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ChatGPT in Climatology: Transforming Climate Research with Conversational AI

Jacob L. Fields[1], Geddy R. Davis[1], Zachary T. Leasor[2], Jason Cervenec[1]

[1] *Byrd Polar and Climate Research Center & State Climate Office of Ohio, The Ohio State University*
[2] *Missouri Climate Center, School of Natural Resources, University of Missouri*

Corresponding Author: Geddy Davis, davis.5694@osu.edu

In recent years, advancements in the field of artificial intelligence have increased exponentially, culminating in widely available user-based tools such as ChatGPT. Although fairly new, these tools have as of yet been underutilized by the scientific community, including climatology. As a large language model, ChatGPT's strong ability to accurately respond to prompts allows it to be used as a comprehensive tool with a variety of applications in climatology, which this article groups into practical and conceptual applications. Practically, ChatGPT excels in the assistance of code creation and troubleshooting, allowing for efficient automation of data collection, as well as the process of basic data sorting. Conceptually, the tool gives a foundation for researchers to "fill the knowledge gap" by gaining a basic understanding of supplementary information presented in the literature review portion of a research project. While ChatGPT is powerful, it contains significant limitations that hinder its status as a standalone tool, such as occasional inaccurate responses, lack of transparency, and absence of data protection. Despite these setbacks, use of ChatGPT in a responsible and ethical manner with awareness of its limitations can be efficient, dynamic, and adherent to the principles of scientific integrity.

1. Introduction

In the year since its release in November 2022, ChatGPT has reached the forefront of discussion in academic and applied research fields as a tool with the potential to transform the way research is conducted. As an artificial intelligence chatbot, ChatGPT was developed to be a generative language model with the ability to accurately interpret prompts and return nuanced, coherent responses that are easily understood, making it a potentially powerful tool to enhance the efficiency and accuracy of scientific research. While ChatGPT is a major step forward in conversational AI, the technology behind it is not new. The concept of artificial intelligence, as well as the potential uses of the technology, has existed for as long as the concept of modern-day computers. The famous Turing Test, developed in 1950 by Alan Turing, is a measure of how well a machine can imitate human behavior. If a machine can fool a human into thinking it is another human, it passes the test (Oppy & Dowe, 2021). In the years since its conception, artificial intelligence technology has developed with the goal of passing the Turing Test, setting the notion that AI should not only match the intelligence of humans but eventually surpass it. In recent years, the push towards conversational AI – culminating in tools like ChatGPT – have come closest to this goal. While no machine has yet passed the Turing Test, the innovations in AI have expanded the technology's applications exponentially.

Much like a traditional search engine, ChatGPT's responses can be as complex as the vast amount of data to which it has access. For example, ChatGPT-3.5's pre-training dataset contains 45 terabytes of data, giving it a huge base of information from which to draw (Wu et al., 2023). Many articles concerning the practical applications of ChatGPT within a wide variety of fields, such as healthcare (DiGiorgio and Ehrenfeld, 2023), education (Lund and Wang, 2023), business (George et al., 2023), and law (Oltz, 2023), have been published. Though there have been studies focused on the use of ChatGPT in the study of global warming (Biswas, 2023), environmental research (Zhu et al., 2023), and climate model development (Trajanov, 2023), there is a notably small volume of literature concerning applications of the tool in the development of climate research, specifically related to coding development. This article aims to fill that gap by outlining a series of potential uses of ChatGPT, specifically version ChatGPT-3.5, to improve otherwise time-consuming and data-intensive tasks in the realm of atmospheric sciences, while also acknowledging the limitations and ethical concerns of artificial intelligence tools in a field where human input is imperative.

2. Practical Applications

2.1 Data Collection

Weather and climate data are the foundation of any climatology research project. While some researchers may conduct laboratory measurements or fieldwork to collect their own data, many rely on downloading data from web-based application programming interfaces (APIs) and servers. These climate datasets have varying file formats and file sizes, and frequently require the use of programming languages to optimize data downloads, often necessitating the use of third-party tools and browser extensions. While some data formats are more popular than others, there is no standard file type or organizational system for different datasets used in climate research. Therefore, due to widely varying coding backgrounds that the researchers in a project may have, there is also not a centralized code repository or programming language that can be used for data collection. Instead, most of the time researchers need to write code that is unique to the project in order to query and acquire the necessary datasets. Downloading, formatting, and organizing the data are frequently time-intensive tasks that can hinder progress at the beginning of a project before conducting data analysis. This is where the innovations provided by ChatGPT could be most critical to climate research by reducing the workload at the beginning of a research project. In this way, scripting data collection using artificial intelligence could provide an initial resource for researchers. While oversight and correction are likely required, this is much less intensive than beginning to outline and develop the necessary code on one's own, with little to no prior knowledge of a given coding language.

As a language model, ChatGPT excels in understanding complex instructions. While inclusion of specific keywords is important, prompts with casual and nuanced wording can be understood and responded to much more thoroughly than with a standard search engine. In the realm of coding, this ability allows ChatGPT to construct code that accomplishes highly specific objectives. With this, given the necessary factors of a coding project outline (i.e., purpose, coding language, coding parameters, etc.), it will return efficient and straightforward drafts of code that fulfills the project's requirements, pending refinement by the researcher. This makes ChatGPT uniquely applicable to data collection, in that it can construct comprehensive code that allows researchers to automate the process. For example, climate-related APIs generally

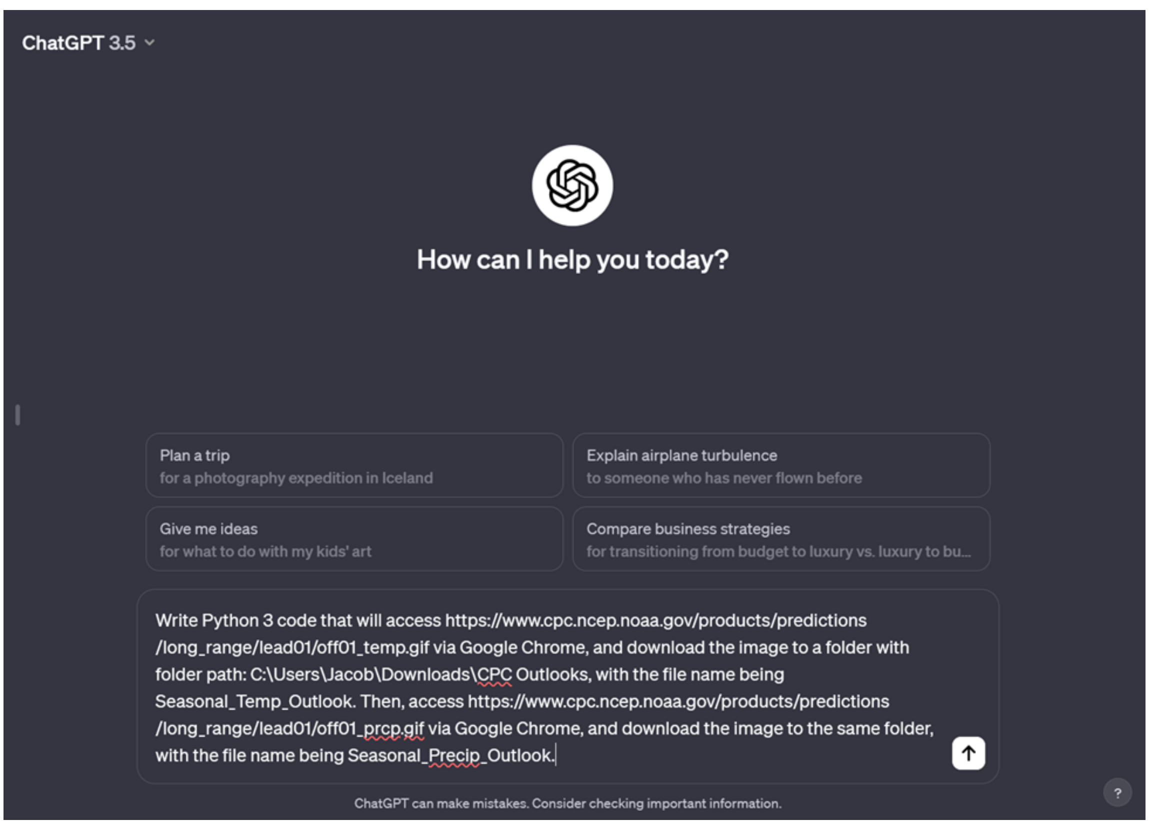

FIGURE 1: Initial user prompt to ChatGPT-3.5 requesting code that will download data from a browser into a pre-existing folder.

sort datasets based on factors such as location, timespan, and environmental characteristics. Data collection usually requires specification of these factors to accumulate datasets that are applicable to research. While identifying data that conforms to these specifications can be exceedingly time consuming, it is a highly automatable process. With an efficient code creation process using ChatGPT as a tool, automation becomes a worthwhile time-saving endeavor.

For simple requests, ChatGPT will usually return working code on the first try, though as prompts become more complicated, it will begin to create lines of code that, while still conforming to the conceptual objective of the initial prompt, do not functionally work as intended. While this is an area for improvement, it leads to another area in which ChatGPT excels: troubleshooting. Most traditional troubleshooting methods involve a long and tedious process of diagnosing specific lines of code and manually searching for solutions. ChatGPT, when prompted with the associated error message, will determine the issue and provide a potential alternative to the faulty section. While it may not return the correct solution every time, the process may be iterated, with ChatGPT working through multiple possible solutions to the error until it finds the one most applicable. In some cases, this iteration may be extensive, but is generally more efficient than traditional troubleshooting methods for issues that the researcher is unfamiliar with or unable to address independently.

To illustrate the use of ChatGPT in data collection, it is relevant to mention the State Climate Office of Ohio, which publishes monthly and quarterly climate summaries that are focused on Ohio and are primarily written by the first author of this article. These summaries heavily rely on visualizations of temperature, precipitation, soil moisture, energy consumption, and other variables to communicate climate trends to the public. Due to the wide range of information displayed, these visualizations are gathered from a similarly wide range of sources, including the Midwestern Regional Climate Center, the National Centers for Environmental Information, the Climate Prediction Center (CPC), NASA, and others. While manual compilation of at least fourteen total visualizations from these sources is tedious and time-consuming, attempts to automate the process from scratch without relevant coding experience are constrained due to the time requirement involved. This illustration will show that even with very limited relevant coding knowledge, this challenge can be overcome through the use of ChatGPT, increasing the overall efficiency of projects requiring automation and improving the user's coding experience through repetition.

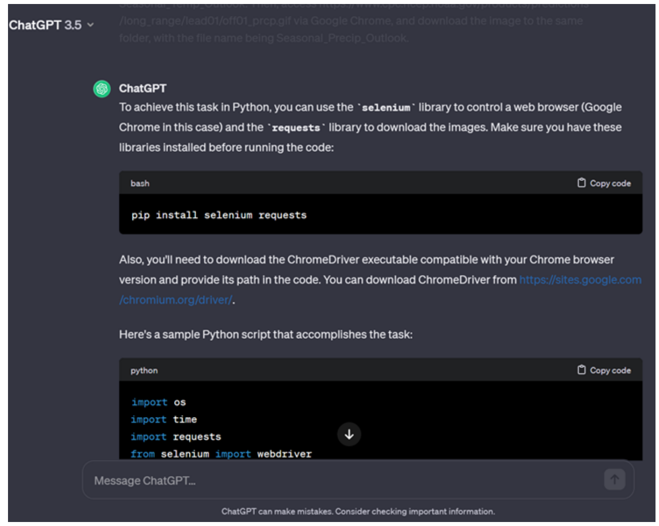

FIGURE 2: Start of ChatGPT-3.5's response to the initial prompt from the user, including code and associated instructions.

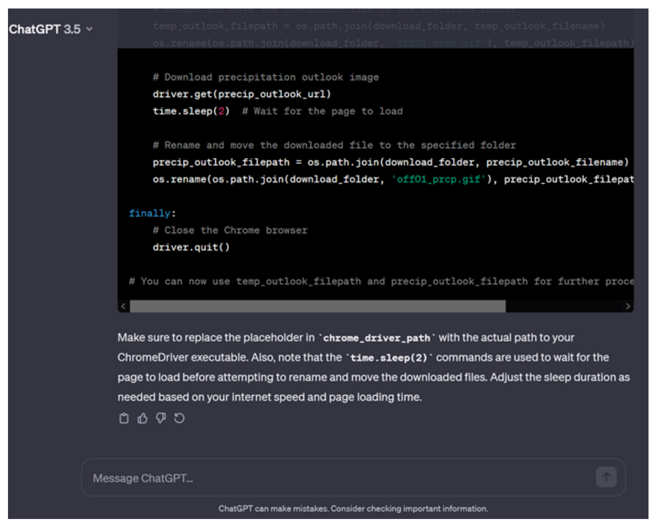

FIGURE 3: End of ChatGPT-3.5's response to the initial prompt from the user, including code and associated notes for the user.

For this example, ChatGPT-3.5 is employed, as it is the most recent version of the tool that is free and publicly available at the time of writing (OpenAI, 2024). Additionally, code is written in Python 3 via Jupyter Notebook 6.4.12, the most recent version of a commonly used platform in the atmospheric sciences. The goal of this example is to automate the download of the CPC's seasonal temperature and precipitation outlooks onto a local drive. The first step of the process is to give ChatGPT a detailed description of the required task, as shown in Figure 1. The AI will then respond with a description of the necessary steps to complete the task as well as annotated code that can be copied and pasted into Jupyter Notebook (Figures

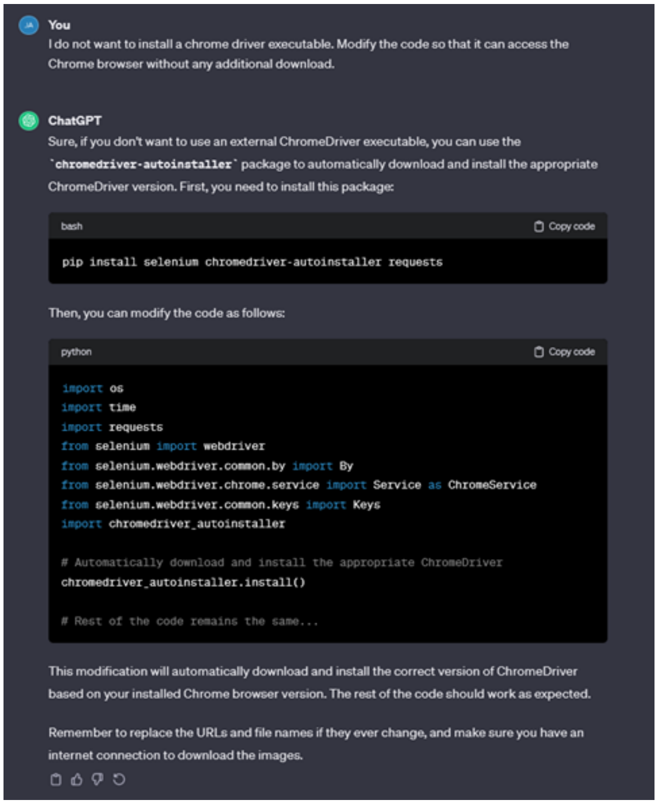

FIGURE 4: Clarification of the initial prompt by the user, followed by ChatGPT-3.5's response, which includes applicable modifications to the initial code.

2 and 3). While ChatGPT may respond with the correct solution on the first try, it should be expected that the initial output will be incorrect. The tool is not generating code intuitively but is instead imitating the patterns it has recognized from similar code in its training dataset. In this example, the user does not want to manually install a ChromeDriver executable, as they need the code to be viable across multiple devices with minimal changes. To address this, the user responds to ChatGPT's output with a clarification of their intention, which the AI then counters with a modification to the code (Figure 4). Here, there is an additional problem. While ChatGPT now recognizes the intention of the task, its code is incorrect, resulting in an error message. In response, the author may begin the troubleshooting process, in which the error message is copied and pasted into the ChatGPT text box, resulting in the AI providing further modified code (Figure 5). This process of copying code from ChatGPT and relaying the error message can be repeated until the working code is finally generated (Fields, 2024a). While in some cases this process may be repetitive, it almost always results in useable, annotated code that can be modified and shared at the user's discretion (Figure 6). For this example, the troubleshooting process took nineteen iterations and about 45

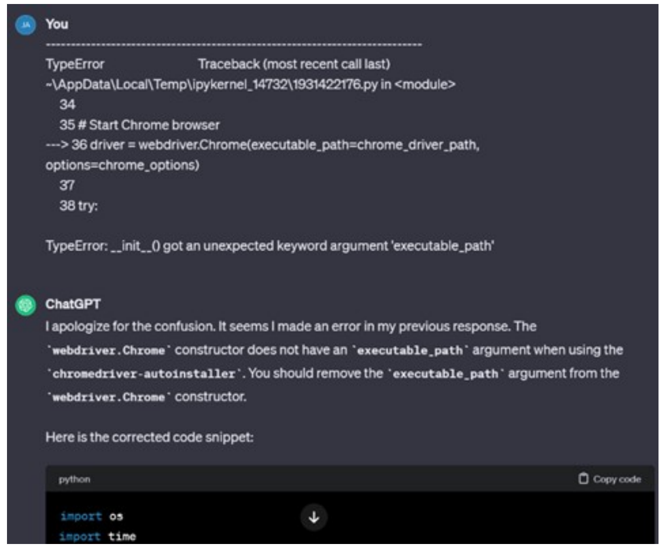

FIGURE 5: User prompt including the error message created from ChatGPT-3.5's code, followed by ChatGPT's response, including further modifications.

minutes to complete, but it may take more or less time depending on the user and their programming proficiency.

2.2 Basic Data Sorting

After data collection, data sorting is needed to manage and present data in a tractable form before conducting further analysis. The extent of data sorting, quality control, and file format modification that is necessary depends upon the application of the project and the preferences of the researchers responsible for analyzing the data. Regardless, all climate research requires some amount of data sorting which is conducted using programming languages or spreadsheet and database software. Similar to data collection, there is a wide variety of code repositories and software that researchers prefer to use for this process. Significant time must be spent specifying data needs, writing code, troubleshooting, and executing the data sorting process. This is often an iterative task because it is common that the organization or structure of the data needs to be respecified to meet the input requirements for data analysis (e.g. input for a model or statistical test). The difficulty of this process can be quickly exacerbated by very large or unwieldy datasets, where code runtime and data storage must be considered. Large datasets are common in climate research, where a large number of observations, time steps, and variables can be combined to create millions of data points. Each dataset is often organized differently or using a different file format. Therefore, the time spent programming or working with the data sorting process is significant relative to the project.

In both manual and automated data sorting processes, the

```
In [19]: import os
         import requests

         # Set the folder path for downloads
         download_folder = r'C:\Users\Jacob\Downloads\CPC Outlooks'

         # Set URLs for temperature and precipitation outlook images
         temp_outlook_url = 'https://www.cpc.ncep.noaa.gov/products/predictions/long_range/lead01/off01_temp.gif'
         precip_outlook_url = 'https://www.cpc.ncep.noaa.gov/products/predictions/long_range/lead01/off01_prcp.gif'

         # Create the download folder if it doesn't exist
         if not os.path.exists(download_folder):
             os.makedirs(download_folder)

         # Download temperature outlook image
         temp_outlook_filepath = os.path.join(download_folder, 'Seasonal_Temp_Outlook.gif')
         response_temp = requests.get(temp_outlook_url)

         with open(temp_outlook_filepath, 'wb') as temp_outlook_file:
             temp_outlook_file.write(response_temp.content)

         # Download precipitation outlook image
         precip_outlook_filepath = os.path.join(download_folder, 'Seasonal_Precip_Outlook.gif')
         response_precip = requests.get(precip_outlook_url)

         with open(precip_outlook_filepath, 'wb') as precip_outlook_file:
             precip_outlook_file.write(response_precip.content)
```

FIGURE 6: Final working code created by ChatGPT-3.5, shown in Jupyter Notebook.

novel and distinct nature of each individual project can be severely limiting to efficiency and time management. With consistently unique problems, effective solutions may not always be available with traditional methods. In contrast, ChatGPT's capacity to understand original and diverse prompts and respond appropriately makes it useful for data sorting. While automation and troubleshooting usually involves pulling from past projects and experience, ChatGPT gathers and combines trends from its extensive datasets to identify unique solutions to coding problems. As a result, neither the novelty nor the size of a dataset will substantially limit the efficiency of automation with ChatGPT. While the tool cannot outright work with data files, it can write code that can change dataset properties. For example, researchers will many times require data within a specific numerical range and will filter the data to contain only the intended values. While this can be completed with programs such as Excel, doing so with extremely large and unwieldy datasets can be highly time consuming, assuming that the relevant file types are compatible in the first place. Using ChatGPT, the same process can be completed by having the AI write a small amount of code that filters data automatically, regardless of data volume. It is important to note that while ChatGPT can provide a foundation for data sorting automation, it must be manually supervised and tested before working with full data sets. Though it works well as a tool, ChatGPT cannot replicate human judgement, and should not be used to sort valuable data sets without approval.

As a part of its usefulness in working with datasets, ChatGPT is proficient in simplifying the incorporation of niche file types that may be unfamiliar to the researchers in a project. For example, the NetCDF file format is popular in the atmospheric sciences due to its ability to store multi-dimensional scientific data such as temperature, humidity, pressure, etc. Because of this configuration, viewing a NetCDF file usually requires use of a coding interface such as Jupyter Notebook, which can be a daunting task for those who are unfamiliar with the file type. This simple illustration will show that by using ChatGPT-3.5, this challenge can be overcome quite easily. Firstly, the user must provide an initial prompt detailing the action they would like to have completed. In this case, the user wants to open a pre-downloaded NetCDF file with a defined file path, as well as view it in an array using Python in Jupyter Notebook (Figure 7). In response, ChatGPT provides the

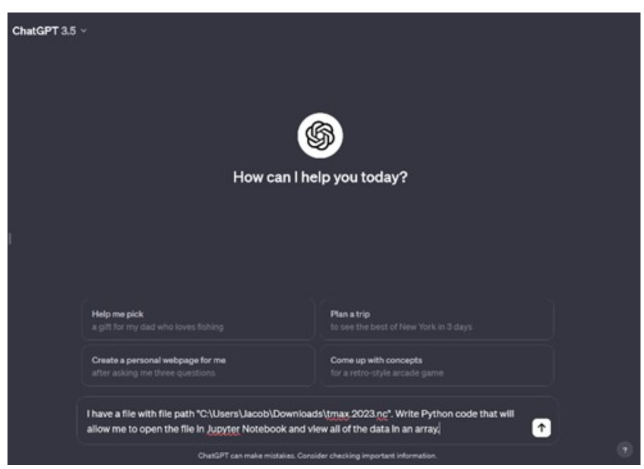

FIGURE 7: Initial prompt to ChatGPT-3.5 requesting code that will open a NetCDF file in Python and allow the user to view the data in an array.

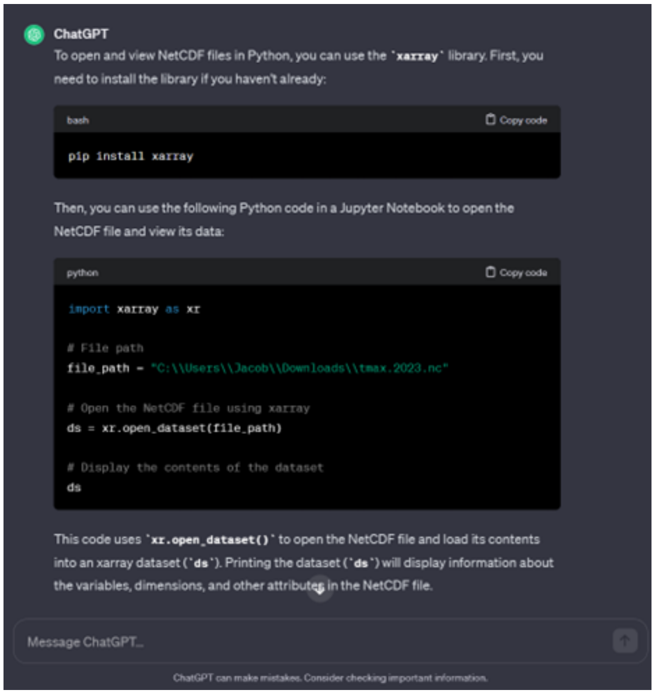

FIGURE 8: ChatGPT-3.5's response to the initial prompt from the user, including code and code notes for each line. Additionally, there is extra information detailing the intention of the code.

necessary code to create an array in Jupyter Notebook, as well as explanations for each code line (Figure 8). Once copied into Jupyter Notebook, the code successfully uses xarray to open the file's contents in an array (Figure 9). In this specific example, ChatGPT was successful on the first try, with no need for further iteration. Although further work is required to work with the data in the file, ChatGPT was able to complete the initial request in under a minute (Fields, 2024b).

3. Conceptual Applications

3.1 Filling the Knowledge Gap

In any research project, there is some level of unfamiliarity in understanding the data, methods, previous research, and theoretical information. There is always some amount of work to be done in order to overcome this unfamiliarity, especially at the beginning of a project. To learn about unfamiliar topics, a balance between accessibility and quality of information is critical. Peer-reviewed literature is an excellent source of information but can require time to read through papers that discuss complex and unfamiliar topics. With experience, researchers often become

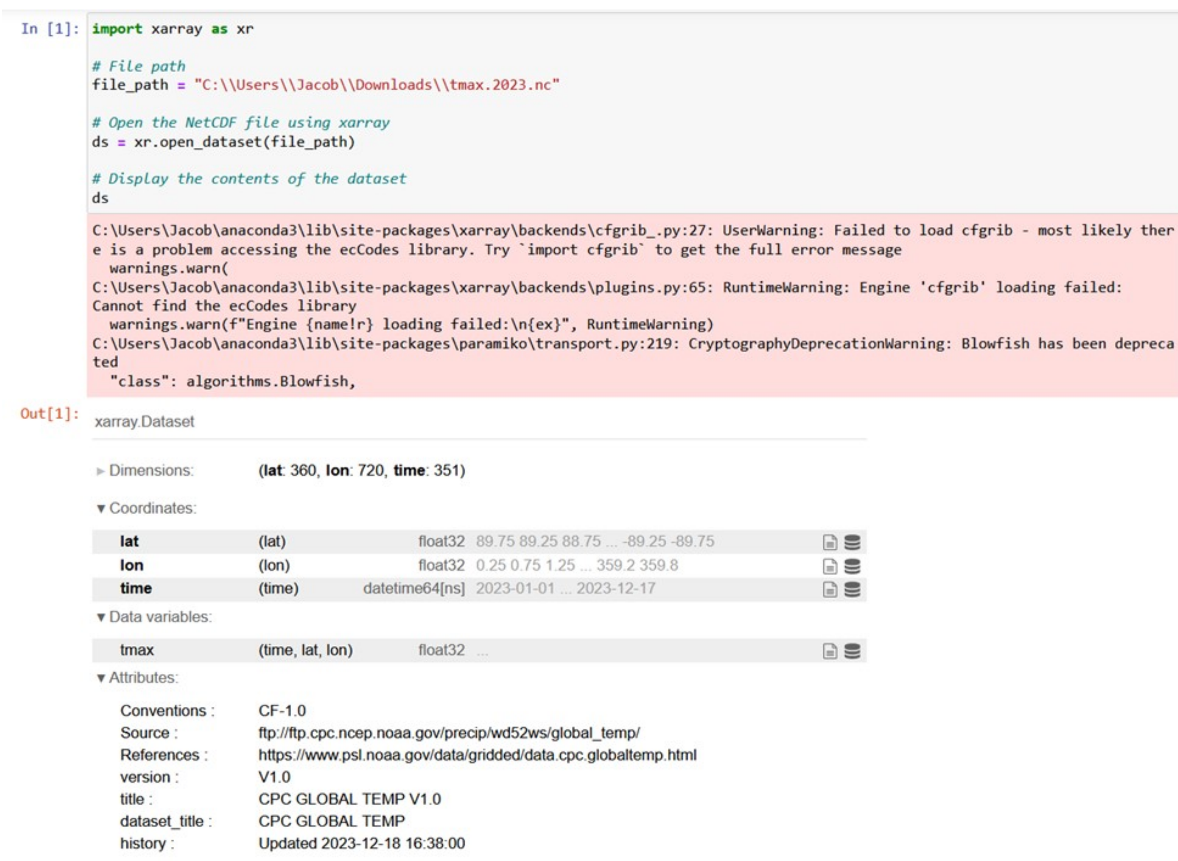

FIGURE 9: Result of code copied from ChatGPT, including the information associated with the file's data array.

more efficient in filtering and retrieving necessary information, allowing for a quicker process over time. Despite a vast amount of information available through publications and web-based resources, it is still common for researchers to have difficulties finding specific information about a topic. Often, consultations with colleagues or subject matter experts themselves can help to acquire useful information more directly. In this case, relationships with other researchers can help navigate a network of knowledge and expertise. With an established network, researchers are often quick to consult others. Otherwise, it may take more time to find an individual with relevant subject matter expertise and initiate communication.

While traditional methods for information gathering are effective, they commonly fail to provide in-depth descriptions of material. In contrast, the source of ChatGPT's greatest acclaim – and controversy – is its ability to respond to conceptual queries with detailed and nuanced explanations. The most powerful feature of this ability is its extensive flexibility; users can specify the length, amount of detail, level of comprehension, and extent of field-specific terminology in the answers to their prompts. Whether it's an individual with no prior knowledge or a researcher with a PhD, ChatGPT can cater explanations to the user's needs. In climatology, a field that is inherently cross-disciplinary, familiarity with a wide range of topics is essential to research. As such, in cases where traditional investigative methods prove to be insufficient, ChatGPT can provide a valuable starting point for filling the wide-ranging knowledge gap. To present information, ChatGPT draws from a neural network (Leong, 2018) that contains data from sources such as scientific journals, public libraries, encyclopedias, textbooks, government agencies, etc. (Junge, 2023). When it recognizes key words in a query, it incorporates all relevant information from the network into an appropriate response. The result is detailed explanations for an incredibly wide variety of topics spanning nearly every field for which established literature exists. The search for supplementary information in a research project is a frequent and time-consuming process, with a significant portion dedicated to uncovering scraps of information from wide swaths of material. Using ChatGPT as a supplementary tool, this obstacle to the literature review section and other conceptual requirements of a research project can be significantly reduced.

3.2 Limitations

Though ChatGPT is widely applicable to literature review and code creation, inherent and severe limitations substantially impact its suitability as an unaided tool. As with every major advancement, the technology behind ChatGPT has flaws that have not yet been resolved, mainly associated with the mechanics behind its neural network. To search for data, ChatGPT relies on keywords to recognize general trends in its source material and gather all relevant information; it does not know or recognize topics like humans do. Consequently, it may sometimes present information that appears plausible on the surface but is actually nonsensical and factually incorrect upon further analysis, an occurrence colloquially known as "hallucination". For uses such as coding where results may be immediately checked for validity/accuracy or failure to run, this issue is less severe. In situations where ChatGPT's outputs cannot be quickly or easily verified, the problem becomes significant. For example, when prompted to present scientific sources for a specific topic, ChatGPT will return a list of citations for publications. At first glance, these citations seem to be legitimate in both format and content, but upon investigation, it becomes apparent that the publications do not exist, and that the AI assigned plausible titles to random (and sometimes non-existent) authors. With such behavior, ChatGPT cannot be trusted to give citations for information it provides without spending time to verify both the AI's sourcing and the facts within it. Furthermore, while the tool offers a reasonable initial foundation for information gathering and may assist in the further investigation of material, it should not be relied on as an independent, definitive source. As previously mentioned, when learning unfamiliar topics, there is a critical balance of accessibility and quality of information. Although ChatGPT is a leader in accessibility, the low quality of information it sometimes provides disqualifies it for total reliance as a source. As with every unexplored technology, nuance and healthy skepticism is crucial to finding success with ChatGPT.

4. Ethics

As a developing and exceptionally impactful technology, artificial intelligence has been the focus of intense legal and ethical scrutiny in recent years. Though this focus has mostly been on the ethical programming of AI and the protection of user data, recent developments in user-based tools such as ChatGPT have shifted discussion towards the ethical usage of artificial intelligence. In the context of climatology and related research, user-end ethics mainly concern the preservation of scientific integrity, avoidance of plagiarism, and protection of private data. Firstly, ChatGPT cannot conduct research, nor can it provide reliable conclusions from data. It lacks transparency and accountability, and as such, a research project that employs ChatGPT as a replacement to human researchers instead of a research tool cannot have scientific integrity and therefore cannot be credible. Secondly, ChatGPT responds to prompts by retrieving data from a vast pool of resources, none of which is available to the user. If directly copied, AI-generated information not only introduces the risk of plagiarism but also puts the project into an unclear and emerging area of copyright law (The Ohio State University Teaching & Learning Resource Center, 2023). Finally, data given to ChatGPT is not considered protected and is not confidential. Every conversation with the AI is logged and used as training data, putting information at risk not only for future use by ChatGPT itself but also for data breaches from third parties. It is important to note that only information directly typed to ChatGPT is at risk, not data referenced tangentially, such as in data sorting. Consideration of these concerns is essential for the credibility and security of a research project and demands a high degree of responsibility by a user of ChatGPT. Knowing ChatGPT's standing as a tool, its lack of transparency in sources and methodology, and its inadequate protection of data is a requirement for working with the technology. While user-based AI is an impactful and prominent technology, it is still in the infancy of its development, and as it grows and changes, the ethical requirements for its use will change in turn. It is critically important to be aware of the suitable operation of tools such as ChatGPT and the consequences of inappropriate use.

5. Summary and Conclusion

After considering the practical and conceptual workflows of climatology research, there is significant potential for the inclusion of ChatGPT and AI technology in the research process. Considering data collection and sorting, ChatGPT can produce unrefined code that is a relevant starting point for many automated processes. Human researchers will still need to improve the code to better suit the needs of the project, but this is still more efficient than developing all of the code themselves, saving valuable time in the early stages of a project. While more difficult to organize in a logical framework, there are also aspects of knowledge collection that ChatGPT can streamline. This technology is likely most effective in providing a base of information on a specific topic or helping to summarize key findings relevant to the research project, if used correctly. There are likely points where researchers may need to rely on their own knowledge and interpersonal networks to find information, but ChatGPT can again save time in the early stages of gathering information. It should be acknowledged that there are likely negative impacts and ethical concerns with this technology, such as improper attribution of work, but constant human intervention can help to refine ChatGPT as a tool for research. Researchers should understand the need for oversight and review of output for AI technologies and use this experience to improve technology for research purposes. While this article is limited to just the capabilities of ChatGPT and their relevance to climate research, artificial intelligence is a wide and developing field that has the potential to expand on the applications described here in the near future. As a powerful technology, it is important to be aware of not only the improvements in efficiency that can be made to a research project but also the inherent drawbacks and limitations inherent to AI.

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