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 data literacy to critically evaluate evidence. This study presents a Python-based module using authentic atmospheric carbon dioxide (CO_2) data from the Keeling Curve to build science data literacy in science-gifted high school students. Students analyze 67 years of Mauna Loa measurements, learn to access authoritative sources, apply computational visualization and analysis, and connect data to climate change conclusions. Assessments of 36 12th-grade students indicated improved ability to interpret scientific data and reason about measurement uncertainty.

Keywords: climate change education; science data literacy; Keeling Curve; Python; science-gifted students.

Introduction

Background: The Keeling Curve has documented atmospheric CO_2 since 1958 and is a cornerstone dataset for climate change education (Keeling, Bacastow, Bainbridge, Ekdahl, Guenther, Waterman, & Chin, 1976; Keeling, 1960). Yet many students lack the data literacy needed to critically engage with such evidence.

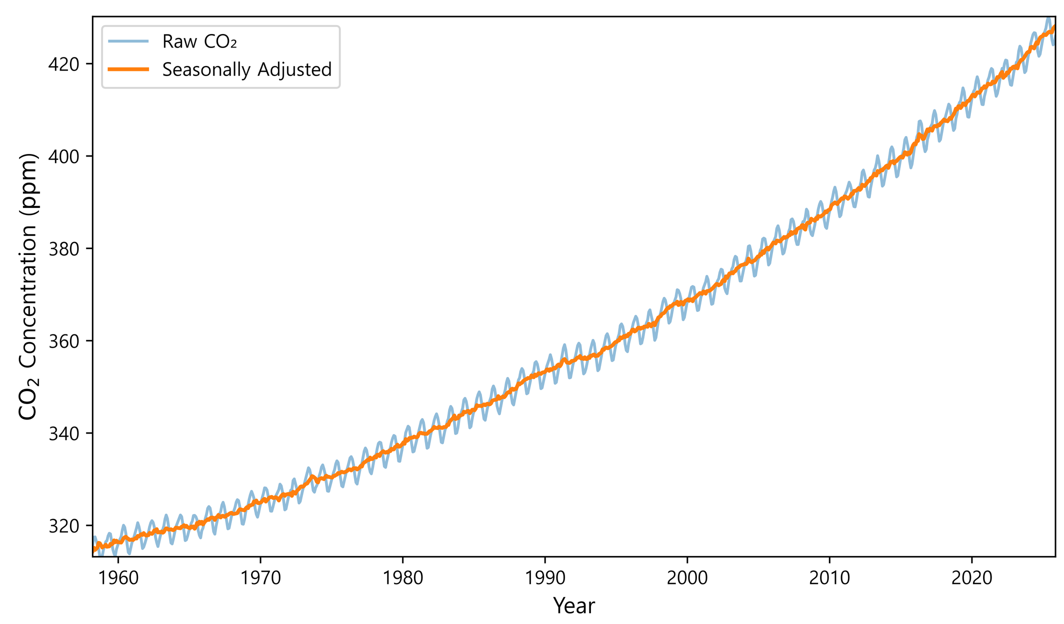

Fig. 1: Example of Keeling Curve visualization showing seasonal variation and long-term trend

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 and actively engage with primary data sources (National Research Council, 2012).

Role of Computation: Python and Jupyter notebooks make authentic datasets accessible and support 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 instructional framework (Bybee, Taylor, Gardner, Van Scotter, Powell, Westbrook, & Landes, 2006):

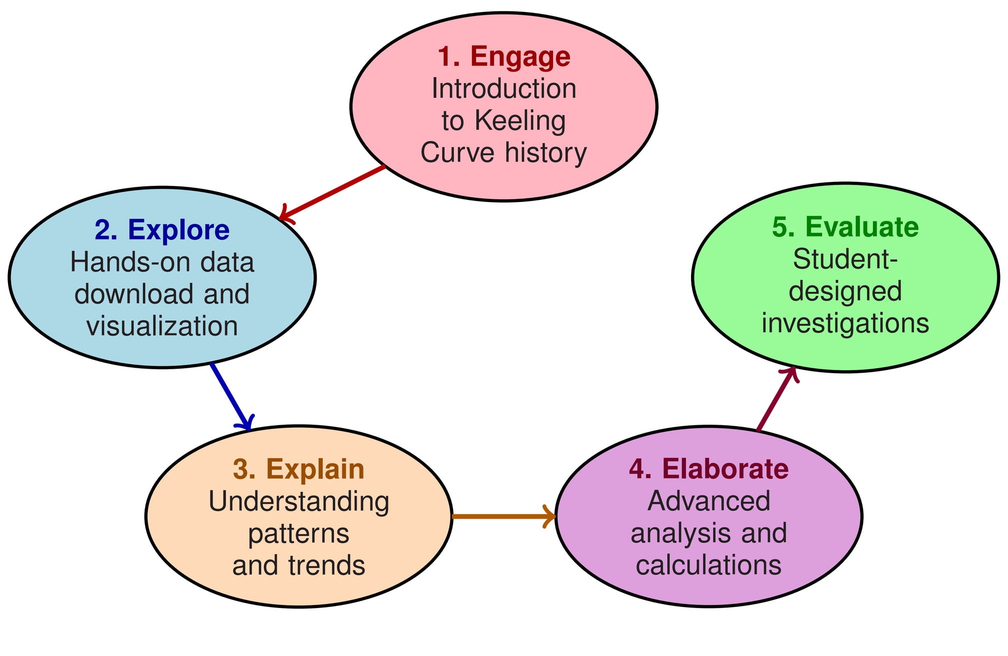

Fig. 2: The 5E instructional model used in this module

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 provides the longest high-precision record of atmospheric carbon dioxide and underpins understanding of anthropogenic climate change. Its long time span and rigorous quality control make it well suited 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

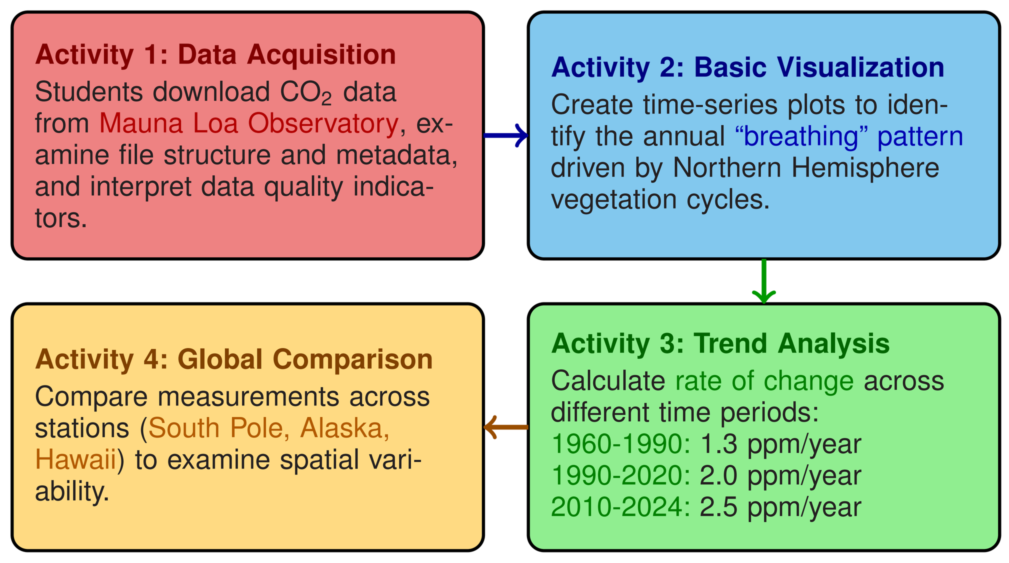

Fig. 3: Student learning activities aligned to the 5E cycle

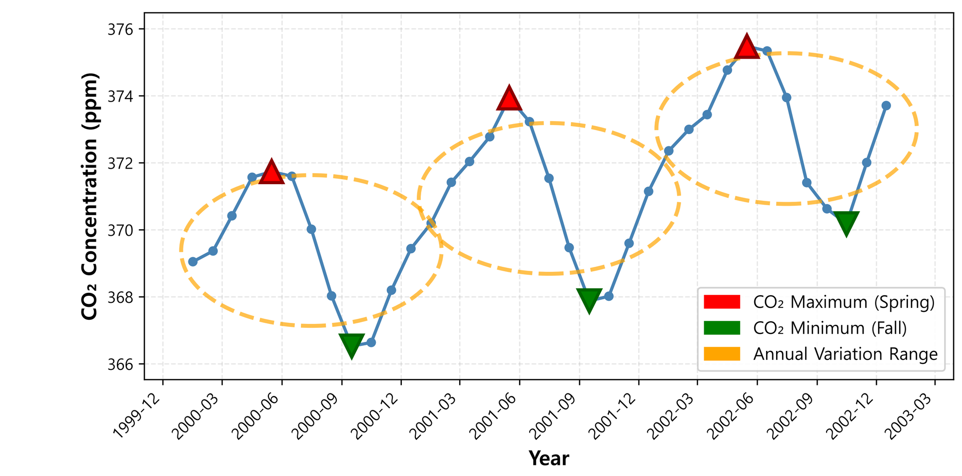

Fig. 4: Keeling Curve seasonal variation detail (2000-2002): understanding Earth́s "breathing" pattern

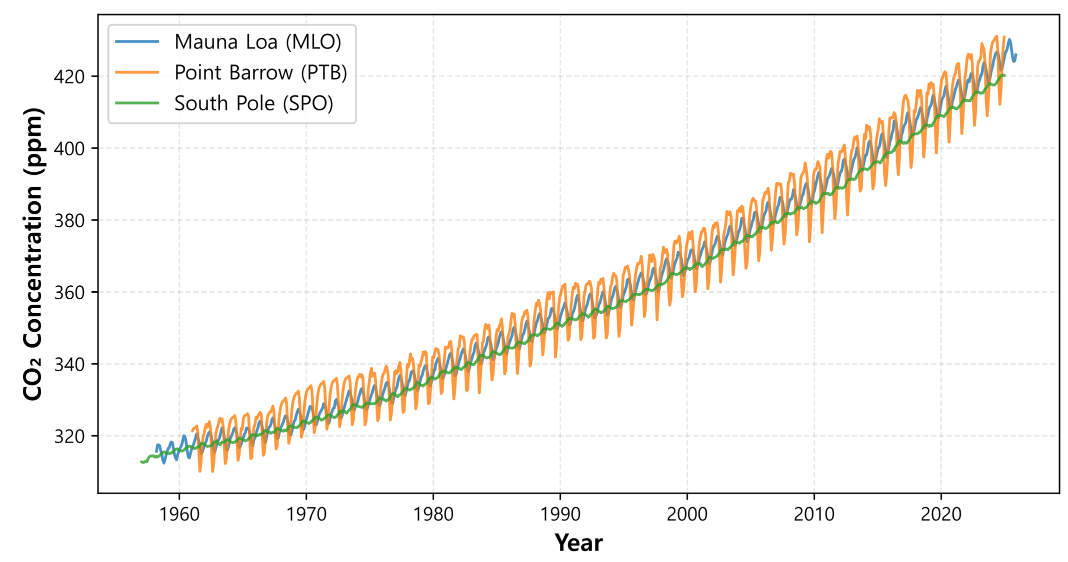

Fig. 5: Comparison of atmospheric CO_2 across Mauna Loa, Point Barrow, and the South Pole

Science Data Literacy Development

Critical Thinking Questions Throughout the activities, students address questions that cultivate 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 situate their findings in real-world benchmarks (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 the Industrial Revolution**

Results

Student Learning Outcomes Assessments of 36 12th-grade students at a science-gifted high school showed significant gains 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 executed Python code, modified it to answer new questions, wrote original code for calculations, and applied DataFrame operations.

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

Discussion & Conclusions

Strengths of the Approach

- **Authentic Science:** Using real data from authoritative sources (Scripps Institution) provides authentic scientific experience (Kjelvik & Schultheis, 2019)
- **Scaffolded Learning:** Progressive complexity allows learners to engage at appropriate levels
- **Interdisciplinary:** Integrates Earth science, mathematics, computer science, and communication
- **Evidence-Based:** Students see climate change in data rather than 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 engage successfully with authentic scientific datasets using computational tools (Weintrop, Beheshti, Horn, Orton, Jona, Trouille, & Wilensky, 2016)
2. Direct interaction with data 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 shows that climate change education can move beyond passive information consumption to active scientific inquiry. By building data literacy with the Keeling Curve dataset, students gain 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/blob/main/appendix/The_Keeling_Curve_in_Action.ipynb

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