Climate Change in Your Backyard: The Role of Local Governments

Supplementary Table 1. Climate change discourse in local government meetings (BERT sentiment)

	DV: Sentiment Gap			
	(1)	(2)	(3)	(4)
Heat Index	-0.0005 (0.0008)			
Environment Stress Index		-0.0006 (0.001)		
WBGT JME			-0.0006 (0.001)	
Ratio of Conservatives	0.014 (0.044)	0.015 (0.044)	0.015 (0.044)	0.015 (0.044)
Constant	0.265*** (0.025)	0.264*** (0.025)	0.265*** (0.026)	0.262*** (0.024)
District FE	√	√	√	√
Month FE	√	√	√	√
Year FE	√	√	√	√
N	15117	15117	15117	15117

District-clustered standard errors: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

To validate the findings from Analysis 2, this study employed BERT (Bidirectional Encoder Representations from Transformers), a transformer-based architecture pre-trained on large-scale text corpora to capture both word-level context and sentence-level nuances (Devlin et al., 2019). Given its capability to perform contextualized sentiment analysis, BERT was fine-tuned specifically for sentiment classification in Korean.

The fine-tuning process utilized a comprehensive sentiment lexicon derived from three widely recognized datasets: (1) the Korean Movie Review dataset (146,182 reviews), (2) the Korean Sentiment Analysis Corpus from Seoul National University (7,713 sentences extracted from news articles), and (3) the Kunsan National University Sentiment Lexicon (14,843 idioms and sentence structures). Fine-tuning was conducted using Python's Hugging Face transformer library, with a batch size of 32, a learning rate of 2e-5 (optimized via Adam), and three training epochs.

Following training, the model tokenized each speech into sentences and assigned sentiment scores (positive = 1, others = 0) based on both word and sentence contexts. These sentence-level scores were then aggregated to determine the overall sentiment of each speech, which was subsequently averaged by month to generate a time-series sentiment measure.

To assess the reliability of the model, a human annotation process was conducted on a randomly selected subset of 2,000 articles. The sentiment labels assigned by human annotators were compared against those generated by the BERT model, using the combined sentiment lexicon datasets. The comparison revealed an 82% agreement between the model's predictions and human annotations. Additionally, inter-rater reliability among human annotators was assessed, yielding a Cohen's kappa of 0.82, which further validated the consistency of human annotations. The results obtained from BERT-based sentiment analysis are presented in Table B1.

Supplementary Table 2. Prompt (in Korean)

```
import torch
import pandas as pd
from transformers import AutoTokenizer, AutoModelForSequenceClassification

# ===== Step 1: Load Llama 3 Model & Tokenizer =====
MODEL_NAME = "meta-llama/Llama-3-7B"  # Change if needed
tokenizer = AutoTokenizer.from_pretrained(MODEL_NAME)
model = AutoModelForSequenceClassification.from_pretrained(MODEL_NAME)

# Force CPU execution to avoid GPU issues
device = torch.device("cpu")
model.to(device)

# ===== Step 2: Load Excel Data =====
file_path = "/mnt/data/sentiment_data.xlsx"  # Ensure this file is uploaded here
df = pd.read_excel(file_path)

# Ensure 'speech' column exists
if 'speech' not in df.columns:
    raise ValueError("The column 'speech' is missing from the dataset.")

# ===== Step 3: Function for Sentiment Classification =====
def classify_sentiment(text):
    prompt = (
        "분석 대상: 주어진 문장에서 기초단체의원에 대한 감정을 분류하세요.\n"
        "규칙:\n"
        "- 긍정적인 언어: 긍정적인 내용을 포함하는 경우.\n"
        "- 중립적인 언어: 감정적 편향이 거의 없거나 사실을 서술하는 경우.\n"
        "- 부정적인 언어: 부정적인 내용을 포함하는 경우.\n\n"
        "문장:\n"
        f"{text}\n"
        "위 문장의 감정 분류 결과를 제공합니다:"
    )

    # Tokenizing input text
```

```
    inputs = tokenizer(prompt, return_tensors="pt", truncation=True, padding=True).to(device)

    # Perform inference without computing gradients
    with torch.no_grad():
        outputs = model(**inputs)
        logits = outputs.logits
        predicted_class = torch.argmax(logits, dim=1).item()

    # Sentiment Mapping
    if predicted_class == 0:
        return 1  # Positive
    elif predicted_class == 1:
        return 0  # Neutral
    else:
        return -1  # Negative

# ===== Step 4: Apply Sentiment Classification to Each Row =====
df["sentiment"] = df["speech"].apply(classify_sentiment)

# ===== Step 5: Save the Updated DataFrame =====
output_file = "/mnt/data/sentiment_classified.xlsx"
df.to_excel(output_file, index=False)

# ===== Step 6: Display & Provide Download Link =====
import ace_tools as tools
tools.display_dataframe_to_user(name="Sentiment Classification Results", dataframe=df)

# Provide a download link
print(f"Download classified data: {output_file}")
```

Supplementary Table 3. Party classification

	Party	Description	Note
1	Conservatives	Conservative parties were coded as a single conservative group, Similarly, Democratic Party of Korea, other liberal and left-leaning parties were coded as a single liberal groups. Conservative parties: (국민의힘 (People Power Party), 미래통합당 (United Future Party), 미래한국당 (Future Korea Party), 새누리당 (Saenuri Party), 자유한국당 (Liberty Korea Party), 바른정당 (Bareun Party), 바른미래당 (Bareunmirae Party), 국민의당 (People's Party)) * In the context of Korean politics, the People Power Party, despite undergoing several name changes over time—including Democratic Liberal Party (민주자유당), Grand National Party (한나라당), United Liberal Democrats (자유민주연합), United Future Party (미래통합당), Future Korea Party (미래한국당), Saenuri Party (새누리당), and Liberty Korea Party (자유한국당)—are widely regarded as a single, continuous political entity.	
2	Liberals	Liberal, Left-leaning parties: (더불어민주당 (Democratic Party of Korea), 더불어시민당 (Citizen's Party of Korea), 민주당 (Democratic Party), 민주통합당 (Democratic United Party), 새정치민주연합 (New Politics Alliance for Democracy), 열린민주당 (Open Democratic Party), 민생당 (Minsaengdang), 정의당 (Justice Party), 진보당 (The Progressive Party), 통합진보당 (The Unified Progressive Party)	

		** In the context of Korean politics, the Democratic Party of Korea, despite undergoing several name changes over time—including the Democratic Party (민주당), Democratic United Party (민주통합당), National Congress for New Politics (새정치민주회의), New Politics Alliance for Democracy (새정치민주연합), and Open Democratic Party (열린민주당)—are widely recognized as a single, continuous political entity.	

Supplementary Table 4. Data information

	Data	Description	Source
1	Heat Index (HI)	The Heat Index (HI) represents the perceived temperature by considering both air temperature and relative humidity. It is commonly used in meteorology to assess human thermal comfort. Formula: $HI = c_1 + c_2T + c_3RH + c_4TRH + c_5T^2 + c_6RH^2 + c_7T^2RH + c_8TRH^2 + c_8T^2RH^2$ Where: - HI = Heat Index (℉) - T = Air temperature (℉) - RH = Relative humidity (%) - c_1=-42.379, c_2=2.04901523, c_3=10.14333127. c_4 =-0.22475541. c_5 =-0.00683783, c_6 =-0.05481717. c_7=0.00122874. c_8=0.00085282. c_9=-0.00000199	https://www.ecmwf.int/en/era5-land
2	Environment Stress Index (ESI)	The Environmental Stress Index (ESI) is a composite indicator that integrates multiple meteorological variables, including temperature, humidity, wind speed, and solar radiation, to estimate environmental heat stress on humans. Formula: *ESI = 0.63T+0.03RH+0.002SR-0.0054WS-5.74* Where: - T = Air temperature (℉) - RH = Relative humidity (%) - SR = Solar radiation (W/m²) - WS = Wind speed (m/s)	https://www.ecmwf.int/en/era5-land
3	WBGT JME	The Wet Bulb Globe Temperature (WBGT) is one of the most widely used heat stress indices, incorporating temperature, humidity, wind speed, and solar radiation. The JME version (WBGT JME) refers to a modified version of WBGT based on the Joint Meteorological Evaluation standards. The JME model calculates WBGT using the following formula:	https://www.ecmwf.int/en/era5-land

		$WBGT_{JME} =$ $0.735T_{\alpha} + 0.0347RH + 0.0022T_{\alpha}RH + 7.619SR - 4.557SR^2 - 0.0572WS - 4.064$ Where: - T_{α} = Air temperature (℃) - RH = Relative humidity (%) - SR is the total solar radiation (kW/m²) - WS is the wind speed (m/s)	
4	Political Composition	$\frac{Conservative\ members}{Total\ council\ members\ of\ local\ government}$	https://clik.nanet.go.kr/potal/search/searchList.do
5	Meeting minutes of local government	Meeting minutes of 226 local government	https://clik.nanet.go.kr/potal/search/searchList.do?collection=minutes&searchSelect=Y#

Differences Among Climate-related Indices and Their Measurement

While all three indices are designed to assess climate-related environmental conditions, they capture different aspects of climate change:

- Scope of Measurement: ESI integrates multiple climatic factors to provide a broader assessment of environmental stress, making it useful for analyzing overall climate variability[45]. HI, in contrast, is more focused on human thermal comfort, emphasizing perceived temperature rather than broader climate dynamics. WBGT JME is specifically designed for heat stress evaluation in occupational and outdoor environments, making it particularly relevant for safety standards in extreme heat conditions.
- Sensitivity to Climate Change: ESI is a holistic measure that reflects long-term environmental stress trends influenced by climate change, while HI is more reactive to short-term variations

in temperature and humidity, such as heat waves[45]. WBGT JME is crucial for understanding localized impacts of rising temperatures, particularly in urban and industrial settings where heat exposure poses significant health risks.

- Application in Policy and Analysis: ESI is often used in ecological and environmental studies to assess climate-driven stress on populations and ecosystems. HI is widely utilized in public health and emergency preparedness, helping authorities issue heat advisories. WBGT JME is used for workplace safety regulations and athletic training guidelines, providing direct implications for labor and sports-related activities.

These distinctions highlight the complementary nature of the indices in capturing various dimensions of climate change. By incorporating all three, this study ensures a comprehensive analysis of how climate variability influences political discourse and governance at the local level.

Supplementary Table 5. Descriptive statistics

Variable	N	Mean	Std dev	Min	Median	Max
HI	98250	12.185	10.399	-15.23	12.712	40.932
ESI	98250	5.787	5.575	-9.75	6.164	16.722
WBGT JME	98250	10.667	8.799	-11.835	11.081	26.128
Political composition	98250	0.532	0.247	0.1	0.6	0.9
Climate Change Mentions	98250	0.718	1.269	0	0	10
Sentiment Gap	15117	0.113	0.094	0	0.117	0.395