# The Construction of Knowledge and Classification of Nature: Cloud Identification as a Lens to Scientific Inquiry

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# Table of Contents

# Abstract

*"The sciences do not speak of the world but, rather, construct representations that seem always to push it away, but also bring it closer" (Latour 1999, 30)*

This paper examines the production process behind cloud identification and the network of tools, algorithms, and instruments that shape our understanding. Clouds are an integral component of our atmosphere and are involved in complex interactions that regulate the climate of our Earth. The production of scientific knowledge on clouds relies on numerous instrumental observations and human fabricated frameworks. Even though objective observations of clouds are elusive, it is necessary to have a comprehensive record of both cloud type and cloud cover in order to document temporal changes, better understand atmospheric processes, and to validate with model's predictions. Constructing an automated cloud classification algorithm for sky images confronts problems of observational subjectivity and examines the validity of technological solutions. Confronting this problem by examining the production process within a specific cloud observing technology and method of automatic cloud identification leads to the conclusion that we can not objectively measure reality, but rather construct representations that further our knowledge.

# Acknowledgements

There are so many people that helped guide me through this process, but I will try and keep it short. First of all, I need to thank Professor Jessica Kleiss for introducing me to the world of clouds and image processing. None of this would be possible without the feedback and support of my other steering committee members Jim Proctor and Liz Safran. And of course, my editors and moral support team, my sister, Joseph Arzt, and my parents. In solidarity, I must thank all my fellow environmental studies majors for the inspiration, snacks, and much needed commiseration.

# 1 Introduction

## 1.1 Motivating a Production Process Approach

While science method attempts to reduce bias, scientific findings are reliant on a network of actors, human and otherwise, that have biases. These biases can enter in at many different steps in the production process, as Sundberg (2005, 19) points out, "facts are the result of a collective process of persuasion, equipment, laboratories, paper publishing, and citations in which people, natural things, and artifacts participate." The complexity of this collaborative process motivates studying the influences involved in the production of knowledge as well as the uses of such knowledge. This collective process of knowledge production is also "interwoven with issues of meaning, values, and power in ways that demand sustained critical inquiry" (Jasanoff 2004, 15). Meaning, values, and power all introduce bias to scientific inquiry at an unknowable magnitude. However, these meanings and values are also affected and changed by scientific discoveries. Few other other fields face the kind of public and political backlash that climate science does. Since meteorology and climate science are such large and diverse fields, the knowledge production process is complex and involves a diverse network of actors.

The observational challenges and role of technology, makes cloud research an intriguing subject to examine the production of knowledge. Clouds are an essential and pivotal component of both weather and climate. As well as being an integral part of the hydrologic cycle, clouds regulate the temperature of the Earth and atmosphere by both keeping the Earth insulated as well as reflecting solar radiation. However, these processes vary dramatically with the type of cloud, aerosol, and radiation. Humans introduce different kinds of aerosols from burning and industrial activities which changes the amount and types of clouds that form. Changes in the composition of the atmosphere have serious consequences for the climate of Earth, which motivate scientists to research the complex interactions between clouds, aerosols, and radiation. While cloud cover and cloud type data has a multitude of uses within meteorology, climate science, and hydrology, the process of interpreting meaning from the data is an undertaking by itself. Since biases can be introduced by many different actors at varying stages of the scientific process, it is necessary to examine and evaluate this process.

The scientific representations of clouds in graphs, models, or equations is dependent on our observations and the meanings we attribute to them. Furthermore, "our understanding of science depends on an understanding of the local setting in which it is produced and that the conditions of knowledge depend on the naturalist's location in a social and physical space"(Jankovic 2000, 5). Scientists rely on unique previous experiences and assumptions in order to make observations and give those meaning. The physical place where data collections occurs is also unique and thus, the observations will be specific to that place. These influences may be small, however, they still affect the outcomes. In the physical sense, many scientific observations happen on a local scale which are aggregated and interpolated or extrapolated to say something about a larger area. Especially in meteorology and climate science, the production process relies on remote sensing instruments and models which distance the observer from the subject. However, even if the data collection is primarily automated, meaning is embedded from the scientist's personal experience and background. As you will see later, automatically identifying cloud type from sky images relies on scientists to both translate visual characteristics of a cloud into code and manually classify images to use for validation. Studying the production process of cloud research acknowledges the particularities and complexities of the people, places, and instruments involved.

## 1.2 Framing Question

Broadly, I will address the question, *how is knowledge constructed in science and how is its validity assessed?* by looking at a specific cloud observing instrument and method of cloud type identification. This two-part question has different implications depending on the answer to the first question. For example, if scientific knowledge is purely constructivist, how do we assess the validity of the results? This question deals very broadly with the production of scientific knowledge and the validity of the outcomes. I will look at how our understanding clouds is co-created from both material reality and our own meanings and conceptions. With an emphasis on the production of knowledge I explore how standardized measurements, models, and instrumentation change the perspective of the researcher and distance them from the subject of observation. I will also consider how issues of scale, temporal and spatial, affect our understanding of clouds. I intend to situate these themes by looking at current cloud classification research through a production process lens as well as a data science approach to understand the validity of automated classification results.

## 1.3 Paper Outline

First, in section 2.1 I explain the production process approach and how I will use it in the context of cloud classification. Then, in section 2.2 I will provide necessary background on how clouds are understood from a scientific perspective and why they are important. To frame my research, I will examine three different concepts in the context of the production of knowledge. First, in section 2.3, I talk about how weather and clouds are hybrids of both Nature, things not caused by humans, and Culture, the things humans made (Latour 1993). While this is relevant in that anthropogenic emissions have changed the composition of the atmosphere, it is more pertinent to think of how our knowledge of clouds is formed by both our perceptions and observations (Culture) and the material reality (Nature). Then, in section 2.4, I explore how Giddens' (1990) idea of distanciation is present within meteorological research. I provide examples and discuss the implications of standardizing the measurements and the language that describe clouds. I will also look at how models and remote sensing technology separate space from place to collect data and make predictions. In section 2.5, I discuss issues of scale across space and time. This is especially relevant for comparing different kinds of measurements and looking at trends with historic data. These three concepts guide my examination of the production of knowledge, which I do in part 3.3 alongside a technical methodology that attempts to build an automatic classifier for cloud type from sky images. Section 3.4 includes an evaluation of the accuracy of the automatic classification as well as a reflection of how I define this accuracy. This leads to a discussion in Section 4 of how to measure the validity of cloud observations from various instruments and how scientific "truth" is constructed. Finally, I will discuss how these data are given meaning and communicated for other, possibly non-scientific audiences.

# 2 Background

## 2.1 The Production Process Approach

It is uncommon for scientists to reflect on their own production process in technical papers. Instead, researchers in sociology and science studies often do this reflection separately. In *Pandora's Hope*, Latour follows a group of soil scientists to the Amazon (1993). He reflects on how the scientists pull from many different fields to produce information and grapples with the idea that scientific understanding can be both realist and constructivist. Latour attempts to resolve this apparent contradiction through the idea of references. Researchers create references through measurements and language that would not be possible without material reality. The researchers crumble a sample between their fingers to test the clay content and compare the color to a standardized soil color notebook, called the Munsell code. By creating these references, they transform the physical soil into something archivable, transportable, and comparable to other soil samples. This approach gives a perspective not usually seen within a scientific publication and gives me a model to reflect on my own production process in building an automatic cloud classifier for sky images. However, before reflecting on the production of knowledge, it is useful to examine the scientific understanding of clouds and why they are important.

## 2.2 How does science understand clouds?

In this section I will explain why clouds are relevant to the Earth system and provide background necessary to understand some of the processes and terms used later on.

In order for a cloud to form, there have to be small particles called cloud condensation nuclei assist water vapor to condense into a liquid. In order for the water to condense around the nuclei, air must be at or beyond its point of saturation. This often occurs when air cools because the saturation vapor pressure is reduced. Different types of clouds form depending on the altitude and the process causing saturated air to cool. For example, when a cold front moves in, warm air is pushed up and cooled causing cloud formation. Often, towering nimbostratus which indicate precipitation are seen with cold fronts. Rotational storms, like hurricanes, have very distinctive cloud formations. The standard cloud types and subtypes are displayed in figure 1, however, this is not a complete list of all possible cloud formations. The sky is much more chaotic than the cloud charts can convey.

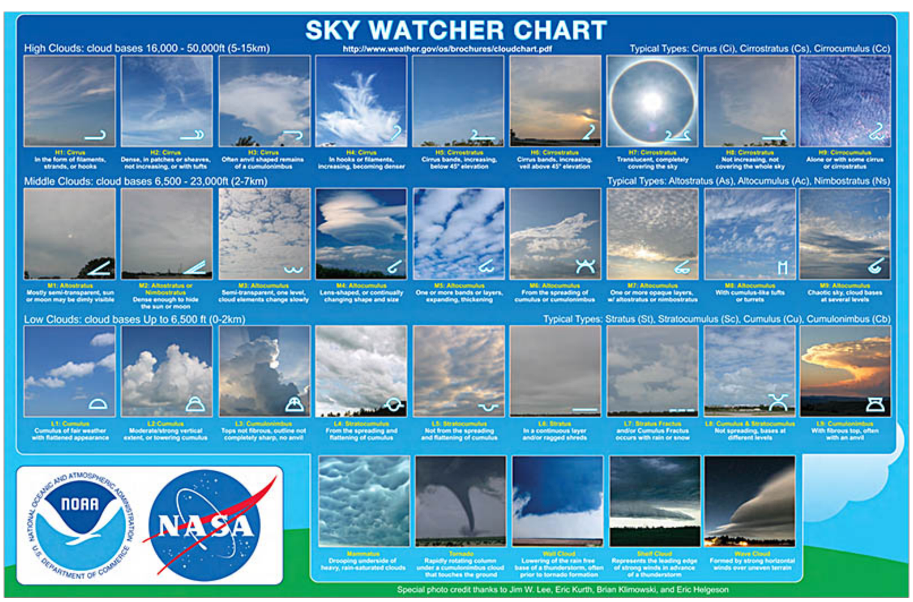


*Figure 1 Many different cloud classes are displayed in this Sky Watcher Chart. It is clear how much variation can exist under one cloud type as well as the possible sources for confusion.*
*Source: National Weather Service*

Aerosols that can act as condensation nuclei come from many different sources. Some of the most common atmospheric anthropogenic aerosols are from fossil fuel and biomass burning, while volcanic ash, dust, various organic compounds and sea salt exist naturally. These aerosols can remain in the atmosphere from weeks to years and while there is usually a point source, they can circulate globally as visualized in figure 2. The aerosols also interact with cloud formation in diverse, interesting ways. Recently, a team of scientists out of California linked biomass burning in Northern Africa to reduced cloud convection, leading to more fires because of the decreased convective precipitation (Tosca et al. 2015). However, it is quite difficult to establish a clear causal relationship between aerosols and cloud formation. In the fifth IPCC assessment report, Boucher et al. states, "clouds and aerosols continue to contribute the largest uncertainty to estimates and interpretations of the Earth's changing energy budget" (Boucher et al. 2013, 573). This uncertainty is due to a number of factors including the difficulty of observations, representation in models, and poorly understood microphysical processes. In order to fully understand cloud formation, one must know not only about interactions with aerosol on the micro scale but also large-scale properties of circulation.

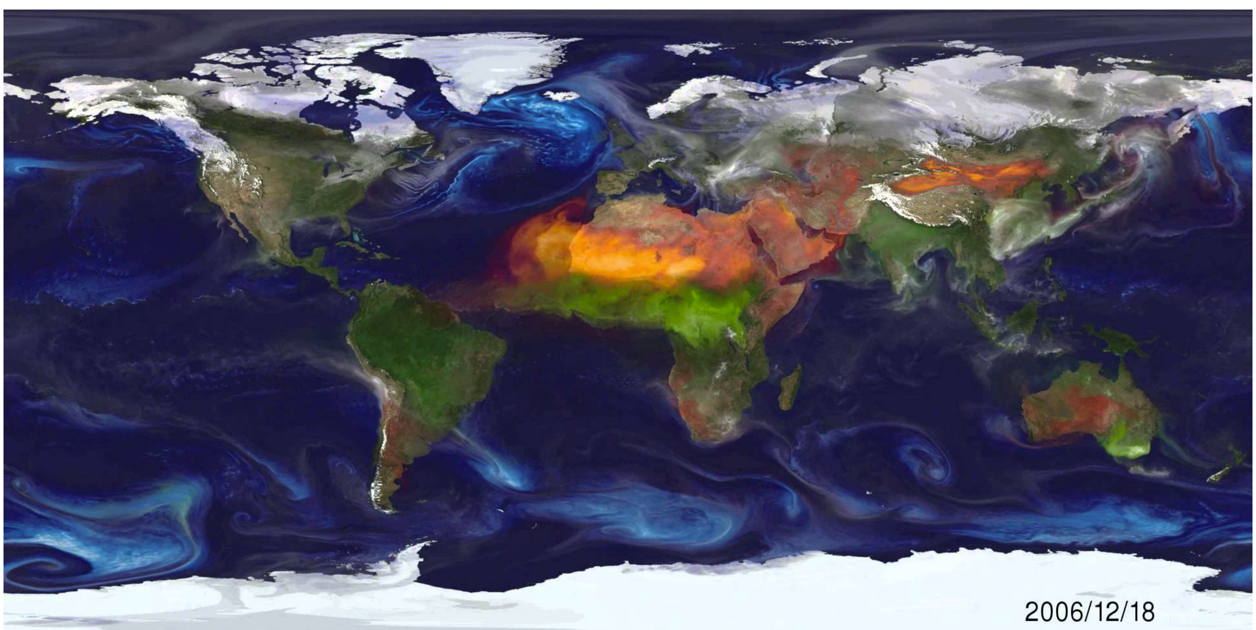


*Figure 2 Atmospheric aerosol (blue=sea salt, white=sulphate, red=dust, green=black and organic carbon) circulation from NASA's GEOS-5 10 kilometer simulation. This still image of the simulation is from December 12, 2006.*

*Source: William Putman, NASA/Goddard*

Clouds are an important consideration in weather and climate with complex feedbacks involving precipitation, temperature, radiation, and aerosols. Pivotal to how clouds fit into meteorology and climate science is the idea of Earth's radiative budget shown in figure 3. The radiation budget is a balance between incoming solar radiation and outgoing terrestrial radiation. The incoming solar radiation is predominantly short wave, while the radiation the Earth emits is in the long wave. These radiative fluxes interact differently with various types of clouds depending on their altitude, thickness, size, and reflectivity. To simplify, thick clouds are very reflective of solar radiation and absorb and reemit terrestrial radiation. Thin, high clouds let most of the solar radiation through but are cold enough that they don't reemit much terrestrial radiation. Looking at this balance of radiation in versus radiation out is very important. If the two don't even out in the long term, the temperature of the atmosphere will warm or cool and affect the climate of the Earth. Factoring in other forces like aerosols, greenhouse gases and patterns of global circulation complicates this picture.

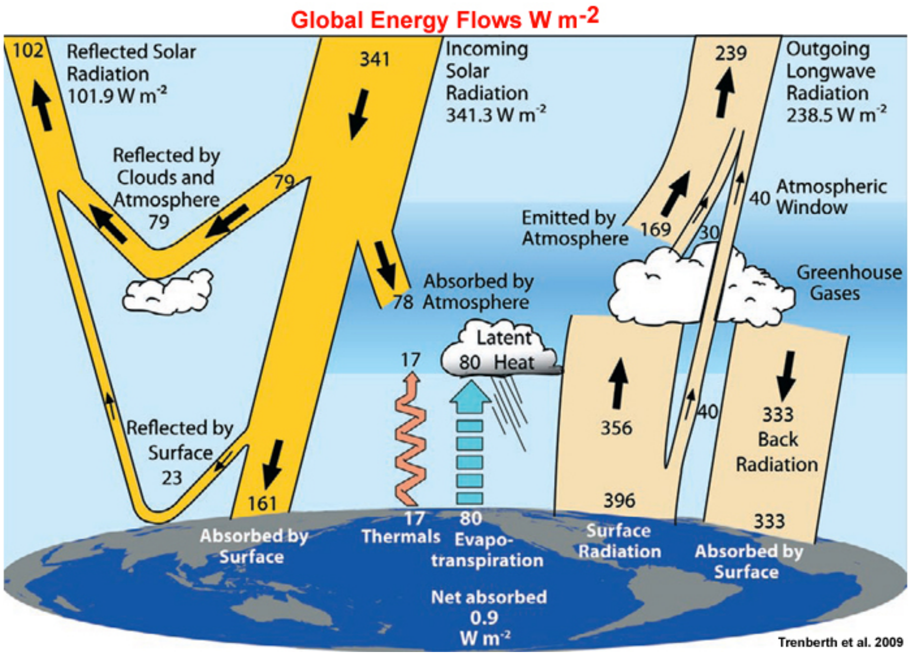


*Figure 3 The Earth's radiation budget is a balance between incoming solar radiation and outgoing terrestrial. These both interact with atmospheric phenomena like clouds and greenhouse gases.*
*Source: Trenberth et al. 2009*

The short story is that clouds play an integral role in weather and climate. A large portion of this role is through their interactions with aerosols and radiation. However, clouds also play a central part in many natural disasters like hurricanes and convective storms (which can produce tornados, hail, and flash flooding). Since humans release aerosols and greenhouse gasses into the atmosphere, the processes that determine weather and climate are changing. Having reliable data and observations of both cloud cover and cloud type to investigate these processes is very important as it often changes our understanding as well. The next section will highlight the ways that human interact with and define clouds and how scientific understanding is created.

## 2.3 Defining Clouds: An Argument for Hybridity

Throughout this paper, I will use a lens of hybridity to approach thinking about clouds and our definition of them. Bruno Latour's *We Have Never Been Modern* explains how the mindset of modernity attempts to purify objects and processes into distinct categories, Nature and Culture (1993). The concept of a hybrid object recognizes, “the ways in which we know and represent the world (both nature and society) are inseparable from the ways in which we choose to live in it” (Jasanoff 2004, 3). Hybridity in the construction of scientific knowledge implies that facts are co-produced from the material reality and human observations. Our observations and classifications define the characteristics of a cloud and our understanding is inseparable from how we experience them.

Humans are intricately connected to the weather, although individually they have different experiences of it. Vladimir Jankovic begins his book *Reading the Skies: A Cultural History of English Weather* by emphasizing the enormous role that weather plays in people's lives. In the case of England, the "weather was not just about its rains, but also about national commerce, politics, religion or the aesthetics of 'skyscapes'"(Jankovic 2000, 2). The human experience is inseparable from the conditions outside. People can experience the same weather in the same locale yet have very different perspectives and observations. We rely on specific weather for agriculture, drinkable water, transportation (especially by plane or boat), and recreation. We marvel over different shapes in the clouds, rejoice with sunny clear days, and religiously follow extreme storms. Human culture is inseparable from weather and thus weather has been rigorously studied through religious, artistic, and scientific lenses throughout history. The scientific study of weather is particularly relevant given both the hazards associated with devastating storms and changing patterns due to climate change. However, if each person experiences weather differently, then it may be impossible for many people to observe cloud conditions in completely agreement.

Mike Hulme in *Cosmopolitan Climates: Hybridity, Foresight and Meaning* argues that weather has become a hybrid of nature and culture (2010). His justification for hybridity is that weather and climate are entangled with our experiences and thus cannot be purely natural. He states, "the scientific narrative of global climate change – and its regional manifestations – thus becomes entangled with the irrepressible personal experiences of local weather, whether these be traditionally proximate and sensuous experiences or newly vicarious and manufactured ones." (273). Weather and climate both blur the boundaries of what is natural and what is cultural. They are experienced in a local, personal capacity and this shapes how we understand them from different disciplines like science, art, or religion.

Our experience of clouds is evident in the language we use to describe them. Since we primarily observe clouds visually, the classification system is based off of optical characteristics. Luke Howard, an English meteorologist, who applied the Linnaean classification to clouds, developed the framework for how we study clouds. In his work, *Essay on the Modification of Clouds*, first published in 1803, Howard stresses that the path to knowing more about clouds is through direct visual observation. He warns the "young student of meteorology ... against limiting his conceptions of the Modifications to the particular [cloud] forms here represented; A correct comprehension of the subject is only to be obtained by a habitual observation of nature" (Howard 1865, viii). He thought that the mariner and husbandman, whose labor depended on the weather, were more successful than the philosopher (and his instruments) at recognizing certain clouds and their significance. Lacking the kinds of instruments for monitoring clouds we have now, Howard's system is based on direct visual observations. Unfortunately, the visual markers that define each cloud type are quite subjective. Thus, there can be a fair amount of disagreement among human observers as well as instrumental observations.

Recognizing that our understanding of clouds is produced by an inseparable "combination of scientific third-person observation and cultural second-person meanings" (Ntamack 2012, 465) informs how we think about the production process of scientific knowledge. By acknowledging clouds as a hybrid object I can recognize my own experience and background in my own methodology. This partially explains my choice to have two different narratives in my methodology.

## 2.4 Distanciation in the Sciences

Many aspects of the scientific process exhibit Giddens' concept of space-time distanciation (1990). Distanciation takes place, "the physical settings of social activity as situated geographically" (18), and turns it into space, an independent and empty dimension. Space and "empty" time are best understood in the context of standardized measurements, which allow "for the representation of space without reference to a privileged locale which forms a distinct vantage-point" (19). Scientists rely on different kinds of spatial and temporal measurements and classification systems in order to collect data. These observations, however, could not be compared or communicated if they were only relevant to a specific locale. The emptying of space and time allows for the standardization of measurements, meaning that an inch or an hour is the same independent of one's location. In meteorology and climate science, scientists are often removed from their subject by the use of remote sensing instruments. Unlike observations taken in the field, remote sensing separates the scientists from the physical experience of locale and reduces that place to a data stream. Models also exemplify distanciation because they attempt to simulate real processes through series of equations. Distanciation allows for modern organizations to "connect the local and the global in ways which would have been unthinkable in more traditional societies" (20) with no standardized measurements. However, distanciation does not remove the role of the researcher or their own experiences from the practice of science.

In observing the weather, Jankovic (2000, 3) says, "the ability to separate the immediate experience from its scientific representation - believed to be a sine qua non of the scientist's ability to observe the fundamental and ignore the irrelevant - requires alienation from the setting's sights, sounds, smells, or surprises." Distanciation helps scientists represent complex and experiential phenomena scientifically. He asks a very poignant question- "How can science assimilate these life-shaping agencies into a dimension of mere "nature"?" (3). Standardized taxonomies, models, and measurements along with routine, systematic observations are two of the ways scientist address studying such personally experienced subject as weather.

In many ways the evolution of scientific language for describing weather propelled the separation between the subject and the observer. For example, our treatment and understanding the the atmosphere differs from how we would treat the heavens. By the 19th century, philosophers could discuss different sky phenomena separately from the divine (Moore 2015, 4). Moore explains, "unlike the heavens, the atmosphere was as deserving of rational analysis as a human heart, the corolla of a flower or a sandstone rock"(4). With a new understanding of gases and a language to describe atmospheric phenomena, the sky could be studied much like any other scientific field. And unlike remote biomes or laboratory experiments, the weather was free for anyone to observe.

Likewise, the classification system for clouds allows for a systematic approach to cloud observations worldwide. This classification system assumes that, say, a cumulonimbus cloud is the same independent of place. Luke Howard's classification system was modeled after the Linnaean system and was in Latin, it was more universally applicable than other contemporary classification systems. This helped Howard's system gain popularity and become standard in systematic weather observations (Jankovic 2000).

While there is no set date for the beginning of systematic weather observations, a number of forces came together at roughly the same time that helped meteorology become more routine and more like laboratory sciences. One of these factors was Luke Howard's cloud classification system, even though this was primarily visual and qualitative. Many discourses on meteorology in the early 19th century remarked that the theory behind meteorology had not yet come together and blamed the lack of systematic observations or data (Jankovic 2000, 35). Quantitative data collection was touted as the most legitimate way to study weather. Jankovic remarks that because of this change of focus, "measurement was everything: data was collected and tabulated for daily, monthly and annual course of temperature, wind direction, atmospheric electricity, pressure and humidity" (35). With a network of meteorological outposts and the telegraph, data could be aggregated across large areas. However, this necessitated standardized instruments, measurements, and record sheets. Unusual sky phenomena still captured the attention of the public, but meteorology moved on to a seemingly more scientific approach to understand the weather.

Distanciation also happens within models which try and encapsulate key processes and facilitate predictions, but are often scrutinized and misunderstood. Gerrit Lohmann (2015, 28) describes the role of models in the context of Earth System Science, saying that they "provide the perspective beyond the local information from observations/reconstructions and show that spatial and temporal patterns are fundamental to understanding Earth systems and processes." Challenges can arise however, as Sundberg (2005, 183) points out, "the tension between the different representations arises because there is an assumption that there is a real atmosphere that both measurements and models are trying to get at. The problem is how to represent it. But modeling is not about working with this atmosphere and the practical problem is to solve what a measurement point represents in the simulated atmosphere." Models further distanciate place through representation by series of equations. Some equations may more closely represent processes than others, but the physicality is still lost in the transition.

This simulated place in models is a necessary reduction of complex real world processes. However, models, standardized measurements, and remote sensing all allow us to see a dimension that would have been otherwise inaccessible. So distancing simultaneously gives us a more intimate perspective bringing us closer to material reality. It is also important to note that while distanciation represents place with empty spatial dimensions, the place and social context that the researcher occupies is still influential and important in the production process. As Latour (1993, 20) says, "the sciences do not speak of the world but, rather, construct representations that seem always to push it away, but also bring it closer."

## 2.5 Issues of Scale Across Space and Time

There are many problematic aspects of studying globally occurring phenomena like aerosols and clouds. The scale to which data is collected affects the scale and certainty of the outcomes. Many problems arise from data records that are inconsistent temporally and/or spatially. This is especially true studying clouds because observing them can be highly subjective and the relevant observations span molecular to global scales.

Despite clouds being a global phenomenon, ground based observations are only able to capture a small portion of the atmosphere. We can imagine this as a conceptual "soda straw" view of the atmosphere in which "solar radiation that hits the top of a straw is either reflected back, transmitted all the way through to the bottom of the straw, or absorbed along its length" (Ackerman and Stokes 2003, 39). Terrestrial radiation is also absorbed in transit from the Earth's surface to the cosmos. As discussed previously, this is highly dependent on the types of clouds and aerosols present. Since individual clouds cover a very small area and there may be multiple types of clouds in a grid area, it is very tricky to represent them in global scale circulation models (see figure 4). The cloud conditions in a grid of a global circulation model are inferred from other atmospheric conditions (like temperature, pressure, and humidity), leading to a very simplified representation. Clouds, while extremely relevant for global circulation and climate models, often exist on a much smaller scale than the global circulation model grid size.

While the problems mentioned above are mostly spatial, switching methodology of observations or switching instruments are common temporal problems. It is difficult to have a reliable long term record when the data come from multiple sources. Spatial problems in data collection come in the form of data "holes" and geographic variation. Often data holes occur in developing regions and over the ocean where it is difficult to collect data. A long historic record that covers a large area is desirable in order to validate climate models and observe climatic trends, but sometimes these issues cannot be resolved.

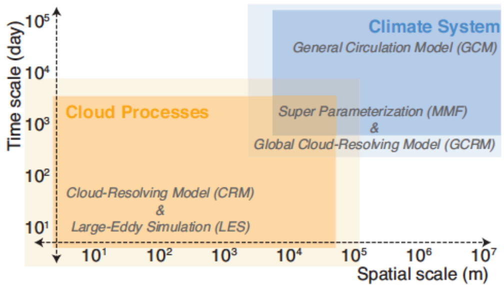


*Figure 4 Cloud processes exist on a different temporal and spatial scale than the climate system. This is reflected in the scale of cloud resolving models versus global circulation models.*
*Source: Boucher et al. 2013*

A tempting question to ask about cloud trends is whether cloud coverage is increasing or decreasing. However, even if we had a robust record of cloud observations, we still could not answer well what is happening to clouds *globally* because patterns of cloud formation are very different across land and ocean as well as across land formations like mountains and deserts. Also, trends may be different for different kinds of cloud (e.g. there could be a decrease in low level clouds and an increase in high level clouds). A single global average would miss these nuances would not tell the whole story. For example, the trend in cloudiness across the land and ocean may have opposite signs that cancel out when averaged. Even an average across a country would miss the nuances of the land formations. While it is often hard to see what patterns emerge from global cloud coverage and types, work has been done to aggregate cloud data in specific countries.

Unfortunately, while there are many physically related measurements like sunshine and diurnal temperature range "surface cloud observations have provided the only historical record for establishing long-term cloud climatologies" (Dai et al. 2006, 598). One such study based in Spain aggregated historic cloud observations to look at the trends of cloud cover. This study emphasizes the limitations regarding "well-known difficulties to record objective observations of clouds and quantify cloudiness variations" (Sanchez-Lorenzo et al. 2012, 1199). Measurements like precipitation and temperature are generally more reliable, especially since we rely on standardized technology. They use data from 1865 to 1950 recorded as the number cloudy days out of each month. The recent observations from 1961 to 2004, originally recorded in octas, were transformed to the earlier method of cloudy days during a month period in order to get a longer trend. Regarding this technique, Sanchez-Lorenzo et al. reason, "cloudless and overcast conditions are more easily detectable by the observer than partially cloudy conditions, and consequently less sensitive to inhomogeneities due to changes in the observers or observational criteria" (Sanchez-Lorenzo et al. 2012, 1203). Out of 39 stations, only 8 of them had records that spanned the whole time. These gaps were filled in by using the next most highly correlated station with available data. It is important to note that even though Spain is a smaller sample, and very developed, Sanchez-Lorenzo et al. still ran into complications due to the geography of the regions, inhomogeneous data records, and changes in observational technique.

Another example of aggregating cloud observations across space and time highlights the difficulties of changing instruments. Since the 1990's manual observations of clouds have been decreased in an effort to modernize and cut costs (Dai et al. 2006, 599). Of the 1,590 weather stations operated by both the National Weather Service and the Federal Aviation Administration only 82 of them had human observers in 2006 (Dai et al. 2006, 599). Instead of a human perspective of the sky, from horizon to horizon and of many different layers of cloud types, weather stations now employ a laser focused at one point in the sky. The laser returns the height of a cloud directly above unless there is no cloud or a cloud out of the range of the laser. The returns for the instrument, called a ceilometer, are averaged across a 30-minute time period to give the fractional sky coverage. If a single cloud stays over the laser the whole time, the instrument will record an overcast sky.

It is a clear that a human and a laser see the sky very differently but is it possible to compare the two? In figure 5, it is clear that the modernized weather stations with the ceilometers are not easily reconcilable with historical human observations. It is evident that changing instruments can affect the long-term observed trends. Ceilometers do not operationally return cloud cover above a height of 12,000 feet, so many cirrus clouds would not be recorded. Another shortcoming in the automated ceilometer observations is that they do not provide cloud type or opacity information that human observers can. However, ceilometers can operate equally well during night and day, can take continuous observations, are reproducible, and provide direct observations of cloud base altitude. As with other cloud observing instruments, the ceilometer has strengths as well as weaknesses. While not reconcilable with human observers, it provides vital cloud observations for The National Weather Service and the Federal Aviation Administration.

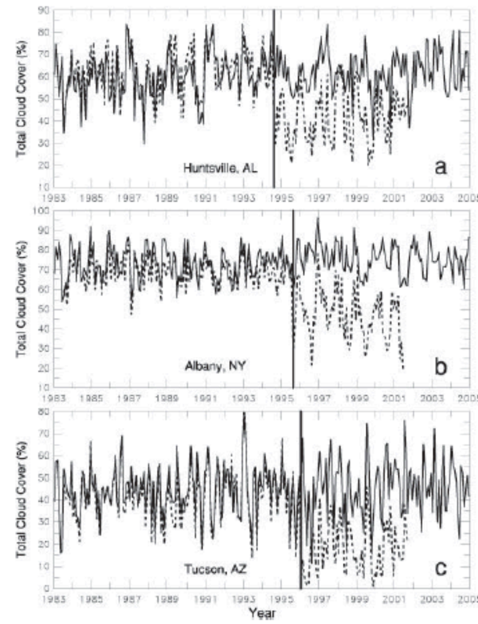


*Figure 5 These graphs of mean cloud cover in (a) Huntsville, Al, (b) Albany, NY, and (c) Tucson, AZ show the difference between human visual observations in the solid line and the National Weather Station observation in the dashed line which switched to automatic ceilometer observations at the vertical line. If not corrected for, trends can easily be misrepresented. Source: Dai et al. 2006*

These case studies also both emphasize the importance of time scale in looking at trends. Most findings agree on an increase in cloudiness from about 1950 to 1980 in the US and a decrease in cloudiness after the 1980's (Dai et al. 2006, 598). However, over the ocean, observations suggest that cloud cover in both total clouds and low clouds increased by 1.9%–3.6% from 1952 to 1995 (Norris et al. 1999). The signal and magnitude of these trends varies substantially from study to study depending on the location, methodology, and technology (Sanchez-Lorenzo et al. 2012, 1201). These evolving representations of reality motivate investigating the production process. How can it be that multiple reputable scientists find contradicting results? As discussed previously, the choice of temporal and spatial scale affects how trends are portrayed. While distanciation by standardization helps to systematize the production process despite issues of space and time, we see that the specificities of the observer, place, and instrument play a big role. Given the difficulties in constructing cloud climatologies across space and time, it is clear that instruments and observations struggle to measure objective reality. However, this does not mean that cloud observations are not useful or necessary. Just in the last couple decades, a plethora of cloud observing instruments, both ground based and satellite borne, has been commissioned to help fill the gaps in our observations and understanding.

### 2.5.1 How do we measure clouds?

Satellite observations revolutionized how we study and perceive the Earth, as well as how we study clouds. The first weather satellite, launched in 1960, provided images of cloud cover. Finally, large-scale cloud regimes governed by atmospheric circulation could be observed over the ocean, stratosphere, and data poor areas in the Global South (Atlas 1997, 2). Ackerman and Stokes (2003, 43) highlight the difficulties of ground-based observations by saying, "in the past, atmospheric observations at midlatitudes were insufficient for creating the single-column and cloud resolving models. There were too few observations, they had rather large measurement errors, and they did not capture small-scale motions." Thus, satellites can be thought of as a turning point in meteorology and climate science (Sundberg 2005, 84) because orbiting satellites generally have a large spatial coverage, much bigger than ground observations could ever be. Having these large-scale observations proves crucial to building accurate models. However, we still see some major errors with satellite observations as well, especially with earlier technology.

While satellites provide another perspective, ground based observations are still crucial because the observations do not always agree. Dai et al. highlight some of these issues saying, "surface and satellite observations of cloud cover are not fully comparable quantitatively because of their differences in the view angle and detection method (e.g., for thin cirrus), it is worrisome that even the sign of the trends (which are large) in the surface and satellite cloud data differs completely for tropical" (2006, 600). Since the observations are not compatible and not temporally homogenous, the cloud record for satellites cannot replace ground observations (Sanchez-Lorenzo et al. 2012, 1200). Also, usable satellite records only go as far back as the 1980's, which is not yet enough time to see a whole climatic period which is generally at least 30 years. While satellites are not as useful for seeing long term trends, since their launch we have learned much more about cloud-aerosol interactions.

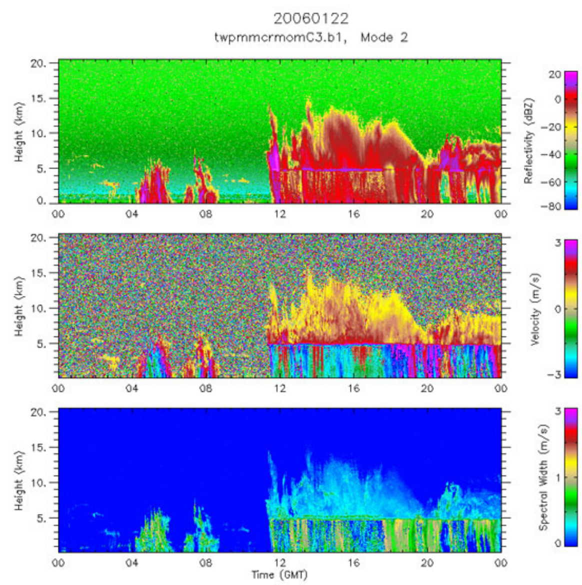


*Figure 6 These images were made from observations taken on January 22, 2006 by a millimeter cloud radar in Australia. The cloud shown is a precipitating convective cloud. Even though the human eye is not used to seeing clouds in a vertical profile, the cloud shape is still visible even though we are actually looking at the measured reflectivity, velocity, and spectral width. Source: Mather 2006*

Cloud radars provide a different perspective of the sky than visual observations. Radars transmit electromagnetic waves and measure the return signal from different hydrometers like cloud particles, rain, ice, and snow. The cloud radar is specially tuned to pick up cloud base and tops, particle size and mass. Unlike other instruments, it picks up hard to detect high clouds well and can provide a fine temporal and spatial resolution (Kollias et al. 2007). Once the return signal has been processed, one can examine at slices of the sky like the images in figure 6. Frische et al. (2002) devise a method of identifying clouds from the millimeter cloud radar by identifying water droplet size. One assumption in this analysis is that continental stratus clouds have a droplet concentration of 200 drops per cubic centimeter. Instead of visual characteristics defining a cloud, this method uses a threshold of droplet concentration. Millimeter cloud radars have shaped our understanding of weather and clouds through methods that would be inaccessible to a human ground based observer.

I have mentioned satellites, radars, and ceilometers briefly, but what other cloud observing technology is there? Professional human cloud observers are still available in a few stations, although they are being phased out by instrumentation including cloud radars and Light Detection And Ranging (LiDAR) instruments. Many cameras have been employed to monitor cloud conditions, although this method requires either grueling human verification or a rigorous automated analysis in order to retrieve useful data from the images. Many of the cameras have fish eye lenses to capture the whole sky while others have cameras that point downward at a mirrored hemispheric dome which also captures the whole sky from horizon to horizon. These cameras replicate what a human observer sees when they look up at the sky, however, in order for these cameras to be useful the process of classifying these images must be automated.

In the next section I will outline a methodology to build an automatic cloud type classifier for these sky images. So far I have shown a number of examples in the production of knowledge that highlight distanciation, hybridity, and issues of scale. These three themes are all evident with research involving cloud observing instruments.

Relying on remote sensing instruments, photographs, statistics, and other representations of real world phenomena all distanciate the observer from the subject. However, this distanciation does not remove all traces of bias. Coming from a hybrid perspective, scientific measurements and observations create references to material reality that rely on fabricated frameworks. This has powerful implications for what scientists consider to be objective measurements. Another consideration is that ground-based instruments generally only measure local weather and sky conditions; thus the desired scale must be considered. The ground-based cloud observing instrument I work with and the process of extracting meaning from the data exemplify these themes. I will immerse myself in this scientific production process, attempt to evaluate the validity of these results, and reflect on how cloud hybridity, distanciation, and issues of scale in space and time unfold within my research.

# 3 Procedure

## 3.1 Situated Context

Cloud classification exists within a network of agencies and organizations, instruments and data streams, and algorithms and models. It is my intention to investigate how these actors lead to our understanding of clouds and inform cloud classification. By exploring in depth how closely an instance of automated cloud classification replicates human observations, I will gain first hand experience with the production process. Throughout this methodology, I ask myself about how the tools and algorithms have led to these results. I will attempt to answer the question, *Where does our understanding of cloud classification come from and how do we assess its validity?* using a two part methodology. In order to look at the accuracy or validity of the outcomes from this research, I will develop an automated cloud classifier from sky images and evaluate how accurately an algorithm classifies cloud type in comparison with manual classifications and briefly with other instruments. I will also analyze the tools and algorithms I am using to see their origin and factor in how they contribute to cloud classification. Then, I will connect this methodology with narrative sections in which I ask myself how I am producing knowledge in the context of cloud classification.

*In order to weave together ideas about distanciation in science, the hybridity of clouds, and issues of scale from the beginning of this paper to this technical methodology, I will occasionally interject to consider any assumptions I am making and discuss where this knowledge comes from. These are my personal observations of the production process and so are specific to my experience and not to cloud classification in general. These kinds of observations do not traditionally have a place within a scientific methodology, which is why they will appear separate although interspersed throughout. In considering how I am producing knowledge, I also must acknowledge my place within this network of cloud classification. I am a student researcher in Professor Jessica Kleiss' lab, which began as a summer* *internship position with Roger Summer Science Program. This position utilized my mathematics background, but the experience was otherwise new to me. What gave this research meaning for me was the role that clouds play in regards to climate change. However, one of the main goals was to provide a value added product for cloud researchers that we had been in correspondence with at the Pacific Northwest National Laboratory. I learned to execute the technical work and developed a deeper understanding of current cloud and climate research. However, I never reflected on the process that I was involved in. These interjections in italics will signify a changing of hats, from scientific researcher to anthropologist studying the production of knowledge within cloud classification.*

Automated cloud classification is motivated by many factors including the importance of having robust cloud type and cover observations, validating other instruments and models, and also has applications in air traffic control. These are some reasons that scholars who have published on cloud classification provide. These published papers provide a glimpse into the network of actors that produce and fund scientific investigation. A quick survey of publications working with ground-based instruments in the last century shows that more than 50% of them are from the United States. China, Greece, Switzerland, the UK and Spain have the next highest amount of published papers. Most authors work out of universities, although others are affiliated with national laboratories or meteorological services. Given the differences in funding and other support, it is common for authors to use data from an instrument owned by a governmental meteorological department. The instruments are usually quite expensive  and best run long term in a monitoring operation. This is more feasible for an agency to oversee than an individual research group. Funding for this work is often provided by grants from the specific country's meteorological or science agencies. However, this funding challenge also motivates experimenting with low-cost alternatives. There is a lot of variety in the configuration of the instruments used. Some use infrared cameras, some fish eye lenses, and some use a hemispheric mirror with a camera. A lot of work has also been done for cloud classification from satellite images, which provides a different challenge given the origin of the observations. Since cloud image data can be downloaded remotely, this research is not tied to the place the instrument is located. With this interdisciplinary research, collaboration happens among many fields including computer scientists, physicists, meteorologists, and those with backgrounds in image processing. Cloud classification extends into a diverse set of fields, instruments, and methodologies each of which provide an interesting perspective to explore the production process.

### 3.2.1 Atmospheric Radiation Measurement Program

The Atmospheric Radiation Measurement (ARM) Program is a significant actor in studying cloud, aerosol, and radiation interactions in the United States. ARM was established by the Department of Energy (DOE) to better understand the role clouds and radiation play in the climate of our atmosphere and Earth. The undertaking was directly influenced by our need to improve climate models in order to better understand the causes and predict the effects of climate change. Ackerman and Stokes (2003, 45) highlight the progression of technology within ARM saying, "as the quality of our data has improved over time, the focus of our research has shifted. Much of the initial effort was on instrument development and basic radiative transfer theory. This gradually gave way to studies of atmospheric processes. Now we have moved toward a greater emphasis on comparing models with observations and evaluating parameterizations." Images of the sky can be used to validate the models and verify observations from other instruments. Cloud observations must be taken every day and frequently enough throughout the day in order to have a comprehensive record that captures all changes in sky conditions to validate climate and cloud-resolving models as well as observations from other instruments. This is simply not achievable with manual cloud observations. ARM employs a wide array of technologies to view clouds, aerosols, and radiation in different ways. Their research facility in the Southern Great Plains uses mostly ground-based instruments to make observations and was purposely situated so that the instrument's field of view is not obstructed by tall trees and buildings and can record a variety of sky conditions. One of these instruments, the Total Sky Imager, provides visual, photographic observations which can potentially be processed to return the cloud type.

## 3.3 Technical Methodology

### 3.3.1 Instrument

Figure 7 This Total Sky Imager belongs in ARM and sits in their Southern Great Plains Site. You can see the black bar on the mirror that covered the sun glare.
Source: Madden-Julian Conversation 2011

The Total Sky Imager (TSI) is a camera pointed down at a hemispheric mirror that reflects the whole sky (see figure 7) and records an image of the sky dome similar to what a human would observe. This kind of record is motivated by the need for atmospheric scientists to see actual sky conditions in order to interpret unusual observations from other remote sensing instruments. The TSI provides ground-based observations over a much finer temporal and spatial scale than satellite observations. While many TSIs are in commission, ARM's Southern Great Plains site near Lamont, Oklahoma, houses a TSI that has been taking photos of the sky every 30 seconds since July, 2000. These images provide essential observations of the local sky conditions, record cloud cover, and have the potential to provide cloud type observations. However, each of the images has to be processed in order to be useful. The data, freely downloaded from the ARM website, include original whole-sky images that are slightly compressed into JPG format, as well as a processed image that shows clear sky, thin clouds, and opaque clouds. The devices themselves are manufactured by Yankee Environmental Systems, which provides environmental monitoring instruments to industries, naval and aviation bases, and scientific endeavors.

Since the TSI returns data in the form of images, processing is done so that certain sky conditions like cloud cover can be recorded. Each pixel in the original images has a red, blue, and green component, which combine to create the colors in the image. Clear sky has much more blue than red or green and clouds have a nearly equal amount of red and blue (See figure 8). Thus, by dividing the red channel by the blue channel (R/B) we end up with a greyscale image where each pixel has a single value and the clouds are bright white and the background is dark gray. The grayscale image can be divided based on the R/B value of each pixel. For example, every pixel with R/B over .88 is designated as thick cloud and every pixel with R/B below .6 is designated clear sky.

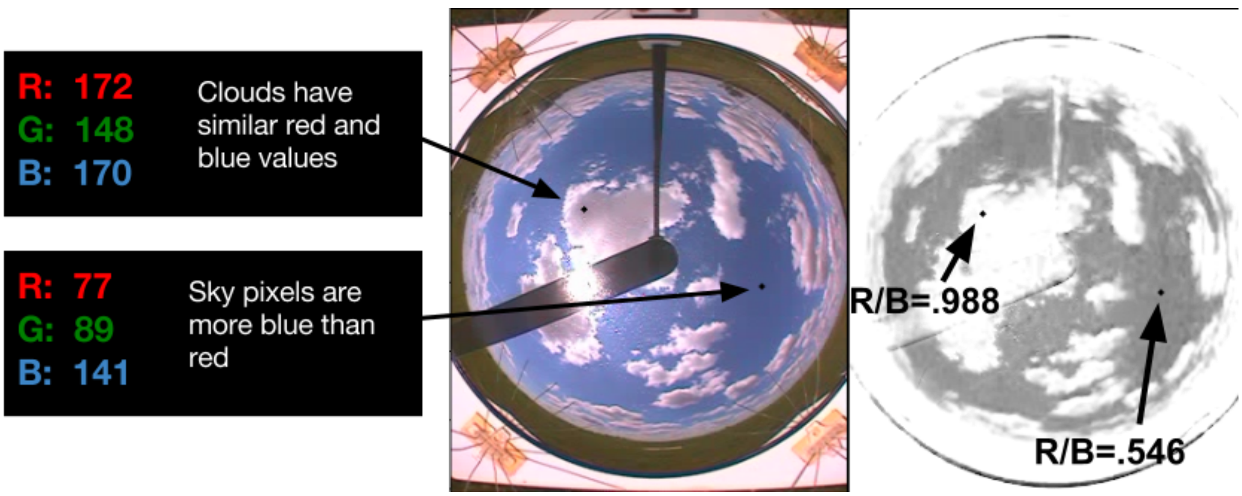


*Figure 8 Each pixel has red, blue, and green components that combine to describe the color. Then, we are able to run statistics on the image. You can also see what the image looks like as the ratio version.*

This technique is called thresholding and is very common in image processing. To get the sky cover after thresholding, the total number of cloudy pixels is divided by the total number of sky pixels. Another step in image processing is removing any pixels that aren't sky, such as the camera housing, trees, and sun bar, with a mask. This masking can also be done to areas of the image that often introduce errors. Even though there is a sun bar, it is not always wide enough to hide the entire glare. The horizon area also tends to be brighter and can be confused with clouds when thresholding, like in figure 9. Removing these areas can help improve the fractional sky cover returned from processing the TSI images (Long 2010, 52).

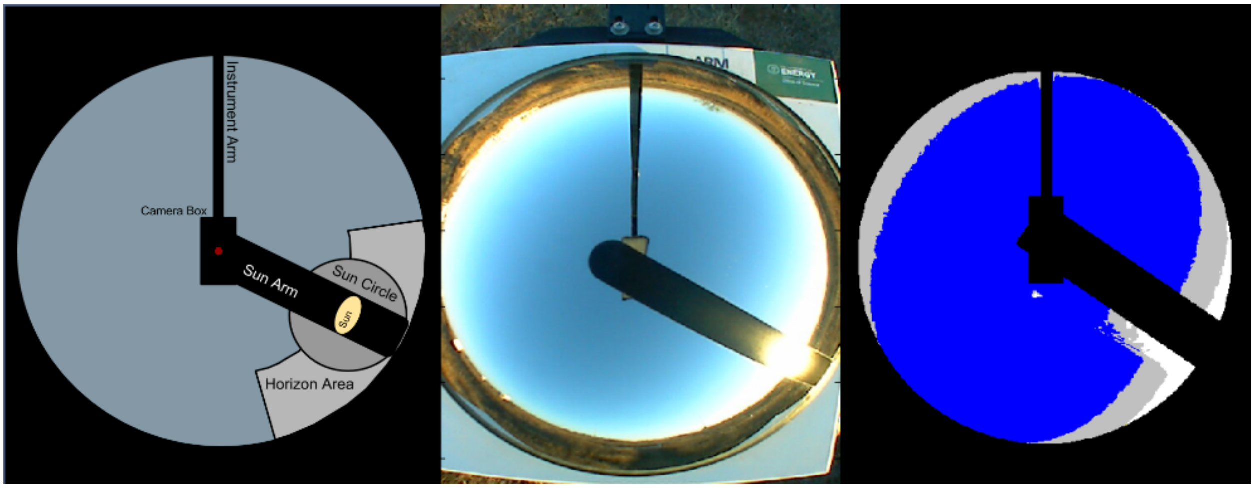


*Figure 9 a.) Areas of TSI images and b.) an example of horizon brightness confused with thin clouds in the c.) thresholded image. You can also see where the mask is misaligned from the image and so it incorrectly introduces cloudy pixels.*

*Figure 8 helps to show how the instrument changes our perspective and attempts to capture the sky within a still image. The TSI reduces the sky to a circle of pixels in a photograph. While it is much easier to record and archive the dynamism of the atmosphere in a picture, this distanciation removes the sensations of sound, touch, and smell from the experience of weather. The researcher can visually assess a photograph without being in the field. In fact, anyone around the world can download these data and look at a circle of sky in Lamont, Oklahoma. This remote approach not only separates the observer from their other senses, but also removes the experience of local, normal weather from observations. While there is no way to know for sure, it is reasonable to suspect that the majority of researchers who use these data do so outside of Oklahoma and have their own conceptions of normal weather.*

*The plain sky images must have value extracted from them by processing, which relies on a toolbox for image processing and computer code. As a human observer of these images, I do not think viewing these images is anything like looking up at the sky outside. Tuning my brain to singularly pay attention to the relevant details of cloud type or cloud cover, I forget that the image on the computer in front of me is a real, physical place and a real sky. I cannot capture the objective reality of the clouds, I can only make references to it using images, classification systems, and statistics. Clouds as hybrid objects are understood though human observations and classification systems but also exist separately from these. We approach an understanding of the processes that surround clouds, but like the TSI images of the sky, we can only reference the material reality. Our references to this reality are increasingly distanciated through the use of instruments, models, and computer code but simultaneously retain the local specificities of the context in which the knowledge is produced.*

### 3.3.2 Preprocessing

All preprocessing, processing, and classifying work is done in Matlab, a computing environment that is commonly used in Earth system science research and facilitates image processing. Matlab contains many built-in functions and packages that allow users to quickly process data without starting from scratch. Matlab Central allows a variety of users to share code and ask for help. This community enables collaboration across disciplinary boundaries, which I relied on to test already written pieces of code and edit them as I needed.

Even though ARM provides already masked and thresholded images, there were major errors that introduced many artifacts into our data. For example, occasionally the masks on the images did not fully cover the instrument arm, which introduced pixels that were classified as if they were sky. We decided to replicate and improve the mask and threshold before moving on with the data processing. The mask went through a number of iterations where the center of the image had to be manually adjusted to account for slight movements in the TSI, the options to include a sun circle and horizon area mask were added, and the sun arm and instrument arm were made fatter. The sun circle and horizon area, which you can see in figure 8, were added as an option if the images in question had glare from the sun that the smaller mask didn't account for. Since this usually shows up when the sun is low in the sky, the glare can also be avoided by only processing images within certain hours of the day. A version with a more conservative mask was used for image processing, but still has some minor errors. Another version of the mask was developed that has the capabilities to mask out dirt on the mirror but slows down the run time.

There are also many discontinuities in the data set, which complicated the preprocessing. The image resolution almost doubled in 2011 so we had to process these sets of images differently. The naming convention changed over time, also complicating the way we wrote the computer code. We renamed the latest images, but mostly developed our code to adjust to the different naming conventions in order to preserve the data set as it was downloaded from the ARM site. As discussed before, the center of the images shifted over time due to changes in the camera rig. We included a list of dates that do not exist in the data or are otherwise compromised. However, with such a large data set there are bound to be issues. Some images have bird feces on the mirror, some have actual birds, some are covered in dust, ice, snow or rain, and there are even some where the device continued to take pictures as it was moved inside a warehouse. Since we know that these images exist, it is important to be wary of them and make sure that they are either weeded out or avoided.

Before processing images, we convert them to ratio images. By dividing the red channel by the blue channel, the clouds are easier to distinguish from the background sky (Long et al. 2001). Calbo and Sabburg also convert their images to the R/B ratio in their 2008 paper on feature extraction from cloud images (2008). However, when Zhou et al. compared the effectiveness of the type of color preprocessing they found that R/B was the worst performing color space (2014). In later iterations of our preprocessing we also calculated statistics on a different color space which performed mid range in Zhou's color space comparison. Since the TSI images are so different from Zhou's images, there are some operations that would be impractical for our images, like dividing the image into blocks with similar textures. We don't have a relatively flat rectangle of sky like Zhou used. However, this rectangle is not representative of the whole sky like the TSI is. Since the images are so different, it is hard to say whether Zhou's method of processing is transferable to the TSI images.

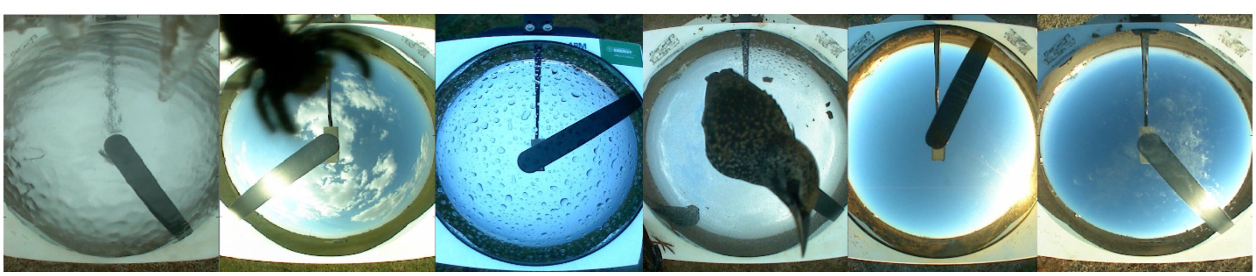

*Figure 10 Some of the various "bloopers" images. a) If the weather gets cold enough, the mirror will ice over for days at a time and the camera housing will develop icicles, b) spiders and ants find home on the instrument. c) Rain is a common occurrence. d) Birds love the mirror which is also evidenced in the occasional fecal matter. e) Here the sun bar is completely askew from the sun, which is most likely a human error. f) Dirt and dust smeared on the mirror, resembling thin clouds.*

*The errors, discontinuities, and variability in this data set all provide a challenge to work around. I assume that even with the inconsistencies, these images are representative of real sky conditions. Weather often provides a challenge for collecting data. Ice can obscure the mirror for days at a time. Whenever it rains the images are compromised, although usually for less time than ice storms. There are month long periods of time where birds roost and defecate on the instrument. If the mirror doesn't get cleaned, the accumulated dirt can be mistaken for a cloud in processing (See Figure 9). Processing these types of images does not return useful information about the cloud conditions. However, the sheer volume of data means that these images hopefully are a minority. I also assume that a human can identify the sky conditions from a photo well enough to then translate this into computer code. Technology is so often assumed to remove the subjectivity, but it is important to recognize the flaws and biases inherent in any type of observation. Though the TSI is mostly automated and a majority of the image is sky, the place is still present in this data through weather patterns, birds, and horizon features. While we try to be selective about the images we use and mask out any features we don't need, the line we draw between a compromised image and an uncompromised image is not always straightforward.*

### 3.3.3 Feature extraction

Our first automatic classifier utilized statistics calculated from each image's pixel values. We used mean (ME), standard deviation (SD), third moment (TM), uniformity (UF), entropy (EY), and smoothness (SM) calculated from the R/B images. Using Matlab's built-in image gradient function, I also calculated a mean gradient (MG) statistic. These statistics alone were very successful in differentiating clear, overcast, and mixed sky cases. However, once we replicated ARM's spatially dependent threshold, we could pull out more cloud features and possibly differentiate among clouds in the mixed sky classification. I followed the basic procedure of Liu et al. (2011) to define the cloud masses and the gaps of clear sky in between them. I hypothesized these features would be more effective at differentiating cumulus-like clouds. Following Liu et al. (2011), I calculated the cloud ratio by dividing each cloud area by the total area. I then calculated a number of different statistics on both the gap area and the cloud area found below.

Following Heinle et al. (2010) we also calculate six features based on the different color channels, like the red channel minus the blue channel. In total, we have 33 features that describe the color, texture, and masses present in each image. By calculating all these statistics on each image, the classifiers can identify the cloud type in each image by comparison to the statistics of images with known cloud type.

*The sky, already reduced to an image, is decomposed into a plethora of statistics. Through these successive hybrid representations of the material world, there are many compromises. The practical side of capturing sky images is that I can flip through days of images in a matter of minutes. This makes it much easier to compare sky conditions side-by-side, a feat that is impossible in the field. Latour describes these scientific compromises saying, "what we lose in matter through successive reductions, we regain a hundredfold in branching off to other forms that reductions- written, calculated, and archival- made possible" (Latour 1999, 55). So while these reductions take us farther from the physicality of the world, they allow us to practically study subjects at too vast or too small of scales, in diverse locations, or that are otherwise unreachable. I rely on these reductions to identify clouds from the images.*

*Throughout this process, it is helpful to think about how I recognize a cloud. The most apparent characteristic is perhaps color, however, clouds can range from dark grey to almost iridescent. The next defining characteristics may be texture or shape. We attempt to capture both color, texture, and shape information with statistics. One similarity of these characteristics is that they are both based on visual cues, as are the archetypical cloud classes Luke Howard first developed. I assume that these classifications will be able to describe the clouds represented in the images because we have also defined statistics based on visual observations.*

### 3.3.4 Classification

Before classification, three different researchers familiar with identifying cloud type in images manually classified 2,852 images. Manually classifying this image set took around 3 hours for the checkers which included Professor Jessica Kleiss, Isabel Suhr, and myself. The images were chosen from eight different times during each day in 2015 in order to get a representative sample of a year of clouds. Each of the images was manually classified with clear, cirrus, altocumulus/cirrocumulus, altostratus/cirrostratus, cumulus, stratocumulus, stratus/fog, rain, mixed cloud cases, unsure, dirt/bird/ice/bugs and no image. The three manual classifications were aggregated and only images with a consistent classification by all three checkers were used in further analysis. Half of these images were used to train the classifiers. The other half acted as a test set to check the classifier's skill.

For the automatic classifiers, we leaned heavily on the findings of Zhou et al. (2014) who compare the methodologies of some of the primary cloud classification papers. Unlike our images, the images they use are more similar to images taken by standard cameras, meaning they are portions of the sky with minimal distortion. Since the instrument captures the sky with a mosaic of images, the sun can be more easily avoided. Interestingly, in terms of the linguistic method of classification, "Liu et al. (2011) argued that the criteria developed by the WMO (1975) for classifying different cloud types is unsuitable for automatic cloud classification" (Zhou et al. 2014, 85). This is made evident in many cloud classification papers, like Lui et al. (2011), who group cloud classes like cirriform, cumuliform or waveform. However, there is no consensus on this convention. More standard is the practice of leaving out rare cloud classes because of a lack of a robust training data. In this analysis, two classifiers are used: the Support Vector Machine (SVM) and the k-Nearest Neighbor (*k*-NN).

The Support Vector Machine (SVM) is a type of supervised machine learning, which analyzes data for classification and is also used in regression analysis. While the concepts and pieces of SVM have been around since the 20th century, the application for pattern recognition was introduced in the 1990's and then continually tuned and refined (Suykens and Vandewalle 1999, 1). The specifics of the algorithm are complex and varied; but very simply, the algorithm constructs optimal hyperplanes between the data points to separate them into different classifications. This is very difficult to visualize in higher dimensions, but you can see a two dimensional representation in figure 10.

The *k*-NN classifier is much easier to explain and implement since it classifies based solely on a distance measurement. When fed an unknown image, the *k*-NN classifier calculates the distance between an unknown images' statistics and statistics from the training set. The nearest neighbor is the image in the training set whose statistics are closest to the unknown image. If the nearest neighbor is cirrus, for example, then image is classified as cirrus. If the nearest neighbor is defined, as say, five then the most common class among five neighbors is used. A number of cloud classification papers use *k*-NN including Peura et al. (1996), Singh and Glennen (2005), Isosalo et al. (2007), and Heinle et al. (2010).

Even though it is one of the simpler machine learning algorithms, it is favored among cloud classification researchers.

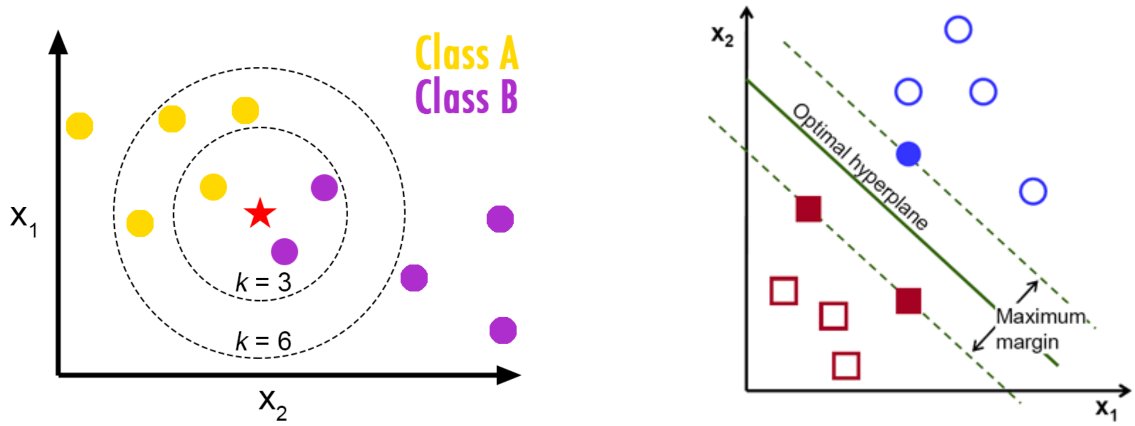


*Figure 11 a) The k-NN classification works with distance to assign the type of the closest point(s). For example, if k=3 the starred point would be purple but if k=6 the classification would be a yellow circle. b) SVM finds the optimal line to divide two or more groups of data points.*
*Sources: a) Dewilde 2012*
*b) http://docs.opencv.org/2.4/doc/tutorials/ml/introduction_to_svm/introduction_to_svm.html*

Zhou et al. found that, in terms of the effectiveness of the classifier, the SVM performed the best (2014). The *k*-NN with just the single closest neighbor was the next best. Then came *k*-NN with three and five nearest neighbors. For comparison purposes we use *k*-NN with various numbers of neighbors in this analysis.

*This process highlights how much we rely on other examples of cloud classification in scientific publications. We experiment with whether their process is replicable or perhaps improved upon for the TSI images. These techniques contribute a base of knowledge to build a classifier for the TSI images. However, the classifiers are specific to neither cloud classification nor even image recognition. The base of knowledge is built across many disciplines. I am not producing knowledge in isolation, rather, I am relying on a network of scientists in fields ranging from image processing to machine learning.*

*Through my eyes, the classifiers seem like a bit of a black box in this methodology. I feed in statistics and the classifier outputs a cloud type. Granted, I helped write the code and I know theoretically what is happening. However, it seems so out of reach because I can't imagine doing this work by hand. This project requires a significant amount of computing power. Even so, it can take the computer days to calculate the images' statistics over the course of a year. By using technology, this knowledge is now achievable. However, for me, it obscures a part of the process that I would prefer be more transparent.*

## 3.4 Results of Automatic Classification

Since we developed so many features, it was important to have an idea of how well each of them functions. I ran a code which uses distance to evaluate which feature best distinguishes each cloud type. I found that cloud mass features differentiate mixed cloud cases the best. Running the classifiers with just the top five of these features, we find that *k*-NN with nine neighbors identifies the most correctly, with 65% agreement between the algorithm and the human classification. These results are shown in the confusion table in figure 11. The mixed cloud cases cirrus (Ci), altocumulus (Ac), cumulus(Cu), and shallow cumulus (ShCu) are used. The algorithm classification is on the x-axis and the human classification is on the y-axis. The cirrus was classified the same 87% percent of the time, while shallow cumulus is confused with cumulus most often. We also checked the classification using all the features as well. We found that this increased the percent agreement. The SVM classifier now performed the best, although the *k*-NN with 9 nearest neighbors performed quite well also. The SVM had an 89% percent agreement which you can see in figure 12 and the k-NN had a 68% percent agreement. However, this decreased sharply to 76%, figure 13, when clear and overcast cases are taken out. There are more errors within the mixed cloud cases than the clear and overcast sky cases.

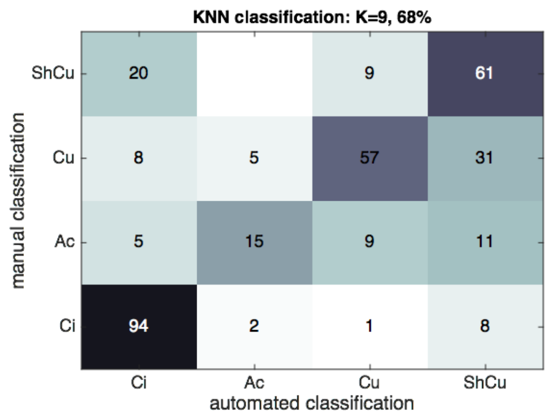


*Figure 11 The confusion table for k-NN with nine nearest neighbors and just five features. The numbers inside the boxes are the number of cloud images*

Unlike Zhou et al. (2014, 80) who found that "the feature selection step is needed if a large number of features are extracted because pattern recognition algorithms are known to degrade in classification accuracy when faced with many features that are not necessary for predicting the desired output," we found that using all 33 of the features returned results with greater agreement.

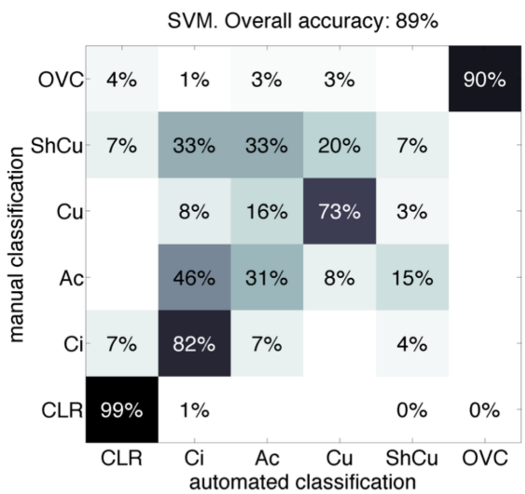


*Figure 12 Confusion table for the SVM classifier with all features and all cloud classes has a 89% agreement.*

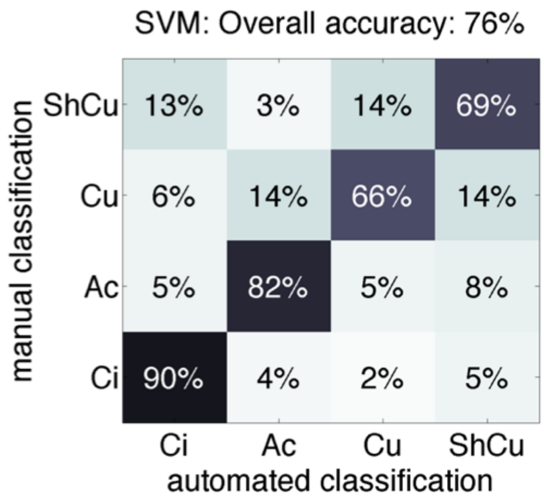


*Figure 13 Confusion table for SVM with all features for only mixed clouds lowers the agreement to 76% but improves the agreement in the altocumulus category.*

It is important to note that we are checking the algorithm results with the classification from humans and we are also using carefully selected images that have no mixed cloud cases or images with obstructions to the lens or mirror. Since our "truth" in this case is the agreement of three amateur cloud classifiers, it is important to also check how the researchers classified the images. We only had a 76% percent agreement among all three of us, although the pairwise agreement hovered around 85% percent. My experience manually classifying influenced my perception of what "good" results were. I felt like I got better at classification the more images I looked at. There were some cases that I felt were only meaningfully classified when compared to other images. For example, for altocumulus, you have to rely on the size of the clouds and how high they appear to be. This difference is more straightforward when looking at a cumulus and an altocumulus next to each other but not in isolation. We also all had to subjectively estimate cloud coverage. We defined clear sky as under 1/10$^{th}$ cloudy and overcast as over

$9/10^{th}$. However, it is very difficult to imagine ten pie slices of clouds in the sky images. Images with cloud cover around $1/10^{th}$ or $9/10^{ths}$ of the sky can easily fit into multiple cloud types. For example, a cumulus cloud that fills a tenth of the sky could either be classified as clear sky, cirrus, or cumulus.

These confusions between the definition of cloud types support a different taxonomy for automatically classified clouds. However, this would introduce a number of problems since this taxonomy is standard for manual classification. Since most automatic classifiers have difficulty classifying similar cloud types or cloud types based on height, which is not always obvious in images, these taxa would most likely be grouped into larger categories. However, research has found that some very specific cloud types have very specific interactions with radiation, like cumulus humilis and different kinds of cirrus clouds (Berg et al. 2011). Cirrus images are hard to classify from images because they are thin and look more blue than white. Cumulus humilis have proven very difficult to recognize in cloud images because their classification is not only based on visual cues. They are primarily convection based and they are defined by other surrounding conditions like precipitation, time of day and height of the cloud. A classifier based on images alone will not be able to include other variables and non-visual cloud characteristics. Other recent cloud classification findings range between an overall accuracy of 60% to 90% (Zhou et al. 2014). This puts our results on the higher end of this range although direct comparisons are difficult to make across diverse methodologies and instruments.

*In summary, I am producing knowledge through remote instruments, interdisciplinary algorithms, statistics, collaboration with research partners, and subjective cloud observations. In manually classifying the images, I can only rely on my visual observation from an image of the sky. Since the sky is often more complicated than the simple cloud classes and there are sometimes obstructions in the image, it is hard for me to be confident about how well the classifier would work on a random image. I am both physically and temporally separated from those sky conditions which happen 1,500 miles away and as long as 16 years ago. Even though I am physically separated, I am still able to visually assess a majority of the sky images and feel that my place is still incorporated into the production process. While there are temporal "holes" in the data, they are usually not more than a few days. I rely completely on computational power, statistics, and computer code. I also rely on different disciplines and the foundation of previous cloud classification scholarship. This process has highlighted the fact that though this work depends on distanciation, partly to minimize subjectivity, local information and specificities still* *contribute to the production of knowledge. Thus, distanciation helps to create a hybrid understanding that encompasses both information about the real world and fabricated frameworks.*

# 4 Discussion

## 4.1 Instrument Comparison

While knowing how one instrument classifies cloud type is helpful in specific circumstances, it is often necessary to compare these results with those of other instruments to see when and if they agree. We checked our classifier with human classified images, but we also could have compared cloud type observations from a different instrument. Depending on the instrument, we would not expect exact alignment especially with harder to classify cloud types since the instruments work in different ways and with different perspectives.

Wu et al. (2014) compare six different instruments that record cloud fraction: three ground-based, including the TSI, and three satellite borne. They emphasize the different field of view and spatial scales of each instrument. For example, the observations from pencil-beam instruments like cloud radar and LiDAR have a field of view less than .5 degrees, while the TSI has a field of view around 160 degrees. Based on the instruments' different fields of view, spatial extent, and sensitivities, Wu et al. (2014) did not find identical cloud fractions from each instrument. However, they highlight the importance of knowing the limitations of each instrument and magnitude of the difference so that there is less confusion in applications like model validation. For example, the millimeter wavelength cloud radar usually misses high clouds and cannot distinguish clouds during precipitation events. Because of the visibility of the cloud sides as well as bottoms near the horizon, the TSI may overestimate the cloud fraction so Wu et al. (2014) restrict the TSI to 100 degrees instead of 160 degrees. Retrieving cloud fraction from satellites is not clear cut either. The spatial scale and temporal scales of satellite observations are much larger compared to most ground based measurements. They found three of the instruments showed an increase in cloudiness from 1998 to 2009 and three showed no trend between these times. The TSI is among the group that showed no significant trend, as did one of the satellite data sets. Wu et al. (2014, 19) concludes saying that, "any activity that professes to produce a value for cloud fraction should also give some valuation of what limit is used to delineate between cloud and no cloud." This limit could be a color-based threshold, like in our methodology, or altitude, field of view, or aerosol content based.

While the data records of these instruments may not be completely comparable, they each have their strengths and weaknesses. Choice of instrument depends on the application and the features that need to be emphasized. There is no objective truth, even for human observations, when it comes to cloud cover and maybe even less so when it comes to cloud type. Boers et al. (2010) also highlights the complications of getting cloud cover from various instruments. These complications are especially relevant during instrument changes, like the switch from humans to ceilometers at weather stations. Boers et al. say that "for the interpretation of long climate records such discontinuities are very hard to handle and subject to debates that are difficult to steer toward acceptable conclusions" (2010, 15). This also highlights the social consequences of incompatible data records that lead to heated debates. As climate models are already heavily criticized, it is problematic that a crucial feature within them has so much uncertainty in the data record. Unfortunately, these comparison studies "demonstrate that a universal definition of cloudiness, which depends on some subjective form of threshold detection such as LiDAR- based optical depth may be out of reach by the more commonly deployed instruments" (15). If the definition of cloudiness is in question then cloud type, which is possibly more subjective, is also in question. This leads me to reflect on my own experience classifying clouds.

## 4.2 Reflection on scientific facts

Doing this research, I regularly challenge myself to identify the cloud cover and cloud types both looking up at the sky and at our data, and I find myself at a loss. There are clouds that don't fit into the neat definitions and clear examples that I was taught to recognize. These observational difficulties are concerning to me and other scientists in this field especially as we learn more about the particular effects of different cloud phenomena. A recent study by Koren et al. (2007) found that the wispy part of clouds around the edges play a huge role in determining Earth's radiative budget. With the uncertainty I have, how do I program a computer to return a cloud cover or cloud type?

Not many studies have compared multiple different instruments' observations of cloud type. Partly, this is because of the difficulty of aggregating the results with different methodologies and cloud type breakdowns. The studies that do compare instruments assessing cloud type generally use human observations of cloud type as the "truth," as I have done above. The classic cloud classes primarily use visual cues to identify, whereas many instruments use other techniques. One study found an overall agreement between the cloud radar and a human observer to be about 64% (Wang and Sassen 2001, 1674), but they ran into difficulty finding current human records of cloud type and were restricted temporally and spatially. We have to ask ourselves if a 64% agreement is good enough to rely on for cloud observations. Cloud type, even more so than cloud cover is dependent on the eyes of a human observer and the classifications systems we have defined.

While the TSI seems like a reasonable choice to try and replicate the cloud type observations of humans, it is also necessary to justify why these observations *should* be replicas. It is necessary to be transparent about the downsides of the Total Sky Imager. The TSI and other cloud observing technology are costly for implementation by anyone other than large organizations. This price point means that sparse spatial sampling is the norm. While the perspective of the instrument is similar to a human observer, the classification and image processing cannot perfectly replicate the observations. Thus, these data do not seamlessly append to a manual cloud record. Even though we often refer to these instruments as automated, there is still a fair amount of hands-on work. The instrument needs to be cleaned regularly and the placement conditions should be free from disturbances and obstruction. Not to mention, the algorithms for processing the images, while somewhat standard, will vary depending on the placement. The process of making a mask is difficult for the TSI in the middle of nowhere, and a city based TSI would even require even more processing. While the TSI has downsides to consider, we have shown that it is possible to retrieve cloud type from the images closely in line with a human observer. Whether or not the visual observations from humans should be considered “truth” remains somewhat in question. Today, instruments like the cloud radar collect non-visual cloud measurements that are much more powerful and sensitive than a human observer could be. However, the transition to an instrument’s “truth” would require overhauling the classification system and thus fracturing the long term record.

## 4.3 Back to the Questions

### 4.3.1. Focus Question

**Where does our understanding of cloud classification come from and how accurate is it?**

So far I have explored the production process behind automated cloud classification and evaluated the accuracy of these results. I have shown how the words we use to describe clouds reflect how we interact with them and therefore inform automated cloud classification. Distanciation in the form of standardization tries to capture the boundless iterations of the sky with a limited vocabulary. Even with standardization, different instruments as well as humans observe clouds in different and sometimes incompatible ways. While instruments that observe clouds differently than humans are not necessarily incorrect, for our cloud type classification, human observations were considered objectively true. Using that standard for classifying images from the TSI, the algorithm performs with 89% accuracy. However, this accuracy is for images that have been selected as example images for these cloud types and included easily classifiable clear skies. Just as the human observations disagree for complicated cloud images, the algorithm would perform much more poorly if the images were completely random. The research question asking *How accurate is our understanding of classification?* is slightly misleading as we first have to identify the measure for truth. We also have to ask ourselves about the uses of the data, as some observation and instruments may be better suited to different tasks. Given the subjectivity and assumptions built into this process of cloud identification, it may be that an objective cloud reality is elusive. Our understanding of clouds is based off of references which approach reality but cannot fully encompass the physical phenomena. However, the references we create with the help of instrumentation and algorithms help us to create meaningful and useful representations to further our understanding.

From my own reflection on the production process, I realize how personal and nuanced writing code, making decisions about the methodology, and manually classifying clouds is. There is no cut and dry path even when I follow other scholars. Somehow I am bringing together all these different pieces from different disciplines and producing knowledge. Having been part of the process, I am both more skeptical of other scientific results and impressed by others' processes. While I am part of this bigger picture, I am distinctly and singularly aware of my personal experience. So while much of what I am doing could fit into the context of distanciation, the actual process is still intimate and tied to the physical and conceptual place that I occupy.

### 4.3.2 Framing Question

**How is knowledge constructed in science and how is its validity assessed?**

Parts of the process of cloud classification exhibit distanciation, hybridity, and issues of scale, but these are not specific to meteorology or climate science. Scientific discovery arises from a social context, one which helps construct meaning from material reality. The production process takes this into account along with the location, instruments, and algorithms that knowledge arises from. Latour's concept of references explains how science understands the physical world through constructed frameworks. Since our understanding of objects like clouds is co-produced from the material reality and human observations, it is beneficial to think of them as hybrids. This idea helps explain a paradox in which scientific representation pushes the real world farther away but also brings it closer (Latour 1999). My experience producing knowledge supports this apparent paradox because I simultaneously distanced myself to create representations while getting closer to the outcomes of my study and while being ensconced in my personal physical and conceptual place.

In a broader sense than just my research, spatial scale ends up being very relevant for how knowledge is produced in cloud research. Cloud observations are dependent on the geographic location as well as the perspective and methodology of the human observer. However, as the spatial or temporal scale of observations increases in order to see a signal or trend, the local particularities of the individual observations which add noise to the data are smoothed over. Thus, compromises are made between resolution and the extent of the data. Within meteorology and climate science, models play an integral role in expanding the scale both spatially and temporally. However, when simulating phenomena on a global scale, features like clouds are not modeled well. Sundberg (2005) describes this phenomena “as simulation models shape interaction to an increasing extent, they grant increasingly less influence (“agency”) to the natural things they represent and replace – the clouds, air masses, droplets, and aerosols” (2005, 229). We see that modeling influences the kind of data we collect and the gaps in the models have inspired greater attention in particular to studying cloud-aerosol interactions and collecting more rigorous cloud observations.

Instrumentation also influences the outcomes of the scientific process and changes the perspective of a human observer. Instrumentation distanciates humans from direct observations but simultaneously allows us to see far more than we ever could with just our senses. However, it does not remove the subjectivity and can introduce numerous problems as well. It is important to note that instruments do not offer an objective truth and have their own specificities and sensitivities. Their validity is still assessed by a human observer, albeit with the help of statistics and other instruments.

Addressing the second part of the question proves very difficult because I never specified *who* or *what* was evaluating the validity of the classification results. Obviously there are scientific, statistically rigorous ways of looking at different variables. Throughout this methodology, we assessed the validity by comparison with human classifications. However, since cloud cover and cloud type are subjective measurements we shouldn't expect complete agreement among human observers. Thus, the validity could be different depending on which method and even which humans we use to check our results. From a hybrid approach, our understanding is co-created by Nature, the material reality, and Culture, the imposed meaning. Since we struggle to objectively measure material reality without imposing meaning, we should not expect all observations to converge on a single truth. Besides statistical methods and comparisons, there are also gut feelings and emotional, value driven reactions that one may use to assess validity with. While these are not necessarily taken seriously in the scientific community, they play a huge role in the way we communicate scientific results.

The communication of scientific results is part of the production process. However, the knowledge must go through another simplification, reduction, and representation for each different audience. Since individuals will understand and retain information differently, this knowledge is continually evolving past its scientific origin. Considering the role scientific knowledge plays in mitigating risk and enacting policy, communication is no less important in the production process than collecting and interpreting data.

## 4.4 Further Study

### 4.4.1 Communicating Complex Data

Clouds play a significant role in global climate change. Through scientific references and different representations of clouds, we have learned a lot about this role. Global warming is predicted to change the amount and types of clouds which will in turn affect the temperature of the earth (Eastman and Warren 2012). One prominent positive feedback is that in a warmer climate, the air above tropical oceans will dry causing reduced low-cloud amounts which then reduces the reflectivity of the earth causing further warming (Bony et al. 2015). In terms of changes to global circulation, climate change is causing a shift in location of storm tracks, moving large rotational storm clouds poleward (Eastman and Warren 2012). Additionally, partially in response to increased convection in a warmer climate, severe storms are predicted to increase in frequency (Del Genio et al. 2007). Clouds have major implications for risk management and mitigation because of long term changes in climate and their role in catastrophic storms. Climate change skeptics often claim that the effects of global warming will be counterbalanced by a cooling effect from growing cloud cover, however, current research shows that clouds, if anything, will contribute to increased warming (Dessler 2010).

Placing clouds within the climate change debate necessitates a discussion about data communications and policy. Fortunately, there are many free online portals to robust data on weather and atmospheric phenomena. This is exciting for many reasons, but chiefly because it means that users of all backgrounds can utilize and process all sort of data. Dutton (2002, 1303) describes the recent advancements in weather and climate services, saying they "are becoming more distributed (in the sense of more nodes in the network), more varied, and more widely available as a consequence of advancing information technology and broader demand " There are many more opportunities for people to participate in science in addition to data processing. Elementary schools can participate in weather and cloud observations though NASA's online portal S'COOL. Miniature weather stations from BloomSky encourage users to collect their own data and sync up with other devices all around the world. Citizen science allows a larger audience to be part of the production process especially in complex fields with involved data streams.

Unfortunately, the tools to make sense of large and complex data streams like the one from the TSI are out out of reach for most people thus, "without organizational filters we would not have information at all, only noise" (Raynor 2012, 110). Just like the process of representing the whole sky with statistics, communicating results is a necessary reduction. Raynor explains, "sense-making is possible only through processes of exclusion. Storytelling is possible only because of the mass of detail that we leave out. Knowledge is possible only through the systematic 'social construction of ignorance'" (2012, 111). This simplification is necessary so that people, and specifically policy makers, can act in the face of 'wicked problems.' Wicked problems, like global climate change, escape a singular explanation, cause, or solution. Rayner calls the simplified representation of science "uncomfortable knowledge" because there is often denial and tension in unsolved or conflicting storylines. The simplified storyline facilitates finding 'clumsy solutions' which are the counterparts to wicked problems (Rayner 2012). This process of representation, communication, and solution implementation are all part of a complex production process

Filtered through an individual's values and attitudes, scientific discoveries can be controversial and spark debate. Jasanoff reminds us that, in fact, "science and technology operate, in short, as political agents" (2014, 14). Science is funded and otherwise supported by political agencies and politics decides what, if any, action comes from the discoveries. Every course of action is not motivated by hard science, for "what we know about the world is intimately linked to our sense of what can we can do about it, as well as to the felt legitimacy of specific actors, instruments and courses of action" (Jasanoff 2004, 14). In the case of clouds and climate change, it seems like the public's perceived illegitimacy of science hinders possible problem solving. Perhaps this is because the theory behind the science is inaccessible or a gut distrust of models. Or perhaps this felt illegitimacy is spurred on by the fact that we cannot directly measure reality. Though hybridity explains how scientific understanding can be both realist and constructivist, scientist often create an illusion of objectivity (Glaserfeld 2001). This illusion, while tempting, does not recognize the human constructed frameworks, the significance of place, and instrumental specificities that are essential in developing scientific knowledge.

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## Table of Figures