Enhancing Science Data Literacy Through Interactive Analysis of the Keeling Curve: A Case Study with Science-Gifted Students

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Abstract

Climate change education requires students to develop data literacy skills to critically evaluate evidence. This study presents a Python-based educational approach using authentic atmospheric carbon dioxide (CO_2) data from the Keeling Curve to develop Earth science data literacy among secondary school students. Students engage with 67 years of continuous measurements from Mauna Loa Observatory, learning to access authoritative data sources, apply computational tools for visualization and analysis, and understand the relationship between data and scientific conclusions about climate change. Assessment results demonstrate significant improvements in students' ability to interpret scientific data and understand measurement uncertainty (Gould, Machado, Ong, Johnson, Molyneux, Nolen, Tangmunarunkit, Trusela, & Zanontian, 2016; Kjelvik & Schultheis, 2019).

Introduction

Background: The Keeling Curve, documenting atmospheric CO_2 concentrations since 1958, provides one of the most powerful datasets for climate change education (Keeling, Bacastow, Bainbridge, Ekdahl, Guenther, Waterman, & Chin, 1976; Keeling, 1960). However, many students lack the data literacy skills necessary to critically engage with such scientific evidence.

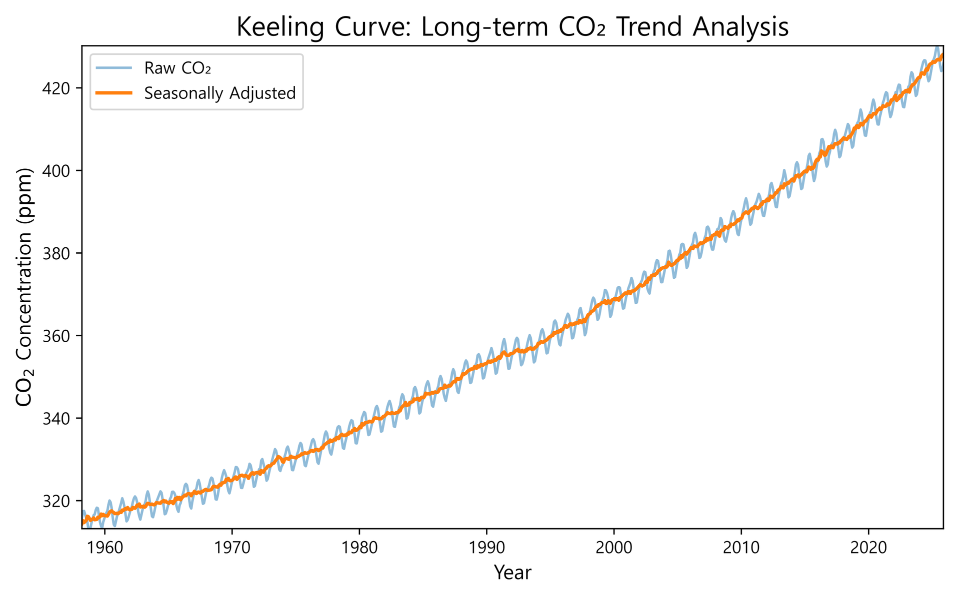

Fig. 1: Example of Keeling Curve visualization showing seasonal variation and long-term trend

Why Data Literacy Matters: Data literacy—the ability to read, work with, analyze, and argue with data (Wolff, Gooch, Cavero Montaner, Rashid, & Kortuem, 2016)—is essential for understanding climate science. Students must move beyond passive consumption to actively engage with primary data sources (National Research Council, 2012).

Role of Computation: Python and Jupyter notebooks provide accessible tools for students to engage with authentic scientific datasets, developing both conceptual understanding and practical skills (Barba, Barker, Blank, Brown, Downey, George, Heagy, Mandli, Moore, Lippert, et al., 2019; Weintrop, Beheshti, Horn, Orton, Jona, Trouille, & Wilensky, 2016).

Educational Framework

1. Learning Objectives Students will be able to:

- Access and evaluate authoritative scientific data sources
- Apply Python tools for data visualization and analysis
- Interpret temporal patterns in atmospheric CO_2 data
- Understand the relationship between data and climate science conclusions

2. The 5E Instructional Model This module follows the evidence-based 5E framework (Bybee, Taylor, Gardner, Van Scotter, Powell, Westbrook, & Landes, 2006):

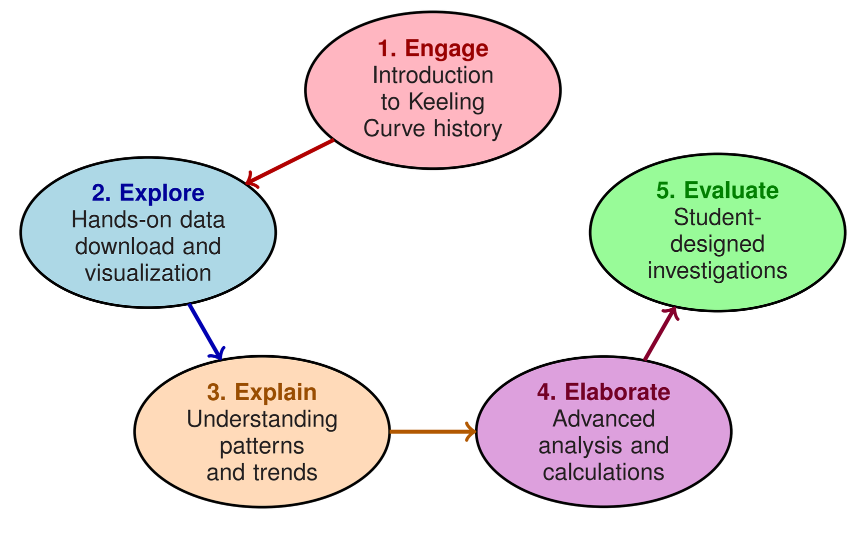

Fig. 2: The 5E instructional model used in this module

3. Alignment with Standards This approach aligns with Next Generation Science Standards (NGSS), emphasizing science practices, particularly analyzing and interpreting data (National Research Council, 2012; NGSS Lead States, 2013).

4. The Keeling Curve Dataset The Scripps CO_2 Program's continuous atmospheric measurements provide the longest high-precision record of atmospheric carbon dioxide, serving as the foundation for understanding anthropogenic climate change. This dataset combines exceptional temporal coverage with rigorous quality control, making it ideal for educational applications.

- **Source:** Scripps CO_2 Program, Mauna Loa Observatory
- **Duration:** 1958-present (67 years of continuous data)
- **Significance:** Shows both seasonal variation and long-term trend (Keeling, Bacastow, Bainbridge, Ekdahl, Guenther, Waterman, & Chin, 1976; Thoning, Tans, & Komhyr, 1989)
- **Current level:** 422.5 ppm (parts per million; 52% above pre-industrial)

Methodology

Technical Implementation

- **Platform:** Jupyter Notebook with Python 3.8+
- **Libraries:** pandas, matplotlib, numpy
- **Cloud Option:** Google Colab for easy access
- **Data Source:** Scripps CO_2 Program

Student Learning Activities

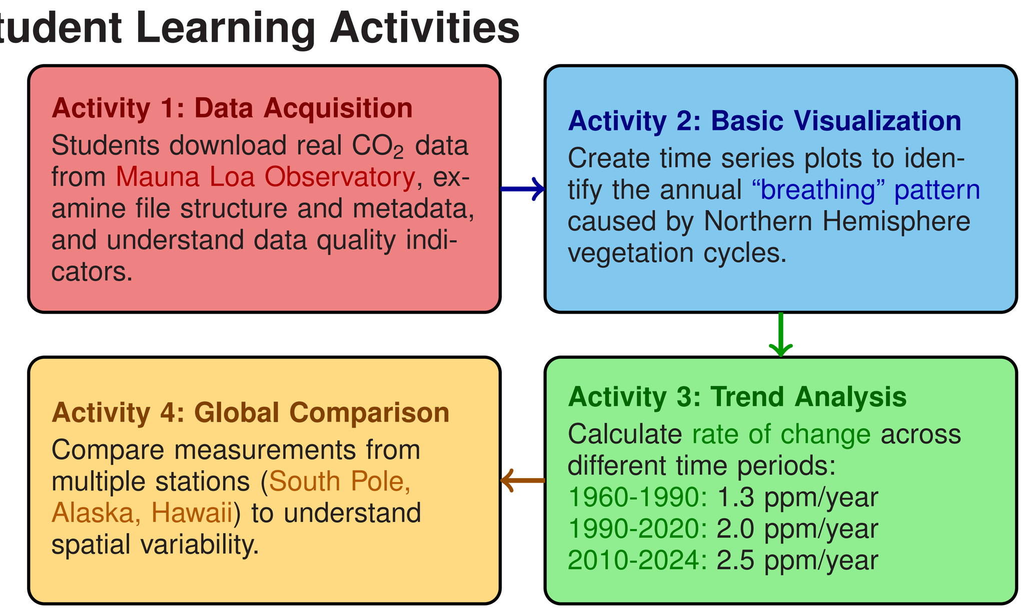

Fig. 3: Student learning activities aligned to the 5E cycle

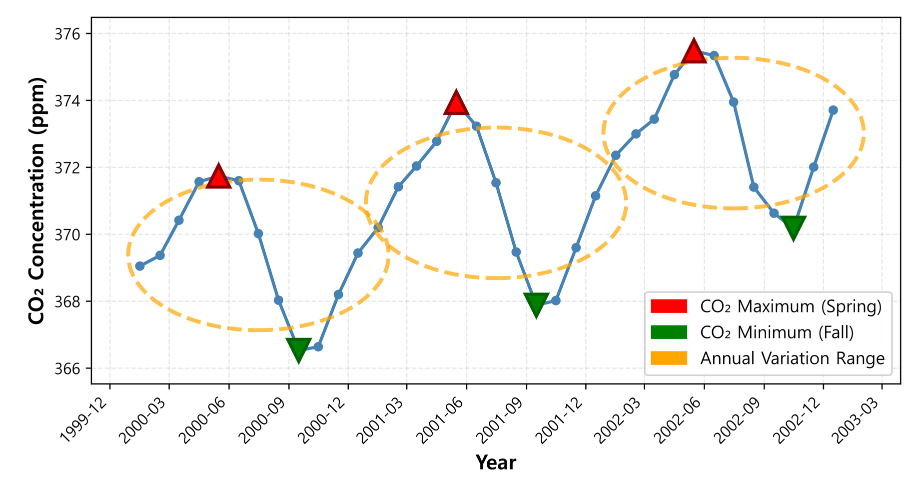

Fig. 4: Keeling Curve: Seasonal Variation Detail (2000-2002) Understanding Earthś "Breathing" Pattern

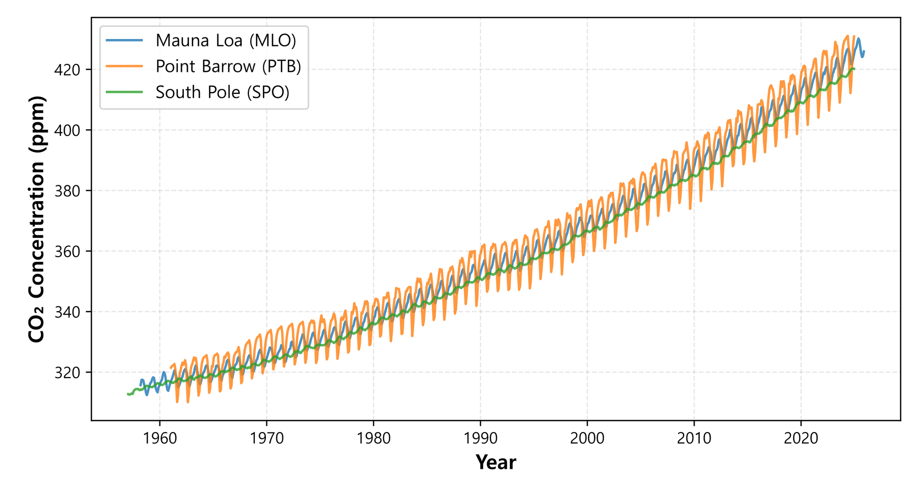

Fig. 5: Comparison of atmospheric CO_2 across Mauna Loa, Point Barrow, and the South Pole

Science Data Literacy Developm

Critical Thinking Questions Throughout the activities, students engage with questions that develop analytical thinking (Chinn & Malhotra, 2002):

- Why was Mauna Loa chosen as the measurement location?
- What causes the annual "breathing" pattern in CO_2?
- How does the rate of increase compare across decades?
- How can we distinguish natural variation from human-caused trends?

Key Science Data Literacy Skills Developed

1. **Data Source Evaluation**
   - Verifying data provenance (Scripps Institution)
   - Understanding measurement methodology
   - Recognizing authoritative vs unreliable sources
2. **Data Quality Understanding**
   - Handling missing data
   - Understanding measurement precision (± 0.3 ppm)
   - Recognizing quality control procedures
3. **Statistical Interpretation**
   - Distinguishing trend from variation
   - Calculating rates of change
   - Understanding seasonal adjustment
4. **Computational Skills**
   - Loading and processing CSV data with pandas
   - Creating publication-quality visualizations
   - Writing Python code for analysis

Real-World Connections Students contextualize their findings (Monroe, Plate, Oxarart, Bowers, & Chaves, 2019):

- Pre-industrial CO_2: 280 ppm
- Start of Keeling measurements (1958): 315 ppm
- Current level (2024): 422.5 ppm
- **52% increase since industrial revolution**

Results

Student Learning Outcomes Assessment of 36 12th-grade students at a science-gifted high school who completed the module showed significant improvements across multiple dimensions (Pellegrino, 2013).

Conceptual Understanding:

- Correctly explained seasonal CO_2 oscillations
- Identified the long-term increasing trend
- Successfully calculated rate of change across decades
- Explained why Mauna Loa is appropriate for measurements

Data Literacy Skills:

- Demonstrated ability to access authoritative data sources
- Correctly interpreted data quality indicators
- Distinguished raw vs seasonally-adjusted data
- Created appropriate visualizations

Computational Competency: Students successfully executed Python code, modified code to answer new questions, wrote original code for calculations, and understood DataFrame operations.

Engagement Metrics: Engagement increased across several indicators: higher interest in climate science, preference for real data over textbook examples, and expressed interest in using Python for future projects.

Discussion & Conclusions

Strengths of the Approach

- **Authentic Science:** Using real data from authoritative sources (Scripps Institution) provides genuine scientific experience (Kjelvik & Schultheis, 2019)
- **Scaffolded Learning:** Progressive complexity allows diverse learners to engage at appropriate levels
- **Interdisciplinary:** Integrates Earth science, mathematics, computer science, and communication
- **Evidence-Based:** Students see climate change in data, not just rhetoric (IPCC, 2021)

Challenges and Solutions

- *Challenge:* Limited programming experience
  Solution: Provide pre-written code cells; use cloud platforms (Google Colab)
- *Challenge:* Time constraints
  Solution: Modular design allows flexible implementation
- *Challenge:* Mathematical prerequisites
  Solution: Visual explanations before formal treatment

Key Findings

1. Students successfully engage with authentic scientific datasets using computational tools (Weintrop, Beheshti, Horn, Orton, Jona, Trouille, & Wilensky, 2016)
2. Direct data interaction significantly enhances understanding of climate evidence
3. Data literacy skills are transferable to other scientific contexts and align with NGSS standards for science practices (NGSS Lead States, 2013)

Broader Significance This approach demonstrates that climate change education can move beyond passive information consumption to active scientific inquiry. By developing data literacy through the iconic Keeling Curve dataset, students gain both conceptual understanding and practical skills essential for 21st-century citizenship (Monroe, Plate, Oxarart, Bowers, & Chaves, 2019).

Future Directions

- Integration with temperature, ocean, and ice datasets
- Machine learning applications for predictive modeling
- Web-based interfaces for broader accessibility
- Cross-cultural adaptation and translation

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Data Availability: All Jupyter notebooks and educational materials are available at: `https://github.com/Kiehyun/ISCCE2026`

Atmospheric CO_2 data courtesy of Scripps CO_2 Program, Scripps Institution of Oceanography, UC San Diego (https://scrippsco2.ucsd.edu/).