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Preparing Teachers for Teaching Spatial Computational Thinking With *Integrated Data Viewer* Visualization of Weather Data: A Discipline-Based Perspective of Computational Thinking

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Abstract

This study was grounded in the spatial computational thinking model developed by the *3D Weather* project funded by the NSF STEM+C program. The model reflects a discipline-based perspective towards computational thinking and captures the spatial nature of computational thinking in meteorology and the reliance of computational thinking on spatial thinking for geospatial analysis. The research was conducted among nineteen teachers attending the summer workshop offered by the project in its third project year to prepare them for teaching spatial computational thinking with IDV (*Integrated Data Viewer*, downloadable at https://www.unidata.ucar.edu/software/idv/) visualization of weather data. Quantitative survey data were collected measuring these teachers' meteorology content knowledge, spatial computational thinking, self-efficacy for teaching spatial computational thinking, and epistemic cognition of teaching meteorology. The data were analyzed to examine the effects of the workshop in terms of these variables and the correlations among them were also explored.

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Introduction

Wing argues in her seminal article of 2006 that computational thinking (CT) is a fundamental skill to be taught to all students alongside reading, writing, and mathematics. Ever since then, computational thinking has received considerable attention from STEM educators and researchers with continued efforts to teach it to K-12 students as an important problem-solving skill set. In the same year, the National Research Council (2006) published the report *Learning to Think Spatially* highlighting spatial thinking as the thought process that "is integral to everyday work of engineers and scientists" and "has underpinned many scientific and technical breakthroughs" (p. 5). This report has sparked a new interest among researchers to examine spatial thinking in STEM education, especially in those spatially demanding STEM disciplines, such as geoscience, chemistry, and mechanics (Hegarty, 2010). Although recent years have seen emerging efforts (e.g., Città et al., 2019; Ham, 2022; Moschella & Basso, 2020) to put computational thinking and spatial thinking under the same lens, they are mostly treated as separate thinking processes in the K-12 STEM education arena.

What's missing in the landscape of computational thinking and spatial thinking research is a discipline-based perspective that recognizes the reliance of computational thinking on spatial thinking in some STEM disciplines, such as meteorology. Meteorologists can envision atmospheric movement, forecast upcoming weather, and predict weather events by analyzing and interpreting two-dimensional weather maps and satellite imagery, and visualizing large scale weather data obtained through a mix of weather satellites and on-the-ground weather sensors. Besides meteorological knowledge, computational thinking alone does not explain how meteorologists make sense of three-dimensional atmospheric processes because the maps, images, and numerical data they use encode a large amount of spatial information that needs to be processed by thinking spatially. The three-dimensional nature of the atmosphere and the consequent spatial nature of the tasks undertaken by meteorologists in geospatial analysis determine that computational thinking in meteorology takes place in spatial contexts and builds on spatial thinking. This is a special type of computational thinking referred to as "spatial computational thinking" by the *3D Weather* project.

Funded by NSF STEM+C program[1], the *3D Weather* project designed and developed IDV visualization modules to teach spatial computational thinking through visualization of real weather data with IDV. Summer workshops were offered to prepare teachers for using the modules to teach spatial computational thinking. The research reported in this paper was conducted on the teachers who attended the project's third year summer workshop for the purpose of assessing the workshop's impact on these teachers in terms of spatial computational thinking, epistemic cognition of teaching meteorology, and self-efficacy in teaching spatial computational thinking with IDV visualization of weather data.

Background

K-12 Computational Thinking Education: A Lack of Discipline-Based Perspective

Computational thinking is defined as an approach to problem solving that draws on concepts and mental tools in computer science (Brennan & Resnick, 2012; Grover & Pea, 2013; Wing, 2006). Ever since Wing's paper, computational thinking has become a buzzword in the K-12 education research field driving researchers to define it and identify its skill set. There is a lack of consensus on the skills that fall within the domain of computational thinking. We reviewed 15 computational thinking frameworks or models (including Wing's) that are highly cited in the literature: Angeli et al.(2016), Atmatzidou and Demetriadis (2016), Barr and Stephenson (2011), Brennan and Resnick (2012), Gouws et al. (2013), Grover and Pea (2018), KaleliOğlu et al. (2016), Moreno-León et al. (2015), National Research Council NRC (2010), Palts and Pedaste (2020), Selby and Woollard (2013), Shute et al. (2017), Weintrop et al. (2016), Wing (2006), Yadav et al. (2014). Table 1 lists the top 15 computational thinking skills in these reviewed frameworks or models.

Wing's (2006) article ignited the K-12 educational enthusiasm in computational thinking over the past 16 years, but the term "computational thinking" was first used by

Table 1. Top 15 Computational Thinking Skills Based on Literature Review.

Computational Thinking Skills
• Abstraction
• Decomposition
• Algorithms (algorithmic thinking/design)
• Debugging
• Data (management, collection, manipulation, analysis, representation, visualization)
• Generalization
• Parallelism (parallelization)
• Automation
• Iteration
• Simulation (modelling and simulation)
• Evaluation
• Logical thinking (logic)
• Pattern recognition
• Procedures
• Modularization (modularity)

Seymour Papert in 1980 (Città et al., 2019; Lodi & Martini, 2021). According to Lodi and Martini (2021), Papert's CT has a different nuance of meaning related to his constructionist approach emphasizing the social and affective involvement of students in constructing computational artifacts. Despite the difference, both Papert's CT and Wing's CT carry the idea that competencies acquired as computational thinking in computer science will transfer easily or even automatically to other disciplines. This unverified claim, explaining the appeal of CT in K-12 education (Lodi & Martini, 2021), has unfortunately led to the widespread practice of (1) using the values, norms, and practices in computer science to shape the discourse around CT integrated STEM education curriculum and pedagogy, and (2) ignoring how CT is practiced by practitioners in other STEM disciplines. Unsurprisingly, the extensive use of programming to teach CT in K-12 and a history in research of using programming for CT skill development have perpetuated the confusion that CT is the same as programming and has to, at least, involve programming (Voogt et al., 2015).

Such confusion originates from and reflects the lack of a disciplined-based perspective towards CT that goes against providing students with authentic CT experiences as taking place in real world STEM fields. Although recent years have seen more science educators using science content (such as ecosystem) and scientific practices (such as modeling) as contexts for CT development (Yang, et al., 2021), spatial thinking as meaningful contexts for computational thinking and CT development is still a missing piece in K-12 STEM+CT education and research.

Spatial Thinking and Spatially Demanding STEM Disciplines

Spatial thinking represents our spatial ability to generate, retain, retrieve, and transform well-structured visual images (Lohman, 1993). Compared with computational thinking, spatial thinking has much longer research history especially in the field of cognitive psychology. More than 100 years' psychology research focused on identifying the skill set of spatial ability has made it one of the most researched human cognitive processes (Carroll, 1993). According to Lohman (1993), spatial ability "is not a unitary construct, and there are, in fact, several spatial abilities, each emphasizing different aspects of the process of image generation, storage, retrieval, and transformation" (p. 3). Lohman's definition highlights the dynamic and multidimensional nature of spatial ability that has driven psychology research for more than a century. Prior research using the psychometric approach of factor analysis yielded different factor structures of spatial ability, such as the three-factor structure by Lohman (1979) (i.e., spatial relations, spatial orientation, and spatial visualization) and Linn and Petersen (1985) (i.e., spatial perception, mental rotation, and spatial visualization); and the five factor-structure by Carroll (1993) (i.e., visualization, spatial relations, speed of closure, flexibility, and perceptual speed). Uttal and his colleagues (Uttal et al., 2013) identified five spatial sub-skills based on their analysis of 217 research studies: mental rotation, spatial visualization, spatial perception, perspective taking, and disembedding.

Parallel to the above psychometric research path are research efforts on the relationship between spatial ability and STEM education. Invited by NSF 65 years ago, Super and Bachrach (1957) worked with an advisory panel to review published research and theories and identified and emphasized spatial ability, throughout their advisory panel report, as one of the essential aptitudes of scientists, mathematicians, and engineers. Ever since then, research evidence has accumulated supporting a positive link between spatial ability and creativity, achievement, and expertise development in STEM fields (e.g., Cheng & Mix, 2014; Lowrie et al., 2017; Rochford, 1985; Small & Morton, 1983; Sorby et al., 2013; Uttal et al., 2013). Longitudinal studies (e.g., Austin & Hanisch, 1990; Shea et al., 2001; Wai et al., 2009; Webb et al., 2007) provide further evidence confirming the positive link between spatial ability and educational-occupational achievements in STEM.

The National Research Council (2006) published the report *Learning to Think Spatially* that approaches the nature of spatial thinking from its three elements: spatial concepts, tools of representation, and processes of reasoning. The report delivers a clear discipline-based perspective on spatial thinking by acknowledging that, though spatial thinking is a universal mode of thinking, it has distinctly different manifestations in different disciplines: while there are general spatial concepts and spatial reasoning processes common across the STEM disciplines, these three elements can also be discipline-specific for different STEM disciplines. As such, expertise in spatial thinking is also discipline-specific (National Research Council, 2006):

- Expertise in spatial thinking draws on both general spatial skills that cross many domains of knowledge and spatial skills that are a particular domain of knowledge.
- Expertise in spatial thinking develops in the context of specific disciplines and becomes transformed and refined through training and extensive practice. (p. 5)

Reflecting the discipline-based perspective of spatial thinking from the National Research Council report is the disciplined-focused lens used by Atit et al. (2020) in their review of (1) research on spatial thinking skills used by experts in structural geology, surgery, and chemistry, and (2) their personal experiences and research as experts in these disciplines. Findings reported by Atit et al. (2020) regarding spatial thinking in STEM discipline include: (1) solving spatial problems require using domain knowledge, and spatial thinking in STEM is context-dependent and domain knowledge-integrated; (2) spatial problems occurring in STEM contexts are more complex than those spatial tasks in psychometric spatial skill tests and, consequently, spatial thinking as practiced by STEM practitioners in solving spatial problems is of greater complexity as compared to the thinking processes captured by psychometric measures of spatial thinking skills; (3) spatial skills that involve using and interpreting specific tools of representation reflect disciplinary core ideas of a STEM discipline and are important for reasoning and understanding within the discipline.

Spatial Computational Thinking and 3D Weather IDV Visualization Modules

Research has indicated that spatial thinking and spatial ability play an important role in many STEM fields, including physics, chemistry, mathematics, engineering, geoscience, and medicine (Atit et al., 2020; Kastens & Ishikawa, 2006). While space becomes the unifying theme across such spatially demanding STEM disciplines, spatial thinking is discipline-specific in terms its contexts, domain knowledge, and tools of representation (Atit et al., 2020). Meteorology is the scientific study of the atmosphere that focuses on weather processes and forecasting, and it is highly spatial due to the atmosphere being a thick "ocean" of air moving in different and constantly changing directions. In geospatial analysis for understanding, interpreting, and predicting atmospheric processes, meteorologists analyze and visualize geographically distributed weather data displayed through representations of 2D or 3D maps, charts, plots, and images. Spatial thinking sits at the core of the cognitive processes during geospatial analysis. The highly spatial nature of the tasks in geospatial analysis dictates that meteorologists' computational thinking for problem solving relies on their ability to think spatially.

Embracing a discipline-based perspective towards computational thinking and spatial thinking in meteorology, the *3D Weather* project followed three learning design principles in developing its IDV Visualization Modules: (1) having a spatial computational thinking model that captures the spatial nature of computational thinking in meteorology; (2) grounding computational thinking on domain knowledge-based contexts of meteorology, and (3) involving the use of a tool of representation that is important for reasoning and understanding within meteorology. Following these principles, the project team developed the *3D Weather Spatial Computational Thinking*

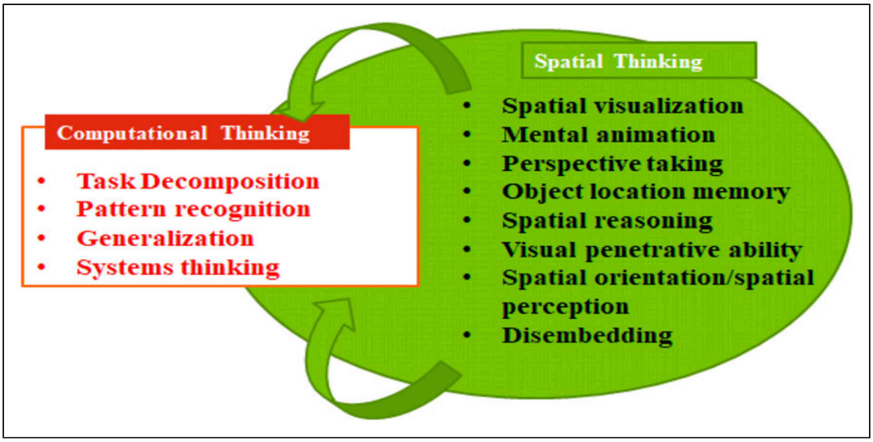

Figure 1. *3D Weather* spatial computational thinking model.

Model (Figure 1) through a literature review of computational thinking and spatial thinking skills and a Delphi study (Linstone & Turoff, 1975). Specifically, the project team (1) identified a list of computational thinking and spatial thinking skills based on a literature review of computational thinking (see Table 1) and spatial thinking (e.g., Carroll, 1993; Ekstrom et al., 1976; Gagnier et al., 2017; Hegarty, 1992; Hegarty & Sims, 1994; Hsi et al., 1997; Linn & Petersen, 1985; Lohman, 1979, 1996; Uttal et al., 2013; Voyer et al., 2007) with special attention paid to spatial thinking research in geosciences (e.g., Kali & Orion, 1996; Kastens & Ishikawa, 2006; McNeal, 2017; McNeal et al., 2019; Reynolds, 2012); (2) created a survey including these computational thinking and spatial thinking skills and their definitions; (3) sent the survey to the geosciences faculty at Mississippi State University asking them to identify computational thinking and spatial thinking skills relevant to geospatial analysis in meteorology; and (4) finalized the *3D Weather Spatial Computational Thinking Model* based on the survey responses.

The computational thinking and spatial thinking skills in the above model are not two separate sets of cognitive skills. Instead, they represent two inseparable cognitive dimensions in geospatial analysis or weather data visualization tasks. The "Computational Thinking" dimension reflects the nature of problem solving in weather data visualization tasks undertaken by meteorologists: diagnosing a complex weather system by decomposing tasks or interactions that contribute to the weather system (i.e., task decomposition) while taking into consideration various relationships and interactions among the components (e.g., atmosphere, water, solar energy) in the Earth and climate systems (i.e., systems thinking) for the purpose of recognizing patterns in weather phenomena or atmospheric processes (i.e., pattern recognition), and identifying shared features in these weather patterns and using them for understanding and predicting future weather conditions (i.e., generalization). The "Spatial Thinking" dimension represents the spatial thinking skills (i.e., spatial visualization, mental animation, perspective taking, object location memory, spatial reasoning, visual penetrative ability, spatial orientation/spatial perception, and disembedding) that are essential to use with computational thinking for problem solving in visualization tasks. Table 2 lists the definitions of the spatial thinking skills in the *3D Weather Spatial Computational Thinking Model*.

The *3D Weather* project team developed 24 IDV visualization modules (Table 3) that require using the computational thinking skills along with the spatial thinking skills in Figure 1 for weather data visualization tasks. These tasks are authentic in nature reflecting realistic and messy problems dealt by meteorologist that demand using multiple computational thinking skills and spatial thinking skills at the same time. This authentic nature distinguishes the *3D Weather* IDV visualization modules from those traditional K-12 computational thinking activities or spatial thinking psychometric tests that involve one specific skill at a time. Figure 2 offers an overview of an IDV visualization task from Module 11 that focuses on wind and pressure patterns of the "1993 Super Storm" on March 13, 1993.

Table 2. Spatial Thinking Skills and Their Definitions.

Spatial Thinking Skill	Definition
Spatial visualization	The ability to generate a mental image and operate various mental manipulations (such as rotation) to the image
Mental animation	The ability to infer motion from information given in static 2D or 3D images
Perspective taking	The ability to envision how something would appear from different vantage points, orient oneself to the external framework of the surrounding environment, and coordinate spatial relationships from different viewpoints
Object location memory	The ability to remember the spatial locations of previously seen objects or phenomena
Spatial reasoning	The ability to construct mental presentations for spatial objects and reason about their relationships and transformations
Visual penetrative ability	The ability to visualize the cross section of the interior of an object as it is sliced at different locations and at different angles
Spatial orientation/spatial perception	The ability to identify the position or direction of objects or points in space (Benton & Tranel, 1993), and to recognize and comprehend the relationship between one's location in space and objects in the external environment
Disembedding	The ability to process visual information in a complex or chaotic display by selectively focusing on specific important features or patterns ("the signal") and ignoring those distracting, nonessential ones ("the noise")

As demonstrated in the example in Figure 2, the visualization task involves using multiple computational thinking skills (i.e., task decomposition, pattern recognition, and systems thinking) and spatial thinking skills (i.e., spatial visualization, mental animation, object location, spatial orientation/spatial perception, and disembedding). The term "spatial computational thinking" has been used in the *3D Weather* project and this paper to capture (1) the reliance of computational thinking on spatial thinking for problem solving in spatial demanding contexts, and (2) the cognitive process and ability to apply computational thinking and spatial thinking effectively for completing weather data visualization tasks.

Each of the 24 IDV visualization modules includes a .xidv file that was created using publicly available NWP (Numerical Weather Predication) model data. Table 3 lists the 24 IDV visualization modules and their data sources. The first 12 modules are structured into four units corresponding to the four themes of temperature (modules 1–3), atmospheric moisture (modules 4–6), pressure and wind (modules 7–9), and mid-latitude cyclones and fronts (modules 10–12). Each of the four units contains two individual lecture-type presentations that cover various topics to furnish teachers and students with necessary domain knowledge-based contexts for completing the IDV

Table 3. 3D Weather IDV Visualization Modules and Data Sources.

IDV Visualization Module	Weather Data Source*
Module 1: Global temperature patterns	1° × 1° GFS output for Jun 5, 2020 @ 0000 UTC
Module 2: Seasonal temperature cycle	1° × 1° GFS output for 1st day of each month for 2018 @ 0000 UTC [12 files]
Module 3: Diurnal temperature cycle	13-km RAP output for May 15, 2019 from 0000 - 2300 UTC [24 files]
Module 4: Global moisture Distribution	1° × 1° GFS output for 1st day of each month for 2018 @ 0000 UTC [12 files]
Module5: Visualizing Cloud	1° × 1° GFS output for Jun 5, 2020 @ 0000 UTC
Module 6: 3D structure of moisture transport	12-km NAM output for Apr 30 – May 4, 2010 @ 0000 UTC for each day [5 files]
Module 7: Visualize global pressure and wind patterns	.5° × 0.5° GFS output for Jan 22, 2018 @ 1200 UTC
Module 8: Visualize pressure and wind fields at different levels	12-km NAM output for Jan 22, 2018 @ 1200 UTC
Module 9: Visualize the jet stream	12-km NAM output for Jan 22, 2018 @ 1200 UTC
Module 10: Temperature structure of a mid-latitude cyclone	32-km NARR output for Mar 13, 1993 @ 1200 UTC
Module 11: Wind and pressure patterns in a mid-latitude cyclone	32-km NARR output for Mar 13, 1993 @ 1200 UTC
Module 12: Evolution of a mid-latitude cyclone	32-km NARR output for Mar 10–14, 1993 @ 1200 UTC for each day [5 files]
Module 13: Katrina versus Tip	.25° × .25° GFS output for Aug 29, 2005 @ 0000 UTC
Module 14: Hurricane sandy	.25° × .25° GFS output for Oct 25, 2012 @ 1800 UTC
Module 15: Indian monsoon	.25° × .25° GFS output for Jan 7th, 2018 @ 1800 UTC and Jul 7th, 2018 @ 1800 UTC [2 files]
Module 16: ITCZ	.25° × .25° GFS output for Oct 19, 2021 @ 1200 UTC
Module 17: Heat wave	12-km NAM output for Jul 7, 2021 @ 0000 UTC
Module 18: Blizzard	.25° × .25° GFS output for Sep 30, 2021 @ 0000 UTC
Module 19: 2010 Nashville flood	12-km NAM output for May 1st, 2021 @ 1200 UTC
Module 20: 2011 tornado outbreak	12-km NAM output for Apr 27, 2021 @ 0600 UTC
Module 21: ENSO – Defining Module22: Teleconnections	1° × 1° GFS output for Feb 12, 2011 and Feb 12, 2019 @ 1800 UTC [2 files]
Module 22: ENSO – Weather impacts US	.25° × .25° GFS output for Jan 1, 2016 (El Nino) @ 0000 UTC and Dec 26, 2017 (La Nina) @ 0000 UTC
Module 23: Polar vortex	.25° × .25° GFS output for Jan 3, 2019 @ 0600 UTC
Module 24: Southern hemisphere polar jet	.25° × .25° GFS output for Jun 10, 2019 @ 1800 UTC

*Note: Data source description includes the spatial resolution and model type, as well as the valid date and time for each output file (UTC = Coordinated Universal Time). The acronyms for the model types are as follows: GFS = Global Forecast System; RAP = Rapid Refresh; NAM = North American Mesoscale; NARR = North American Regional Reanalysis. For modules using more than one file, the total number of files is listed in brackets. All model files are in gridded binary format.

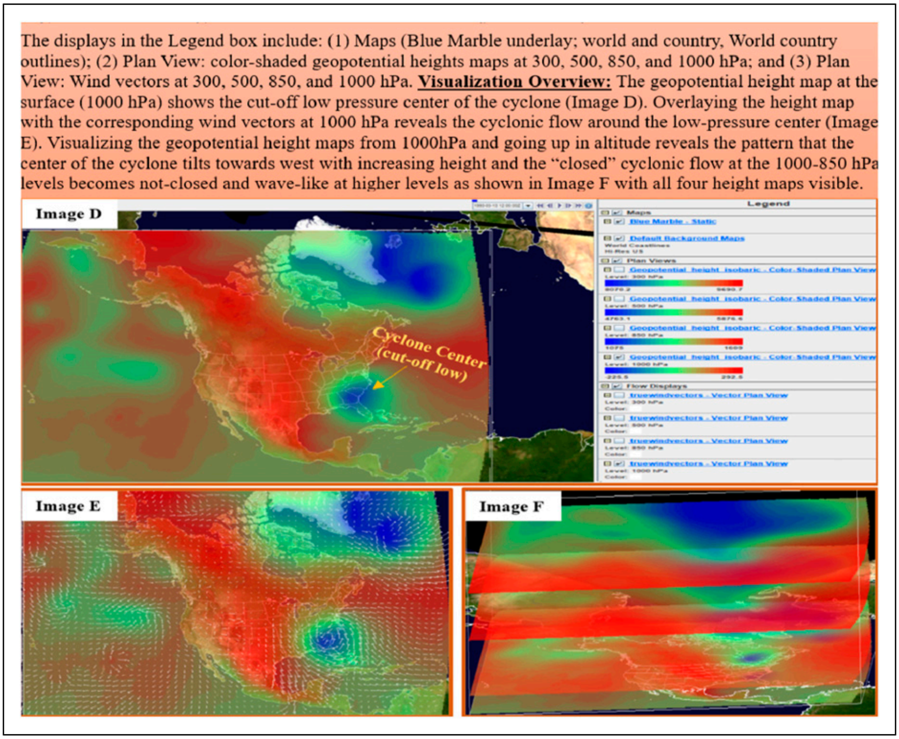

Figure 2. Visualizing wind and pressure patterns of "1993 super storm" on 3/13/1993.

visualization modules. The lecture-type presentations were developed by the subject matter expert on the project using a variety of sources from textbooks, internet sources, and other educational materials. The topics covered in the presentations are listed below. As shown in Table 3, modules 13–24 are based on extreme weather events in history and were developed as comprehensive applications of knowledge and spatial and computational thinking skills developed in modules 1–12.

➢ Unit 1: Temperature
  Presentation 1: Global Temperature Patterns (Topics: global energy balance, energy balance over oceans and land, and vertical temperature pattern)

Presentation 2: Daily Seasonal Temperature Variations (Topics: understanding sun angle, seasonal temperature cycles, and diurnal temperature cycles)

- ➢ Unit 2: Atmospheric Moisture
  Presentation 1: Defining Moisture and Saturation (Topics: What is “air”?, the three phrases of water, and what is “humidity”?)
  Presentation 2: Measures of Atmospheric Moisture (Topics: measures of atmospheric moisture, relative humidity, and dew point)
- ➢ Unit 3: Pressure and Wind
  Presentation 1: Overview of Pressure and Wind (Topics: What is atmospheric pressure?, What causes changes in air pressure?, and What causes wind?)
  Presentation 2: Pressure and wind at different atmospheric levels (Topics: surface pressure and wind patterns, Why does wind speed increase with height?, and What are atmospheric jets and why do they exist?)
- ➢ Unit 4: Mid-latitude Cyclones and Fronts
  Presentation 1: Cold and Warm Fronts (Topics: air masses, structure of a worm front, and structure of a cold front)
  Presentation 2: Life cycle of a Mid-latitude cyclone (Topics: What is a mid-latitude cyclone?, stages of a mid-latitude cyclone, and structure of a mid-latitude cyclone)

In accordance with the third learning design principle mentioned earlier, IDV was the tool of representation chosen by the project team for developing the visualization modules. Although a variety of software packages exist that allow for visualization of gridded scientific data, IDV meets both the project’s and teachers’ needs because it is freely available, has a broad variety of visualization tools within a relatively compact graphical user interface (GUI) environment, is purpose-built for meteorological data so that it can ingest common NWP model files, and is flexible across platforms as a Java-based software program. With the visualization tools available in IDV and the real weather data used for visualization, *3D Weather IDV Visualization Modules* provide unique learning experience for developing computational and spatial thinking skills. This is authentic learning (Strobel et al., 2013; Sun et al., 2019) anchored in meteorology and reflecting what professionals do in geospatial analysis.

3D Weather *Summer Workshop*

The *3D Weather* project offered summer workshops to help teachers teach spatial computational thinking to their students with the *IDV Visualization Modules*. The workshop reported in this paper was the third-year summer workshop in 2022. This is a two-week workshop with the first week being online through a self-paced Canvas course and the second week in-person. While the first week online course covered the lectures of domain knowledge in the four units of temperature, atmospheric moisture, pressure and wind, and mid-latitude cyclones and fronts, and an overview of the spatial computational thinking skills (Figure 1), the second week in-person training provided ample hands-on opportunities for teachers to explore IDV visualization of weather data and for teaching spatial computational thinking. Specifically, the in-person training consisted of three major components for the first four days from Monday to Thursday:

(1) the IDV visualization of weather data component led by the subject matter expert that included: exploring the visualization features in IDV, using IDV to visualize atmospheric processes or patterns in modules 1–12, introducing weather-event-based modules, and creating . xidv files of the teachers' own choice of weather data.
(2) the teaching spatial computational thinking with IDV visualization component led by the STEM education researcher in the project team that included: exploring the computational thinking and spatial thinking skills in the *3D Weather Spatial Computational Thinking Model* through specific examples, discussing the teacher's guides created by the project team on teaching spatial computational thinking with IDV visualization of weather data, and learning how to teach with the "Engage, Observe, and Explain & Communicate" pedagogy as modeled in the IDV visualization activities in the teacher's guides.
(3) the lesson planning component that allowed the teachers time to create their lesson plans for teaching spatial computational thinking with IDV visualization in the Fall and Spring semesters following the workshop and work in seven groups to prepare their group mini lessons for Friday.

On the Friday of the in-person training week, each of the seven groups taught their mini lesson of about 15 minutes followed by a discussion and feedback session with the project team.

Theoretical Framework

Embracing a discipline-based perspective towards computational thinking and spatial thinking, *3D Weather IDV Visualization Modules* (1) introduced a new pedagogy for teaching spatial computational thinking contextualized in meteorology, and (2) created an innovative science education opportunity for leveraging the positive link between spatial ability and educational-occupational achievements in STEM. Teachers are the active agent whose competency and willingness will determine if the pedagogy and the science education opportunity can take place in K-12 classrooms. Therefore, the research in this study focused on examining and understanding the effects of the *3D Weather* summer workshop on teachers. The research was guided by the teacher knowledge and belief framework built on a teacher knowledge-based perspective and a teacher belief-based perspective. From the teacher knowledge-based perspective, the study focused on teachers' domain knowledge in meteorology and spatial computational thinking skills to quantify their relationship and to investigate the effects of the summer workshop.

From the teacher belief-based perspective, the study specifically looked at two teacher related constructs: epistemic cognition and teacher self-efficacy. Epistemic cognition refers to people's beliefs about knowledge and the process of knowing, and it "concerns how people acquire, understand, justify, change, and use knowledge in formal and informal contexts" (Greene et al., 2016, p. 1). Teachers' epistemic cognition provides insight into their development as teachers and their teaching practices (e.g., Lunn Brownlee et al., 2011, 2016) and can be classified according to different developmental levels that are subject to change (Feucht, 2011). It has been revealed that teachers with availing epistemic cognition are receptive to epistemic development and less resistant to educational reform, which in turn influences teaching practices, students' epistemic cognition, and the epistemic climate of the classroom (Feucht, 2011). Compared to epistemic cognition, the construct of teacher self-efficacy is more straightforward: while self-efficacy, in general, is people's belief in their capabilities to organize and execute the courses of action to produce given attainments (Bandura, 1997), a teacher's self-efficacy refers to his/her ability to successfully cope with teaching and learning related tasks and challenges (Caprara et al., 2006; Lazarides & Warner, 2020). Research has shown that teachers with higher levels of teacher self-efficacy are more open to new teaching methods and more willing to deal with challenges and adjust teaching strategies when facing difficulties (Lazarides & Warner, 2020). In the context of *3D Weather* summer workshop, the study quantitatively examined teachers' epistemic cognition of teaching meteorology and their self-efficacy of teaching spatial computational thinking with IDV visualization to reveal the effects of the workshop on these two constructs and their relationship with teachers' domain knowledge and spatial computational thinking skills.

Methodology

Research Design

Adopting a quantitative survey research design, this study collected data from the teachers who attended the *3D Weather* summer workshop in 2022. The data were analyzed to answer the research questions: (1) How does the summer workshop affect teachers' spatial computational thinking, self-efficacy in teaching spatial computational thinking with IDV visualization of weather data, and epistemic cognition of teaching meteorology? and (2) How is teachers' domain knowledge in meteorology related to their spatial computational thinking and self-efficacy in teaching spatial computational thinking with IDV visualization of weather data?

Participants

The project team reached out to the six partner school districts in Mississippi listed in the original grant proposal to recruit teachers. Nineteen teachers from 12 schools in these school districts were recruited on a voluntary basis to attend the *3D Weather* 2022 summer workshop that included one-week online Canvas course and one-week in person training. These teachers completed the assessment tests in the Canvas course and responded to the pre- and post-surveys. Their assessment test results and responses to the surveys were analyzed to answer the research questions. The demographic information regarding these teachers' gender, race, subject area & grade level, and years of teaching experience was presented in Table 4.

Instruments

The instruments used in this study included (1) four knowledge assessment tests corresponding to the four units of temperature (24 questions), atmospheric moisture (24 questions), pressure and wind (32 questions), and mid-latitude cyclones and fronts (27 questions), and (2) an online survey that includes questions about teachers' demographic information and three subscales: subscale I of spatial computational thinking (13 items), subscale II of epistemic cognition of teaching meteorology (23 items), and subscale III of self-efficacy of teaching spatial computational thinking with IDV visualization (7 items). Each of the four knowledge assessment tests has a total score of

Table 4. 3D Weather 2022 Summer Workshop Teachers' Demographic Information.

Category		*n*
Gender	Male	1
	Female	18
Race	African american	7
	Caucasian	12
Subject area & grade level	All subjects (K-6)	1
	Math & science (3^{rd} – 5^{th} grades)	5
	Gifted (all subjects) (3^{rd} – 8^{th})	1
	Highly gifted (all subjects) (2^{nd} – 5^{th})	1
	Math (5^{th} and 6^{th} grades)	1
	Math (6^{th}, 7^{th}, or 8^{th})	4
	Science (6^{th})	1
	Science (7^{th} & 8^{th})	1
	Science (special ed) (7^{th}, 8^{th}, & 10^{th})	1
	Math, science, & English (special ed) (11^{th} & 12^{th})	1
	ELA and math (6^{th} – 8^{th})	1
	ELA interventions	1
Years of teaching experience	1–5 years	1
	6 – 10 years	4
	11 – 15 years	3
	16 – 20 years	4
	21 – 25 years	3
	26 – 30 years	2
	More than 30 years	2

100 points. All items in the three subscales use a 6-point Liker scale from "strongly disagree" (scored as "1") to "strongly agree" (scored as 6). Of the 23 items in subscale II, 10 items reflect the epistemic cognition of teaching meteorology with traditional method (i.e., scientific facts and rote learning based), 7 items reflect the epistemic cognition of teaching meteorology with computational thinking and practices (i.e., practices involving using computational tools, such as IDV, for weather data visualization), and 6 items reflect the epistemic cognition of teaching meteorology with scientific practices (i.e., practices reflected in such science education methods as hands-on science experiences, project-based science learning, and inquiry-based science learning).

Measures and Data Analysis

The teachers took each of the four knowledge assessment tests after completing the corresponding unit on Canvas during the first week of the summer workshop. The mean of the four knowledge assessment tests was calculated to give each teacher a knowledge score. The survey was administered to the teachers both before and after the summer workshop. The mean item score was calculated respectively for subscale I and subscale III both for pre- and post-workshop survey responses. For subscale II, the mean item score for each of three types of epistemic cognition was calculated for both pre- and post-workshop surveys. Table 5 summarizes the variables measured in this study and their operational definitions. Spearman correlation tests, Friedman rank-sum tests, and Wilcoxon signed rank tests were conducted using SPSS (version 28) for data analysis.

Results

All variables in Table 5, except Knowledge Score, were dependent variables (DV) and had both pre- and post-workshop data. Knowledge Score was an independent variable (IV) and had only post-workshop data. The descriptive statistics of the pre- and post-workshop data are reported in Table 6 below.

Impact of Summer Workshop on Spatial Computational Thinking Score

A Wilcoxon signed rank test was conducted to compare the pre- and post-workshop S-CT Scores. The test result indicates that post-workshop S-CT scores (MD = 4.77, n = 19) were significantly higher than pre-workshop S-CT scores (MD = 4.00, n = 19), z = 3.42, $p < .001$.

Impact of Summer Workshop on Self-Efficacy Score

To compare the pre- and post-workshop Self-efficacy Scores, another Wilcoxon signed rank test was conducted. The test result indicates that post-workshop Self-efficacy

Table 5. Variables and Operational Definitions.

Variable (IV or DV)	Operational Definition
Knowledge score (IV)	This variable represents teachers' knowledge of the meteorology content presented in the units of temperature, atmospheric moisture, pressure & wind, and mid-latitude cyclone & fronts and is measured as the mean score of the four knowledge assessment tests
Spatial computational thinking (S-CT) score (DV)	The variable represents teachers' spatial computational thinking ability contextualized in meteorology and IDV visualization and is measured as the mean score of the 13 items in subscale I
Epistemic cognition Score-1 (DV)	This variable represents teachers' epistemic cognition of teaching meteorology with traditional science education method and is measured as the mean score of 10 items out of the 23 items in subscale II.
Epistemic cognition score-2 (DV)	This variable represents teachers' epistemic cognition of teaching meteorology with computational thinking and practices and is measured as the mean score of 7 items out of the 23 items in subscale II.
Epistemic cognition score-3 (DV)	This variable represents teachers' epistemic cognition of teaching meteorology with scientific practices and is measured as the mean score of 6 items out of the 23 items in subscale II.
Self-efficacy score (DV)	This variable represents teachers' perception of their efficacy in teaching spatial computational thinking with IDV visualization and is measured as the mean score of the 7 items in subscale III.

Scores (MD = 4.43, n = 19) were significantly higher than pre-workshop Self-efficacy Scores (MD = 3.00, n = 19), z = 3.83, $p < .001$.

Correlation Between Spatial Computational Thinking Score and Self-Efficacy Score

Two Spearman correlation tests were conducted with one on pre-workshop S-CT Score and Self-efficacy Score data and the other on post-workshop S-CT Score and Self-efficacy Score data. The results indicate that: (1) there was a significant positive correlation between pre-workshop S-CT Score (MD = 4.00, n = 19) and Self-efficacy Score (MD = 3.00, n = 19), r_s (17) = .626, p = .004, and (2) there was no significant correlation between post-workshop S-CT Score (MD = 4.77, n = 19) and Self-efficacy Score (MD = 4.43, n = 19), r_s (17) = .336, p = .160.

Two new variables were created with S-CT Score Difference representing the difference between post-workshop and pre-workshop S-CT Scores and Self-efficacy

Table 6. Descriptive Statistics of the Variables.

Variable	Descriptive Statistics											
	Pre-Workshop						Post-Workshop					
	Mean	MD	SD	Range	Min	Max	Mean	MD	SD	Range	Min	Max
Knowledge score	/	/	/	/	/	/	92.07	92.50	4.25	19.5	78.75	99.25
S-CT score	3.84	4.00	.69	2.54	2.31	4.85	4.76	4.77	.45	1.62	3.92	5.54
Epistemic cognition Score-1	3.41	3.50	.52	2.10	2.20	4.30	3.46	3.30	.86	2.80	2.30	5.10
Epistemic cognition score-2	5.07	5.00	.44	1.57	4.43	6.00	5.22	5.29	.59	2.15	3.17	5.86
Epistemic cognition score-3	5.01	4.83	.38	1.50	4.33	5.83	5.03	5.00	.46	2.16	3.67	5.83
Self-efficacy score	2.89	3.00	.98	3.43	1.00	4.43	4.23	4.43	.78	2.57	2.43	5.00

Score Difference representing the difference between post-workshop and pre-workshop Self-efficacy Scores. The Spearman correlation tested conducted on these two new variables indicate that S-CT Score Difference (MD = 1.00, n = 19) and Self-efficacy Score Difference (MD = 1.14, n = 19) were significantly correlated, r_s (17) = .605, p = .006.

Correlation of Knowledge Score *With* Spatial Computational Thinking Score, *and* Self-Efficacy Score

Two Spearman correlation tests were conducted to examine if *Knowledge Score* is correlated with post-workshop *S-CT Score* and *Self-efficacy Score*. The results indicate that: (1) there is no significant correlation between Knowledge Score and post-workshop S-CT Score r_s (17) = −.380, p = .108; and (2) there is no significant correlation between Knowledge Score and post-workshop Self-efficacy Score r_s (17) = −.176, p = .472.

As shown in the normal Q-Q plot in Figure 3, there is an outlier in the Knowledge Score data. The case associated with the outlier was deleted from the data set and two Spearman correlation tests were conducted on the remaining 18 teachers' Knowledge Scores, post-workshop S-CT Scores, and Self-efficacy Scores. The results indicate that: (1) there was a significant negative correlation between Knowledge Score and post-workshop S-CT Score r_s (16) = −.592, p = .010; and (2) there was still no significant

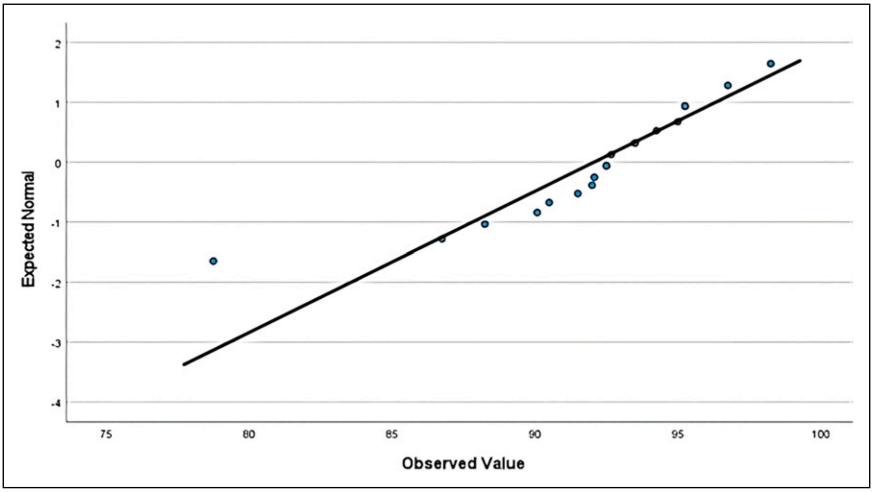

Figure 3. Normal Q-Q plot of Knowledge Score.

correlation between Knowledge Score and post-workshop Self-efficacy Score r_s (16) = −.233, p = .352.

Impact of Summer Workshop on Epistemic Cognition Scores

Epistemic Cognition Score-1, Epistemic Cognition Score-2, and Epistemic Cognition Score-3 were treated as repeated measures for each teacher in both pre- and post-surveys. A Friedman rank-sum test was conducted to compare the three epistemic cognition scores from the pre-workshop survey. The result indicated a significant difference in the three epistemic cognition scores, χ^2 (2) = 28.74, p < .001. Three subsequent Wilcoxon signed rank tests were conducted for pairwise comparisons of the three scores with a Bonferroni adjusted α level of .017. The results indicated: (1) Epistemic Cognition Scores_2 (MD = 5.00, n = 19) were significantly higher than Epistemic Cognition Scores_1 (MD = 3.50, n = 19), z = 3.82, p < .001; (2) Epistemic Cognition Scores_3 (MD = 4.83, n = 19) were significantly higher than Epistemic Cognition Scores_1 (MD = 3.50, n = 19), z = 3.82, p < .001; (3) Epistemic Cognition Scores_2 (MD = 5.00, n = 19) were not significantly different from Epistemic Cognition Scores_3 (MD = 4.83, n = 19), z = .91, p = .37.

Another Friedman rank-sum test was conducted to compare the three epistemic cognition scores from the post-workshop survey. The result indicated a significant difference in the three epistemic cognition scores, χ^2 (2) = 24.99, p < .001. Three subsequent Wilcoxon signed rank tests were conducted for pairwise comparisons of the three scores with a Bonferroni adjusted α level of .017. The results indicated: (1) Epistemic Cognition Scores_2 (MD = 5.29, n = 19) were significantly higher than

Epistemic Cognition Scores_1 (MD = 3.30, *n* = 19), z = 3.66, $p < .001$; (2) Epistemic Cognition Scores_3 (MD = 5.00, *n* = 19) were significantly higher than Epistemic Cognition Scores_1 (MD = 3.30, *n* = 19), z = 3.70, $p < .001$; (3) Epistemic Cognition Scores_2 (MD = 5.29, *n* = 19) were not significantly different from Epistemic Cognition Scores_3 (MD = 5.00, *n* = 19), z = 2.24, $p = .025$.

Discussion

The statistically significant results from the two Wilcoxon signed rank tests comparing the pre- and post-workshop S-CT scores and the pre- and post-workshop Self-efficacy scores provided evidence that the *3D Weather* summer workshop is effective in improving teachers' spatial computational thinking and self-efficacy in teaching spatial computational thinking with IDV visualization. This effectiveness is also supported by the result of teachers' improvement in their spatial computational thinking through the workshop being positively correlated with their improvement in self-efficacy of teaching spatial computational thinking with IDV visualization of weather data. When the pre-workshop and post-workshop data for S-CT Score and Self-efficacy Score were analyzed separately with Spearman rank correlation, the results were different: the correlation was statistically significant pre-workshop but not significant post-workshop. The change from a significant correlation before the workshop to a non-significant correlation after the workshop leads us to reflect how the teachers' lived experience in the workshop would affect their perceptions of their spatial computational thinking ability and their ability to teach spatial computational thinking with IDV visualization. The relationship between these perceptions may mainly be affected by teachers' exiting knowledge and their beliefs of "what they are capable or not capable of doing" before the workshop, but would be impacted by many of other factors that were not captured by the surveys, such as their experience of using IDV for weather data visualization, their understanding of the spatial nature of meteorology through the IDV visualization experience, and their pedagogical judgement of the technology and the visualization activities to be implemented in their classrooms. An understanding of these factors through future qualitative research components (e.g., interviews and open-ended survey questions) would shed light on the above-mentioned discrepancy in the correlation analysis results of pre-workshop and post-workshop S-CT Score and Self-efficacy Score data, and more importantly, would help learn and improve teachers' lived experience in learning and understanding spatial computational thinking in meteorology and IDV visualization of weather data as an effective tool for teaching spatial computational thinking.

From the discipline-based perspective of spatial thinking (Atit et al., 2020; National Research Council, 2006) that emphasizes the importance of domain knowledge for spatial thinking and solving spatial problems in a given STEM discipline, it seems reasonable to expect a positive correlation between teachers' Knowledge Scores and their S-CT Scores. But this is not supported by the Spearman correlation test results. While the Spearman correlation test on the original 19 teachers' Knowledge

Scores and post-workshop S-CT Scores did not yield significant correlation, the other test excluding the teacher with the outlying knowledge score yielded a significant negative correlation indicating that teachers' domain knowledge in the four topics (i.e., temperature, atmospheric moisture, wind and pressure, and mid-latitude cyclone and fronts) is negatively correlated with their spatial computational thinking skills contextualized in meteorology and IDV visualization. It is unknown if the outlying knowledge score represents the natural variation in Knowledge Score data. But if yes, this significant correlational result would not lead to a valid inference. Nonetheless, both the test on the original 19 teachers' data and the one on the remaining 18 teachers' data yielded a negative correlation coefficient. Does the negative correlation suggest that domain knowledge functions differently in a context that requires both computational thinking and spatial thinking? Or, spatial computational thinking in meteorology, being totally new to teachers, does not fit into their intuition about weather that has been shaped by domain knowledge in the past? Future research efforts are definitely needed to provide answers to these questions and many others related to the relationship between domain knowledge and spatial computational thinking in meteorology.

The results of the Friedman rank-sum tests comparing the teachers' Epistemic Cognition Score-1, Epistemic Cognition Score-2, and Epistemic Cognition Score-3 indicate that the patterns of teachers' epistemic cognition of the three types of teaching practices stay similar pre-workshop and post-workshop: with the preference for teaching meteorology with computational thinking and practices or with scientific practices over teaching meteorology with the traditional method. The statistical results will lead us to the inference that teachers who are willing to participate in professional development programs like *3D Weather* summer workshop will be more likely to teach meteorology with the methods of using computational thinking and practices or using scientific practices rather than with the traditional method that emphasizes scientific facts and rote learning. This inference aligns with the project team's experience in recruiting the teachers and working with them in the two week's summer workshop. Teaching meteorology with spatial computational thinking and IDV visualization is an innovative pedagogy that reflects professional practices in real world settings. According to Rogers' (2003) Diffusion of Innovation theory, there are five established categories of adopters of an innovation (i.e., Innovators, Early Adopters, Early Majority, Late Majority, and Laggards) and people adopting an innovation early have different characteristics than those adopting it later. If the teachers attending the *3D Weather* workshop can be identified as "Innovators" or "Early Adopters" based on Rogers' (2003) Diffusion of Innovation theory, the patterns of the pre-workshop and post-work epistemic cognition from the Friedman rank-sum tests may represent one of their characteristics as "Innovators" or "Early Adopters". Future research exploring other characteristics of such teachers and the characteristics of teachers who are late adopters will lead to a better understanding of what will help or hinder adoption of this innovation and thus provide valuable information about how to promote the innovation among teachers.

Conclusion, Limitations, and Implications

The *3D Weather* summer workshop is a teacher professional development program to prepare teachers for using the *IDV Visualization Modules* to teach spatial computational thinking. The Wilcoxon signed rank test results revealed that this professional development program is effective in improving teachers' spatial computational thinking and their self-efficacy of teaching spatial computational thinking with IDV visualization of weather data. This finding renders empirical evidence supporting the future use of the hybrid training model (i.e., one week virtual and one week in person training) and the professional development activities in the *3D Weather* summer workshop for preparing teachers to teach the *IDV Visualization Modules* and spatial computational thinking.

Teachers' self-efficacy of teaching spatial computational thinking with IDV visualization, as indicated by the Spearman correlational analysis results, are not correlated with their meteorology content knowledge and their spatial computational thinking ability. Due to the limitation of this study focusing on quantitative methods, its findings are not able to capture and reveal how other factors or the experiences in the workshop may be related to the improvement of teachers' self-efficacy. Another limitation of this study is related to the teacher recruitment being limited to the six partner school districts originally listed the grant proposal. This may consequently lead to the lack of representativeness of these teachers recruited. It is envisioned that future research will include more representative teacher samples and investigate the qualitative side of the story to help teacher professional development programs like *3D Weather* summer workshop better prepare teachers for teaching spatial computational thinking with IDV visualization.

3D Weather summer workshop is not a professional development program mandated by school districts and teachers' participation in the program is voluntary. The epistemic cognition data analysis results revealed that behind teachers' willingness to participate in the professional development program is the epistemic cognition that reflect their receptiveness of teaching meteorology with spatial computational thinking and practices. To encourage more teachers to adopt this approach, efforts need to be made to effect epistemic cognition changes in those teachers whose beliefs about the process of knowing in meteorology are still greatly framed by traditional science teaching and learning methods. This practical implication from the study calls for future research to furnish more insights about the characteristics of teachers' epistemic cognition about teaching meteorology and how to bring about positive changes in their epistemic cognition to support the process of knowing that reflect real world professional practices in the field of meteorology.

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