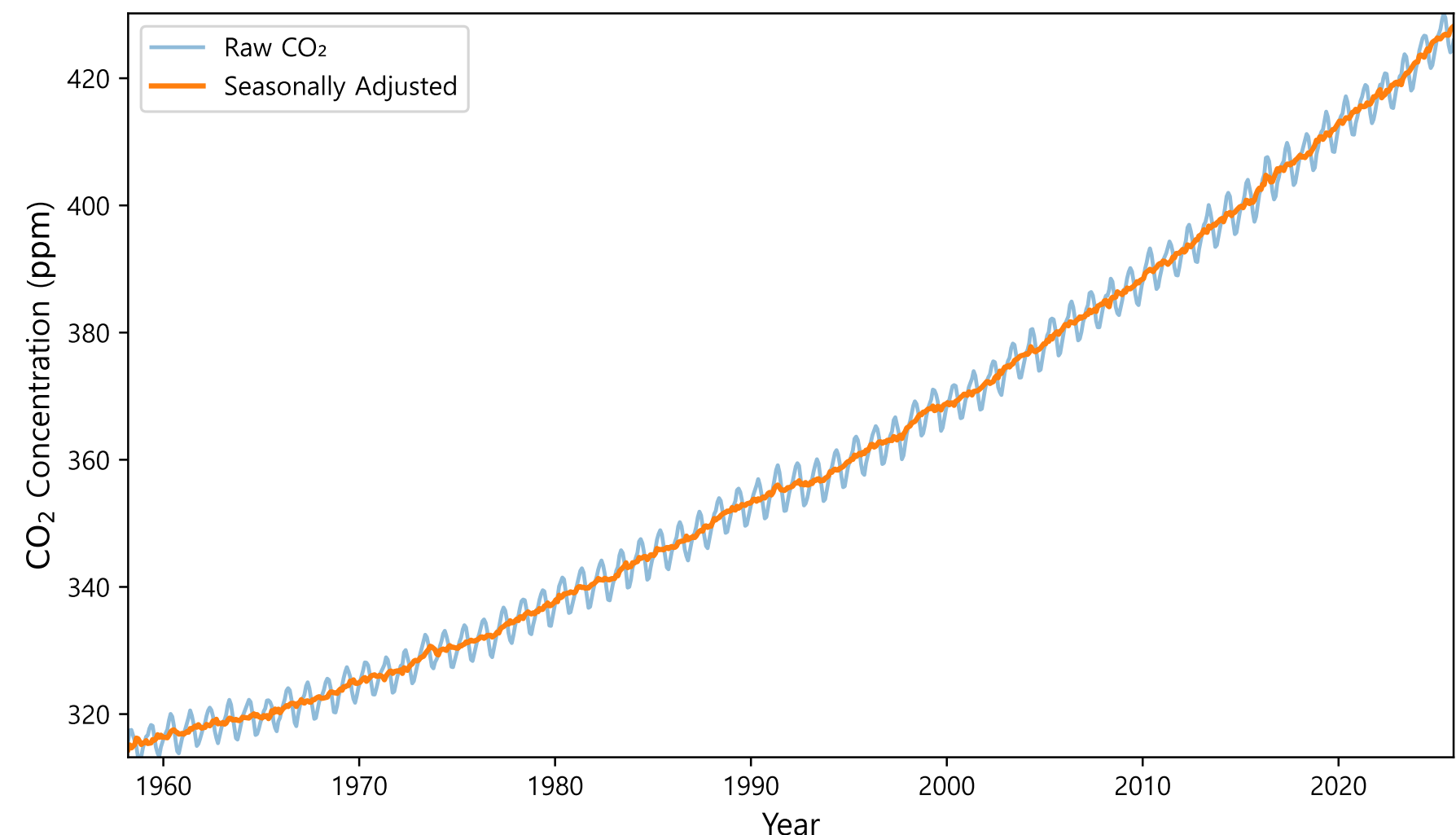


## Abstract

Climate change education requires data literacy to critically evaluate evidence. This study presents a Python-based module using authentic atmospheric carbon dioxide (CO<sub>2</sub>) data from the Keeling Curve to build science data literacy in secondary 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 show significant gains in interpreting scientific data and understanding measurement uncertainty (Gould, Machado, Ong, Johnson, Molyneux, Nolen, Tangmunarunkit, Trusela, & Zanonian, 2016; Kjellvik & Schultheis, 2019).

## Introduction

**Background:** The Keeling Curve has documented atmospheric CO<sub>2</sub> 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, Caverio 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).

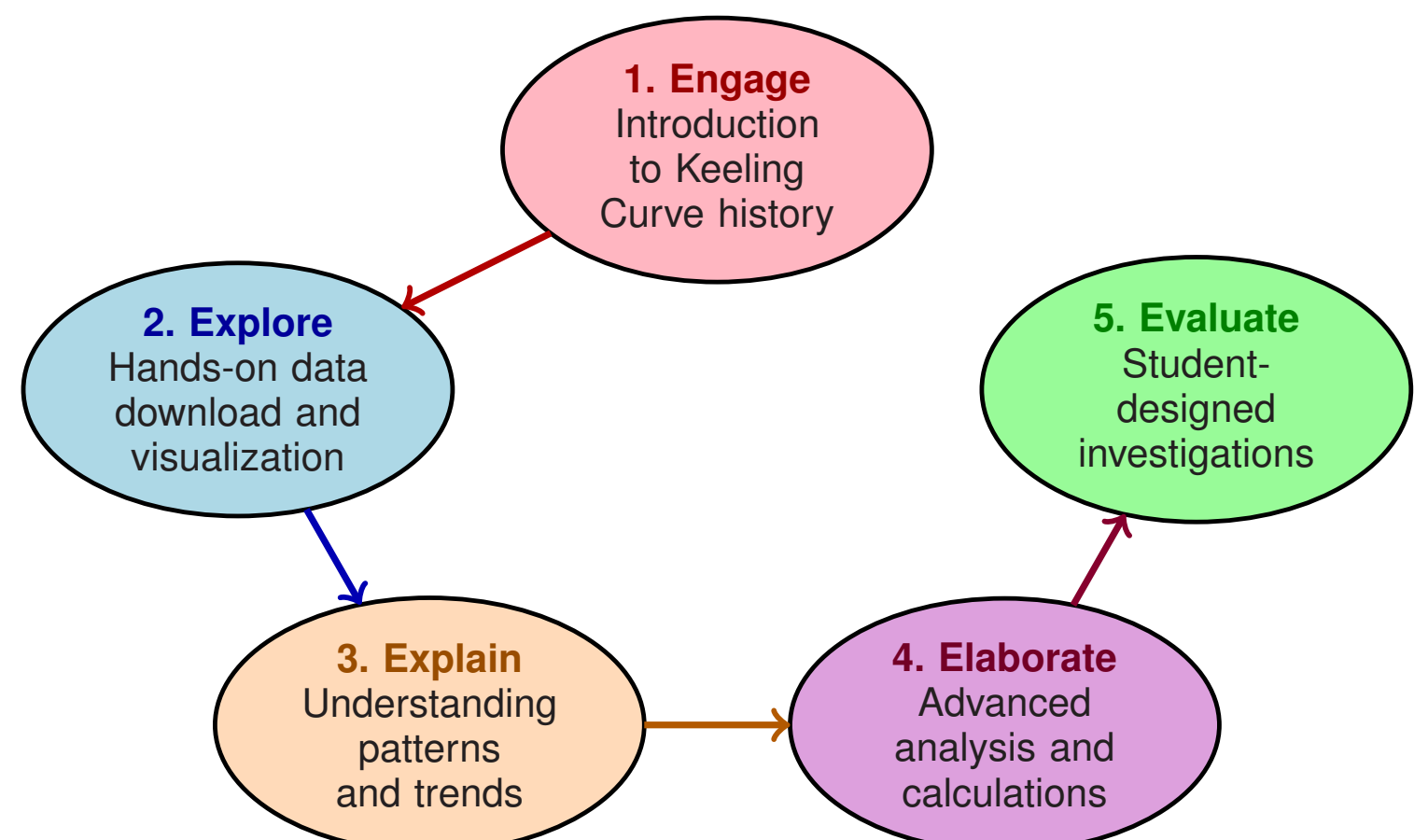
**Role of Computation:** Python and Jupyter notebooks make authentic datasets accessible and support both conceptual understanding and practical skills (Barba, Barker, Blank, Brown, Downey, George, Heagy, Mandli, Moore, Lippert, et al., 2019; Weintrop, Beheshti, Horn, Orton, Jona, Trouille, & Wilensky, 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<sub>2</sub> 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<sub>2</sub> 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.

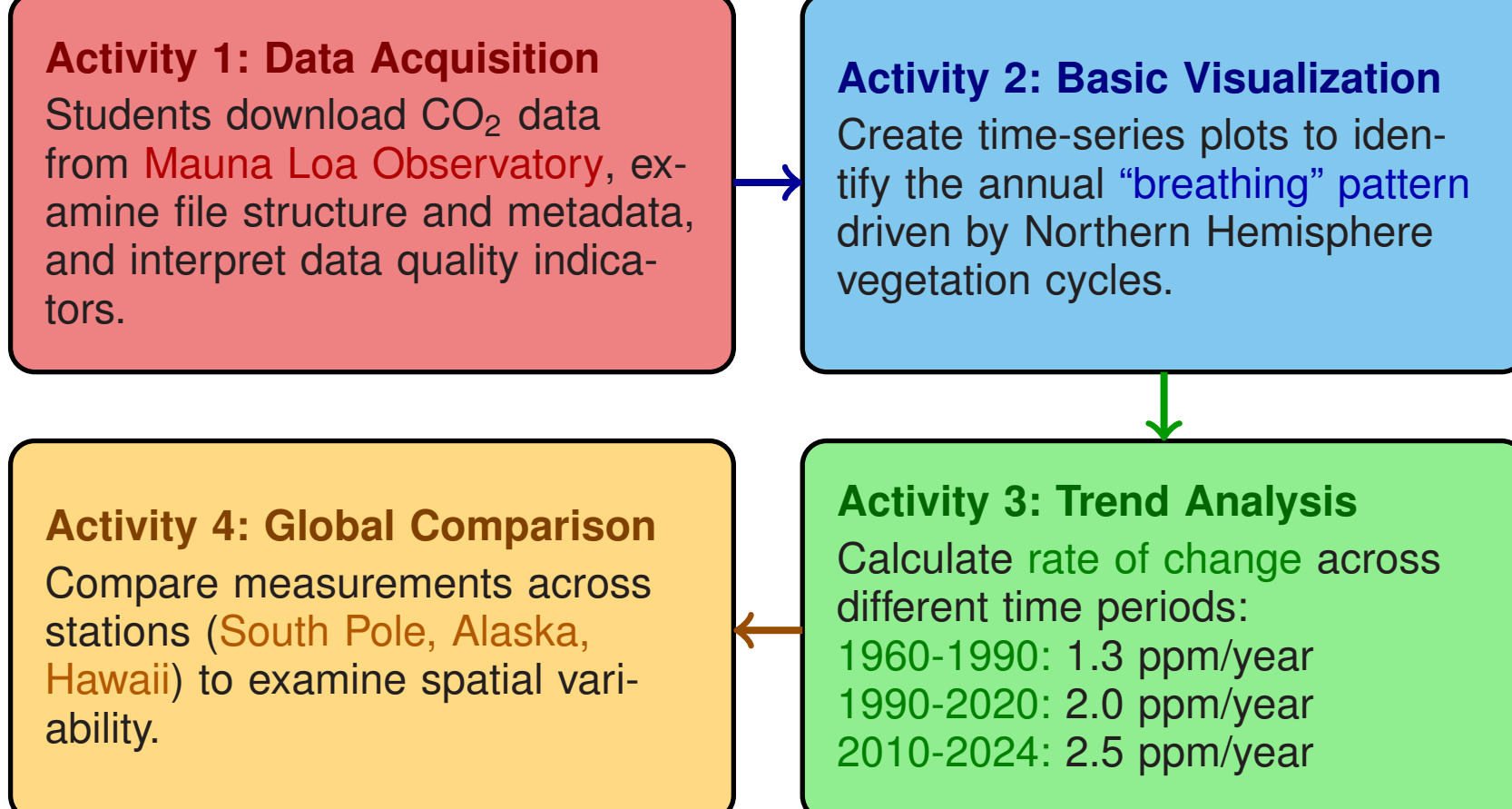
- Source:** Scripps CO<sub>2</sub> Program, Mauna Loa Observatory
- Duration:** 1958-present (67 years of continuous data)
- Significance:** Shows both seasonal variation and long-term trend (Keeling, Bacastow, Bainbridge, Ekdahl, Guenther, Waterman, & Chin, 1976; Thoning, Tans, & Komhyr, 1989)
- Current level:** 422.5 ppm (parts per million; 52% above pre-industrial)

## Methodology

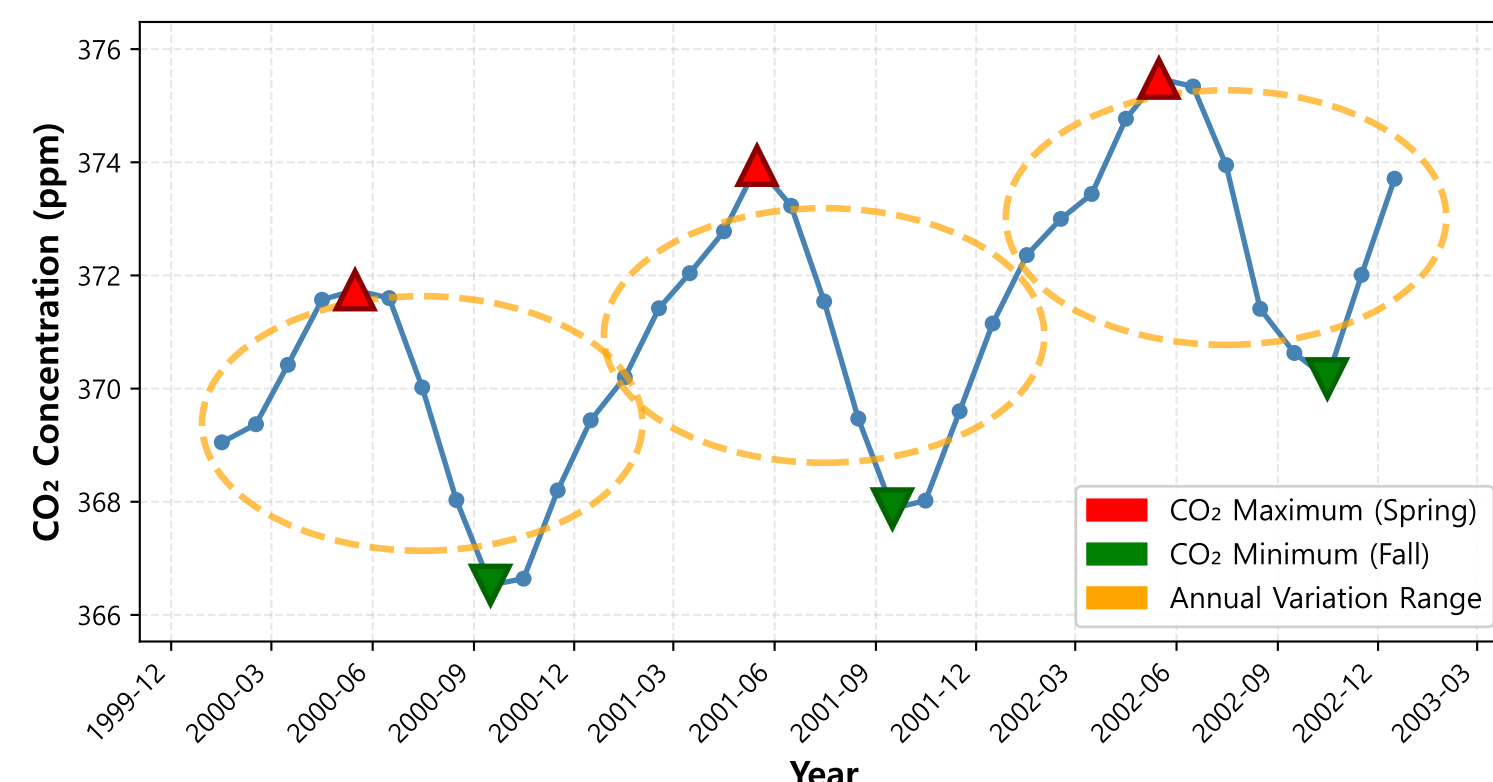
### Technical Implementation

- Platform:** Jupyter Notebook with Python 3.8+
- Libraries:** pandas, matplotlib, numpy
- Cloud Option:** Google Colab for easy access
- Data Source:** Scripps CO<sub>2</sub> Program

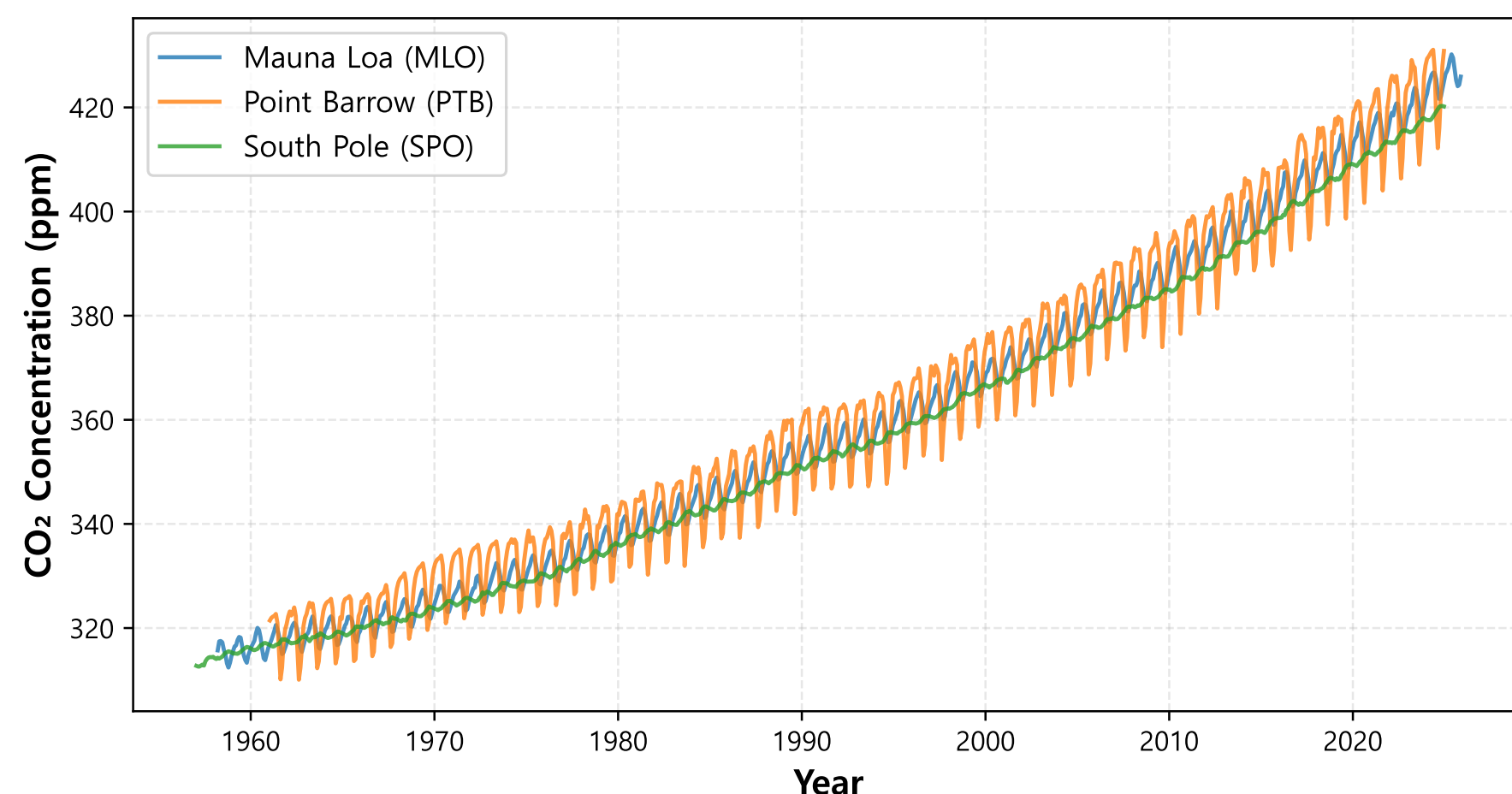
### Student Learning Activities



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



**Fig. 4:** Keeling Curve seasonal variation detail (2000-2002): understanding Earth's "breathing" pattern



**Fig. 5:** Comparison of atmospheric CO<sub>2</sub> 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<sub>2</sub>?
- 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

- Data Source Evaluation**
  - Verifying data provenance (Scripps Institution)
  - Understanding measurement methodology
  - Recognizing authoritative vs unreliable sources
- Data Quality Understanding**
  - Handling missing data
  - Understanding measurement precision ( $\pm 0.3$  ppm)
  - Recognizing quality control procedures
- Statistical Interpretation**
  - Distinguishing trend from variation
  - Calculating rates of change
  - Understanding seasonal adjustment
- 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<sub>2</sub>: 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<sub>2</sub> 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 (Kjellvik & 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

- Students engage successfully with authentic scientific datasets using computational tools (Weintrop, Beheshti, Horn, Orton, Jona, Trouille, & Wilensky, 2016)
- Direct interaction with data significantly enhances understanding of climate evidence
- 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

## References

- Barba, L. A., Barker, L. J., Blank, D. S., Brown, J., Downey, A. B., George, T., Heagy, L. J., Mandli, K. T., Moore, J. K., Lippert, D., et al. (2019). Teaching and learning with jupyter. *Recuperado*: <https://jupyter4edu.github.io/jupyter-edu-book>, 1–77.
- Bybee, R. W., Taylor, J. A., Gardner, A., Van Scotter, P., Powell, J. C., Westbrook, A., & Landes, N. (2006). The bscs 5e instructional model: Origins and effectiveness. *Colorado Springs, Co: BSCS*, 5(88-98).
- Chinn, C. A., & Malhotra, B. A. (2002). Epistemologically authentic inquiry in schools: A theoretical framework for evaluating inquiry tasks. *Science Education*, 86(2), 175–218. <https://doi.org/10.1002/sce.10001>
- Gould, R., Machado, S., Ong, C., Johnson, T., Molyneux, J., Nolen, S., Tangmunarunkit, H., Trusela, L., & Zanonian, L. (2016). Teaching data science to secondary students: The mobilize introduction to data science curriculum. *lase-Web. Org*.
- IPCC. (2021). *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press.
- Keeling, C. D., Bacastow, R. B., Bainbridge, A. E., Ekdahl, C. A., Guenther, P. R., Waterman, L. S., & Chin, J. F. (1976). Atmospheric carbon dioxide variations at Mauna Loa Observatory, Hawaii. *Tellus*, 28(6), 538–551. <https://doi.org/10.1111/j.2153-3490.1976.tb00701.x>
- Keeling, C. D. (1960). The concentration and isotopic abundances of carbon dioxide in the atmosphere. *Tellus*, 12(2), 200–203. <https://doi.org/10.1111/j.2153-3490.1960.tb01300.x>
- Kjellvik, M. K., & Schultheis, E. H. (2019). Getting messy with authentic data: exploring the potential of using data from scientific research to support student data literacy. *CBE—Life Sciences Education*, 18(2), es2. <https://doi.org/10.1187/cbe.18-02-0023>
- Monroe, M. C., Plate, R. R., Oxarart, A., Bowers, A., & Chaves, W. A. (2019). Identifying effective climate change education strategies: A systematic review of the research. *Environmental Education Research*, 25(6), 791–812. <https://doi.org/10.1080/13504622.2017.1360842>
- National Research Council. (2012). *A Framework for K-12 Science Education: Practices, Cross-cutting Concepts, and Core Ideas*. National Academies Press.
- NGSS Lead States. (2013). *Next Generation Science Standards: For States, By States*. The National Academies Press.
- Pellegrino, J. W. (2013). Proficiency in science: Assessment challenges and opportunities. *Science*, 340(6130), 320–323. <https://doi.org/10.1126/science.1232065>
- Thoning, K. W., Tans, P. P., & Komhyr, W. D. (1989). Atmospheric carbon dioxide at Mauna Loa Observatory: 2. Analysis of the NOAA GMCC data, 1974-1985. *Journal of Geophysical Research: Atmospheres*, 94(D6), 8549–8565. <https://doi.org/10.1029/JD094iD06p08549>
- Weintrop, D., Beheshti, E., Horn, M., Orton, K., Jona, K., Trouille, L., & Wilensky, U. (2016). Defining computational thinking for mathematics and science classrooms. *Journal of Science Education and Technology*, 25(1), 127–147. <https://doi.org/10.1007/s10956-015-9561-5>
- Wolff, A., Gooch, D., Caverio Montaner, J. J., Rashid, U., & Kortuem, G. (2016). Creating an understanding of data literacy for a data-driven society. *The Journal of Community Informatics*, 12(3), 9–26.
- Data Availability:** All Jupyter notebooks and educational materials are available at: [https://github.com/Kiehyun/ISCCCE2026/blob/main/appendix/The\\_Keeling\\_Curve\\_in\\_Action.ipynb](https://github.com/Kiehyun/ISCCCE2026/blob/main/appendix/The_Keeling_Curve_in_Action.ipynb)
- Atmospheric CO<sub>2</sub> data courtesy of Scripps CO<sub>2</sub> Program, Scripps Institution of Oceanography, UC San Diego (<https://scrippsco2.ucsd.edu/>).