

Using AI Tools to Explore the UN Sustainable Development Goals (UN SDGs) & Relevant Remote Sensing Instruments & Data Sets to Monitor Indicators of Progress Towards Achieving the SDGs with a Focus on SDG-6 (Water)
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[Union Session U13B:U13C: Union Session: Beyond the Black Box—Advancing Geo-ML by Incorporating Context with Specialized Architectures, Benchmark Datasets, and Tailored Notions of Interpretability II Poster]

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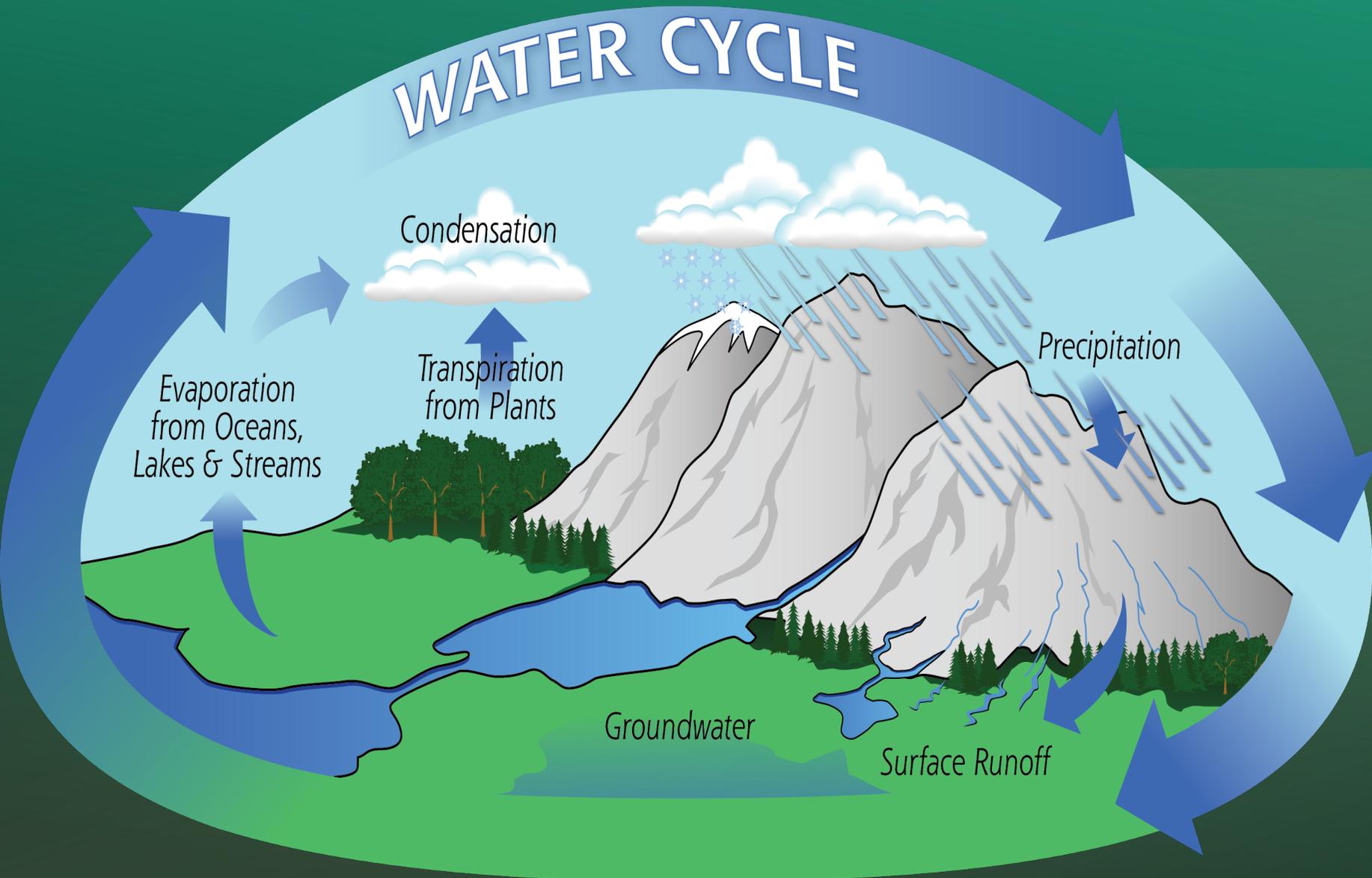
**Using AI tools to
explore the UN
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[On-Line Version;]**

The United Nations Sustainable Development Goals (SDGs) framework was established in 2015 to motivate progress towards achieving 17 SDGs by 2030. They include all aspects of the Earth system and reference Goals & Indicators for managing natural, industrial, environmental & socioeconomic resources. A key question is how to access & simplify the available “global” documentation into concise information to assist the national/international community design monitoring systems to assess progress towards achieving the SDGs. The urgency for such action arises from the target date of 2030 set by the UN for the achievement of most of the SDGs. We show how ChatGPT3.5 (created by OpenAI) and similar LLMs (Large Language Models/Generative AI models) such as Google-Bard, Microsoft-Bing-AI can be used to iteratively develop increasingly informative and precise descriptions on the SDG Goals, Targets, Indicators, remote sensing platforms, and data sets to help build the needed end-user applications. We begin with a broad exploration of all UN-SDGs and then progressively focus on SDG-6 (Water) due to intersection of the global water cycle with nearly all other sectoral themes of the SDGs. We explore SDG-6’s Goals, Targets and Indicators, followed by specifications of available remote sensing instruments and data sets. During this process, we noted that the LLMs were also prone to errors and “Hallucinations,” termed “Hallucins” in this paper. Hallucins come across as authoritative and convincing. They need to be independently verified. Curiously, questioning the LLM itself for additional substantiation of a suspected Hallucin led to LLMs admitting to the error. All LLMs also have disclaimers mentioning that the information they present may not be accurate. The challenge to the end-user: Verification/validation of the LLM response/results to a query/investigation. That said, their performance was impressive overall & they could pull together relevant information almost instantly from large data bases—an action that would take a human considerable time to collect and analyze in more traditional ways.

Motivation & Formulation

- AI (& all derivatives) are visibly getting infused into all activities.
- The power and capabilities of AI are increasing exponentially.
- There are concerns about how AI is being used or misused.
- It would be useful to optimize or maximize the potential benefits of AI in science exploration and reporting while, at the policy level, safeguards are built for protection against possible misuse and/or the accidental (or otherwise) generation of misinformation.
- **Here, we explore the response** of some well established and rapidly advancing AI Large **Language Models (LLMs)** that use a specific neural network architecture called “Transformer.” All LLMs are also “Generative AIs” because they can create new content such as text or images based on the information, depending on their data sets and neural network architecture. That is, they don’t merely stitch together pieces of data or text from their respective data bases. **As an example, I had ChatGPT3.5 generate a well phrased poem with a prompt “write a Zen Poem.”** Such feature make them seem almost human-like in performance. Depending on which “benchmark” is used, some predict that AI’s will approach human-intelligence-like capacity in a few decades—i.e., by about 2040 – 2050 (Reference: Müller, Vincent C. and Bostrom, Nick (forthcoming 2014), ‘Future progress in artificial intelligence: A Survey of Expert Opinion, in Vincent C. Müller (ed.), Fundamental Issues of Artificial Intelligence (Synthese Library; Berlin: Springer)
- A “transformer” can read vast amounts of text, spot patterns in how words and phrases relate to each other, and then make predictions about what words should come next. In a sense, we find that they are capable of creating or synthesizing new material based on the question and information input. Their response depends on their internal neural architecture and the training data bases used and the level of real-time access to current data & information updates.
- **We consider 3 LLMs---ChatGPT3.5, Google-Bard & Microsoft-Bing(AI).** ChatGPT is based on OpenAI’s Generative Pre-Trained Transformer (GPT) large language model (LLM)). Google Bard is based on Google’s own model called LaMDA, also a Generative AI which allows for a level of creativity/adaptability intended to be human-like. MS-Bing starts with ChatGPT4 but goes beyond text and can generate images. GPT relies on training data sets to process text and can help with data summarization and related tasks. GPT3.5 is free while GPT4 requires a subscription. Google-Bard is linked to real-time information in addition to Google’s vast data training data sets of text and code. MS-Bing is based on GPT4 which is the latest iteration of OpenAI’s Generative Pre-trained Transformer (GPT).
- **We ask them a series of questions and study their responses & compare them to reference material known to be 100% accurate. The following slides show the results.** Highlighted in “Red” are the departures from the reference—here called “Hallucins”—short for hallucinations.

WATER CYCLE. Source NASA Global Precipitation Mission (<https://gpm.nasa.gov/education/water-cycle>)



QUESTION-Q1a (Given to, ChatGPT, As an example LLM):

Describe Essential Water Variables given the following parameter list.

PRIMARY EWVs: Precipitation. Evaporation. Evapotranspiration. Snow. Soil moisture. Soil temperature. Groundwater. Runoff/streamflow/river discharge. Surface water extent. Lake/Reservoir Levels & Aquifer volumetric change; terrestrial water storage Mass balances of glaciers and Ice sheets. Water use/demand (agriculture, hydrology, energy, urban, others...) .Water quality (Including T, D-O₂, N, P, ph/Salinity, TSS, Chl-a, HAB, heavy metals, hydrocarbons, pesticides, herbicides, fecal coliform...).

[Also shown (On-Line Version Only): The Q's (Q1b) and RS's (R1b) for Supplemental EWVs were similarly reasonably well phrased].

Essential Water Variables (EWVs) are a set of critical measurements used to assess and monitor the state and trends of water resources in various ecosystems. They provide valuable insights into the water cycle, hydrological processes, and overall water availability and quality. These variables are essential for understanding and managing water resources sustainably. Among the EWVs, there are Primary EWVs that play a foundational role in water monitoring and management. Here, I'll describe the Primary EWVs you've listed:

1. **Precipitation:** The amount of water, in various forms (rain, snow, sleet, etc.), that falls from the atmosphere to the Earth's surface over a specific area and time period. Precipitation is a crucial input to the hydrological cycle.
2. **Evaporation:** The process by which water is converted from liquid to vapor and released into the atmosphere from water bodies, soils, and vegetation surfaces.
3. **Evapotranspiration:** The combined process of water vapor loss through both evaporation from soil and water surfaces and transpiration from plants. It represents the total water flux from the land to the atmosphere.
4. **Snow:** Measurement of snowfall and snow cover extent, which is particularly important in regions where snowmelt contributes significantly to water resources.
5. **Soil Moisture:** The amount of water present in the soil, indicating the availability of water for plants and the potential for runoff or infiltration.
6. **Soil Temperature:** Monitoring soil temperature helps understand its impact on soil processes, including plant growth, microbial activity, and water movement.
7. **Groundwater:** Monitoring the level and quality of groundwater helps assess the sustainability of groundwater resources and their potential impact on surface water bodies.
8. **Runoff/Streamflow/River Discharge:** The measurement of water flowing in rivers and streams, which is crucial for understanding water availability, flood forecasting, and ecosystem health.

Conclusion: Excellent descriptions (i.e., quite plausible and no obvious errors) generated entirely by the ChatBot beginning with ONLY a simple list of variables and no other prompt

RESPONSE R1a (from ChatGPT):

RESPONSE R1a (from ChatGPT)
Contd.:

9. Surface Water Extent: Monitoring changes in the extent of surface water bodies, such as lakes, rivers, and wetlands, helps assess water availability and ecosystem health.

10. Lake/Reservoir Levels & Aquifer Volumetric Change: Monitoring the water levels of lakes and reservoirs provides information about storage capacity, while changes in aquifer volume help assess groundwater availability.

10b. Terrestrial Water Storage: Monitoring changes in the amount of water stored in terrestrial ecosystems, including soil moisture, groundwater, and snow, helps in understanding regional water balances.

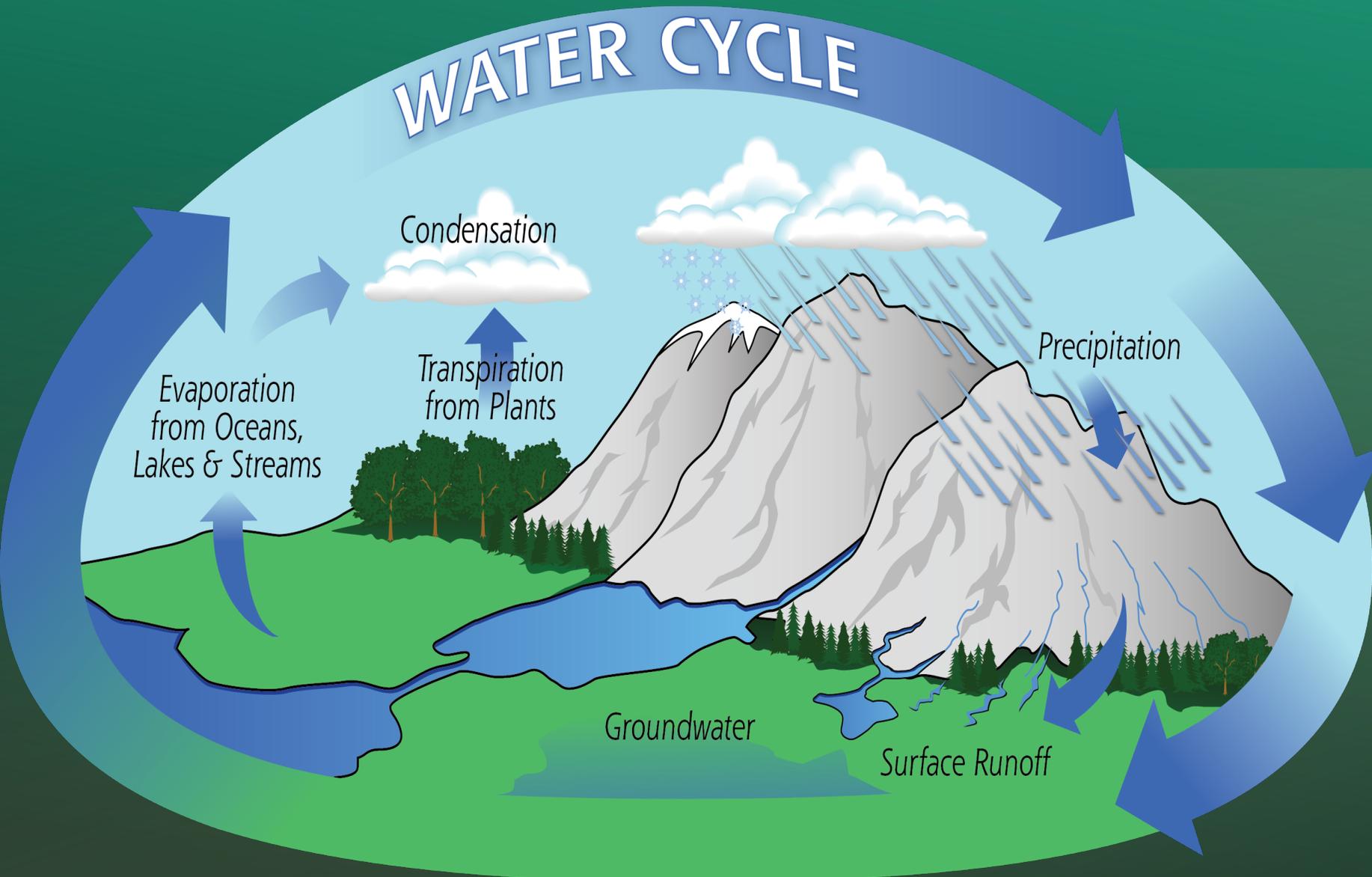
11. Mass Balances of Glaciers and Ice Sheets: Tracking the mass balance of glaciers and ice sheets helps assess their contributions to sea-level rise and regional water availability.

12. Water Use/Demand: Monitoring water consumption across various sectors (agriculture, hydrology, energy, urban, etc.) helps in water resource planning and management.

13. Water Quality: Monitoring various parameters, such as temperature, dissolved oxygen, nutrients (N, P), pH, salinity, total suspended solids (TSS), chlorophyll-a (Chl-a), harmful algal blooms (HABs), heavy metals, hydrocarbons, pesticides, herbicides, and fecal coliform, helps assess the health and suitability of water for different uses.

Conclusion: Excellent descriptions (i.e., quite plausible and no obvious errors) generated entirely by the ChatBot beginning with ONLY a simple list of variables and no other prompt

WATER CYCLE. Source NASA Global Precipitation Mission (<https://gpm.nasa.gov/education/water-cycle>)



QUESTION-Q1b (Given to, ChatGPT, As an example LLM; On-Line Version Only):

Describe EWVs given:
Parameter list of SUPPLEMENTARY EWVs:
Surface meteorology
Surface and atmospheric radiation
Clouds & water vapor
Aerosols
Land cover, vegetation
Permafrost
Surface altimetry
Bathymetry
Elevation/topography
Geological stratification
Land use.

RESPONSE R1b (from ChatGPT):

1. Surface Meteorology: This includes measurements of meteorological parameters at the Earth's surface, such as air temperature, wind speed, wind direction, humidity, and atmospheric pressure. Surface meteorology data are crucial for understanding local weather patterns and their influence on the water cycle.

2. Surface and Atmospheric Radiation: Monitoring incoming solar radiation, outgoing longwave radiation, and atmospheric radiation levels helps understand energy exchange between the Earth's surface and the atmosphere, which has direct implications for temperature and the overall dynamics of the water cycle.

3. Clouds & Water Vapor: Measurements related to cloud cover, cloud type, and water vapor content in the atmosphere are important for assessing the distribution of moisture and potential precipitation patterns

4. Aerosols: Aerosols are tiny particles suspended in the atmosphere that can affect cloud formation, precipitation, and radiation balance. Monitoring aerosol properties provides insights into atmospheric interactions that influence the water cycle.

5. Land Cover, Vegetation: Information about land cover types (e.g., forests, grasslands, urban areas) and vegetation health is essential for understanding evapotranspiration rates, runoff patterns, and ecosystem dynamics.

6. Permafrost: Monitoring the temperature and extent of permafrost, which is permanently frozen ground, is crucial for understanding its stability, potential thawing, and impact on hydrological processes.

7. Surface Altimetry: Measuring the height of the Earth's surface relative to a reference point helps in monitoring changes in elevation due to factors like tides, land subsidence, and sea-level rise.

Conclusion: Excellent descriptions (i.e., quite plausible and no obvious errors) generated entirely by the ChatBot beginning with ONLY a simple list of variables and no other prompt

RESPONSE R1b (from ChatGPT)
Contd.:

8. Bathymetry: Bathymetric measurements focus on mapping the underwater topography of oceans, seas, and lakes. This information is important for understanding water depth variations and the shape of underwater landforms.

9. Elevation/Topography: Accurate elevation data are essential for hydrological modeling, floodplain mapping, and understanding the movement of water across landscapes.

10. Geological Stratification: Knowledge of the geological layers beneath the surface can impact water movement, especially in terms of groundwater flow and the potential for contamination.

11. Land Use: Tracking how land is used, whether for agriculture, urban development, or other purposes, is important for assessing changes in runoff, water availability, and potential pollution sources.

Conclusion: Excellent descriptions (i.e., quite plausible and no obvious errors) generated entirely by the ChatBot beginning with ONLY a simple list of variables and no other prompt

Question Q2: Describe UN-SDG-6 Indicators. [Here we compare the response of the three LLMs with the “ground truth” – The Official UN list.

Response R2: Examples of variations between LLMs in responses to Queries or Questions. Response to other Indicators were similar. [Hallucins or remarks in **RED**]

ChatGPT	Google-BARD	MS-Bing	UN-SDG (Reference)
<p>Indicator 6.1.1: Percentage of the population using safely managed drinking water services</p>	<p>6.1.1 Proportion of population using safely managed drinking water services; improved drinking water source, in-premises improved drinking water, and safely managed drinking water services).</p>	<p>Indicator 6.1.1: Proportion of population using safely managed drinking water services. [Correct response]</p>	<p>Indicator 6.1.1: Proportion of population using safely managed drinking water services. [Reference]</p>
<p>Indicator 6.3.1: Proportion of wastewater (missing text) flows safely treated.</p>	<p>6.3.1 Proportion of wastewater collected and treated, by country income group and, where possible, by urban/rural disaggregation.</p>	<p>Indicator 6.3.1: Proportion (missing text) of wastewater flows safely treated.</p>	<p>Indicator 6.3.1: Proportion of domestic and industrial wastewater flows safely treated. [Reference]</p>
<p>Indicator 6.5.1: Degree of integrated water resources management implementation</p>	<p>6.5.1 Proportion of water bodies in a good ecological status, by type of water body.</p>	<p>Indicator 6.5.1: Degree of integrated water resources management implementation (0-100)</p>	<p>Indicator 6.5.1: Degree of integrated water resources management [Reference]</p>

Question Q3: Describe the UN-SDG-6 Targets.

Response R3: Examples of variations in responses between LLMs in responses to Queries or Questions.

Response to other Targets were similar. [Hallucinations or remarks in RED]

ChatGPT		Google-BARD	MS-Bing	UN-SDG (Reference)
Target 6.1: By 2030, achieve universal and equitable access to safe and affordable drinking water for all. [Correct response]	Target 6.1: By 2030, achieve universal and equitable access to safe and affordable drinking water for all. [Correct response]	Target 6.1: By 2030, achieve universal and equitable access to safe and affordable drinking water for all. [Correct response]	Target 6.1: By 2030, achieve universal and equitable access to safe and affordable drinking water for all. [Correct response]	Target: 6.1: By 2030, achieve universal and equitable access to safe and affordable drinking water for all. [Reference]
No Target 6.8 [UN-SDG does not have a Target 6.10] [Correct response]	Target 6.8: By 2030, ensure that people everywhere have the relevant information and awareness for the sustainable management of water and sanitation at all levels.	No Target 6.8 [UN-SDG does not have a Target 6.10] [Correct response]	No Target 6.8 [UN-SDG does not have a Target 6.10] [Correct response]	No Target 6.8 [UN-SDG does not have a Target 6.10] [Reference]
No Target 6.10 [Correct response]	Target 6.10: By 2030, reduce the adverse per capita environmental impact of cities, including by paying special attention to air quality and municipal and other waste management.	No Target 6.10. [UN-SDG does not have a Target 6.10]	No Target 6.10 [UN-SDG does not have a Target 6.10]	No Target 6.10 [UN-SDG does not have a Target 6.10] [Reference]

Question Q5: Expand on satellite platforms and data sets for monitoring UN-SDG.

Response: [Comment: Reasonably comprehensive entries for ChatGPT3.5. But Bard and Bing offered additional references for more details], less so for Google Bard, and somewhat limited for MS-Bing. Bard and Bing offered additional references for more details]

Chat GPT	Google BARD	MS-Bing
<p>MODIS sensors on NASA's Terra and Aqua satellites provide daily global coverage, offering data on water temperature, chlorophyll-a concentration, and suspended sediment levels. This data is vital for monitoring water quality, identifying pollution, and tracking algal blooms</p>	<p>MODIS: MODIS is a suite of instruments that are flown on a number of different Earth observation satellites. MODIS data can be used to monitor water availability, water quality, water use, water infrastructure, and water-related ecosystems.</p> <p>Link:https://modis.gsfc.nasa.gov/about/components.php</p>	<p><u>Moderate Resolution Imaging Spectroradiometer (MODIS): Data from MODIS can be used to measure surface water extent at 250 m spatial resolution¹.</u></p>
<p>Landsat Series: Landsat satellites offer multispectral imagery with moderate spatial resolution, useful for monitoring changes in water bodies, urban development, and land cover changes that impact water resources.a</p>	<p>Landsat: Landsat is a series of Earth observation satellites that have been collecting data since the 1970s. Landsat data can be used to monitor water availability, water quality, water use, water infrastructure, and water-related ecosystems.</p> <p>Link: https://www.nasa.gov/mission_pages/landsat/overview/index.html</p>	<p><u>Landsat 5, 7, and 8 with Shuttle Radar Topography Mission (SRTM): These instruments can be used to measure surface water extent at 30 m spatial resolution¹.</u></p> <p><u>Landsat 8 Operational Land Imager (OLI), Sentinel-1, and SRTM: The extent of mangroves can be mapped at 30 m spatial resolution using these instruments¹.</u></p>

Question Q5: Expand on satellite platforms and data sets for monitoring UN-SDG.

Response: [Reasonably comprehensive entries for ChatGPT3.5, less so for Google Bard, and somewhat limited for MS-Bing. Bard and Bing offered additional references for more details]

Chat GPT		MS-Bing
<p>(Sentinel-1 and Sentinel-2): Sentinel-1 offers radar data for monitoring surface water, flood extents, and wetland changes, especially in cloudy regions. Sentinel-2 provides high-resolution multispectral imagery that aids in monitoring water bodies, urban growth, and land cover changes.</p>	<p>(Sentinel-1 and Sentinel-2): Sentinel-1 offers radar data for monitoring surface water, flood extents, and wetland changes, especially in cloudy regions. Sentinel-2 provides high-resolution multispectral imagery that aids in monitoring water bodies, urban growth, and land cover changes.</p>	<p>No specific entry.</p> <p>Generic entry: “In addition to these instruments, there are other remote sensing techniques that can be used to monitor SDG 6 indicators .”</p>
<p>GRACE (Gravity Recovery and Climate Experiment): GRACE satellites measure changes in Earth's gravitational field to track variations in water storage, including groundwater depletion and changes in surface water bodies.</p> <p>SMAP (Soil Moisture Active Passive): SMAP provides soil moisture data, aiding in monitoring drought conditions, assessing water availability, and improving irrigation practices.</p>	<p>GRACE: GRACE stands for Gravity Recovery and Climate Experiment. GRACE data can be used to measure changes in the Earth's gravity field, which can be used to track changes in water mass, such as those caused by droughts or floods.</p> <p>SMOS: SMOS stands for Soil Moisture and Ocean Salinity. SMOS data can be used to measure the soil moisture and ocean salinity, which can be used to track changes in water</p>	<p>No other entries</p>

Question Q5 (Contd.): Expand on satellite platforms and data sets for monitoring UN-SDG.

Response: [Reasonably comprehensive entries for ChatGPT3.5, less so for Google Bard, and somewhat limited for MS-Bing. Bard and Bing offered additional references for more details]

Chat GPT	Google BARD	MS-Bing
<p>GEO AquaWatch: A global initiative providing comprehensive water quality information from various remote sensing platforms, useful for monitoring water quality changes.</p>	<p>AR: SAR stands for synthetic aperture radar. SAR data can be used to penetrate clouds and vegetation, making it useful for monitoring water bodies in areas with limited visibility. Link to: https://www.earthdata.nasa.gov/learn/backgrounders/what-is-sar InSAR: InSAR stands for interferometric synthetic aperture radar. InSAR data can be used to measure changes in the ground surface, such as changes in water levels or land subsidence. Link to paper: https://www.nature.com/articles/s41598-019-50792-y</p>	No other entries
<p>ChatGPT goes on to provide entries titled: Copernicus Marine Environment Monitoring Service; Aqueduct Water Risk Atlas; GReD (Global Reservoir and Dam Database); Global Urban Footprint (GUF); WorldPop; OpenStreetMap; GEO AquaWatch;; Aqueduct Water Risk Atlas.</p>	<p>The choice of satellite platform and data set will depend on the specific indicator that is being monitored and the availability of data. In some cases, it may be necessary to use a combination of different platforms and data sets to get a complete picture of the water situation. No other entries</p>	No other entries

Conclusions—Performance & quality of Responses to Questions from ChatGPT-3.5, Google-Bard & MS-Bing

Conclusions—Performance & quality of Responses to Questions from ChatGPT-3.5, Google-Bard & MS-Bing.

Overall, we found the Generative AI-LLMs (ChatBots) to be potentially useful for science applications, especially consolidating available information, as an excellent beginning point for research projects and science applications, as well as drafting text and reporting.

(1) Rewriting text – e.g., abstract to this paper. **Result: excellent.**

(2) Generating extended descriptions/definitions of Essential Water Variables (Primary & Supplemental) from simple bullet-point lists of variables (just names): **Result: Excellent;** namely, as good as any to be found or prepared by a knowledgeable human expert.

(3) Defining the monitoring Indicators for the UN Sustainable Development Goals—SDG-6 (Water): **Results: Good**, but with some variation between the 3 LLMs and with some (for some Qs, several) **“Hallucins.”** We introduce the term “Hallucins” here to refer to **“hallucinations”** created by LLM systems which can resemble reality but are not necessarily based on factual foundation. This means that all results would require additional checking and validation before they could be considered accurate or credible. If specific data or reference is required, the LLM may or may not provide it. Or, it might provide erroneous answers posing as real. This becomes particularly important if the LLM is expected to be used as a reference for setting up a monitoring system for observations, data collection and analysis, or is to be quoted as factual. The error rate or “Hallucin” can vary from 0% to what we speculate to be about 30% (We have not carried out a statistical analysis). Some other studies have claimed accuracies of about 19%. The problem here is that even with a <5% accuracy, it would not be known where the errors or hallucins are, thus requiring that any LLM presentations be cross-checked/validated before further use.

(4) Defining & describing the SDG-6 Targets: **Results: Good** but with the same caveats as in the case for “Indicators.” Hallucins in one LLM case is sufficient to illustrate the need for cross-validation before the results could be considered credible enough to be quoted or published.

5. Consolidating information on observations and data sets for SDG-6 indicator monitoring; **Results: quite good** with some caveats re. Hallucins and curiously fabricated references with papers and figures not associated with the claimed result In one case, the reference to the paper and figure were both wrong, and the Fig was from a different paper.

6. Self-examination and correction: **Results: Good after follow-up queries.** Here, we checked whether the AI-LLM could examine and correct itself. This was a useful feature that was not expected.

Conclusions (Contd.)—Performance & quality of Responses to Questions from ChatGPT-3.5, Google-Bard & MS-Bing

7. As a side note: Out of curiosity, we looked at the performance of ChatGPT-3.5 in playing NYT Wordle and Connections games. It was terrible at Wordle and had trouble deciphering the rules of the game. It fared quite well with Connections. We didn't try Google-BARD and MS-BING partly because they can access real-time data—e.g., for the connections game. ChatGPT 3.5's training data set is limited to Jan. 2022. Later versions, ChatGPT4 is a paid version and has updated training data sets and much larger parameter space and has access to real-time 2023 data. MS-BING is based on GPT4. Google-BARD has its own Generative AI-LLM.

8. Comparison between the structure of AI-LLMs and the Human Brain (HB) **suggests that they can be very credible and useful and could be approaching (with caveats) the information access and processing talents of the human brain for several functionally useful operational tasks based on pre-training data sets and associated query-response/reflex capabilities.** This statement refers to what we call in this paper as the autonomous (or unconscious) human brain (HB-Auto) that responds, for all practical purpose, in an automated manner for many real-world applications. That is, the HB also relies on large training data sets. Here we make a distinction between the “autonomous human brain and the conscious or analytical (or cognitive/Intelligence) human brain (HB-Anal). We suggest that the HB-A has inherent “thinking” capacity outside their training data base—which the AI system does not. But, at first glance, they perform in a manner that resembles thinking capacity of a Human for many operational practical applications. Moreover, AI systems can be extremely fast, almost instantaneous in their capacity to access, process and consolidate information. The HB-Auto also does this (fast) for many reflexive functions but can be slow for analytical or cognitive processes. [Caveats: Terminology is self-defined and may not be that of established neurological definitions.]

9. Examples of AI-LLMs and number of parameters--a measure of its complexity and ability to learn (Ref.: obtained from: Google Searches)

Chat-GPT-2: 1.5 Billion parameters

Chat-GPT-3: 175 Billion parameters

Chat-GPT-4: 1.76 Trillion parameters

Human Brain: ~ 100 Billion neurons & 100 Trillion synapses. Synapses per neuron is ~ 1000 – 10,000.

Closing: “Short 6-line Zen Poem about the global water cycle.” (Generated entirely by ChatGPT):

Raindrops whisper down,

Clouds weave stories in the sky,

Rivers dance to the sea's call,

Mist embraces mountains tall.

In this cycle, life unfolds,

Water's journey, ancient and bold.

References(Further reading): (1) Figure (Water Cycle): Source: NASA Global Precipitation Mission (<https://gpm.nasa.gov/education/water-cycle>); (2) Future progress in artificial intelligence: A Survey of Expert Opinion. Müller, Vincent C. and Bostrom, Nick (in Vincent C. Müller (ed.), Fundamental Issues of Artificial Intelligence (Synthese Library; Berlin: Springer. (3) The brain's autopilot mechanism steers consciousness, Steve Ayan, December 19, 2018, Scientific American.

Appendix: Additional slides for information (On-Line Only)

Examples of AI-LLMs/Generative AI capability to generate or rewrite/rephrase text. Original Abstract of this paper, followed by One G-AI/LLM's (ChatGPT 3.5) re-phrase. Note: Each time the Q is asked, the response was slightly different; each LLM had different interpretations/responses. All were equally good. : Response quality: **Possibly Excellent. Hence potentially quite useful in scientific summarization & reporting.**

The United Nations Sustainable Development Goals (SDGs) framework was established in 2015 to motivate progress towards achieving 17 SDGs by 2030. They include all aspects of the Earth system and reference Goals & Indicators for managing natural, industrial, environmental & socioeconomic resources. A key question is how to access & simplify the available “global” documentation into concise information to assist the national/international community design monitoring systems to assess progress towards achieving the SDGs. The urgency for such action arises from the target date of 2030 set by the UN for the achievement of most of the SDGs. We show how ChatGPT (created by OpenAI) and similar LLMs (Large Language Models) such as Google-Bard, Microsoft-Bing-AI can be used to iteratively develop increasingly informative and precise descriptions on the SDG Goals, Targets, Indicators, remote sensing platforms, and data sets to help build the needed end-user applications. We begin with a broad exploration of all UN-SDGs and then progressively focus on SDG-6 (Water) due to intersection of the global water cycle with nearly all other sectoral themes of the SDGs. We explore SDG-6's Goals, Targets and Indicators, followed by specifications of available remote sensing instruments and data sets. During this process, we noted that the LLMs were also prone to errors and “Halucinations,” termed “Hallucins” in this paper. Hallucins come across as authoritative and convincing. They need to be independently verified. Curiously, questioning the LLM itself for additional substantiation of a suspected Hallucin led to LLMs admitting to the error. All LLMs also have disclaimers mentioning that the information they present may not be accurate. The challenge to the end-user: Verification/validation of the LLM response/results to a query/investigation. That said, their performance was impressive overall & they could pull together relevant information almost instantly from large data bases—an action that would take a human considerable time to collect and analyze in more traditional ways.

Rephrase/summarization of Abstract by Chat GPT-3.5 (other AI's were similar) (On-Line Only) : Note: This was an example of free-floating text with no reference to any specific data, except programmatic information). **Content Accuracy: Excellent; Quality: Excellent; Errors: None.**

The United Nations introduced the Sustainable Development Goals (SDGs) framework in 2015, outlining 17 goals to be achieved by 2030. These goals encompass various aspects of the Earth system, including natural, industrial, environmental, and socioeconomic resources. A critical challenge is to distill the extensive global documentation into concise information that can guide the design of monitoring systems to track progress towards the SDGs. This need is underscored by the 2030 deadline set by the UN for achieving most of the SDGs.

Large Language Models (LLMs) like ChatGPT by OpenAI, Google-Bard, and Microsoft-Bing-AI can be instrumental in this process. They can iteratively generate increasingly detailed and accurate descriptions of the SDG Goals, Targets, Indicators, remote sensing platforms, and data sets, thereby aiding in the development of necessary end-user applications.

Our exploration begins with a comprehensive overview of all UN-SDGs, gradually narrowing down to SDG-6 (Water). This focus is due to the global water cycle's intersection with nearly all other sectoral themes of the SDGs. We delve into SDG-6's Goals, Targets and Indicators, followed by an examination of available remote sensing instruments and data sets.

However, it's important to note that LLMs are not infallible. They can produce errors and "Hallucinations," or "Hallucins," as we term them in this paper. These Hallucins can appear authoritative and convincing but require independent verification. Interestingly, querying the LLM itself for additional substantiation often leads to the model acknowledging its error. All LLMs carry disclaimers stating that their information may not be accurate.

The challenge for end-users lies in verifying and validating the LLM's responses. Despite this caveat, LLMs demonstrate impressive performance overall. They can rapidly collate relevant information from vast databases - a task that would take a human significantly longer using traditional methods.

Response R4 to Q4
 from Google Bard
 (Q4: Find/Display,
 NASA Earth
 observing
 constellation.)
 [On-Line Only]



Response R4 to Q4
 from Google Bard
 (Q4:Find/Display,
 ESA Earth observing
 constellation.
 Sentinel-Series (2A
 & 2B)
 [On-Line Only]

