

Final Report for June-November 2001

Research Grant No. 07600-068

AER P1017

Controlling the Global Weather

**A Phase 1 NIAC Project under Contract Number
NAS5-98051**

**Submitted to
NIAC**

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**Submitted by
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7 January 2002**

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1 Introduction

- The goal of the project is to calculate the perturbations needed to control the track and possibly the intensity of a hurricane, to determine how big are the perturbations and what is the structure of these perturbations?
- Our approach is to use existing tools and datasets from earlier AER projects to perform convincing simulation experiments during Phase 2. These include the Mesoscale Model 5 (MM5) and the Feature Calibration and Alignment (FCA) system which identifies and corrects the phase errors of the background field in the data assimilation system. During Phase 1, we conducted prototype proof-of-concept experiments.
- The main work of the project has been amply documented in two journal articles (*Hoffman*, 2002; *Hoffman et al.*, 2002 [1, 2]). These are included in this report as appendices. The remainder of the body of this report is a summary and a listing of some details of our work not included in the two appendices.

2 Theory

- Use the 4d-VAR data assimilation system of MM5 version 1 to determine the minimum perturbation of model initial conditions needed to effect a substantial track modification of a hurricane.
- The basic experiment is a variation on 4d-VAR: Consider some initial MM5 forecast of a hurricane. This is the unperturbed run U from time 0 to T with states $U(0)$ and $U(T)$. Suppose we would like the hurricane position at T to be 150 km east of the position in $U(T)$. Use AER's FCA system to create a goal state $G(T)$. Next, use 4d-VAR to find a perturbed simulation P so as to simultaneously minimize the difference from the goal $P(T)-G(T)$ and the initial state $P(0)-U(0)$. $P(0)-U(0)$ is the minimal perturbation to get within $P(T)-G(T)$ of the goal.
- For Phase 1 both the goal mismatch and the size of the initial perturbation will be measured with a simple quadratic energy norm.

3 Progress Report

- We identified an MM5 version 3 dataset from an earlier AER project as the initial condition file for this project: Eastern Pacific Hurricane Iniki (1992) at 06Z 10 September 1992.
- We devised a method to convert MM5 version 3 output into MM5 version 1 input using existing MM5 pre- and post-processors.
- MM5 4d-VAR currently is only available for MM5 version 1 and for rudimentary physical parameterizations. We first determined whether a robust hurricane can be maintained using these degraded parameterizations. To that end, we performed sensitivity simulations using

MM5 version 3 with the MM5 version 1 physics options; they resulted in Iniki's sea-level pressure being 22 *hPa* higher.

- We were able to address the substantial weakening of Hurricane Iniki that was introduced by using the degraded physics options and fewer vertical levels required by the 4d-VAR system of MM5 version 1. Code from one of the MM5 preprocessing programs was modified to increase sea-surface temperatures (SST) by 5°C. The subsequent simulation maintained Iniki as a minimal hurricane with winds of 70-90 knots and a minimum central sea-level pressure of about 990 *hPa*; the storm is now several millibars deeper than the simulation without the SST increase. This is sufficient for our needs.
- Software was developed to convert a target forecast to a file of "direct observations" used in 4d-VAR. This is a critical technical step which creates an important input to 4d-VAR. The target forecast is a 6-h forecast in which the hurricane has been moved by our Feature Calibration and Alignment (FCA) technique from the current forecast position to a more desirable location.
- Slight modifications of existing code were required to tailor the Feature Calibration and Alignment System (FCA) system for this project.
- An MM5 version 1 4d-VAR analysis was created for Hurricane Iniki. The assimilation window was 6 h, and we specified direct observations (*i.e.*, the target analysis) valid at 6 h. The direct observations of Iniki came from a full-physics, high vertical resolution 6-h MM5 version 3 forecast. To produce the direct observations, we interpolated the MM5 fields to a lower vertical resolution (as required by 4d-VAR), and Iniki was moved westward by FCA. In this case, we moved Iniki west of its 6-h forecast position by 112 km. A subsequent trial had a displacement of 18 km to the west.
- We include a 'background field' at time zero as part of the cost function in 4d-VAR.
- To get the MM5 version 1 4d-VAR code into an operable condition, considerable debugging was necessary, because the code is research-grade and wired specifically in a number of places to solve problems different from ours. Also, debugging of the converter utility to create a direct observation file was necessary to insure that we provide 4d-VAR proper "observations".
- At the end of Phase I, we had successfully completed two 4d-VAR analyses and are encouraged by the results. The 6-h targets used to create these two analyses had Hurricane Iniki displaced to the west by about 18 km and 112 km, respectively. 4d-VAR provided modified initial conditions for each case. Using these modified initial conditions, we initialized the MM5 version 1 and produced two 6-h forecasts. Iniki was shifted at the 6-h forecast time close to its position in the 6-h targets.
- We then ran to 48 hours a 6-h control forecast which originated from unmodified initial conditions. At 36 hours in this control simulation, Iniki was making landfall in the Hawaiian Island chain. Next, we extended to 48 hours our earlier 6-h forecasts which originated from initial conditions modified by 4d-VAR. As expected, the track of Iniki is farther west than in the control simulation since our target storm at 6 hours in 4d-VAR is positioned farther west. Interestingly, Iniki is also slower which is encouraging since the control simulation is too fast in making landfall.

- We investigated the Four-Dimensional Variational (4d-VAR) “analysis increments” (*i.e.*, the difference between the modified analysis and unmodified analysis) of temperature. A better understanding of the magnitude and spatial extent of the changes in thermal structure of the hurricane will assist us in the engineering aspect of our Phase II proposal.

4 Meetings/Presentations/Papers

- R. Hoffman attended the 3rd annual NIAC meeting at NASA Ames on 5-6 July 2001.
- R. Hoffman presented our work at the NIAC Fellows Meeting and Workshop which was held on 30-31 October at NIAC Headquarters in Atlanta.
- R. Hoffman presented our work at an invited seminar at MIT at the end of November.
- R. Hoffman’s paper, “Controlling the Global Weather”, has been accepted and will appear in the Bulletin of the American Meteorological Society (BAMS) in February 2002. It is attached as the first appendix.
- We have completed a short paper, entitled “Using 4d-VAR to move a simulation of Hurricane Iniki in a mesoscale model”, to be submitted to Geophysical Research Letters. This paper is attached as the second appendix and contains a complete report of our Phase I scientific research.

5 Future Work

- We anticipate submitting a Phase II proposal to NIAC before the 1/7/02 deadline.
- In Phase 2, we might create a new version of the quadratic energy norm cost function to provide more control. For the goal, only the energy of the mismatch in some region might be included. We would certainly change the control vector: For the initial state, only certain types of perturbations might be allowed, perhaps only geopotential perturbations with a certain shape in the vertical. Or, we could allow changes to the SST or the heat exchange coefficient, C_H . The cost function at the initial time could still be in terms of energy, but might be in terms of gallons of vegetable oil!

Also in Phase 2, we would like to use higher resolution, so that our simulations are more realistic. We could experiment with different physics/resolution in the reality model versus the NWP model to examine the effect of model error. Likewise we could simulate errors in other parts of the system.

6 References

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- [1] R. N. Hoffman. Controlling the global weather. *Bull. Am. Meteorol. Soc.*, 83(2):In press, Feb. 2002.
- [2] R. N. Hoffman, S. M. Leidner, and J. M. Henderson. Using 4d-VAR to move a simulation of Hurricane Iniki in a mesoscale model. *Geophys. Res. Lett.*, 2002. In preparation.

7 Appendices

- Two appendices follow:
 - R. Hoffman’s BAMS paper entitled “Controlling the Global Weather”.
 - A short paper submitted to Geophysical Research Letters which summarizes our Phase I effort. It is entitled “Using 4d-VAR to move a simulation of Hurricane Iniki in a mesoscale model”, to be submitted to Geophysical Research Letters.

CONTROLLING THE GLOBAL WEATHER

BY ROSS N. HOFFMAN

Are "weather wars" conceivable?

It had not been easy to persuade the surviving superpowers to relinquish their orbital fortresses and to hand them over to the Global Weather Authority, in what was—if the metaphor could be stretched that far—the last and most dramatic example of beating swords into plowshares. Now the lasers that had once threatened mankind directed their beams into carefully selected portions of the atmosphere, or onto heat-absorbing target areas in remote regions of the earth. The energy they contained was trifling compared with that of the smallest storm; but so is the energy of the falling stone that triggers an avalanche, or the single neutron that starts a chain reaction. (Arthur C. Clarke, Fountains of Paradise, 1978)

The earth's atmosphere has been hypothesized to be chaotic. Chaos implies that there is a finite predictability time limit no matter how well the atmosphere is observed and the modeled. It is generally accepted that this limit is typically 2 weeks for large-scale weather systems (Lorenz 1982), although some situations may be more or less predictable, and smaller scales are certainly less predictable. Chaos also implies sensitivity to small perturbations. The most realistic numerical weather prediction (NWP) models are very sensitive to initial conditions. It is therefore very likely that the atmosphere is also

extremely sensitive to small perturbations. A series of such perturbations to the atmosphere might be devised to effectively control the evolution of the atmosphere, if the atmosphere is observed and modeled sufficiently well. We present a system architecture to control the global weather that might be implemented within a few decades.

It is a dream of mankind to control the weather—not to make every day the same, but to protect lives and property. We believe that this dream is in fact a possibility. Just imagine: no droughts, no tornadoes, no snowstorms during rush hour, etc. We probably cannot eliminate hurricanes, but we might be able to control the paths of hurricanes, and essentially prevent hurricanes from striking population centers. Our goal is not to change the climate, but to control the precise timing and paths of weather systems. For example, eliminating hurricanes and the associated mixing of the upper layers of the ocean would presumably change the climate in many indirect ways.

Because of the intensive coupling of the weather over different regions of the globe, nothing short of control of the global weather should be considered.

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In final form 25 September 2001
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The nation that controls its own weather will necessarily control the weather of other nations. If there are several nations, each attempting to control the weather over its territory, then each may operate at odds with the others and "weather wars" are conceivable. An international weather control treaty may be prudent now. In the future, an international agency may be required so that weather control is used "for the good of all." Perhaps for the good of all is unattainable. Any change to weather will have both positive and negative effects. How can the interests of both the "winners and losers" be accommodated? Of course, weather always has both positive and negative effects, and there are winners and losers now.

In what follows we present the underlying concepts for our approach and then outline the system architecture of a controller for the global atmosphere, describing the components of such a controller. Legal and ethical questions are only touched on, and the issues of feasibility and cost-benefit trade-offs are only briefly considered. Our proposed controller is similar in general to feedback control systems common in many industrial processes; however, it is greatly complicated by the number of degrees of freedom required to represent the atmosphere adequately, the nonlinear nature of the governing equations, the paucity of observations of the atmosphere, the difficulty of effecting control, and the requirements that control be effected at significant time lags. However, the existence of the technology to implement the weather controller is plausible at the time range of 30–50 yr.

CHAOS, THE LIMITS OF PREDICTABILITY, AND IMPLICATIONS FOR CONTROL.

Theoretical and model studies have established that the dynamics governing the atmosphere can be extremely sensitive to small changes in initial conditions (e.g., Rabier et al. 1996). Current operational practice at NWP centers illustrate this daily. Examples summarized in what follows include data assimilation, generation of ensembles, and targeted observations. The key factor enabling control of the weather is that the atmosphere is sensitive to small perturbations. That is, it is the very instability of the atmosphere's dynamics that makes global weather control a possibility.

Chaos causes extreme sensitivity to initial conditions. Although the atmosphere, and indeed realistic models of the atmosphere, have not been proven to be chaotic, the theory of dynamical systems and chaos provide a useful background for this discussion. In a realistic NWP model, since small differences in initial conditions can grow exponentially, small but correctly chosen perturbations induce large changes in the evolution of the simulated weather.

Therefore we hypothesize that as we observe and predict the atmosphere with more and more accuracy, we will become able to effect control of the atmosphere with sequences of smaller and smaller perturbations. Note the basic difference between predictability and control theory: Predictability theory states that small differences grow; control theory states that a sequence of small perturbations can be used to track a desired solution. By tracking (i.e., following) a desired solution, our control method may overcome differences between model and reality. We will expand and explain these basic ideas in the following paragraphs.

The phase space description of dynamical systems. The evolution of dynamical systems is conveniently discussed using the phase space description of Poincaré (Lorenz 1963). The state of the system is specified by n variables. For continuous systems, such as the atmosphere, we may first approximate the continuous system by discretization and thereby obtain a large number of coupled nonlinear ODEs. For a physically realizable system, the collection of feasible points in the n -dimensional phase space will be bounded.

For a single time, the state of the system is represented by a single point. As the system evolves, the point representing the system will in general describe a curved line. This is termed the trajectory. If the system is in a stable state, the trajectory is just the single point. Small perturbations about the point decay in time toward the stable point. A stable point is an attractor. A stable point is also a fixed point of the system. There can be unstable fixed points. Some trajectories form closed curves—these represent periodic solutions.

For a realistic model of the atmosphere with fixed boundary conditions, periodic solutions probably exist but are unstable. There are many unstable periodic solutions close to chaotic attractors. Chaotic systems are aperiodic, but given enough time, return arbitrarily close to points in the attractor. For the atmosphere, the lack of success for analog forecast techniques suggests that this return time is very long.

Chaotic systems. The strict definition of chaos describes it as a behavior of purely deterministic systems with as few as three components for a continuous phase space flow (e.g., Lorenz 1963), or as few as a single component for an iterated mapping (e.g., Lorenz 1964). Chaotic systems can appear to be random when sampled at timescales that are large compared to the dynamical timescale. The key characteristics associated with chaos are that the system be bounded and pos-

sess at least one positive Lyapunov exponent (Lorenz 1965). A positive Lyapunov exponent implies average growth in the associated direction that is exponential. Typically in the phase space of such systems, a small initial sphere of radius ε will over a short time deform into an ellipsoid. The axes of the ellipsoid might be called the finite time or local Lyapunov directions, and the ratio of these axes to ε might be called the finite time or local Lyapunov factors. As the ellipsoid evolves it tends to flatten parallel to the attractor of the system. Chaotic attractors are also called strange attractors. A characteristic of these attractors is that perturbations perpendicular to the attractor collapse exponentially, while perturbations parallel to the attractor grow exponentially.

It is for these reasons that we say the small perturbations can grow exponentially. A randomly chosen perturbation may be decomposed into contributions from the finite time Lyapunov directions. Some, perhaps most, will decay, but the others will grow. The perturbation may therefore first decrease in size, before growing explosively. A perturbation may also be constructed which projects only onto a particular growing mode. Such a perturbation will initially grow exponentially.

The limits to predictability. Since small differences grow rapidly in chaotic systems, chaotic systems are difficult to predict. Inevitably small errors will exist in our specification of the initial conditions. Further, errors in model formulation induce errors in the model state at every model time step. Although the magnitude of the error may initially decay with time, eventually small errors will begin to grow exponentially and continue to do so until they become large. It is generally accepted that useful forecasts of the instantaneous weather beyond 2–3 weeks are impossible (Lorenz 1982; Simmons et al. 1995).

For the atmosphere, motions occur over a huge spectrum of scales. Smaller spatial scales have shorter timescales. Errors in the smallest scales will completely contaminate those scales on the characteristic timescale associated with that spatial scale. These errors will then induce errors in the next larger scale and so on (Lorenz 1969). In fluids, advection implies that tiny errors on the large scales will in turn cause large errors on the shortest scales. These interactions lead to a finite predictability time limit.

Control of chaotic systems. Since chaos may appear to be random, control of chaos might seem impossible. But sensitivity to initial conditions also implies sensitivity to small perturbations. As we have mentioned, small perturbations in some directions decay quickly,

but properly chosen perturbations grow quickly. Therefore a sequence of very small amplitude but precisely chosen perturbations will steer the chaotic system within its attractor. There have been many studies reported in the literature that support this view (Kapitaniak 1996). We note two examples of the control of chaotic systems.

The first is the phenomena of resonance (Pecora and Carroll 1990). Suppose that there are two copies of an evolving dynamical system. Initially the two system states are arbitrarily different. One system evolves freely but is observed. In particular, one variable of that system is accurately observed. The corresponding variable in the second system is constantly reset to the value observed in the first system. Over time all variables of the second system approach the values of the corresponding variables in the first system. We say that the second system has become entrained by the first system.

Second, within the attractor of a chaotic system, there are a multitude of unstable periodic orbits. Techniques to compute these orbits are available. Once the system is close to one of these orbits, it is possible to continually follow the orbit by regularly applying small perturbations (Ott et al. 1990).

Control of realistic atmospheric models. To control the weather we must effect changes on timescales shorter than those of the examples of the previous section, and to a system of huge complexity. The numerical methods used must be computationally feasible. The NWP community has already taken the first steps to control large dynamical systems. One current NWP data assimilation practice, called 4D-VAR, finds the smallest perturbation at the start of each data assimilation period, which grows to best fit all the available data, thereby demonstrating the practical control of large-scale realistic systems. Current 4D-VAR practice finds the smallest global perturbation, as measured by the a priori or background error covariances, but it should be possible to modify 4D-VAR to find the smallest local perturbation or the smallest perturbation of a particular type. This method is described further in the section about data assimilation systems. Further, some other current NWP technology may be adapted to determine the optimal perturbations to effect control. These techniques are described in what follows.

SINGULAR VECTORS. Singular vectors are the fastest growing perturbations about a given model forecast over a finite time interval, say 24 or 72 h, with respect to a particular measure of difference. (For example, the size of the perturbation might be taken to be its energy.)

Singular vectors are currently calculated operationally at the European Centre for Medium-Range Weather Forecasts (ECMWF) for the purpose of ensemble forecasting (Molteni et al. 1996). In principle, ensemble forecasting introduces equally likely small perturbations in the initial conditions of each ensemble member. In practice, because each of the forecasts within the ensemble is computationally expensive, only perturbations that are rapidly growing are included. The growth rates of these perturbations are explosive—24-h amplification factors of 10–20 are reported for large-scale calculations with limited physics, and much larger amplification factors are expected when smaller scales and moist physics are included. A basic version of control can be effected by calculating the leading singular vectors, determining if a positive or negative perturbation along one of these modes would produce a desired result, and then introducing that perturbation, if it was feasible.

TARGETED OBSERVATIONS. During the last decade there has been considerable research on targeted observations (Lorenz and Emanuel 1998; Bergot et al. 1999; Bishop and Toth 1999). Given a current forecast of some storm of interest, we can backtrack from the forecast to find that region of the initial state that, if better observed, would improve the forecast of that storm. The theory and methodology of this approach have advanced sufficiently so that actual trials were undertaken for several field experiments including FASTEX (Joly et al. 1997), NORPEX (Langland et al. 1999), and WSRP 99 (Bergot et al. 1999).

This technology can be adapted to calculate the optimal perturbation. Determining where to target observations is related to the problem of determining where to introduce perturbations to effect a certain change in the forecast. In both cases we are optimizing a figure of merit or objective function that is calculated in terms of the forecast with respect to some change in the initial conditions. Note that the figure of merit can include both costs and benefits.

THE GLOBAL WEATHER CONTROL SYSTEM. The global weather control (GWC) system we envision is a feedback control system, made complicated by a number of factors. These include the following:

- The number of degrees of freedom required to represent the atmosphere adequately.
- The nonlinear nature of the governing equations. The atmosphere is nonlinear and sometimes discontinuous. For example, clouds have sharp edges.

- The paucity and inaccuracy of observations of the atmosphere. Satellites provide a huge volume of information. However this information is not always in the right place, accurate enough, or of the right type.
- The control must be effected at significant time lags to minimize the size of the perturbations, yet the system is inherently unpredictable at long lead times.
- The difficulty of effecting control. The control mechanisms do not yet exist. The ideal perturbations, while small in amplitude, may be large in scale.
- The ambiguous nature of the figure of merit. For inhabitants of New Orleans, eliminating a hurricane threat to that city may take precedence over all else. But in general attempting to satisfy multiple objectives may result in conflicts.

The GWC system is sketched in Fig. 1. The “controller” and “random effects” perturb the system state. The controller must therefore compete with random effects. However the controller perturbations are designed to grow, while the random effects perturbations tend to decay. The “governing equations” advance the system from time t_n to time t_{n+1} . If we eliminate the “observations” and controller elements in this figure we have a sketch showing how a NWP model approximates the atmosphere. On the other hand, if we remove only the random effects element, we have a sketch of a system that must be simulated within the controller element in order to estimate the system state and then the optimal perturbations. Note the various noise sources: The observations are inexact, the perturbations are effected with some inaccuracies, the model introduces further errors. The statistics of these errors are also inexact and must be estimated empirically (from the time history of the differences between short-term forecasts and observations).

Cost–benefit trade-offs. Controlling small-scale phenomena will not be cost effective. Certainly we want to control destructive tornadoes, but the time- and space scales are so fine that this may be impossible on an individual basis. It may be more effective to eliminate the large-scale conditions leading to the formation of tornadoes. In general, theoretical predictability studies (Lorenz 1969) suggest that doubling the resolution of the observations will ~~not~~ only increase predictability by an amount similar in magnitude to the timescale of the motions of the smallest resolved phenomena. For example, since the timescale for the evolution of a thunderstorm is smaller than 1 h, observing details of individual thunderstorms will improve predictability by no more than 1 h. Effecting control at very large scales

may not be cost effective either. The largest spatial scales have the largest "inertia." These scales have the longest associated timescales and the greatest part of the energy (Nastrom et al. 1984).

The GWC system will be subject to optimization itself. Our control of the weather will increase as we increase the skill of the NWP models, the accuracy of the observations, and the size of the controlling perturbations. All three facets of the problem require resources. A cost-benefit analysis will balance resources devoted to remote sensing, computer power, and perturbations. As advances in the supporting disciplines accumulate, the optimal point will shift, become feasible, and eventually become economically sensible.

Enabling technology. Implementation of the overall system architecture will require major advances in many disciplines. Here we discuss the required discoveries and refinements. Although it is difficult to predict the pace of technological advance, the control of the weather is a plausible outcome of advances in various fields over the time span of a few decades.

NUMERICAL WEATHER PREDICTION. NWP is now a mature science (Kalnay et al. 1998). Advances in computer power will enable the refinement of NWP. Current high-resolution mesoscale models point the way for advances in global models. In early NWP models, many physical processes were either removed by filtering approximations or modeled by parameterizations. As NWP models evolve, more and more of the physics of the atmosphere are resolved explicitly.

A recent report (ECMWF 1999) makes estimates of the spatial resolving power of NWP models over the next decade. In summary, this report predicts horizontal resolution increasing from the current 60 to 15 km by 2008. Extrapolating for another 30 yr suggests global resolution of approximately 250 m. (Currently vertical resolution is much finer than horizontal resolution, but at the much higher future horizontal resolution, the same scale will be appropriate for both horizontal and vertical resolution in the troposphere. This would allow even higher resolution than our simple extrapolation would suggest.)

DATA ASSIMILATION SYSTEMS. Data assimilation systems estimate the state of the atmosphere given limited observations and an imperfect model of the evolution of the atmosphere. This problem is complicated by the paucity of observations, the huge number of degrees of freedom needed to specify the atmosphere, and the extreme nonlinearity of the governing equations. The data assimilation system is a key part of the controller

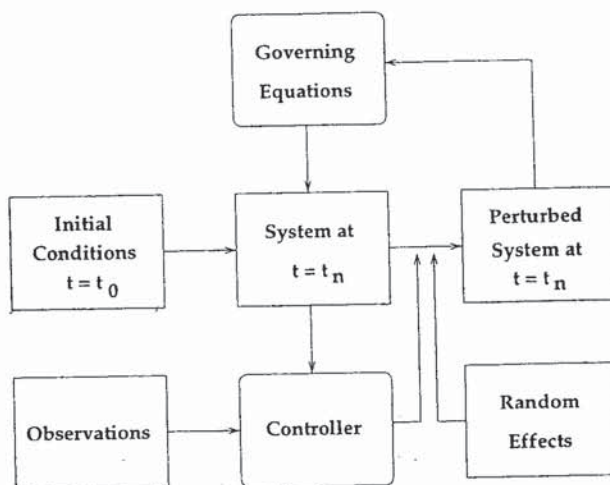


FIG. 1. Schematic global weather controller flow chart.

of Fig. 1—the data assimilation provides estimates of the current state of the atmosphere.

The current state of the art is 4D-VAR or four-dimensional variational data assimilation. Operational 4D-VAR assumes a perfect model over short time periods (6 or 24 h) and finds the initial condition at the start of the period that best fits all available observations during the period (e.g., Thépaut et al. 1993). [This optimization is made efficient by the adjoint technique. In practical implementations, the adjoint model performs a backward in time integration of the sensitivity of the objective function to the model state (Courtier 1997).] Because the NWP model is used to extrapolate the initial conditions, the 4D-VAR solution is necessarily dynamically consistent. The end point of the solution from the previous period is called the background and is used as a special type of observation. The error structure of the background is necessarily complex but has a greatly simplified representation in current versions of 4D-VAR. In the near future we expect to see higher resolution used in 4D-VAR in line with increases in resolution in NWP models, better estimates of the background statistics, and a convergence to the Kalman filter methodology (Todling and Cohn 1994; Houtekamer and Mitchell 1998).

SATELLITE REMOTE SENSING. Satellites observe the atmosphere and the earth's surface with global coverage, rapid refresh, and high horizontal resolution in visible, infrared, and microwave spectral domains. Sensors currently being prepared for launch have very high spectral resolution, which in turn will produce higher vertical resolution for the retrieved temperature and moisture profiles. Advances are expected in terms of higher resolution, greater numbers of satellites, and

higher accuracy in the future. Active sensors, such as the Tropical Rainfall Measuring Mission (TRMM) precipitation radar, may be used more in the future.

The ability to collect observations from space currently outstrips our ability to use these data in global NWP. Typically, the observations are thinned to reduce resolution and quantity. This will be more of a problem with higher spectral resolution sensors. However, advances in computing power and data assimilation techniques will improve this situation.

PERTURBATIONS. Everything mankind does that can be controlled may be considered a source of perturbations. Here we mention a few possibilities:

- Aircraft produce contrails. Contrails are essentially cirrus clouds and influence both the solar and thermal radiation (Poellot et al. 1999). Slight variations in the timing, levels, and routes of aircraft would produce perturbations (Murray 1970).
- Solar reflectors, in low earth orbit, capable of varying orientation, would produce bright spots on the night side, and shadows on the day side, thereby changing the heating of the atmosphere. First steps have already been taken. However, the latest Russian experiment, named Znamya 2.5, failed to unfurl a 25-m diameter thin sheet mirror in space in February 1999 (Beatty 1999). In the future inflatable structures may be used (Dornheim 1999).
- Solar-powered generators in geostationary orbit have been suggested as a low-cost energy source. A concern is that losses from the microwave downlink would be a heat source (Lee et al. 1979). If the spatial area and timing of the downlink were controlled this would be a source of perturbations. In addition, tuning of the microwave downlink frequency would control the height in the atmosphere of the energy deposition.
- An enormous grid of fans that doubled as wind turbines might transfer atmospheric momentum in the form of electric energy.

To be effective the individual actions must be coordinated, so that the total perturbation is one that produces a desired effect. This may be difficult.

COMPUTER TECHNOLOGY. Computer processing capability has been increasing exponentially. The requirements of GWC are truly staggering, but global NWP models at the subkilometer scale seem attainable in the 30–50 yr time frame, if the pace of advances in computer technology can be maintained. (If computer power doubles every year, then after 30 yr it will have increased

1 billion times.) However, current estimates suggest that Moore's laws governing the exponential growth of chip functionality as well as the exponential growth of the cost of chip fabrication facilities will encounter physical obstacles around 2012 (Birnbaum and Williams 2000). Potential breakthroughs in nanotechnology, quantum devices, or in other areas will be needed.

SYSTEM INTEGRATION. The GWC system is a megasystem. Development of tools and methodologies for megasystems engineering is driven by recent defense and aerospace projects, such as the space shuttle, the strategic defense initiative (SDI), etc. In some ways the GWC system is analogous to SDI. Both require huge real-time data gathering, prediction, and command capabilities. For GWC the problem is more complex, but the timescale is more relaxed and there is no active opposing intelligence.

Concluding remarks: The next step. The next step should involve demonstration tests in simulation. We suggest a focus on the hurricane problem. This problem is both important and feasible. Controlling the path of hurricanes will be a first-order priority of GWC. A hurricane track is largely determined by winds of the large-scale environment. Reasonable forecasts of hurricane tracks can be made without modeling the internal dynamics of the hurricane. Recent studies have examined the sensitivity of such a model to changes in initial conditions (Aberson and Franklin 1999; Cheung and Chan 1999).

For the demonstration tests, we would be concerned only with the forecasting and control of the hurricane tracks. For this purpose our "NWP" model could be a simple quasigeostrophic model. The hurricane could be modeled as a vertical tracer. A plausible control mechanism would be localized height perturbations. The goal would be to protect the Gulf and East Coast populations centers. This setup is feasible and capable of exploring some of the issues related to the practicality of global weather control and to quantify, albeit in a limited context, the required resources to ^{Of course application to real hurricanes will} require a model that faithfully predicts hurricane tracks.

On a personal note, I first put the main ideas expressed here on paper in the fall of 1977 as part of a potential thesis proposal. My advisor, E. N. Lorenz, commented that this was an interesting idea but too risky for a thesis topic. Control of the global atmosphere is still a risky research topic, but there have been substantial technological advances in many of the supporting disciplines—computers, models, remote sensing, etc. We believe there is a good reason to pursue this research now.

The concept of global weather control raises a host of sociological, ecological, and political issues. These issues will only receive proper attention when global weather control seems plausible. The questions raised in these arenas will not be easy to resolve, and progress is likely to be slow compared to the advance of technology. Therefore, it seems important to demonstrate this plausibility now, long before technology advances to the point of potential implementation, in order to motivate a thorough discussion of whether or not, and if so, to what extent and under what circumstances we actually do wish to control the weather.

ACKNOWLEDGMENTS. I have benefitted from comments on this paper by R. Rosen, K. Emanuel, J. Hansen, R. Anthes, and an anonymous reviewer. This work was supported in part by the NASA Institute for Advanced Concepts (NIAC) through a grant from the Universities Space Research Association (USRA).

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Using 4d-VAR to move a simulation of Hurricane Iniki in a mesoscale model

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Abstract.

Four-dimensional variational analysis (4d-VAR) is a data assimilation technique that has promise for calculating optimal perturbations for weather control. The Mesoscale Model 5 (MM5) 4d-VAR system is used to calculate “optimal” perturbations to shift the simulated forecast track of Hurricane Iniki 112 *km* westward, during the six hours beginning 06 UTC 10 September 1992. The controlled forecast closely matches the target. The perturbation of the initial conditions are small, but concentrated in the lowest layer temperature field, in a pattern consistent with enhanced heating west of the hurricane.

1. Introduction

Hoffman [2002] has discussed the possibility of controlling the global weather by introducing a series of small, precisely calculated perturbations. In brief: If the earth's atmosphere is chaotic, it is extremely sensitive to small perturbations. Certainly most realistic numerical weather prediction (NWP) models are very sensitive to initial conditions. It is therefore very likely that the atmosphere is also extremely sensitive to small perturbations. It is our purpose here to test a method to calculate "optimal" perturbations, and to estimate the magnitude of such perturbations. As a specific application, we take Hurricane Iniki as a case of interest, and determine a perturbation to shift its track westward. While the current work is very preliminary in many aspects, the results are sensible and point the way for further work.

Hurricane Iniki at 06 UTC 10 September 1992 provides our initial state. Iniki made landfall on Kauai at 0130 UTC 12 September 1992, with a central pressure of 945 *hPa* (Fig. 1). Maximum sustained winds over land were estimated at 140 miles per hour with gusts as high as 175 miles per hour. Six people lost their lives. Damage to property and vegetation was extensive [*CPHC*, 1992].

2. Mesoscale Model Simulations of Hurricane Iniki

The Mesoscale Model 5 (MM5) is used to simulate Hurricane Iniki. The MM5 is described by *Grell et al.* [1994] and by *Dudhia* [1993]. In our experiments the MM5 computation grid is a 97×79 40 *km* horizontal mesh, and ten "sigma" layers in the vertical from the surface to 50 *hPa*. The sigma coordinate system is a terrain following normalized pressure coordinate system [*Holton*, 1992, section 10.3.1]. Simple parameterizations of surface fluxes, cumulus convection, and radiative transfer are used. The observed sea surface temperature is increased by 5° *C* everywhere in our simulations. We find this is enough to maintain the hurricane when

using the simple parameterizations. Only the simple parameterizations are currently available in the MM5 four-dimensional variational analysis (4d-VAR) system. However, MM5 produces very detailed and accurate simulations of hurricanes when increased resolution and better physical parameterizations are used [*e.g.*, *Liu et al.*, 1999; *Tenerelli and Chen*, 2001].

Fig. 2 shows the (unperturbed and controlled) lowest layer winds and pressure relative to the reference state at the initial time. With no perturbations, after a 6 *h* forecast Iniki has travelled NNW ~ 100 *km* and strengthened slightly. The best track, unperturbed forecast track, and controlled forecast track are plotted in Fig. 3. The best track is the official description of Iniki by the Central Pacific Hurricane Center (CPHC) based on all available information, collected either in real-time or later. Comparing the best track and unperturbed forecast track we see that the model simulation of Iniki over the first 12 *h* moves faster and more to the north. Also the forecasts do not strengthen as much as the real hurricane.

3. Methodology to Calculate Perturbations

Four-dimensional variational analysis (4d-VAR) is a data assimilation method which finds the smallest perturbation at the start of each data assimilation period so that the controlled solution best fits all the available data. 4d-VAR is used operationally at ECMWF and Météo France. This demonstrates the practical control of realistic simulations of the atmosphere. Current 4d-VAR practice finds the smallest global perturbation, as measured by the *a priori* or background error covariances, but it should be possible to modify 4d-VAR to find the smallest local perturbation or the smallest perturbation of a particular type. The MM5 4d-VAR is described by *Zou et al.* [1997]. It has been applied recently to assimilate zenith delay observations from global positioning system (GPS) satellites [*De Ponte and Zou*, 2001], and to assimilate cloud-cleared brightness

temperatures from geostationary operational environmental satellite (GOES) sounders [Zou *et al.*, 2001].

The basic experiment reported here is simply a variation on 4d-VAR: Consider some initial forecast of a hurricane. This is the unperturbed simulation U , from time 0 to T (6 h), with corresponding states $U(0)$ and $U(T)$. From $U(T)$ we create a goal state $G(T)$ with the hurricane positioned 112 km west of the position in $U(T)$. We then use 4d-VAR to find an optimal controlled simulation P . This simulation simultaneously minimizes the difference from the goal (*i.e.*, $P(T) - G(T)$) and the initial state (*i.e.*, $P(0) - U(0)$). In other words $P(0) - U(0)$ is the minimal perturbation to get within $P(T) - G(T)$ of the goal.

In these preliminary experiments both the goal mismatch and the size of the initial perturbation are measured with a simple quadratic norm:

$$J = \sum_{x,t,k} \frac{1}{S_{xk}^2} \left[\sum_{i,j} \{P_{xijk}(t) - G_{xijk}(t)\}^2 \right]. \quad (1)$$

Here x ranges over temperature and the eastward and northward wind components, i, j, k range over all the grid points, and t over 0 and T . Note that the other model variables—specific humidity, vertical velocity, and pressure relative to the reference state—are not included in this definition of J . For convenience in writing (1), we define $G(0) = U(0)$, *i.e.*, the goal at $t = 0$ is to stay close to the unperturbed initial conditions. In (1), the model variables are pressure weighted (or “coupled”) variables. For example, $p_* u$ is the coupled eastward wind component, where p_* is the reference pressure difference between the bottom and top model boundaries. Thus p_* depends only on the model surface topography. Below we present the components of J for temperature at different times and levels as the square root of the terms in square brackets in (1) for temperature, normalized by the number of grid points, and dimensionalized assuming

$p_* = 950 \text{ hPa}$, the value over the ocean. The components of J for vector winds are calculated in the same way from the sum of the terms in square brackets in (1) for the wind components.

The scaling S_{xk} depends only on variable and level. It is calculated as the maximum absolute difference between $U(0)$ and $U(\delta t)$ for each variable at each level, with δt taken to be 40 minutes. Fig. 4 shows the vertical profiles of the S_{xk} , again dimensionalized assuming $p_* = 950 \text{ hPa}$. The scales are largest at levels 1, 3, and 9.

As a practical matter, when using the current version of MM5 4d-VAR, there are some differences in how the grids are specified for the “observations”, denoted $G(0)$ here, and for the initial estimate of the solution, denoted $P(0)$ here. As a result there are differences between the solution and the goal (or observations) at $t = 0$ at the start of the minimization in our experiments. Also, to create the goal state we did not simply move the entire grid since this would have created discontinuities at the lateral boundaries. Instead we used a smoothly varying vector field of displacements to adjust the unperturbed forecast. The methodology is analogous to the feature calibration and alignment technique described by *Hoffman and Grassotti* [1996], except that here the adjustment is found by fitting a number of prescribed displacement vectors.

4. Results

The MM5 4d-VAR system positions Hurricane Iniki in the controlled forecast at 6 h ($t = T$) due west of the unperturbed forecast by just the right amount to match the target (Fig. 3). Note that the difference in positions appears to grow exponentially over the 6 h period. The MM5 4d-VAR system uses a general purpose minimizer that solves the minimization iteratively. We required ten iterates. Fig. 5 shows the total objective function and the contributions to the objective function at $t = 0$ and 6 h, denoted J_0 and J_6 , for each of iteration. Note that J , J_0 , and J_6 all seem to be approaching asymptotes at the end of this process. Because of the sensitivity

of the model atmosphere to changes in initial conditions, a large decrease in J_6 requires only a small increase in J_0 .

Individual components of J for temperature and wind are plotted as *rms* differences as a function of model layer in Fig. 6 and Fig. 7, before and after the minimization, and at 0 *h* and 6 *h*. Note the large decrease (by a factor of ~ 2) in differences at 6 *h* after the minimization in both wind and temperature. There are larger differences for temperature near the tropopause (model layer 2), and for lowest layer temperature. At 0 *h*, note the increase in wind differences through much of the troposphere after the minimization, while temperature is little changed except in the lowest layer. After the minimization there are approximately equal differences in winds at both times, but this does not hold for temperature, where the perturbation at the initial time is generally very small, except in the lowest model layer.

The lowest layer temperature and wind perturbations are plotted in Fig. 8. The temperature perturbations correspond to a warming to the west of the hurricane (i.e., in the direction of the target) and a slight cooling at the center of the hurricane and to the NE. It is as if the hurricane is attracted to warmth. This is consistent with empirical and theoretical results that a warm sea surface supplies a hurricane with sensible and latent heat energy.

5. Conclusions

The very preliminary study described here shows that 4d-VAR can be used to calculate “optimal” perturbations to control the track of a hurricane in simulation. Clearly it will be a long time before it is possible to control the track of a hurricane in reality. This goal requires overcoming several complicating technical factors including:

- Solving for the optimal perturbation using a more realistic model is difficult due to the number of degrees of freedom required to represent the atmosphere adequately, and the nonlinear and sometimes discontinuous nature of the physics governing the atmosphere.

- The paucity and inaccuracy of observations of the atmosphere. Satellites provide a huge volume of information. However this information is not always in the right place, accurate enough, or of the right type.

- The control must be effected at significant time lags to minimize the size of the perturbations, yet the system is inherently unpredictable at long lead times.

- The difficulty of effecting control. The control mechanisms do not yet exist. The ideal perturbations, while small in amplitude, may be large in scale.

In addition there are a number of “side issues” in the political, economic, and legal realms. For example, consider the ambiguous nature of the figure of merit: For inhabitants of New Orleans, eliminating a hurricane threat to that city may take precedence over all else. Even so, farmers in the Mid-West might suffer without the resulting rain. Therefore attempting to satisfy multiple objectives will usually result in conflicts.

Further progress on some of the technical issues may be made by refining the 4d-VAR study presented here. In future experiments, we would

- Use higher resolution, and a more accurate version of MM5.
- Examine the effect of different lead times on the size of the perturbations.
- At the target time, include only the energy of the mismatch in some region.
- Modify the control vector so that only certain types of “feasible” perturbations, continuous in time, are allowed.

We should also study the effect of model and perturbation error. The results of a series of experiments with a refined 4d-VAR setup should allow accurate enough estimates of the required perturbation to allow a top level system design and trade studies for a weather control system. One possibility listed by *Hoffman* [2002] is to use orbiting solar reflectors. The number and size of these reflectors could be estimated based on the energies estimated by the 4d-VAR studies.

Acknowledgments. This work was supported by the NASA Institute for Advanced Concepts (NIAC) through a grant from the Universities Space Research Association (USRA).

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FIGURE LEGENDS

- Fig. 1:** Hurricane Iniki makes landfall on Kauai. Image from the CPHC web page. [<http://205.156.54.206/pr/hnl/graphics/iniki.gif>]
- Fig. 2:** Unperturbed and controlled initial conditions in the lowest model layer plotted in light and heavy lines respectively. Winds plotted with barbs in ms^{-1} with each full barb corresponding to $10 ms^{-1}$ and pressure relative to the reference state in hPa . The wind barbs are plotted at every other grid point.
- Fig. 3:** The best track, unperturbed forecast track, and controlled forecast tracks for Hurricane Iniki are plotted as diamonds, triangles, and octagons, respectively, every six hours. The best track starts at 18 UTC 9 September 1992, twelve hours before the forecast tracks.
- Fig. 4:** Profiles of scaling factors for temperature (T), eastward wind component (u) and northward wind component (v) are plotted as solid, dotted, and dashed lines, respectively. Values are calculated from the coupled variables, and then dimensionalized for this plot assuming $p_* = 950 hPa$. The horizontal scale is degrees Celsius for temperature and ms^{-1} for the wind components.
- Fig. 5:** Cost function vs. iteration. The total cost function (in thousands) and the individual parts of the cost function at $t = 0$ and $6 h$ are shown as solid, dotted, and dashed lines respectively.
- Fig. 6:** The *rms* difference profiles for temperature. The components of J are converted into *rms* differences as described in the text. The *rms* differences after the minimization, at $t = 0$ and $6 h$ are drawn with heavy dotted and dashed lines respectively. The *rms* differences at the start of the minimization are drawn with light lines.
- Fig. 7:** The *rms* difference profiles for vector winds. As in Fig. 6.

Fig. 8: Lowest layer wind and temperature optimal perturbation at the initial time. Wind differences are plotted using the barb and thinning conventions of Fig. 2. The scale for temperature is in degrees Celsius.

FIGURES

Fig. 1: *Hurricane Iniki makes landfall on Kauai. Image from the CPHC web page. [http://205.156.54.206/pr/hnl/graphics/iniki.gif]*

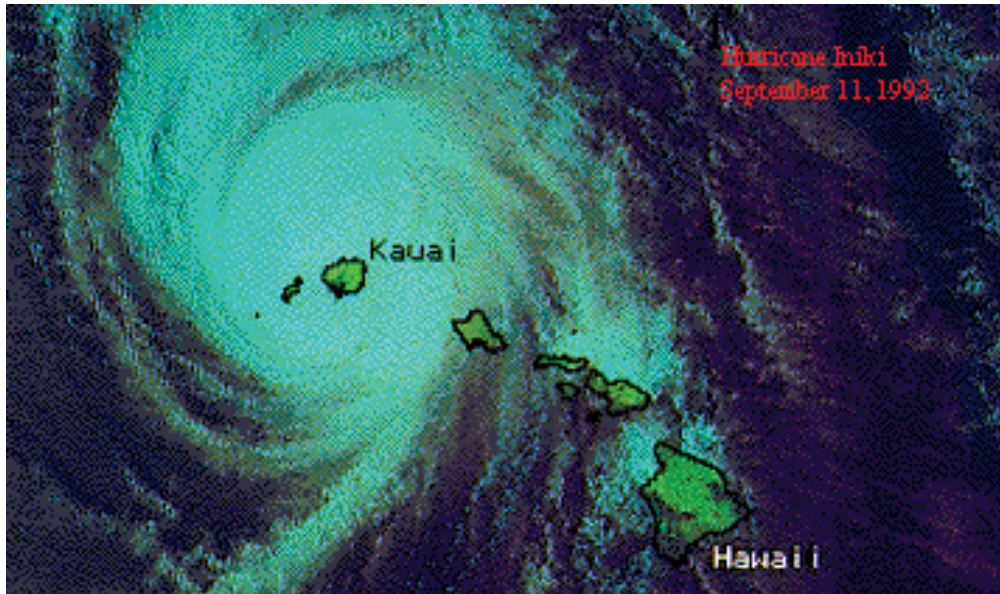


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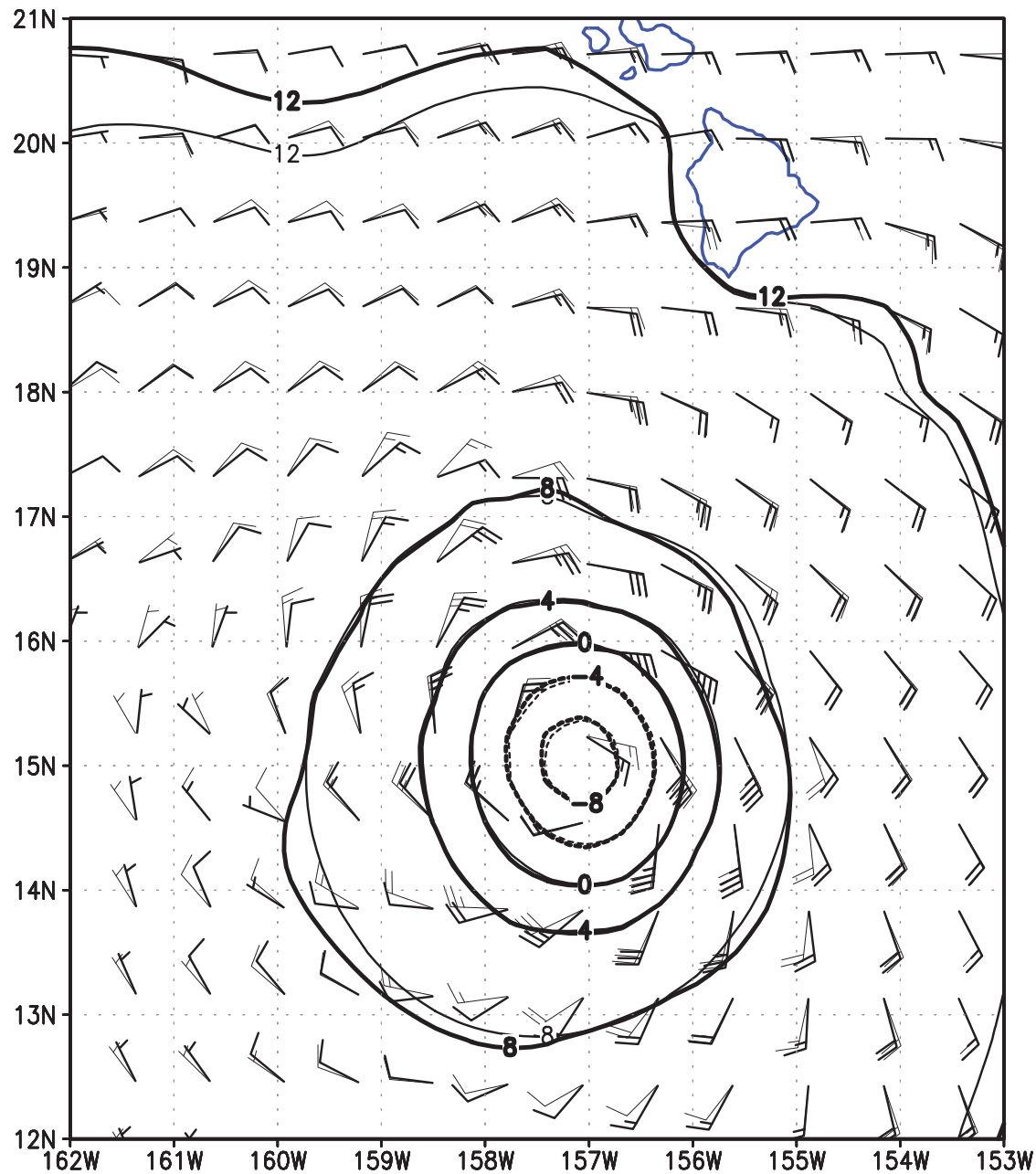


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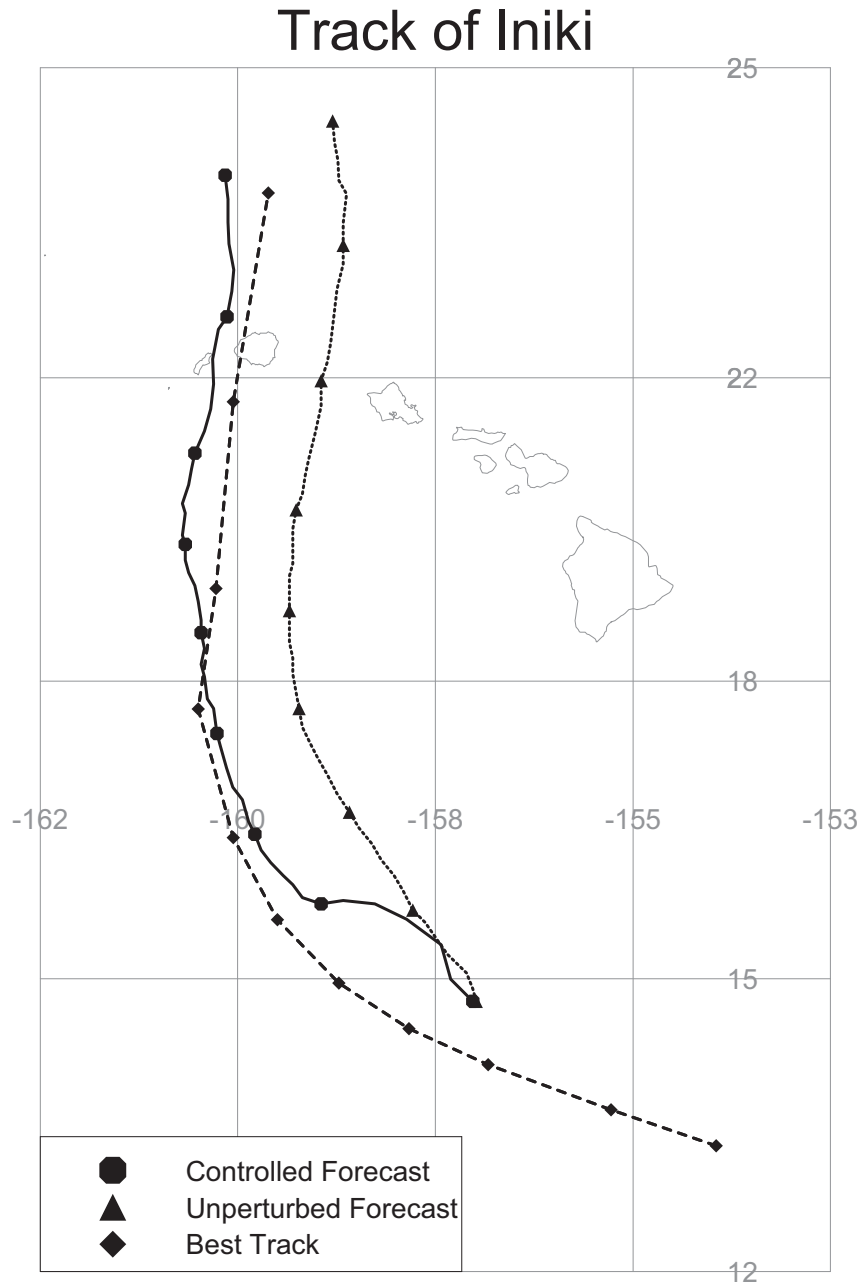


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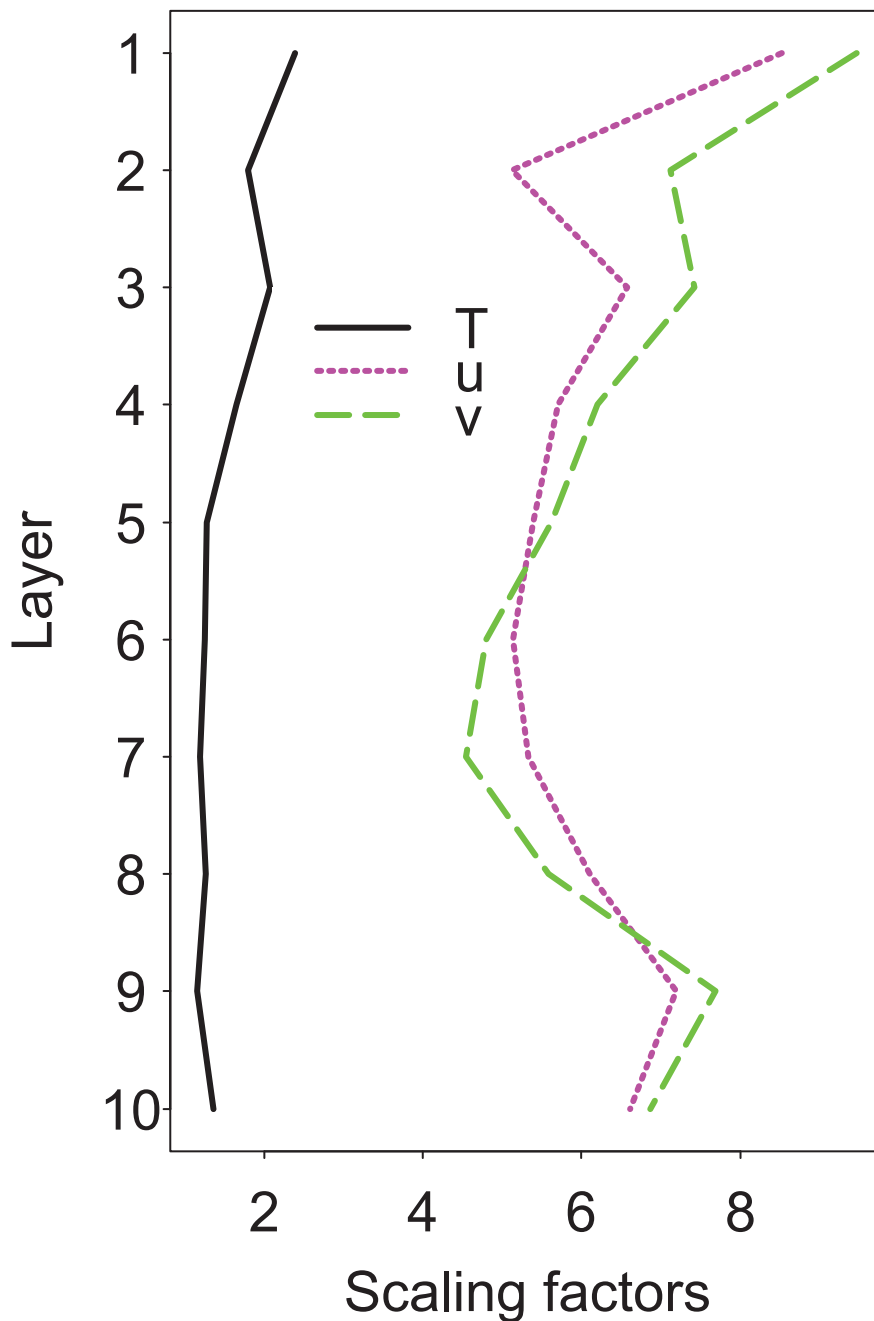


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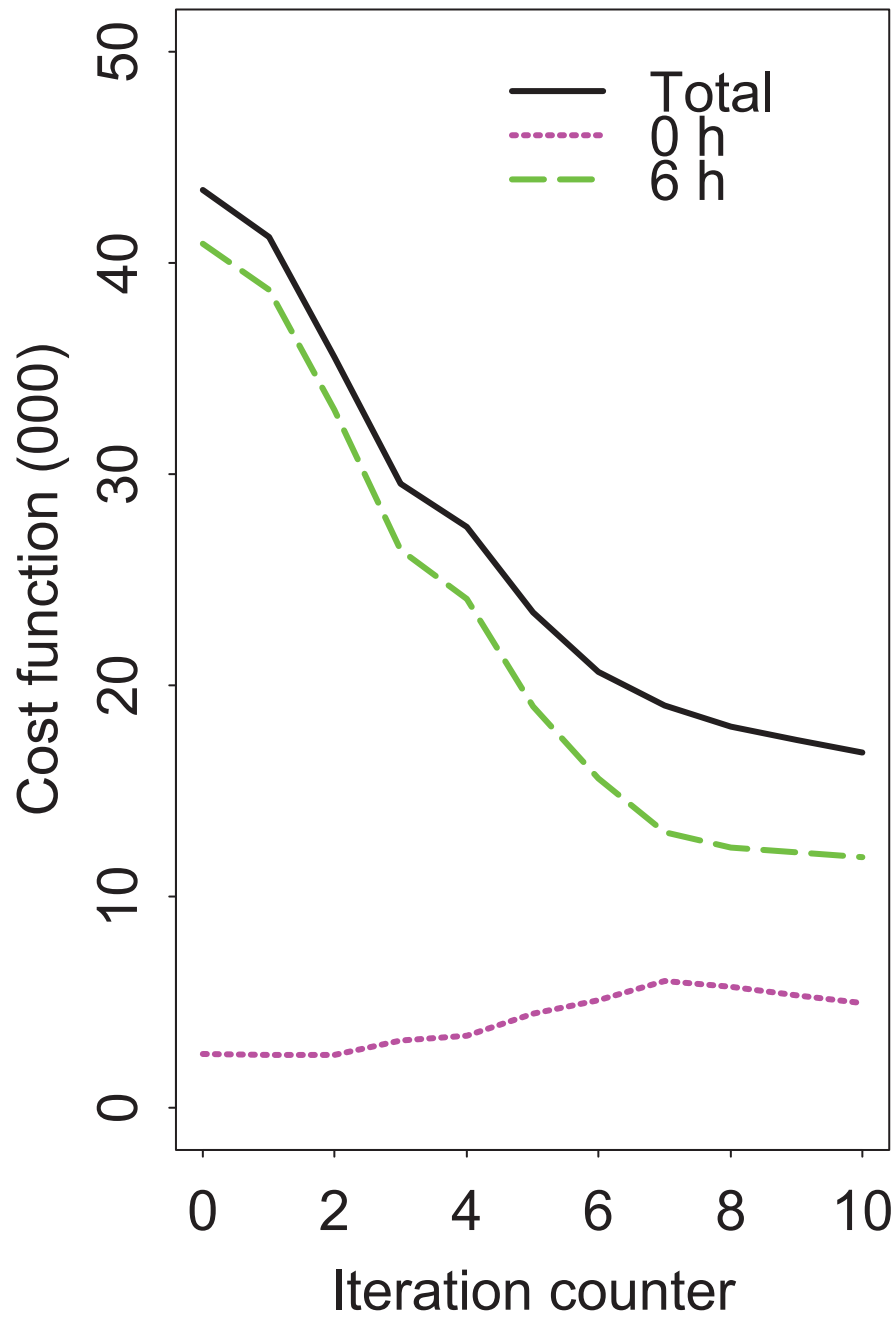


Fig. 6: *The rms difference profiles for temperature. The components of J are converted into rms differences as described in the text. The rms differences after the minimization, at $t = 0$ and 6 h are drawn with heavy dotted and dashed lines respectively. The rms differences at the start of the minimization are drawn with light lines.*

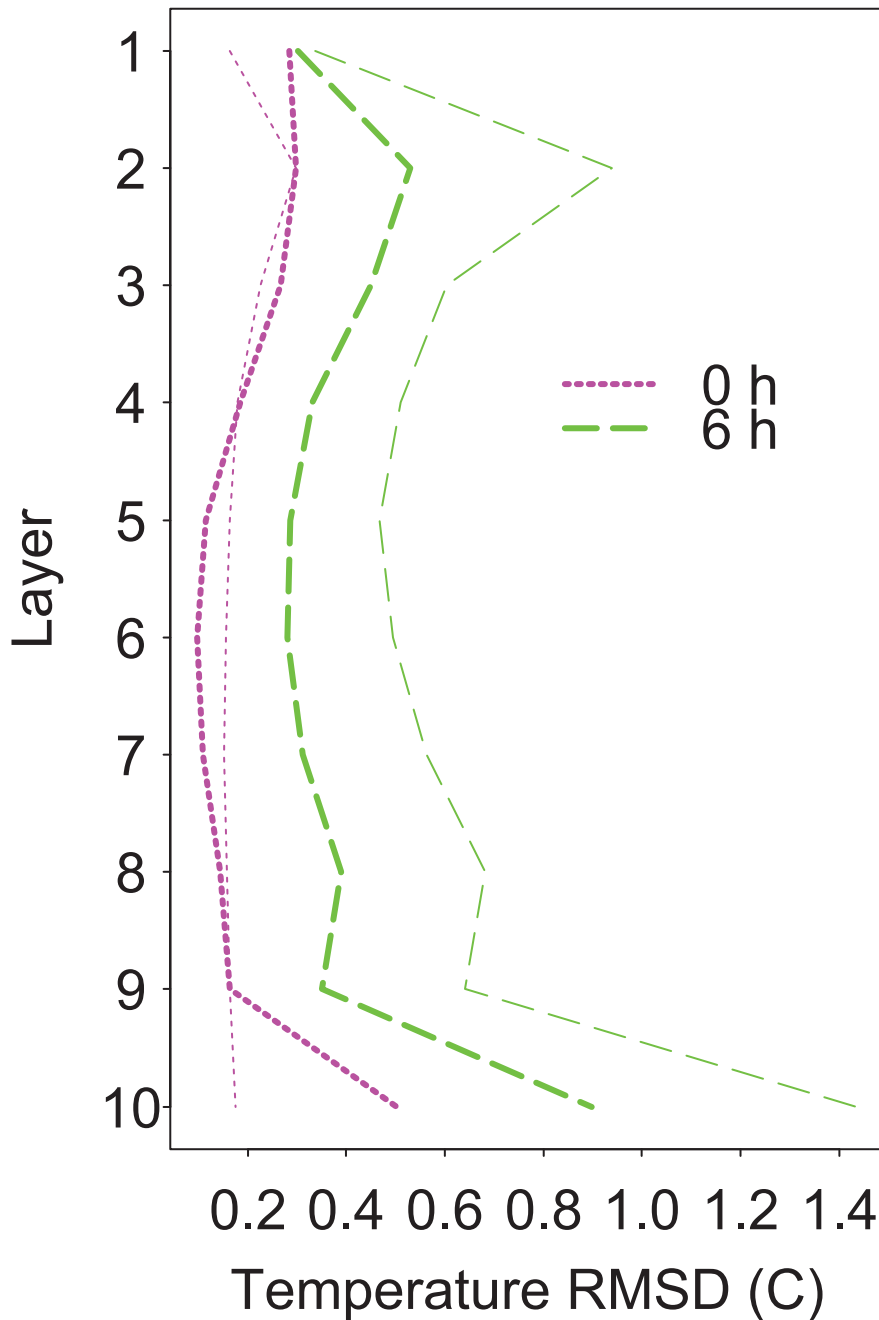


Fig. 7: *The rms difference profiles for vector winds. As in Fig. 6.*

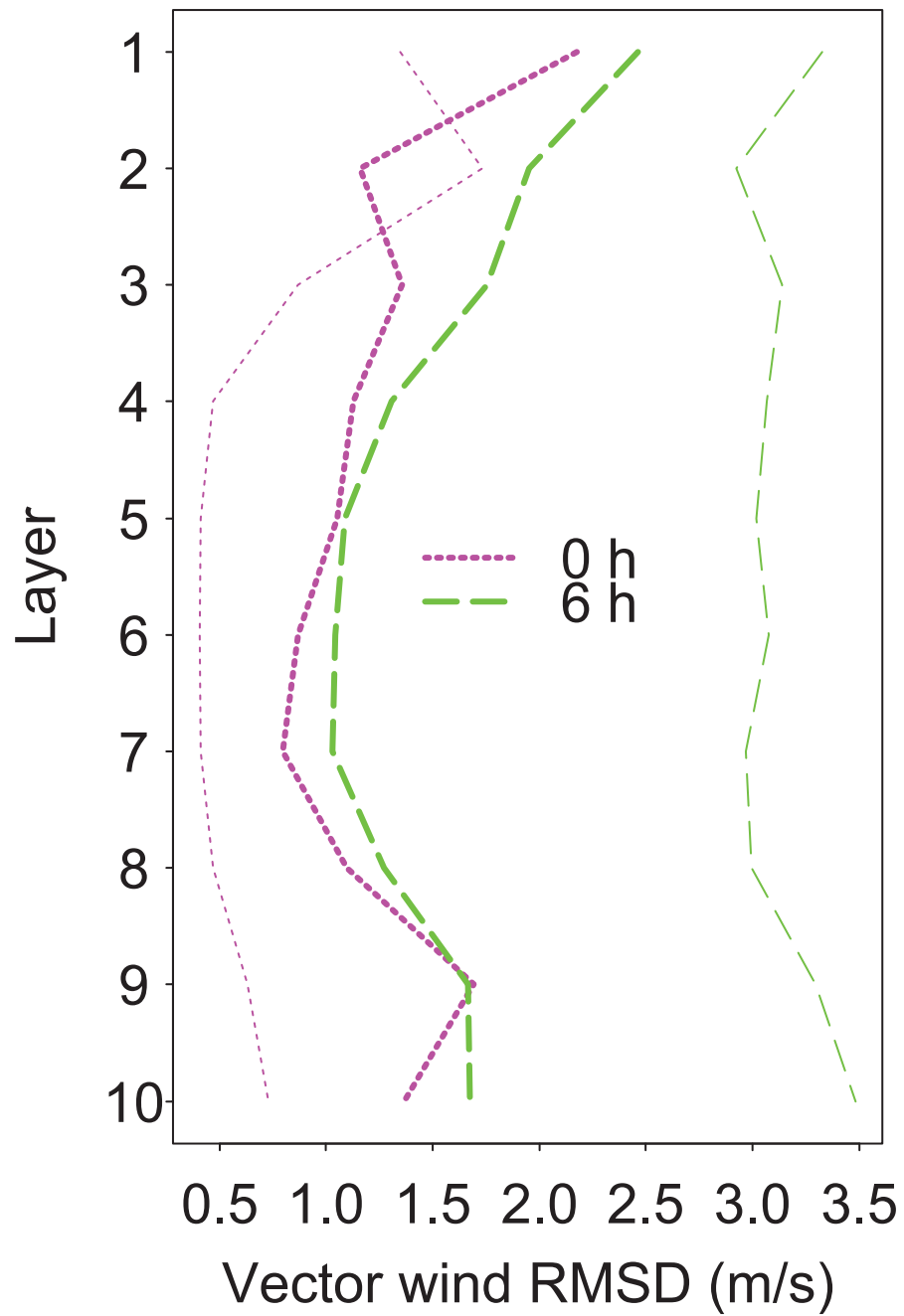


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