The Influence of Large-scale Dynamical Forcing and Meteorological Regime on Arctic Cloud Microphysical Properties

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Arctic clouds: an ongoing challenge

- Arctic is very sensitive to radiative balance
- Modeling clouds correctly is challenging because of the liquid-/ice-water partitioning
- Models are treating the microphysics with more sophistication, but they can still get the IWP and LWP wrong by factors of $\sim$3 (Klein et al. 2009, Morrison et al. 2009)
- What is needed is observational data to examine failure modes of models and fix them

Using ARM data for model evaluation

- Atmospheric Radiation Measurement (ARM) program uses highly instrumented ground stations to study cloud formation processes and their influence on radiative transfer
- Arctic cloud observations since 1998 at North Slope of Alaska (NSA) site in Barrow, AK (+ remote stations)
- Testing and improving model parameterizations of high-latitude processes is an explicit scientific goal of ARM NSA
- Instruments (and value-added products) to measure cloud phase and amount, and radiometry

ARM NSA instruments + VAP's

- Surface meteorology
- LIDARs
- RADARs
- Radiometers

Climatology of Barrow

- 71° N latitude, northernmost point in the United States
- Climatic features of maritime Arctic and polar desert (Serreze and Barry 2005)
- Mixed-phase clouds $\sim$ 50% of the time (all year except peak of summer) (Curry et al. 1996, Shupe et al. 2006)
- About 40% of mixed-phase clouds are multi-layer (Shupe et al. 2007)
- Perfect cloud laboratory!

Classification of meteorological regimes

- We present two independent methods designed to identify meteorological regimes
- The aim of this approach is to divide the observations into ensembles with similar meteorology
- Each ensemble can be used as a test case for climate models
- Material presented is from Mülmenstädt et al. (in preparation)

Classification: two independent methods

Synoptic

- Synoptic-scale meteorology from reanalysis SLP fields
- By expert inspection of charts

Local

- Local surface meteorology
- By automated objective clustering algorithm

Common goal: identify meteorological regimes

- Each regime is an ensemble of many days' worth of observations
- Each regime corresponds to an actual meteorological state
- This enables testing of the climate model parameterizations over the full range of meteorological variability found in nature
- ...while dealing with a manageable number of regimes

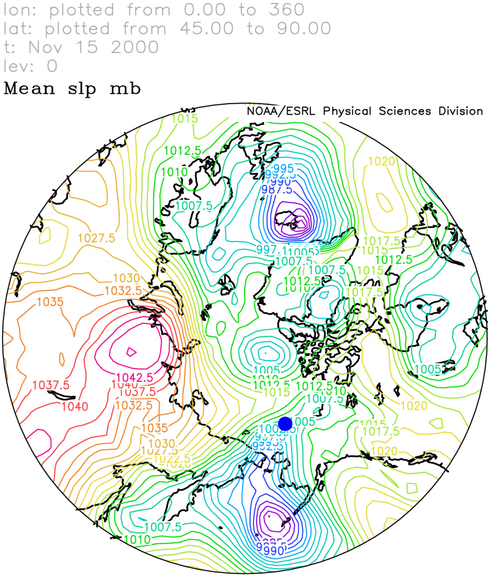
Synoptic classification

Cloud properties are influenced by synoptic systems (large-scale dynamic forcing)

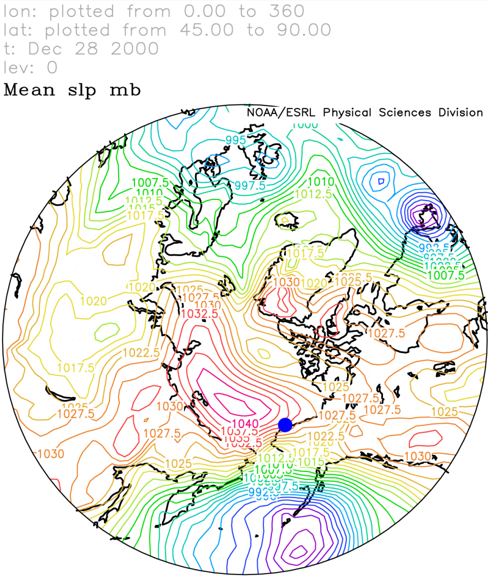
We investigated the daily mean NCEP SLP pressure maps for the year 2000 and 2009 to determine which synoptic regimes control Barrow. We identified:

Synoptic category	Frequency
Arctic Ocean High	166
Aleutian and Bering Sea Low	133
Siberian High	98
Beaufort Sea and Central Arctic Ocean Low	96
Siberian and Chukchi Seas Low	73
Aleutian and Bering Sea High	20

Two examples: Aleutian Low



Two examples: Siberian High



Local objective classification

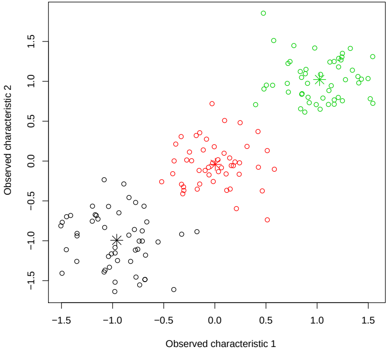
Cloud properties are correlated with local surface meteorology

We applied a clustering algorithm (k-means clustering) to find patterns in surface meteorology from 2000 to 2010, described by

- Air temperature (anomaly relative to calendar-month mean)
- Pressure
- Relative humidity
- Horizontal wind components

k-means clustering

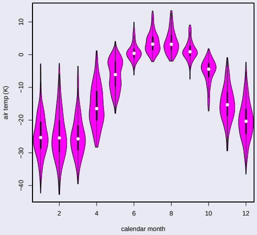
Clustering finds categories in multivariate data sets



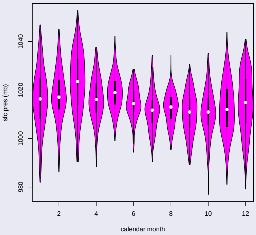
- In a simple (2-dimensional) system, this is what clustering would look like
- Algorithm works in higher dimensions too, unlike the human eye
- And in surface meteorology, we in fact need the extra dimensions to find patterns

Featureless 1D plots

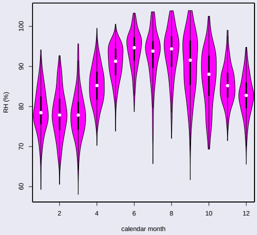
Air temp by month



Sfc pres by month



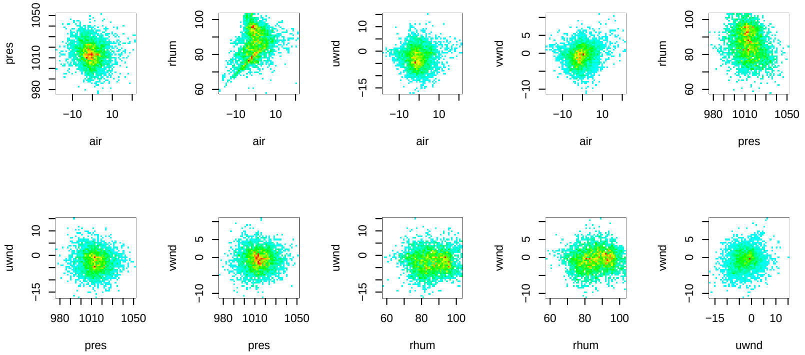
Rel hum by month



Input variables have mostly unimodal distributions

No discernible classification based on 1-dimensional information

Featureless 2D plots



Input variables are mostly uncorrelated

No discernible classification based on 2-dimensional information

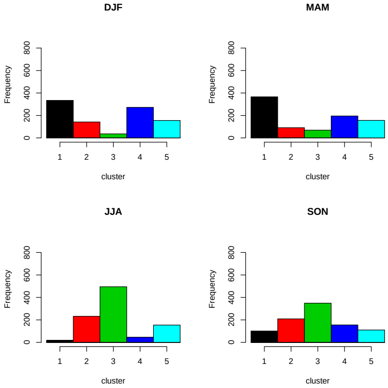
Clustering to the rescue

The challenge

- Each variable by itself is featureless, as are the scatter plots
- Yet, we know there are different kinds of weather, and that they have distinct surface meteorology
- So we need a multivariate method (in our case k-means clustering) to extract information from the higher-dimensional correlations

Clustering results

cluster	temp anom	pressure	rel hum
1	cold	high	very dry
2	avg	low	moist
3	avg	avg	moist
4	avg	avg	dry
5	warm	avg	avg



- Each cluster picks interesting features
- No two clusters have the same combination
- Seasonal variation in prevalence

How is the number of clusters chosen?

- Number of clusters (k) must be prescribed to the k-means algorithm
- Our method: seed algorithm many times with randomly chosen cluster centers
- For certain values of k, the algorithm converges to the same solution regardless of the seeds
- Stable solutions for $k = 3$ and $k = 5$ for this data set

Stability tests

- Comparing clustering of ARM surface observations with clustering of the NCEP-reanalysis
- Clustering with a subsample of the available data
- Large ensemble of randomly chosen initial centers
- Clustering with and without relative humidity (least normally-distributed and most different between NCEP and ARM)
- Anomalies
- Wind direction and wind speed vs *u* and *v* component

In all cases, stable solutions with 3 clusters and 5 clusters were observed, and the meteorological conclusions drawn for these clustering solutions are consistent.

Local categories correlate with synoptic categories

- We don't expect one-to-one correspondence between the two categorization methods (no physical reason)
- But do expect correlation (because the synoptic systems influence the local conditions by advecting airmasses with different properties)
- For 4 of 5 clusters, there is a predominant synoptic picture
- For all clusters, there is a predominant geostrophic wind direction

cluster	synoptic system		wind	
	type/location	frequency	direction	frequency
1	H to N	74%	N	61%
2	L to N	68%	W	88%
3	mixture		S	64%
4	H to N	69%	E	91%
5	L to N	54%	SW	71%

Cloud properties of the meteorological categories

Point of the categories is to provide models with different cloud conditions

Both the synoptic categories and the local categories differ in their cloud properties

cluster	met	wind	ARSCL clear sky frac	ARSCL cloud base	TSI	SKYRAD DLW
1	H to N	N	high	wide	clear	low
2	L to N	W	high	low	wide	low
3	mix	S	low	high	wide	avg
4	H to N	E	low	low	wide	high
5	L to N	SW	low	wide	wide	high

Clusters can be used as test cases for model evaluation

- Cloud properties differ between clusters
- Clusters form ensembles of test cases for cloud properties, physically relevant to actual meteorological states, which can be used to robustly test climate model parameterizations
- Each cluster exposes models to different potential sources of failure. At the same time, the phase space of physically significant cloud variables is reduced to a discrete space of size k
- Advantage over field campaigns: more than a decade of observations
- Advantage over evaluating model accuracy as a function of every relevant variable: the size of the phase space is reduced to the number of clusters, which is typically manageable

Modeling

- Test whether model success depends on cluster number
- Get some high-statistics answers: use multiple years
- Preliminary results presented here; final results in preparation

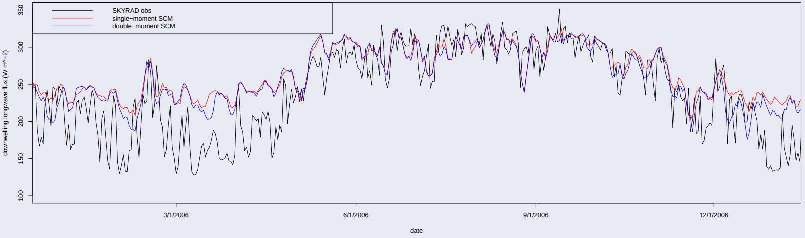
Model setup

- WRF V3.3 in SCM mode centered on Barrow
- Forced from NCEP FNL 6-hourly reanalysis
  - water vapor advection
  - potential temp advection
  - vertical velocity
- Surface currently fixed water/ice (ocean is usually upwind), more sophisticated wind-dependent treatment is in the works
- Two microphysics scheme considered:
  - Single-moment with ice, snow, graupel (Lin et al. 1983)
  - Double-moment ice, snow, rain and graupel (Morrison et al. 2009)

Comparing model results to observations

For an arbitrarily chosen year (2006):

Time series of downwelling longwave radiation in SKYRAD radiometer observations and SCM

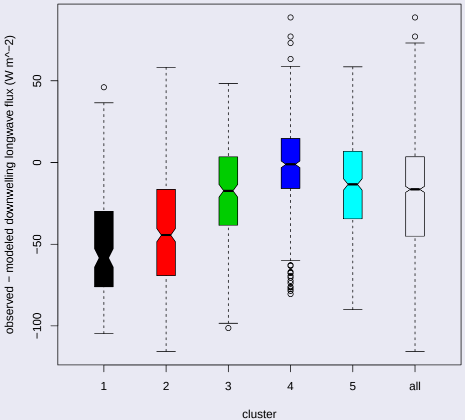


For 2002 to 2009 (SKYRAD operational period):

- Double-moment scheme closer to observation than single-moment (bias is 20 W m^{-2} vs 24 W m^{-2})
- Model disagreement is 35 W m^{-2} (RMS) for both schemes

Model success varies with meteorological regime

Observed − modeled DLW flux, double-moment SCM



Model success differs between clusters

- Not every cluster differs from every other cluster (this is not expected), but some clusters clearly perform better than others
- Narrows down the search for model error
- Large number of days in each category (statistical robustness)

Summary

- Large model uncertainties associated with mixed-phase clouds in the Arctic make it desirable to use long time series of cloud observations for model studies and improvement
- We have applied two methods that assemble long time series of meteorological observations into ensembles of similar meteorological conditions for model evaluation:
  - Synoptic classification based on sea-level pressure field
  - Objective classification algorithm in local surface meteorology
- The members of each meteorological category share properties with each other, but differ from members of the other clusters
- Comparing models to observations separately for each category exposes models to the range of conditions found in nature
- At the same time, the phase space of physically significant variables is assembled into a small number of meteorologically meaningful categories
- This suggests that the categories produced by the method are potentially useful as model-evaluation test cases

Classification is available for use by modelers

- At this website: `http://aerosol.ucsd.edu/supplement/arm-nsa-met`
- Lists meteorological cluster number for each day from 2000 to 2010

Also:

We would gladly accept GCM and RCM runs to see if the same clusters emerge from the model simulations

Acknowledgments

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