THE PENNSYLVANIA STATE UNIVERSITY
SCHREYER HONORS COLLEGE

DEPARTMENT OF METEOROLOGY

# VERIFYING AN AUTOMATED DECISION ALGORITHM USED FOR FLIGHT DECISIONS IN THE SPARTICUS CAMPAIGN

CHRISTOPHER HANLON
Spring 2011

A thesis
submitted in partial fulfillment
of the requirements
for baccalaureate degrees
in Meteorology and Energy, Business, and Finance
with honors in Meteorology

Reviewed and approved* by the following:

Johannes Verlinde
Associate Professor in Meteorology
Thesis Supervisor

Paul Markowski
Associate Professor in Meteorology
Honors Adviser

* Signatures are on file in the Schreyer Honors College.

# ABSTRACT

The quality of flight decisions produced by an automated decision algorithm for the Atmospheric Radiation Measurement (ARM) Small Particles in Cirrus (SPARTICUS) campaign was verified and compared to the quality of flight decisions made by human forecasters on the SPARTICUS team. The SPARTICUS campaign collected data from cirrus clouds over the ARM Southern Great Plains (SGP) site between January 2010 and June 2010. Self-organizing maps, dynamic programming, and relative humidity forecasts from the Global Forecast System (GFS) were used to generate day-ahead yes/no decisions for research flights over the SGP site throughout the 139-day field campaign. SPARTICUS researchers collected 10 "good" days of data, while the algorithm would have collected 12 "good" days, a 20% improvement. This increase in data yield is similar to the improvement shown by an analogous model used on the 2009 ARM RACORO campaign (Small et al., 2011). In addition to increasing the amount of data collected, the algorithm reduces the amount of time and energy spent by researchers on forecasting and decision-making.

# TABLE OF CONTENTS

## ACKNOWLEDGMENTS

I would like to thank Dr. Hans Verlinde for his immense help with this thesis. He was willing and able to answer any questions I had throughout both the data analysis and writing processes. Dr. Verlinde's help in editing and focusing this thesis was indispensable. I would also like to thank Dr. Arthur Small for his assistance in introducing me to this intersection between meteorology and decision science. I am grateful also for Jason Stefik's guidance in understanding his code – he built the decision algorithm and really helped me to understand the workings of the model. I would also like to thank Dr. Paul Markowski for being a helpful honors adviser for my four years at Penn State.

Data were obtained from the Atmospheric Radiation Measurement (ARM) Program sponsored by the U.S. Department of Energy, Office of Science, Office of Biological and Environmental Research, Climate and Environmental Sciences Division.

# Chapter 1

# Introduction

The question of how to allocate resources impacts every step of a meteorological field campaign. In the proposal stage, researchers are expected to request a specific amount of resources. During the field campaign, decisions must be made to determine how best to distribute the resources to collect data. Finally, because the resource distribution affects the amount of usable data collected during the campaign, it affects the post-experiment data analysis. All stakeholders in these field campaigns benefit if resource use is optimized.

Field campaigns collecting in-situ data from aircraft, in particular, experience this optimization problem. Limited budgets dictate a finite number of available flight hours and a finite number of days in the field. Funding for these campaigns does not allow researchers to stay in the field indefinitely, nor does it allow for an unlimited number of flights.

Researchers are thus faced with two challenges when evaluating atmospheric conditions on a particular day. First, researchers must use weather forecasting techniques to assess the expected conditions of the atmosphere for each day. Second, researchers must decide, based on the number of flight hours available and number of days remaining in the campaign, whether conditions are favorable enough to justify using one of the scarce flights from the budget. If there are many flights available and few days left in the project, researchers will be inclined to fly more often than if there are few flights available and many days left. However, when many flights and days are available, researchers typically are too conservative in using flights, hoping for even better conditions. Researchers working on these field campaigns are well-trained to evaluate atmospheric conditions, but not to evaluate the opportunity costs associated with flying or not flying.

During two recent Atmospheric Radiation Measurement (ARM) campaigns, research aircraft were used to collect cloud data over the ARM Southern Great Plains (SGP) site in Oklahoma. The RACORO campaign (Vogelmann et al., 2008) sought in-situ measurements of non-precipitating boundary layer clouds. The SPARTICUS campaign (Mace et al., 2009) sought in-situ measurements of cirrus clouds with no clouds in the lower troposphere. These campaigns shared a common problem: they required specific cloudiness conditions with low probability of occurrence.

An automated algorithm was designed and implemented by Small et al. (2011) to make decision recommendations of whether to fly or not on any given day in the RACORO campaign. The algorithm used historical data to determine the conditional probability of favorable cloud conditions given a certain relative humidity profile predicted by the Global Forecast System (GFS). The algorithm used dynamic programming techniques to calculate the minimum required probability of “good” conditions, also called the “hurdle probability”. The hurdle probability can be generated for any possible combination of number of flights available and number of days remaining based on the climatological probability of favorable conditions. This hurdle probability is compared to the forecast probability of favorable conditions: if the probability of “good” conditions exceeds the hurdle probability, the algorithm recommends flying; if not, the algorithm recommends not flying. During the RACORO campaign, the automated decision algorithm would have gathered 21% more data than the traditional forecasting technique (Small et al., 2011). This paper assesses the performance of the analogous decision algorithm used for the SPARTICUS campaign.

# Chapter 2

# Methodology

The Small Particles in Cirrus (SPARTICUS) project required data collection flights into cirrus clouds over the ARM Southern Great Plains (SGP) site near Lamont, Oklahoma. To best meet project objectives, SPARTICUS investigators preferred the existence of cirrus clouds without low-level clouds. Under these ideal conditions, clouds could be observed by surface remote sensing in addition to the in-situ airplane sampling.

The decision model developed by Small et al. was modified to define ideal cloud conditions using an interpretation of the parameters specified in the SPARTICUS Science and Operations Plan (Mace et al., 2009). According to these parameters, the model considered the following conditions to be requisite for a "good hour": maximum cloud fraction between 6 km and 13.3 km greater than 20% and maximum cloud fraction below 6 km less than 20%. SPARTICUS flights were expected to take place during afternoons and evenings. For any given day, predictions were generated for 20Z +/- 4 hours. A "good day" consists of 4 good hours in the 8 hour range between 16Z and 00Z. The range between 16Z and 00Z corresponds to the range between 12 PM and 8 PM CST and the range between 1 PM and 9 PM CDT.

Building on the success of the decision model used to predict boundary-layer clouds during the RACORO campaign (Stefik, 2010), relative humidity (RH) profiles were used as the predictor for cloud conditions. The ARM Merged Sounding Value Added Product RH data (Troyan, 2010), available from 1998 to 2007 over the SGP site, were used for this project. Self-organizing map (SOM) methodology was used to reduce the large, high-dimensional dataset into a manageable, low-dimensional number of representatives using a neural network and iterative training (Johnson, 2009). The SOM routine was used to distill the large set of RH data into 24 canonical RH profiles, oriented in a 4-by-6 map. Sensitivity analysis performed on the decision model used in the RACORO experiment (Stefik, 2010) indicated that there was no systematic difference in algorithm performance between using any number of SOM profiles between 9 and 64. The 24 resulting canonical profiles are shown in Figure 1.

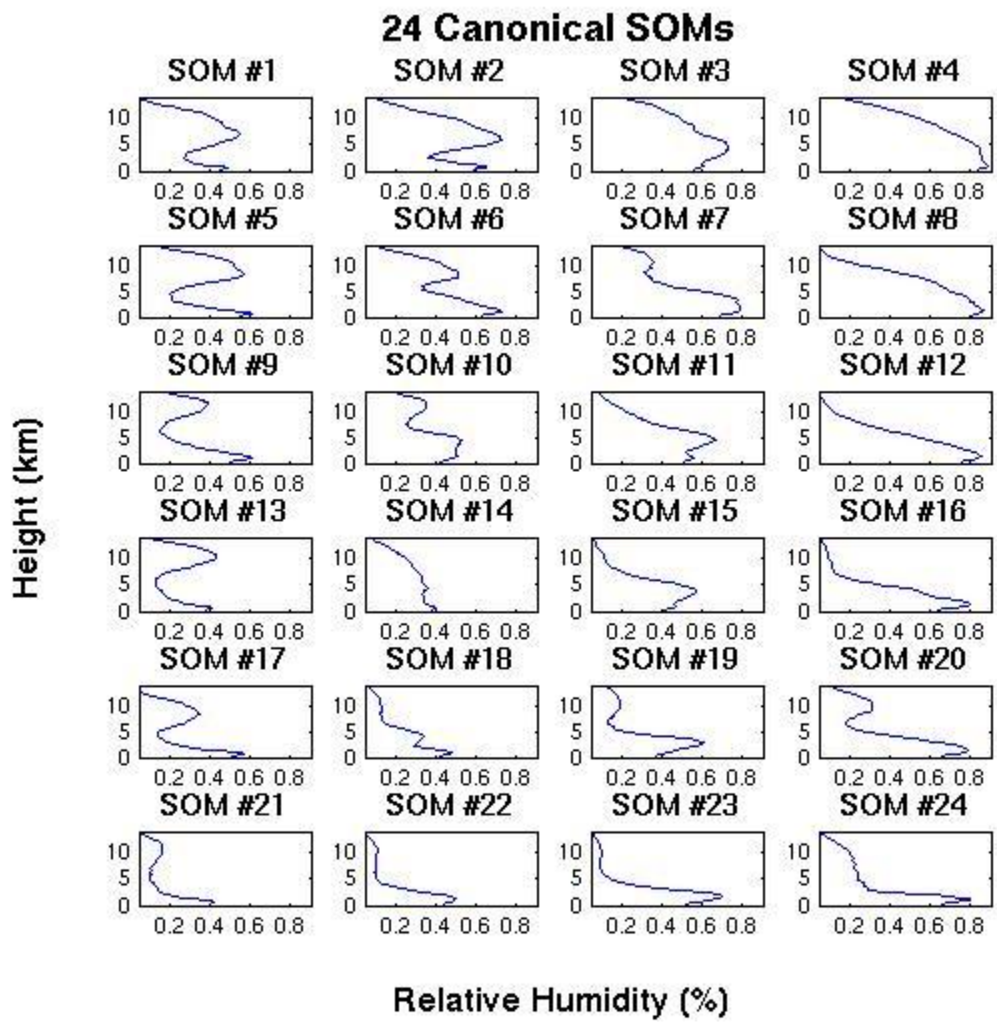


**Figure 1**: The 24 canonical RH profiles that comprise the SOM.

For each day in the period from 1998 to 2007, the best-fit SOM pattern was determined by calculating the root-mean-square difference between the actual RH profile and the RH profile of the 24 characteristic SOMs. The SOM pattern yielding the lowest root-mean-square difference from each day's RH profile determined the canonical SOM pattern to which each day belonged. The distribution of characteristic SOM patterns for each of the days in the period is shown in Figure 2.

## Probability of Occurrence for Each SOM Pattern

| | | | |
|---|---|---|---|
| 2.98% | 3.34% | 2.82% | 3.24% |
| 2.40% | 3.99% | 3.40% | 3.63% |
| 4.38% | 4.15% | 4.83% | 3.79% |
| 3.44% | 4.18% | 4.22% | 3.96% |
| 4.51% | 6.19% | 5.35% | 3.37% |
| 5.67% | 6.49% | 5.06% | 4.60% |

**Figure 2**: Percentage of days in the ARM Merged Sounding Value Added Product period of record that are characterized into each of the 24 canonical SOM patterns. The numbering scheme for the SOM, to be followed throughout this paper, is that the canonical patterns are counted across the SOM. For example, the top row of this table displays the percentage of occurrence for SOM patterns 1, 2, 3, and 4.

To determine the probability of a "good" day conditional on the characteristic SOM pattern present, the RH data were compared to actual cloud conditions for each day. The favorability of cloud conditions for each day was determined from ARM Climate Modeling Best Estimate (CMBE) cloud fraction data (Xie et al., 2010) between the surface and 13 km. By classifying the RH profile for each day into one of the SOM categories and determining whether each day is a "good day", the conditional probability of favorable cloud conditions was determined for each of the 24 SOM profiles (Figure 3). These conditional probabilities support meteorological intuition. For example, the least favorable SOM profiles were SOM #4, #8, and #12. In the period of record, no days with an observed RH profile characterized as any of these SOM profiles had favorable conditions. The RH profiles for each of these SOM patterns demonstrate that such days are likely to have low-level clouds and no cirrus. Conversely, the most favorable SOM profile was SOM #13. Given an observed RH profile characterized as SOM #13, favorable cloud conditions were observed 83% of the time. The RH profile for SOM #13 seems to be the profile of a perfect day: abundant upper-level moisture with little moisture in the lower troposphere.

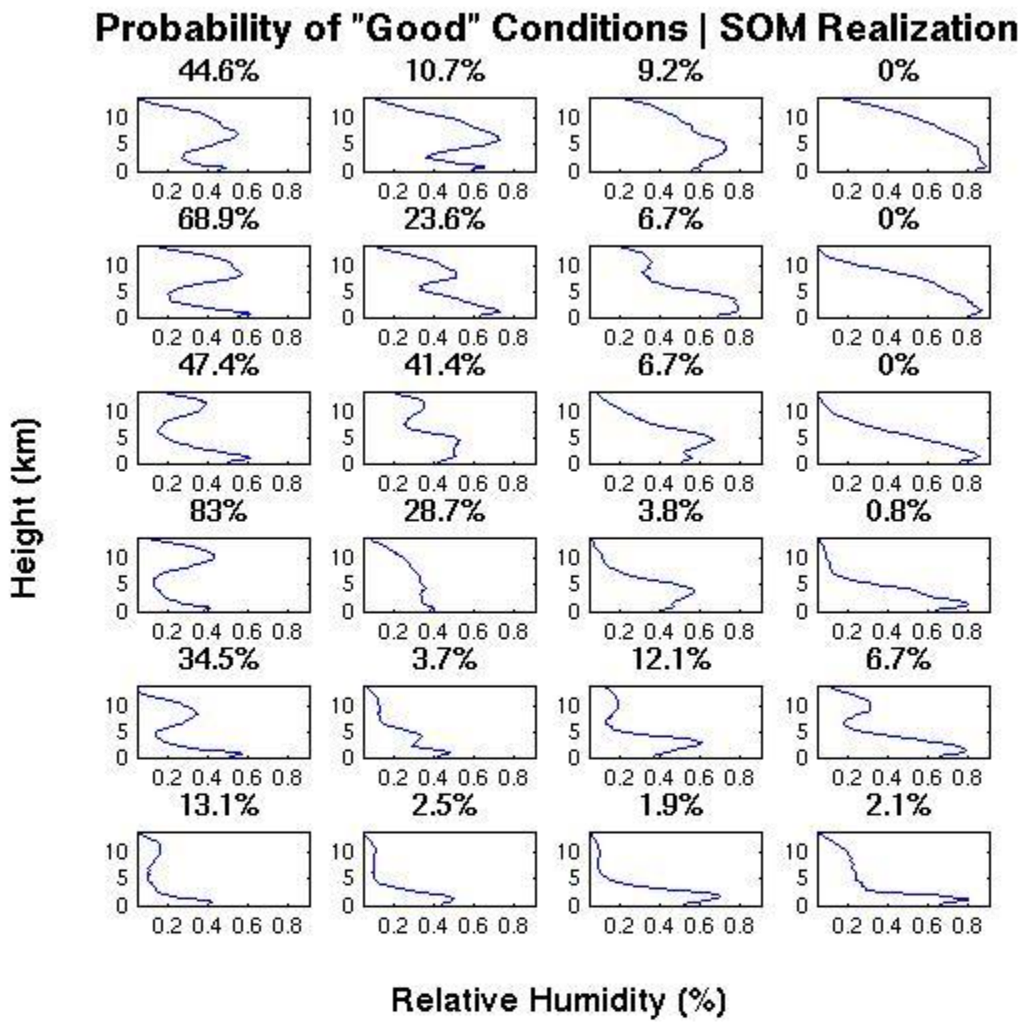


**Figure 3**: The relative humidity profiles associated with each of the 24 canonical SOM patterns and the percentage of days in the period of record in each SOM pattern that qualified as "good" days.

Finally, the conditional probability of "good" conditions given a certain GFS forecast RH profile was calculated. Historical GFS data (Yang et al., 2005) were used to calibrate imperfect model forecasts and determine the signal associated with a given GFS output. GFS data from 2001 to 2007 were used. For each day in this 7-year period of record, the 33-hour-ahead GFS forecast is classified into its characteristic SOM pattern. The realized RH profiles are then verified to determine the signal associated with the GFS prediction of each SOM pattern. For example, given the prediction of an RH profile classified as SOM #1 by the GFS, SOM #1 is realized only 30% of the time. 70% of the days for which SOM #1 is predicted are categorized as a SOM pattern other than SOM #1. In general, we calculate $P(SOM_r = j|\, SOM_p = i)$ for $i, j = 1, \dots, 24$, where $SOM_r = SOM\ realized$ and $SOM_p = SOM\ predicted$. By taking the probability of each SOM being realized conditional on a particular SOM being predicted and combining it with the probability of clouds conditional on each SOM being realized, we calculate the conditional probability of favorable cloud conditions given a specific GFS prediction, using the following equation:

$$P\big(good\big|SOM_p = i\big) = \sum_{j=1}^{24} P(SOM_r = j|\, SOM_p = i)\, P(good|SOM_r = j). \qquad (1)$$

The conditional probability of "good" conditions for each SOM pattern predicted by the GFS is shown in Figure 4. The rank of the SOMs is generally the same; SOM #13 is still the best, while SOM #12 is still the worst. However, the probability distribution after calibration is considerably less sharp than the probability distribution before calibration (Figure 3), a testament to inaccuracies in the GFS RH forecasts.

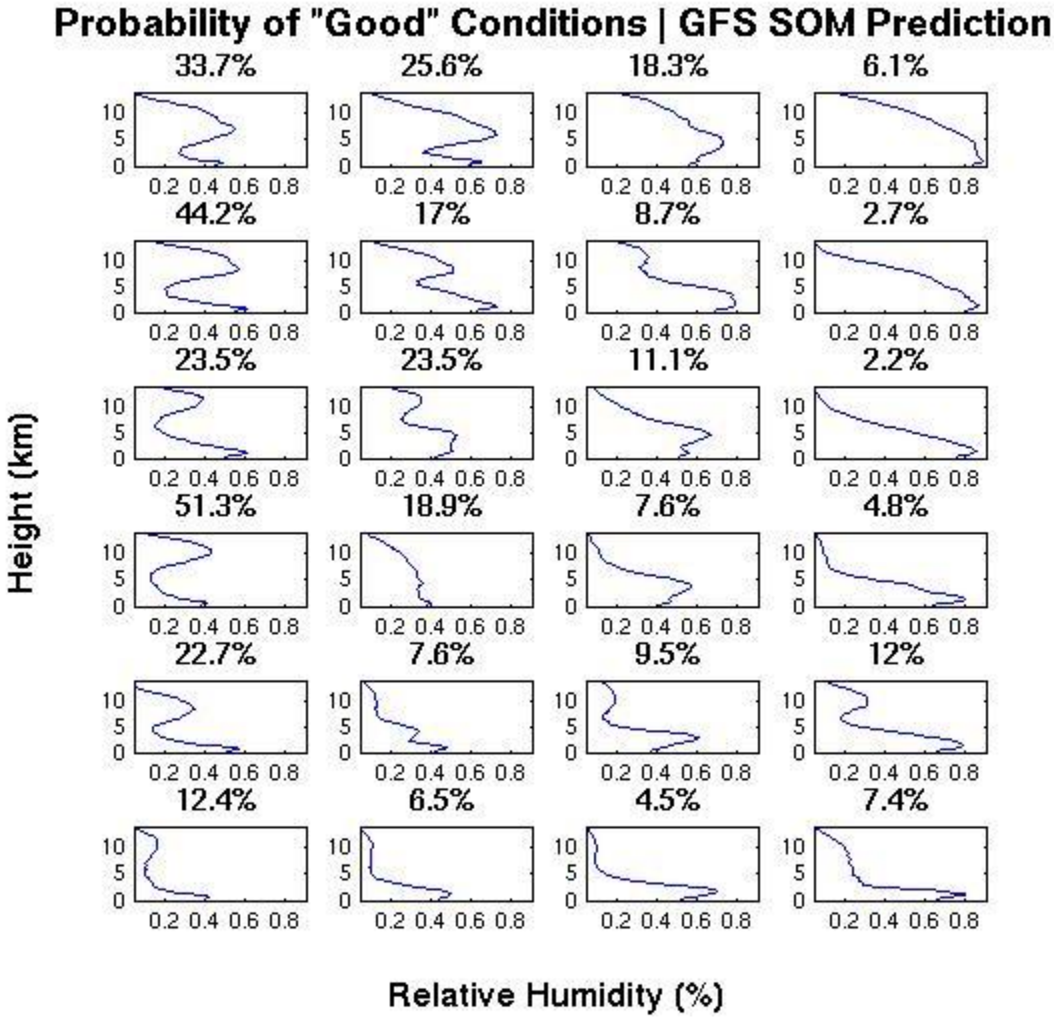


**Figure 4**: This figure displays the same RH profiles as Figure 3, but with the probability of "good" conditions conditional on the 33-hour-ahead GFS predicting an RH profile classified as each of the 24 SOMs.

The approach of presenting a cloud forecast in probabilistic terms rather than deterministic terms has two major benefits. First, the probabilistic presentation provides more information to an end-user than a deterministic presentation. A simple "yes/no" forecast for favorable cloud conditions offers the end-user no information about how confident the forecaster is about the presence of clouds. In statistical terms, a deterministic forecast includes only the mean or median forecast, while a probabilistic forecast includes the mean or median and the variance.

Even more significantly, however, a probabilistic forecast allows for the application of principles of decision science to flight decisions. Given an uncertain forecast, the climatological probability of a "good" day, and the number of remaining days and flight hours, the expected number of successful flights can be determined for any combination of remaining days and flights using well-established dynamic programming techniques.

Let $V(D, F)$ be the number of expected successful flights to be launched for a combination of $D$ remaining days and $F$ remaining flights, given an optimal future path. The following boundary conditions are known:

$$V(D, 0) = 0 \text{ for all } D \tag{2}$$

$$V(x, x) = (x)(climatological\ probability) \tag{3}$$

The boundary condition in (2) holds because if there are no flights left, there can be no successful flights. The boundary condition in (3) holds because if the number of flights equals the number of days, researchers will fly every day regardless of the forecast. In this case, the probability of success on each day is equal to the climatological probability of good conditions. Using these boundary conditions, backwards propagation can be used to calculate $V$ for all possible combinations of $D$ and $F$ under the condition that optimal decisions were made (Stefik, 2010). The values of $V$ for each of the days during the field campaign are shown in Appendix A. Note that $V$ decreases over time because the expected number of successful flights is maximized at the beginning of the campaign when $D$ and $F$ are highest.

The matrix of expected values of $V$ for each possible combination of days and remaining flights allows for the calculation of a hurdle probability for each day during the field campaign. The hurdle probability is defined as the minimum probability of "good" conditions needed to justify flying on a given day. If the probability of favorable conditions exceeds the hurdle probability, the decision model recommends the team to fly. If the hurdle probability exceeds the probability of favorable conditions, the decision model recommends the team not to fly. On any given day with $D$ days and $F$ flights remaining, researchers are faced with the decision to fly or not to fly. Flying provides the opportunity to collect data, but there is one fewer flight in the budget. Conversely, not flying keeps the flight in the budget, but does not provide the opportunity to collect data. Therefore, a flight should only be used on a given day if the probability of "good" conditions exceeds the difference between the value of being on the next day with an extra flight and the value of being on the next day without an extra flight:

$$HP(D,F) = V(D-1,F) - V(D-1,F-1). \quad (4)$$

For example, in Figure 5, the probability "Prob" must exceed $HP(2,1)$ if a flight is to be launched. Even if human forecasters using heuristic processes to produce deterministic forecasts can assess cloud conditions better than an automated algorithm, it is unclear how well they can assess hurdle probabilities and make optimal decisions.

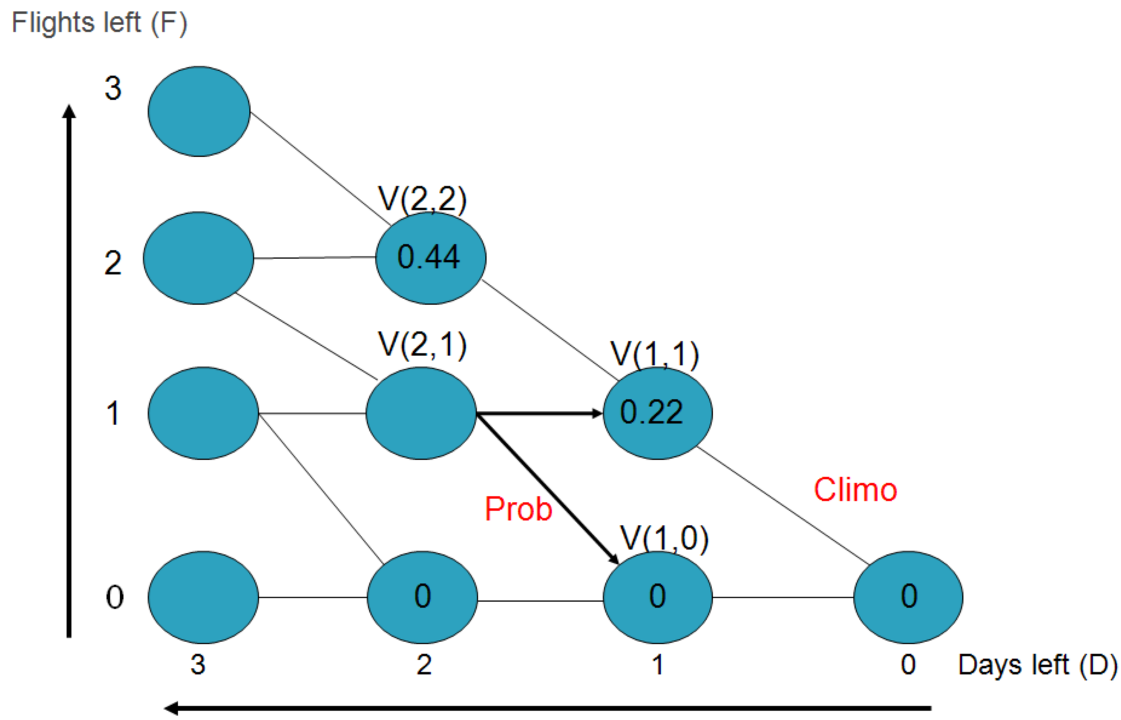


**Figure 5**: A decision lattice showing the boundary conditions to determine the expected value $V$ of successful flights for any combination of days remaining $D$ and flights remaining $F$. (Stefik, 2010)

During the SPARTICUS experiment, the research team made 43 research flights, not including flights to test aircraft or instruments. The SPARTICUS Science and Operations Plan indicated that 60% of their available flight hours would be used on flights to SGP. Of the 43 flights, 26 were over SGP (60%), with the other 17 flights occurring over different parts of the West, often to coincide with the passage of the CALIPSO satellite. The decision model did not consider the passage of the CALIPSO satellite.

After accounting for a period of plane maintenance between April 29 and June 1, the SPARTICUS field campaign ran from January 9 through April 28 and from June 2 to June 30 for a total of 139 days. For each day during the experiment, the probability of "good" conditions was calculated. Because the number of available flights was not well-known in real time, hurdle probabilities were recalculated after the experiment under the assumption that the SPARTICUS team followed the algorithm's recommendations. For example, the SPARTICUS team had 26 flights and 138 days remaining on January 10. On January 10, they did not fly, despite the algorithm recommending a flight. When calculating the hurdle probability for January 11, the algorithm assumed they had 25 flights and 137 days remaining, as if they had flown on January 10. The decision recommendations were then recalculated using the new hurdle probabilities. For reference, the forecast probabilities, hurdle probabilities, expected values, and decisions are included in Appendix A, along with the SPARTICUS team's decision and whether the day was "good".

Initially, flight decisions were submitted to the SPARTICUS team on a given day both for flights that day and flights the next day. For example, on January 6, the model used the f09 and f33 output from the 12Z January 6 GFS run for the grid point nearest to the SGP site. The f09 run was used to generate a decision recommendation for January 6 and the f33 run was used to generate a decision recommendation for January 7. The next-day forecasts were deemed to have a higher value for the science team than the same-day forecasts, because they would be able to begin their preparations earlier, including organizing the flight crew and preparing instruments. Early in the project, the decision was made to eliminate the same-day forecasts and exclusively produce and send next-day forecasts.

Decision recommendations for the next day were sent to SPARTICUS investigators throughout the project via daily emails at 11 AM CT. The recommendations consisted of a forecast SOM pattern, a forecast probability of good conditions, a hurdle probability, and a recommendation to fly or not to fly. The SPARTICUS team's decision pattern suggested that the team was not using the recommendations, which was confirmed through communication with the SPARTICUS Principal Investigator (Mace, personal communication). Their non-use of the recommendations allows us to independently compare the success of the SPARTICUS team in flying on “good days” with the success of the decision model in choosing “good days.”

# Chapter 3

## Results

For each of the 139 days in the field campaign, the cloud conditions were categorized as “good days” or “bad days” using the same criteria used in the development of the algorithm. A “good hour” was categorized as having the following necessary conditions: maximum cloud fraction between 6 km and 13.3 km greater than 20% and maximum cloud fraction below 6 km less than 20%. A “good day” was categorized as 4 good hours in the 8 hour period between 16Z and 00Z.

For the 82-day period of between January 9 and March 31, days were categorized objectively as “good” or “bad” using CMBE data for the SGP site. CMBE data were only available through March 31. For the 57 remaining days (April 1 through April 28 and June 2 through June 30), the categorization of days as “good” or “bad” was done by subjectively using ARM Millimeter Wave Cloud Radar (MMCR) radar reflectivity data and ARM MPL POLFS (Micropulse Lidar polarized, fast sampling) data. (Note: When CMBE becomes available for the period between April and June, those days will be rescored using the objective cloud-fraction data.)

Of 139 days in the period, 23 days were categorized as “good” days. The climatological probability of “good” conditions on any given day was 17.2%. From climatology, 24 “good” days were expected. SPARTICUS researchers flew over SGP on “good” days 10 times. If they had flown on the days that the algorithm recommended, they would have flown on 12 good days, obtaining 20% more “good” data. The number of good days collected by both the algorithm and the SPARTICUS team are depicted in Figure 6.

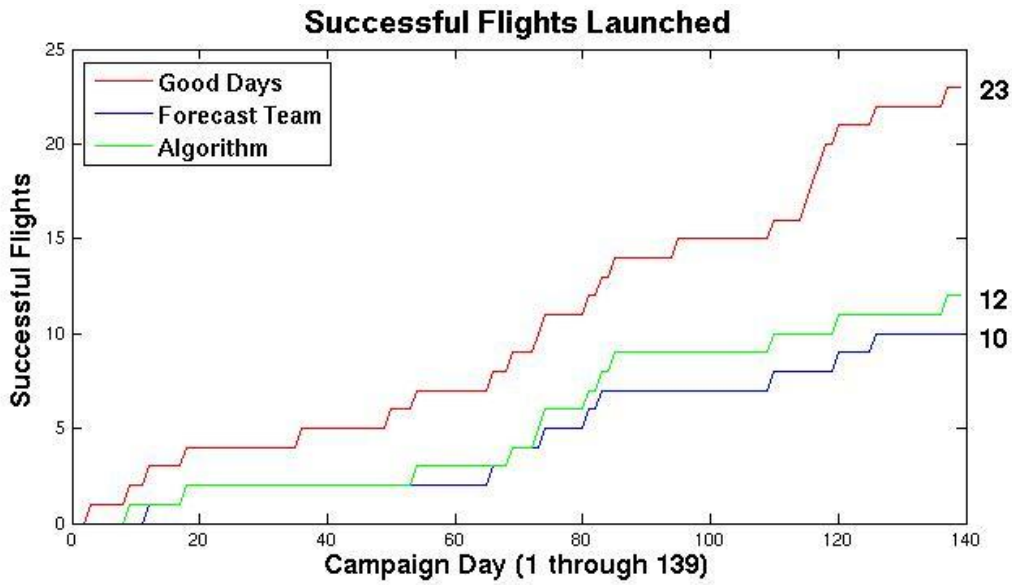


**Figure 6**: The number of good flights collected by the forecasting team (blue line) compared to the number of good flights they would have collected by following the recommendations of the decision algorithm (green line). The total number of "good" days is shown in red.

There were eight "good" days during the campaign for which the algorithm's recommendation differed with the SPARTICUS decision – five good days for which the algorithm recommended a flight and the SPARTICUS team did not fly and three good days for which the algorithm recommended not flying and the SPARTICUS team flew. None of the five good days that we recommended and on which they did not fly to SGP were days that they flew under the CALIPSO satellite.

To further analyze the performance of each algorithm, the scoring of good days and bad days was expanded. While the objectives of the SPARTICUS campaign stated that the ideal conditions for collecting data were cirrus clouds with no clouds in the lower troposphere, there is presumably some value in flying when conditions aloft are good but there are thick clouds in the lower troposphere. Under such conditions, cirrus clouds can be measured by the in-situ instruments on the airplane, but the ground-based lidar cannot see through the low-level clouds. The 16 "bad" days when the SPARTICUS team flew were further examined to determine the reason for their being scored as "bad." To score these days evenly with the algorithm, the 14 "bad" days that the algorithm would have flown were also examined. Each of these days was rescored using only the criterion relating to cirrus clouds, while ignoring the criterion relating to low-level cloudiness. Under this method of scoring, any afternoon with four hours that had a maximum cloud fraction between 6 km and 13.3 km of over 20% would be scored as a "semi-good" day, regardless of the cloudiness of the lower troposphere. It was hypothesized that the SPARTICUS team would collect more "semi-good" days than the algorithm because the algorithm did not distinguish between semi-good and bad days.

Of the 16 "bad" days on which the team flew, 9 took place between January 9 and March 31 and the other 7 took place on or after April 1. Of the 14 "bad" days on which the algorithm recommended flying, 10 took place between January 9 and March 31, while 4 took place on or after April 1. As in the initial analysis, the days on or before March 31 were evaluated using the CMBE data, while the days on or after April 1 were evaluated subjectively. It was hypothesized that the SPARTICUS team would obtain more of these “semi-good” days than the automated algorithm because the algorithm did not distinguish between “semi-good” days and “bad” days.

Of the 16 “bad” days on which the SPARTICUS team flew, 10 qualified as semi-good. Of the 14 “bad” days on which the algorithm recommended a flight, 5 qualified as semi-good. In total, the SPARTICUS team used their 26 flights on 10 good days, 10 semi-good days, and 6 bad days; while if they followed the algorithm, they would have used their flights on 12 good days, 5 semi-good days, and 9 bad days.

# Chapter 4

## Discussion

The SPARTICUS Science and Operations Plan offers insight into the problems with having human forecasters estimate the opportunity costs associated with flying or not flying.  The plan states, in the Operational Considerations section:

"We will keep careful track of our monthly flight hour burn rate. If we find that we are not using our allotted hours rapidly enough with the primary and secondary targets, we will broaden our approach and sample cirrus within the operations area even if it is well away from the SGP site or the A-Train overpasses." (Mace et al., 2009)

This approach shows an attempt to account for the need to optimize the use of flight hours, but rather than using a robust quantitative tool, they simply abandon the primary objective if they are not using enough of their flight hours at a given point in each month.

Two cases in particular among the days that the SPARTICUS team missed served as examples of irrational human thinking impacting scientific decisions and potentially compromising the success of the scientific field campaign.  By removing the human element from these field decisions, the use of an automated decision algorithm removes emotion from the decision-making process.

The SPARTICUS team did not fly over SGP for any of the days in the two-week period from April 2 through April 15.  Had they followed the algorithm's advice, they would have flown on three of those 14 days, one of which would have been a "good" day.  The SPARTICUS team then flew on both April 16 and April 17.  On both days, the algorithm would have recommended them not to fly, and in fact, neither day was scored as a “good day”. According to the subjective analysis, both days had cirrus clouds over SGP, but both had significant cloud cover in the lower troposphere, with cloud fractions much higher than 20%. On both of these days, scarce flight hours were used to measure cloud conditions that were inconsistent with those outlined in the campaign objectives. As shown in their Science and Operations Plan, they were planning to abandon the primary objective if they were not using their flight hours quickly enough. One of the benefits of an automated algorithm is that the algorithm is always “aware” of the probability associated with flying or not flying and cannot be corrupted by emotion. An automated decision algorithm will never be irrationally tempted to fly into mediocre conditions because it has not flown in many days.

Another case offers a potential glimpse at the problems associated with human decision making. On June 24, the SPARTICUS team had one flight and seven days remaining in the field campaign. This combination of remaining flights and days called for them to be moderately choosy with a hurdle probability of 31.08%. The algorithm predicted a probability of good conditions of 6.12%. However, the SPARTICUS team flew on June 24, finding no cirrus clouds. Left without a flight for the last six days, the SPARTICUS team missed the opportunity to collect data on the “good” day on June 28, the day that the algorithm would have used its last flight. The SPARTICUS team acted rashly by flying into bad conditions on June 24, possibly out of fear that they would not be able to use the last flight day on June 30. The algorithm, by using probability rather than emotion and guessing, would have collected an extra day of good data by not flying on June 24.

As noted in the results section, the SPARTICUS team collected data on 10 "semi-good" days, while the automated algorithm would have collected data on 5 "semi-good" days. As the field campaign progressed, the decisions made by the SPARTICUS team suggested that they were relaxing their definition of a "good" day, though this was not specified a priori in the science plan. The decision algorithm can be adjusted for this scenario, but it requires the project scientists to assign relative value to the "semi-good" day. The implemented decision model effectively assigned a value of zero to a "semi-good" day.

Note that the automated algorithm collected more data than the human forecasters while using much less meteorological information. The automated algorithm used RH profiles from the 33-hour-ahead GFS as the only predictor for cloud conditions, while the human forecasters had dozens of forecasting tools at their disposal (including the GFS). The human forecasters were much better equipped to deterministically evaluate the state of the atmosphere. The automated algorithm outperformed the human forecasters despite being at a tremendous forecasting disadvantage. This emphasizes the value of optimal decision-making, suggesting that the decision-making is much more important than the actual forecast; an optimizing decision tool using bad forecasts performs better than humans using good forecasts.

# Chapter 5

## Conclusion

The decision model used for the SPARTICUS campaign produced results consistent with those produced using an analogous model for the RACORO campaign. In both cases, using the automated decision algorithm instead of traditional forecasting and decision-making techniques would have yielded approximately 20% more "good" data.

Field campaigns like RACORO and SPARTICUS collect valuable data to fulfill a specific scientific objective. Atmospheric scientists apply the data collected in these field campaigns to dozens of research projects. Therefore, the stakes for these field campaigns are high. In the SPARTICUS campaign, researchers were funded for the purpose of sampling cirrus clouds using both aircraft and remote sensing. By not optimizing the amount of data collected, SPARTICUS researchers decreased the scientific value of the campaign. Unfortunately, the SPARTICUS approach of forecasting and decision-making is the standard in atmospheric science field campaigns.

The traditional method of forecasting and decision-making is inefficient: scientists are trained to forecast atmospheric conditions but not to evaluate the opportunity costs associated with deciding whether or not to use scarce resources. The strategy demonstrated in the decision algorithms applied to the RACORO and SPARTICUS campaigns outperforms the traditional strategy despite having imperfect forecasts. In a contest of pure forecasting skill, the SPARTICUS forecast team would likely outperform the GFS forecasts used as inputs to the decision algorithm. Despite this disadvantage in forecast skill, the automated algorithm outperformed the SPARTICUS team in data collection. The widespread implementation of automated algorithms like the one used for the SPARTICUS campaign is expected to maximize the amount of data collected, thus maximizing the benefit of these campaigns to the scientific community.

# Appendix A

## Flight and Decision Information

| Day | Date | Hurdle Prob | Forecast | V | Our rec. flights | Their flights | Good days |
|---|---|---|---|---|---|---|---|
| 1 | 9-Jan | 0.2480 | 0.1244 | 9.8603 | 0 | 0 | 0 |
| 2 | 10-Jan | 0.2474 | 0.4418 | 9.8344 | 1 | 0 | 0 |
| 3 | 11-Jan | 0.2507 | 0.1702 | 9.5610 | 0 | 0 | 1 |
| 4 | 12-Jan | 0.2500 | 0.5125 | 9.5355 | 1 | 0 | 0 |
| 5 | 13-Jan | 0.2535 | 0.5125 | 9.2599 | 1 | 0 | 0 |
| 6 | 14-Jan | 0.2572 | 0.4418 | 8.9813 | 1 | 1 | 0 |
| 7 | 15-Jan | 0.2621 | 0.4418 | 8.6997 | 1 | 0 | 0 |
| 8 | 16-Jan | 0.2688 | 0.0612 | 8.4139 | 0 | 0 | 0 |
| 9 | 17-Jan | 0.2675 | 0.5125 | 8.3909 | 1 | 0 | 1 |
| 10 | 18-Jan | 0.2759 | 0.2349 | 8.1004 | 0 | 0 | 0 |
| 11 | 19-Jan | 0.2743 | 0.2562 | 8.0784 | 0 | 1 | 0 |
| 12 | 20-Jan | 0.2728 | 0.2562 | 8.0562 | 0 | 1 | 1 |
| 13 | 21-Jan | 0.2713 | 0.0452 | 8.0338 | 0 | 0 | 0 |
| 14 | 22-Jan | 0.2699 | 0.1702 | 8.0112 | 0 | 0 | 0 |
| 15 | 23-Jan | 0.2685 | 0.2562 | 7.9884 | 0 | 0 | 0 |
| 16 | 24-Jan | 0.2671 | 0.2562 | 7.9655 | 0 | 0 | 0 |
| 17 | 25-Jan | 0.2658 | 0.2269 | 7.9423 | 0 | 0 | 0 |
| 18 | 26-Jan | 0.2645 | 0.4418 | 7.9190 | 1 | 1 | 1 |
| 19 | 27-Jan | 0.2725 | 0.2562 | 7.6310 | 0 | 0 | 0 |
| 20 | 28-Jan | 0.2710 | 0.0612 | 7.6086 | 0 | 0 | 0 |
| 21 | 29-Jan | 0.2695 | 0.0268 | 7.5860 | 0 | 0 | 0 |
| 22 | 30-Jan | 0.2680 | 0.0742 | 7.5632 | 0 | 0 | 0 |
| 23 | 31-Jan | 0.2666 | 0.2349 | 7.5402 | 0 | 1 | 0 |
| 24 | 1-Feb | 0.2653 | 0.1702 | 7.5170 | 0 | 0 | 0 |
| 25 | 2-Feb | 0.2640 | 0.5125 | 7.4936 | 1 | 0 | 0 |
| 26 | 3-Feb | 0.2722 | 0.0612 | 7.2061 | 0 | 1 | 0 |
| 27 | 4-Feb | 0.2706 | 0.0612 | 7.1836 | 0 | 0 | 0 |
| 28 | 5-Feb | 0.2691 | 0.0477 | 7.1609 | 0 | 0 | 0 |
| 29 | 6-Feb | 0.2676 | 0.1702 | 7.1380 | 0 | 0 | 0 |
| 30 | 7-Feb | 0.2661 | 0.0612 | 7.1150 | 0 | 0 | 0 |
| 31 | 8-Feb | 0.2647 | 0.0268 | 7.0917 | 0 | 0 | 0 |
| 32 | 9-Feb | 0.2634 | 0.0742 | 7.0682 | 0 | 0 | 0 |

| Day | Date | Hurdle Prob | Forecast | V | Our rec. flights | Their flights | Good days |
|---|---|---|---|---|---|---|---|
| 33 | 10-Feb | 0.2621 | 0.0612 | 7.0446 | 0 | 0 | 0 |
| 34 | 11-Feb | 0.2608 | 0.1702 | 7.0208 | 0 | 1 | 0 |
| 35 | 12-Feb | 0.2596 | 0.1702 | 6.9968 | 0 | 0 | 0 |
| 36 | 13-Feb | 0.2585 | 0.1826 | 6.9727 | 0 | 0 | 1 |
| 37 | 14-Feb | 0.2575 | 0.0452 | 6.9484 | 0 | 0 | 0 |
| 38 | 15-Feb | 0.2564 | 0.1702 | 6.9240 | 0 | 0 | 0 |
| 39 | 16-Feb | 0.2555 | 0.1110 | 6.8995 | 0 | 0 | 0 |
| 40 | 17-Feb | 0.2545 | 0.4418 | 6.8748 | 1 | 0 | 0 |
| 41 | 18-Feb | 0.2600 | 0.0867 | 6.5954 | 0 | 0 | 0 |
| 42 | 19-Feb | 0.2588 | 0.1702 | 6.5713 | 0 | 1 | 0 |
| 43 | 20-Feb | 0.2577 | 0.1702 | 6.5471 | 0 | 0 | 0 |
| 44 | 21-Feb | 0.2566 | 0.0268 | 6.5227 | 0 | 0 | 0 |
| 45 | 22-Feb | 0.2556 | 0.0268 | 6.4982 | 0 | 0 | 0 |
| 46 | 23-Feb | 0.2545 | 0.1195 | 6.4735 | 0 | 0 | 0 |
| 47 | 24-Feb | 0.2535 | 0.2349 | 6.4486 | 0 | 0 | 0 |
| 48 | 25-Feb | 0.2525 | 0.0612 | 6.4236 | 0 | 0 | 0 |
| 49 | 26-Feb | 0.2515 | 0.0612 | 6.3984 | 0 | 0 | 0 |
| 50 | 27-Feb | 0.2504 | 0.2349 | 6.3730 | 0 | 0 | 1 |
| 51 | 28-Feb | 0.2494 | 0.1826 | 6.3475 | 0 | 0 | 0 |
| 52 | 1-Mar | 0.2484 | 0.1826 | 6.3218 | 0 | 0 | 0 |
| 53 | 2-Mar | 0.2473 | 0.0761 | 6.2959 | 0 | 0 | 0 |
| 54 | 3-Mar | 0.2463 | 0.4418 | 6.2698 | 1 | 0 | 1 |
| 55 | 4-Mar | 0.2513 | 0.2349 | 5.9973 | 0 | 0 | 0 |
| 56 | 5-Mar | 0.2502 | 0.0867 | 5.9718 | 0 | 0 | 0 |
| 57 | 6-Mar | 0.2490 | 0.4418 | 5.9463 | 1 | 0 | 0 |
| 58 | 7-Mar | 0.2545 | 0.0867 | 5.6714 | 0 | 0 | 0 |
| 59 | 8-Mar | 0.2533 | 0.0867 | 5.6466 | 0 | 0 | 0 |
| 60 | 9-Mar | 0.2522 | 0.0268 | 5.6215 | 0 | 0 | 0 |
| 61 | 10-Mar | 0.2510 | 0.0222 | 5.5962 | 0 | 1 | 0 |
| 62 | 11-Mar | 0.2498 | 0.0268 | 5.5708 | 0 | 0 | 0 |
| 63 | 12-Mar | 0.2486 | 0.0268 | 5.5451 | 0 | 0 | 0 |
| 64 | 13-Mar | 0.2474 | 0.2349 | 5.5193 | 0 | 0 | 0 |
| 65 | 14-Mar | 0.2463 | 0.2349 | 5.4932 | 0 | 0 | 0 |
| 66 | 15-Mar | 0.2452 | 0.1702 | 5.4670 | 0 | 1 | 1 |
| 67 | 16-Mar | 0.2441 | 0.1195 | 5.4406 | 0 | 0 | 0 |
| 68 | 17-Mar | 0.2430 | 0.0452 | 5.4139 | 0 | 0 | 0 |

| Day | Date | Hurdle Prob | Forecast | V | Our rec. flights | Their flights | Good days |
|---|---|---|---|---|---|---|---|
| 69 | 18-Mar | 0.2420 | 0.5125 | 5.3871 | 1 | 1 | 1 |
| 70 | 19-Mar | 0.2468 | 0.1826 | 5.1182 | 0 | 0 | 0 |
| 71 | 20-Mar | 0.2456 | 0.0612 | 5.0921 | 0 | 0 | 0 |
| 72 | 21-Mar | 0.2444 | 0.0612 | 5.0657 | 0 | 0 | 0 |
| 73 | 22-Mar | 0.2433 | 0.4418 | 5.0391 | 1 | 0 | 1 |
| 74 | 23-Mar | 0.2488 | 0.4418 | 4.7691 | 1 | 1 | 1 |
| 75 | 24-Mar | 0.2556 | 0.0612 | 4.4945 | 0 | 0 | 0 |
| 76 | 25-Mar | 0.2541 | 0.1244 | 4.4698 | 0 | 0 | 0 |
| 77 | 26-Mar | 0.2526 | 0.4418 | 4.4449 | 1 | 0 | 0 |
| 78 | 27-Mar | 0.2610 | 0.0268 | 4.1671 | 0 | 1 | 0 |
| 79 | 28-Mar | 0.2590 | 0.2349 | 4.1432 | 0 | 0 | 0 |
| 80 | 29-Mar | 0.2572 | 0.4418 | 4.1190 | 1 | 0 | 0 |
| 81 | 30-Mar | 0.2685 | 0.4418 | 3.8373 | 1 | 1 | 1 |
| 82 | 31-Mar | 0.2849 | 0.1244 | 3.5459 | 0 | 0 | 0 |
| 83 | 1-Apr | 0.2817 | 0.4418 | 3.5251 | 1 | 1 | 1 |
| 84 | 2-Apr | 0.3023 | 0.1702 | 3.2222 | 0 | 0 | 0 |
| 85 | 3-Apr | 0.2987 | 0.4418 | 3.2037 | 1 | 0 | 1 |
| 86 | 4-Apr | 0.3223 | 0.1702 | 2.8860 | 0 | 0 | 0 |
| 87 | 5-Apr | 0.3188 | 0.4418 | 2.8701 | 1 | 0 | 0 |
| 88 | 6-Apr | 0.3443 | 0.0948 | 2.5350 | 0 | 0 | 0 |
| 89 | 7-Apr | 0.3407 | 0.0222 | 2.5219 | 0 | 0 | 0 |
| 90 | 8-Apr | 0.3371 | 0.0948 | 2.5084 | 0 | 0 | 0 |
| 91 | 9-Apr | 0.3334 | 0.5125 | 2.4944 | 1 | 0 | 0 |
| 92 | 10-Apr | 0.3635 | 0.2349 | 2.1467 | 0 | 0 | 0 |
| 93 | 11-Apr | 0.3595 | 0.1702 | 2.1356 | 0 | 0 | 0 |
| 94 | 12-Apr | 0.3554 | 0.1195 | 2.1240 | 0 | 0 | 0 |
| 95 | 13-Apr | 0.3512 | 0.2354 | 2.1120 | 0 | 0 | 1 |
| 96 | 14-Apr | 0.3471 | 0.2349 | 2.0996 | 0 | 0 | 0 |
| 97 | 15-Apr | 0.3429 | 0.0612 | 2.0867 | 0 | 0 | 0 |
| 98 | 16-Apr | 0.3386 | 0.0612 | 2.0734 | 0 | 1 | 0 |
| 99 | 17-Apr | 0.3344 | 0.0612 | 2.0597 | 0 | 1 | 0 |
| 100 | 18-Apr | 0.3300 | 0.0612 | 2.0454 | 0 | 0 | 0 |
| 101 | 19-Apr | 0.3255 | 0.4418 | 2.0306 | 1 | 0 | 0 |
| 102 | 20-Apr | 0.3604 | 0.0867 | 1.6896 | 0 | 0 | 0 |
| 103 | 21-Apr | 0.3556 | 0.1195 | 1.6782 | 0 | 0 | 0 |
| 104 | 22-Apr | 0.3508 | 0.0612 | 1.6662 | 0 | 1 | 0 |

| Day | Date | Hurdle Prob | Forecast | V | Our rec. flights | Their flights | Good days |
|---|---|---|---|---|---|---|---|
| 105 | 23-Apr | 0.3458 | 0.1888 | 1.6537 | 0 | 0 | 0 |
| 106 | 24-Apr | 0.3409 | 0.0222 | 1.6408 | 0 | 1 | 0 |
| 107 | 25-Apr | 0.3358 | 0.1195 | 1.6272 | 0 | 0 | 0 |
| 108 | 26-Apr | 0.3306 | 0.2562 | 1.6132 | 0 | 0 | 0 |
| 109 | 27-Apr | 0.3252 | 0.5125 | 1.5984 | 1 | 0 | 0 |
| 110 | 28-Apr | 0.3678 | 0.5125 | 1.2577 | 1 | 1 | 1 |
| 111 | 2-Jun | 0.4150 | 0.2562 | 0.8793 | 0 | 0 | 0 |
| 112 | 3-Jun | 0.4111 | 0.2354 | 0.8736 | 0 | 1 | 0 |
| 113 | 4-Jun | 0.4070 | 0.2354 | 0.8675 | 0 | 0 | 0 |
| 114 | 5-Jun | 0.4024 | 0.3367 | 0.8610 | 0 | 0 | 0 |
| 115 | 6-Jun | 0.3974 | 0.1826 | 0.8540 | 0 | 0 | 1 |
| 116 | 7-Jun | 0.3919 | 0.1826 | 0.8465 | 0 | 0 | 1 |
| 117 | 8-Jun | 0.3859 | 0.0948 | 0.8384 | 0 | 0 | 1 |
| 118 | 9-Jun | 0.3794 | 0.1826 | 0.8296 | 0 | 0 | 1 |
| 119 | 10-Jun | 0.3725 | 0.2354 | 0.8202 | 0 | 0 | 0 |
| 120 | 11-Jun | 0.3652 | 0.4418 | 0.8101 | 1 | 1 | 1 |
| 121 | 12-Jun | 0.4298 | 0.0761 | 0.4339 | 0 | 0 | 0 |
| 122 | 13-Jun | 0.4252 | 0.1195 | 0.4298 | 0 | 0 | 0 |
| 123 | 14-Jun | 0.4201 | 0.0612 | 0.4252 | 0 | 1 | 0 |
| 124 | 15-Jun | 0.4144 | 0.0452 | 0.4201 | 0 | 1 | 0 |
| 125 | 16-Jun | 0.4080 | 0.0477 | 0.4144 | 0 | 0 | 0 |
| 126 | 17-Jun | 0.4008 | 0.0452 | 0.4080 | 0 | 1 | 1 |
| 127 | 18-Jun | 0.3928 | 0.0758 | 0.4008 | 0 | 0 | 0 |
| 128 | 19-Jun | 0.3838 | 0.0649 | 0.3928 | 0 | 0 | 0 |
| 129 | 20-Jun | 0.3738 | 0.0649 | 0.3838 | 0 | 0 | 0 |
| 130 | 21-Jun | 0.3626 | 0.1110 | 0.3738 | 0 | 0 | 0 |
| 131 | 22-Jun | 0.3501 | 0.2354 | 0.3626 | 0 | 0 | 0 |
| 132 | 23-Jun | 0.3360 | 0.2354 | 0.3501 | 0 | 0 | 0 |
| 133 | 24-Jun | 0.3198 | 0.0612 | 0.3360 | 0 | 1 | 0 |
| 134 | 25-Jun | 0.3012 | 0.2354 | 0.3198 | 0 | 0 | 0 |
| 135 | 26-Jun | 0.2797 | 0.1826 | 0.3012 | 0 | 0 | 0 |
| 136 | 27-Jun | 0.2549 | 0.1826 | 0.2797 | 0 | 0 | 0 |
| 137 | 28-Jun | 0.2228 | 0.5125 | 0.2549 | 1 | 0 | 1 |
| 138 | 29-Jun | 1.0000 | 0.0948 | 0.0000 | 0 | 0 | 0 |
| 139 | 30-Jun | 1.0000 | 0.0649 | 0.0000 | 0 | 0 | 0 |

## References

Johnson, N.C., 2009: The Spatial and Temporal Variability of Atmospheric Teleconnection Patterns: A Continuum Perspective. Ph.D dissertation, The Pennsylvania State University, 87 pp.

Mace, J., E. Jensen, G. McFarquhar, J. Comstock, T. Ackerman, D. Mitchell, X. Liu, T. Garrett, 2009: *SPARTICUS: Small Particles in Cirrus Science and Operations Plan*

Small, A.A., J.B. Stefik, J. Verlinde, N.C. Johnson, 2011: The Cloud Hunter's Problem: An Automated Decision Algorithm to Improve the Productivity of Scientific Data Collection in Stochastic Environments. *Mon. Wea. Rev.*, submitted.

Stefik, J.B., 2010: A decision algorithm to improve data collection in stochastic environments. M.S. thesis, Department of Meteorology, The Pennsylvania State University, 36 pp.

Troyan, D., 2010: *Merged Sounding Value-Added Product*.

Vogelmann, A., G. McFarquhar, J. Ogren, G. Feingold, D. Turner, J. Comstock, C. Long, 2008: *RACORO Science and Operations Plan*.

Xie, S., et al., 2010: Clouds and more: ARM Climate Modeling Best Estimate Data. *Bull. Amer. Meteor. Soc.*, 91, 13–20.

Yang, F., H. Pan, S. Krueger, S. Moorthi, S. Lord, 2005: Evaluation of the NCEP Global Forecast System at the ARM SGP Site. *Mon. Wea. Rev.*, submitted.

Christopher Hanlon
717 Windermere Ave
Drexel Hill, PA 19026
(610) 505-7050 (cell)
chrishanlon38@gmail.com

## EDUCATION

**B.S. Meteorology and**
**Energy, Business, and Finance (EBF)** **expected May 2011**
Pennsylvania State University, University Park, PA
- Weather Risk Management option in Meteorology major
- General option in EBF major
- Student in Schreyer Honors College

## PROFESSIONAL EXPERIENCE

**Research Assistant** **January 2011 – Present**
Venti Risk Management, State College, PA
- Developed analytics for a startup weather risk consulting company
- Became proficient at programming in R

**Undergraduate Research Assistant** **Fall 2009 – Present**
Department of Meteorology, Penn State University
- Assist Dr. Arthur Small, Dr. Hans Verlinde, and Jason Stefik with a statistical cloud forecasting project
- Continuing research into 2010-2011 academic year as a basis for an honors thesis
- Became proficient at programming in MATLAB

**Intern** **June 2010 – July 2010**
NOAA IDEA Center, Honolulu, HI
- Worked as an intern as part of NOAA Ernest F. Hollings Undergraduate Scholarship
- Researched a 2004 flood in Manoa Valley, Honolulu and a 2003 flood in Pago Pago, American Samoa
- Aggregated information for placement in web-based event anatomies as part of the EPICS project (Extremes in the Pacific Integrated Case Studies)
- Presented findings to NOAA community in Silver Spring, MD, August 2010

**Teaching Assistant** **Spring 2010**

Department of Energy and Mineral Engineering, Penn State University

- TA for Dr. Arthur Small for EBF 301, Global Finance for the Earth, Energy, and Materials Industries
- Assisted in grading and administration of quizzes and exams
- Held office hours to assist students

## ACADEMIC AWARDS

- recipient of 2009 NOAA Ernest F. Hollings Undergraduate Scholarship
- named to Dean's List in 6 of 7 semesters at Penn State (Spring 2008, Fall 2008, Spring 2009, Fall 2009, Spring 2010, Fall 2010)
- recipient of Schreyer Honors College Academic Excellence Scholarship, 2007-08, 2008-09, 2009-10, and 2010-11 academic years
- recipient of scholarships from College of Earth and Mineral Science, 2008-09, 2009-10, and 2010-11 academic years
- recipient of scholarships from Department of Meteorology, 2008-09, 2009-10, and 2010-11 academic years
- recipient of scholarship from College of Engineering, 2007-08 academic year

## OTHER ACTIVITIES

- Member of Campus Weather Service, Fall 2008-Present
- Campus Weather Service shift manager, Spring 2009
- Member of Atlas THON, Fall 2007-Spring 2009
- Member of Schreyer Honors College Student Council, Service Committee, Fall 2008-Spring 2010
- Participated as Team Leader in Fresh Start Day of Service, August 29, 2009
- Member of Chi Epsilon Pi, Meteorology honor society