2023. doi: 10.1007/978-3-031-35936-1_29.

Saif M. Mohammad. A practical guide to sentiment annotation: Challenges and solutions. In *Proceedings of the 12th Conference on Language Resources and Evaluation (LREC 2020)*, Marseille, France, 2020. European Language Resources Association (ELRA).

Anmol Nayak, Hari P. Timmapathini, Karthikeyan Ponnalagu, and Vijendran Venkoparao. Domain adaptation challenges of bert in tokenization and sub-word representations of out-of-vocabulary words. In *Proceedings of the First Workshop on Insights from Negative Results in NLP*, pages 1–5. Association for Computational Linguistics, November 2020. ISBN 978-1-952148-66-8.

Gebregziabihier Nigusie and Tegegne Tesfa. Lexical complexity detection and simplification in amharic text using machine learning approach. In *2022 International Conference on Information and Communication Technology for Development for Africa (ICT4DA)*. IEEE, 2022.

Kelechi Ogueji, Yuxin Zhu, and Jimmy Lin. Small data? no problem! exploring the viability of pretrained multilingual language models for low-resource languages. In *Findings of the Association for Computational Linguistics: EMNLP 2021*, pages 2433–2444. Association for Computational Linguistics, 2021. doi: 10.18653/v1/2021.findings-emnlp.209.

United Nations Framework Convention on Climate Change. Summary of global climate action at cop 29. Technical report, 2024.

Rafael M. Santos and Reza Bakhshoodeh. Climate change/global warming/climate emergency versus general climate research: comparative bibliometric trends of publications. *Heliyon*, 7(11):1–15, 2021. doi: 10.1016/j.heliyon.2021.e08219.

Binyam Ephrem Seyoum, Yusuke Miyao, and Baye Yimam Mekonnen. Comparing neural network parsers for a less-resourced and morphologically-rich language: Amharic dependency parser. In *Proceedings of the First Workshop on Resources for n Indigenous Languages (RAIL)*, pages 25–30, Marseille, France, May 2020. European Language Resources Association (ELRA).

Nabila Mohamad Sham and Azlinah Mohamed. Climate change sentiment analysis using lexicon, machine learning, and hybrid approaches. *Sustainability*, 14(8):4723, 2022. doi: 10.3390/su14084723.

T. E. Taufek, N. F. Mohd Nor, A. Jaludin, S. Tiun, and K. C. Lam. Public perceptions on climate change: A sentiment analysis approach. *GEMA Online® Journal of Language Studies*, 21(4):209–233, 2021. doi: 10.17576/gema-2021-2104-11.

UNFCCC. Summary of global climate action at cop 28. Technical report, 2023.

Athanasios Valavanidis. Global warming and climate change. fossil fuels and anthropogenic activities have warmed the earth's atmosphere, oceans, and land. *ResearchGate*, 2025.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. In *Advances in Neural Information Processing Systems (NeurIPS)*, volume 30. Curran Associates, Inc., 2017.

M. Wankhade, A. C. Rao, and Chaitanya Kulkarni. A survey on sentiment analysis methods, applications, and challenges. *Artificial Intelligence Review*, 55(1):1–25, 2022. doi: 10.1007/s10462-022-10144-1.

Ifeoluwa Wuraola, Nina Dethlefs, and Daniel Marciniak. Linguistic pattern analysis in the climate change-related tweets from uk and nigeria. In *Proceedings of the 2023 CLASP Conference on Learning with Small Data (LSD)*, pages 90–97. Association for Computational Linguistics, 2023.

Seid Muhie Yimam, Abinew Ali Ayele, Gopalakrishnan Venkatesh, Ibrahim Gashaw, and Chris Biemann. Introducing various semantic models for amharic: Experimentation and evaluation with multiple tasks and datasets. *Future Internet*, 13(11):275, 2021. doi: 10.3390/fi13110275.