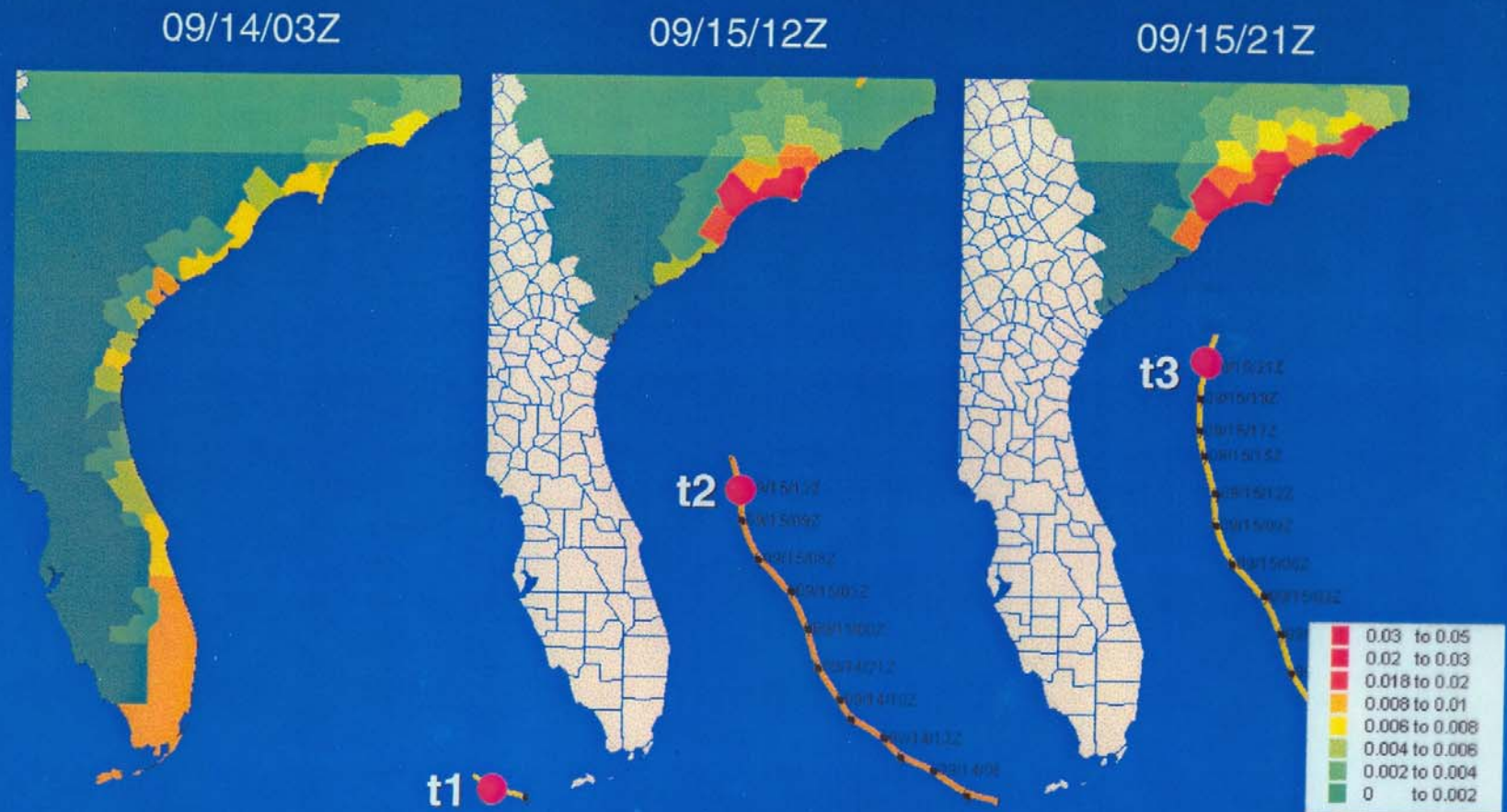




II. EVOLVING 'LOSS COSTS' (LOSS RATIOS)



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13

2 Feb 2006

End-to-End Ensemble Forecasting:

Towards evaluating the economic value of an EFS

Leonard Smith

Centre for the Analysis of Time Series

London School of Economics

Pembroke College, Oxford

www.lsecats.org



Overview

What is the Aim? (“What is the Product?”)

Where is the value? (“Where is their pain?”)

Risk Management, Decision Support and Forecasts

How Ensemble Prediction Systems (EPS) Add Value

Socio-economic valuation of forecast information:

Proofs of Concept, of Information, and of Value

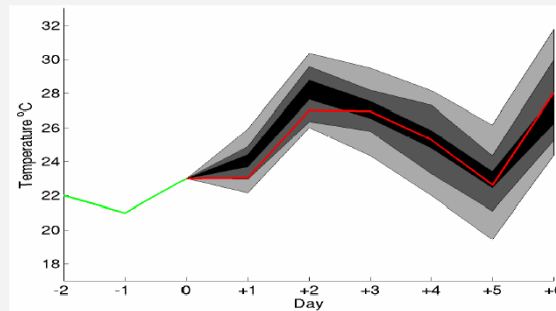
Questions any forecast provider should answer/be asked

What is the Product? (And what is it worth?)

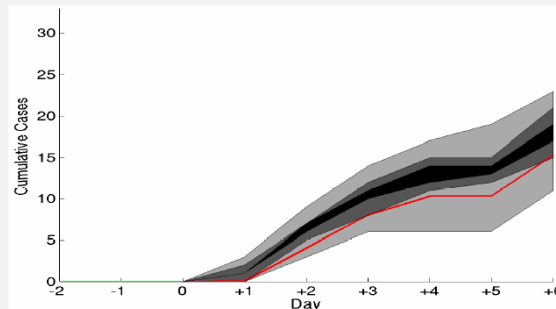
your time, energy, cash

Weather:

LSE-CATS Weather-Health Daily Risk Management Page



| Day | -2 | -1 | 0 | +1 | +2 | +3 | +4 | +5 | +6 |
|---------------|----|----|----|----|----|----|----|----|----|
| Temp | 21 | 20 | 22 | 21 | 23 | 23 | 27 | 27 | 25 |
| Thresh | 23 | 23 | 23 | 23 | 23 | 23 | 23 | 23 | 23 |
| Cases | 0 | 0 | 0 | - | - | - | - | - | - |
| Max Exp Cases | 0 | 0 | 0 | 3 | 7 | 7 | 6 | 3 | 8 |
| Exp Cases | 0 | 0 | 0 | 1 | 5 | 4 | 2 | 1 | 4 |



A

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Is this relevant?

Is it accurate?

Is it useful?

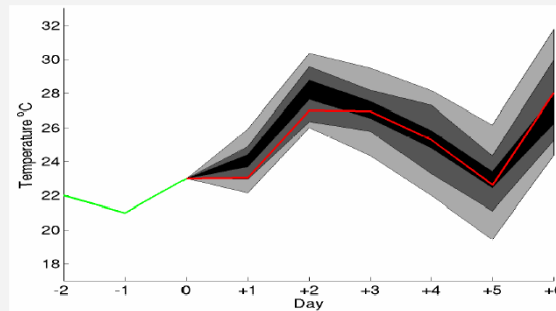
How does it work?

Case Load:

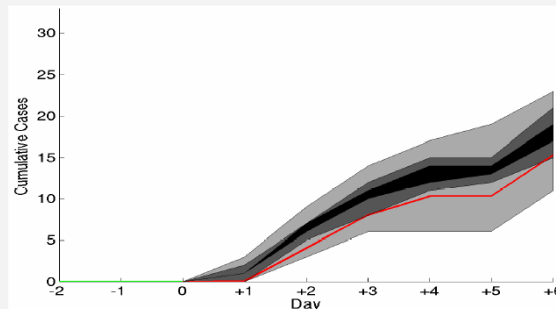
What is the Product? (And what is it worth?)

Weather:

LSE-CATS Weather-Health Daily Risk Management Page



| Day | -2 | -1 | 0 | +1 | +2 | +3 | +4 | +5 | +6 |
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| Max Exp Cases | 0 | 0 | 0 | 3 | 7 | 7 | 6 | 3 | 8 |
| Exp Cases | 0 | 0 | 0 | 1 | 5 | 4 | 2 | 1 | 4 |



A

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Is this relevant?

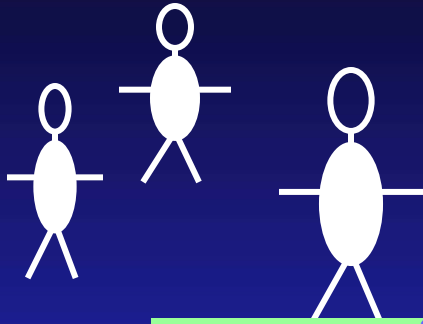
But you have to ask the last two questions down here!

Is it accurate?

Is it useful?

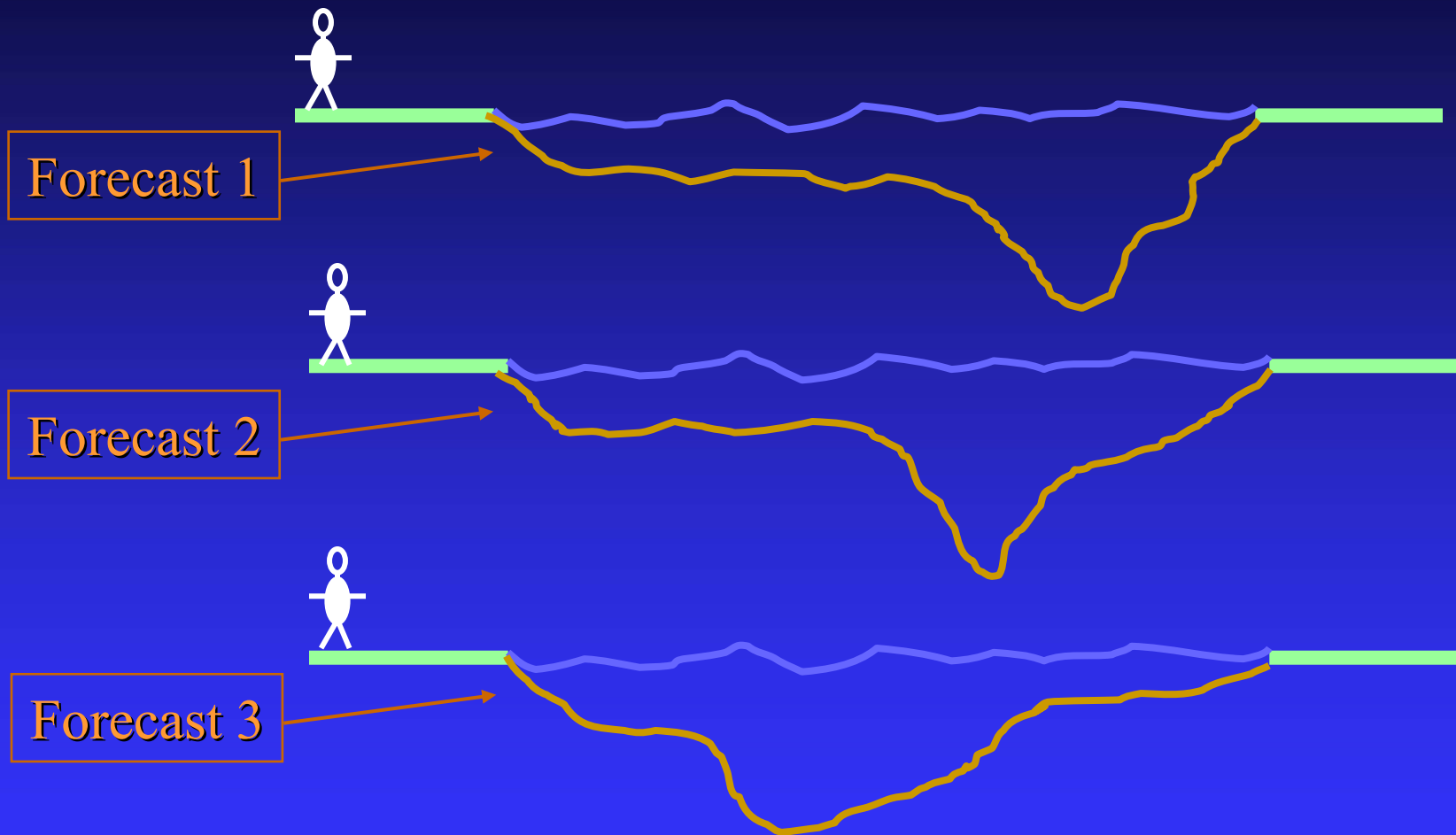
We will come back to a schematic of this figure in the seasonal context. First:
How does it work?

The parable of the three statisticians.



Three non-Floridian statisticians come to a river, they want to know if they can cross safely. (They cannot swim.)

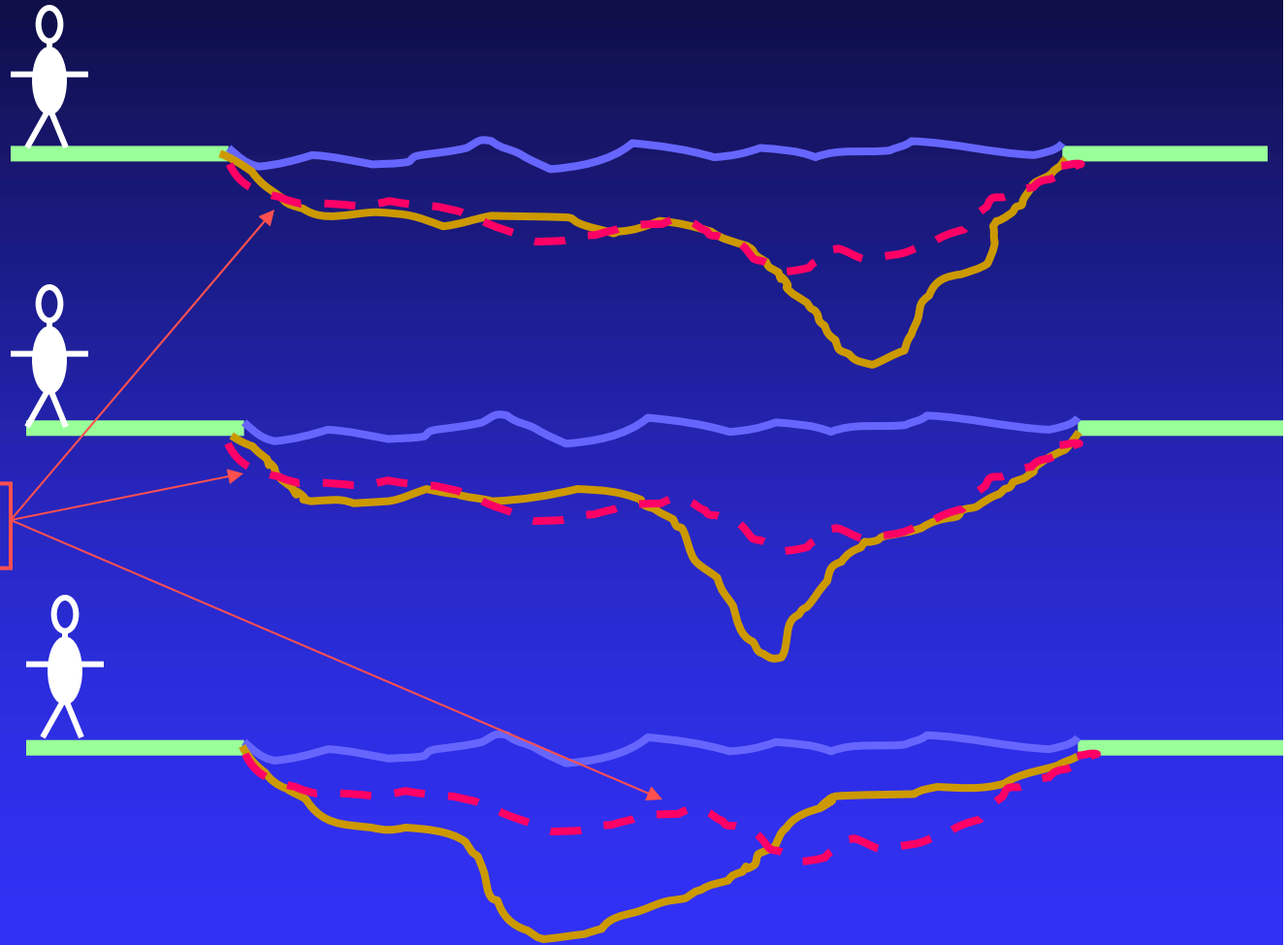
Three non-Floridian statisticians wish to cross a river.
Each has a forecast of depth which indicates they will drown.



So they have an ensemble
forecast, with three members

Three non-Floridian statisticians wish to cross a river.
Each has a forecast of depth which indicates they will drown.
So they average their forecasts and decide based on the ensemble mean...

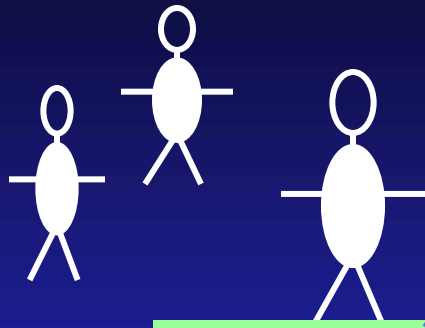
Ensemble mean



Is this a good idea?



No!



Ensembles may have lots of information, we must be careful not to destroy or discard it!

Note that, as in health risk-management, the statisticians:

- have a nonlinear utility function
 - including a very asymmetric risk/utility function (overly deep by 2 inches \ll shallow by 2 inches)
- do not care about the river depth *per se*.

Take Home Message:

If you have an ensemble, use it. (The ensemble mean is meaningless!)

Take Home Message:

If you have an ensemble, use it.

The relevant question is one of decision support, not forecasting.

This is a NAG Board

Uncertainty in the NAG board corresponds to predicting with a collection (ensemble) of golf balls...

Ensembles inform us of uncertainty growth *within our model!*

But reality is not a golf-ball; this EPS must deal with model inadequacy.

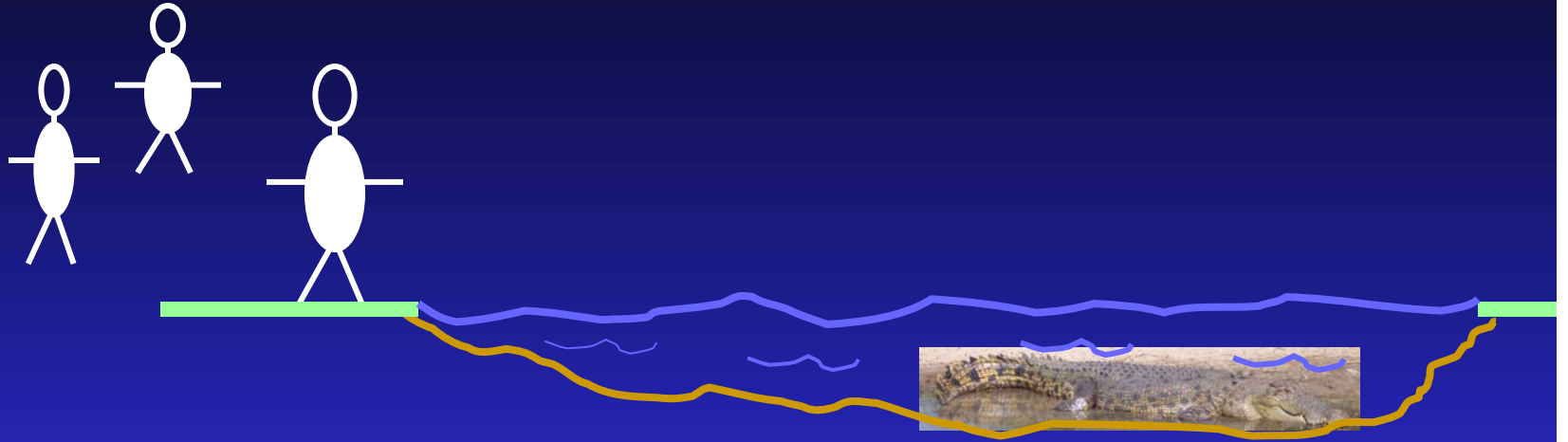
Nevertheless, weather EPS are useful!
Operational Day ~10 Weather Ensembles:
US and European Services: 1992
Canada: Now



The NAG Board (Not a Galton Board)

2 Feb 2006

Model Inadequacy and our three non-Floridian statisticians.

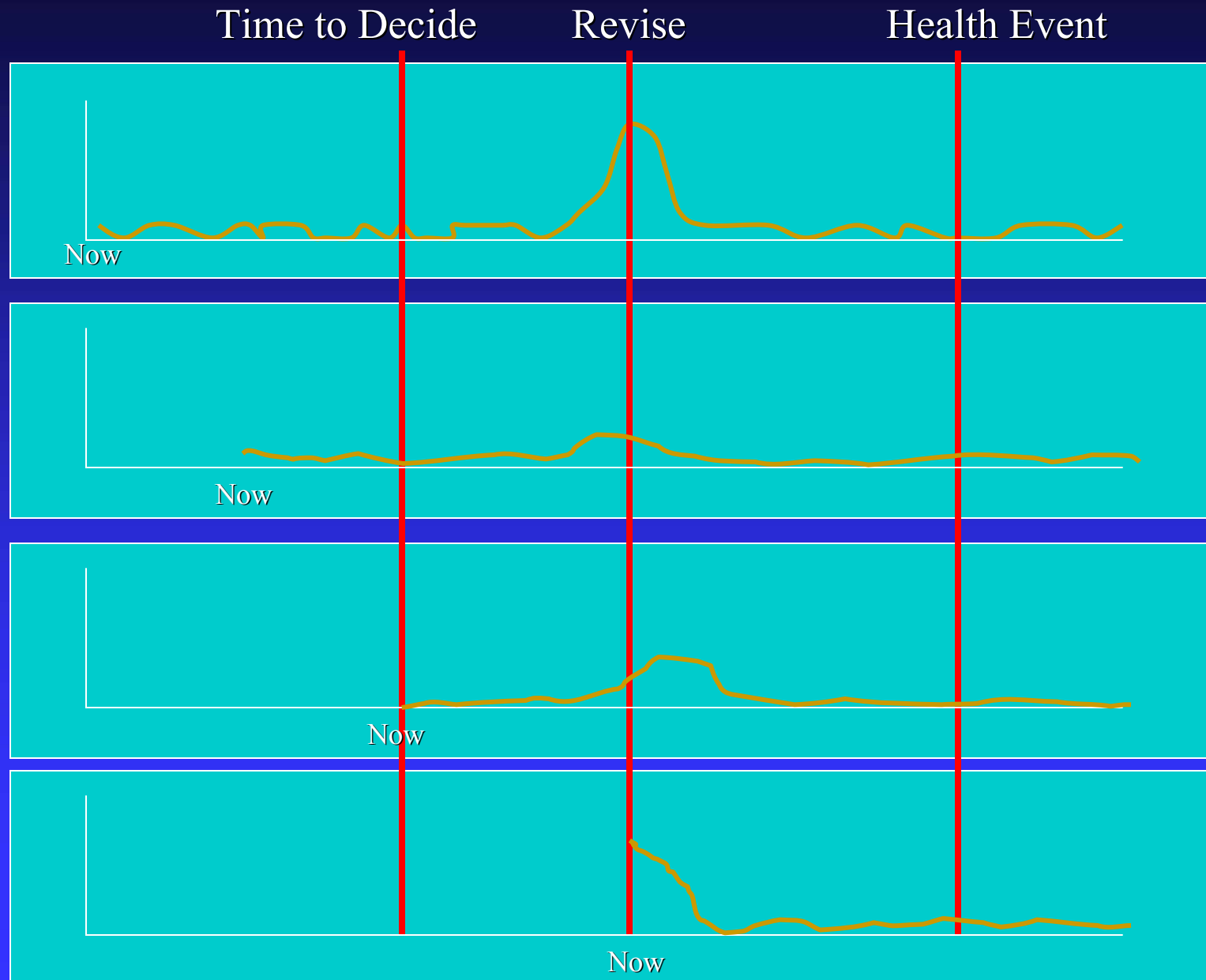


As it turns out, the river is rather shallow.

Model inadequacy covers things in the system but left out of the model.

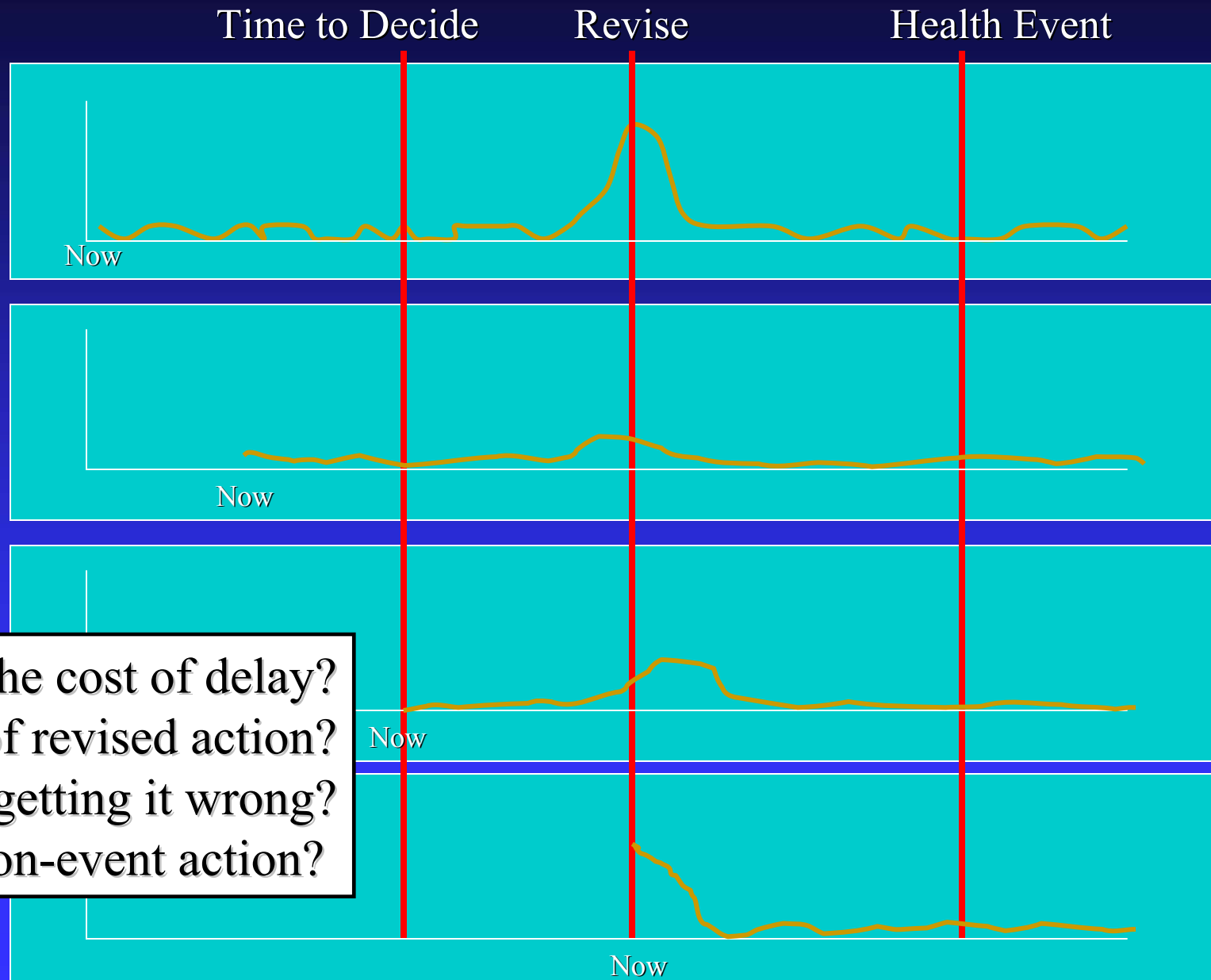
The real question was could they make it across, the depth of the river was only one component...

Decision Support and Forecasts



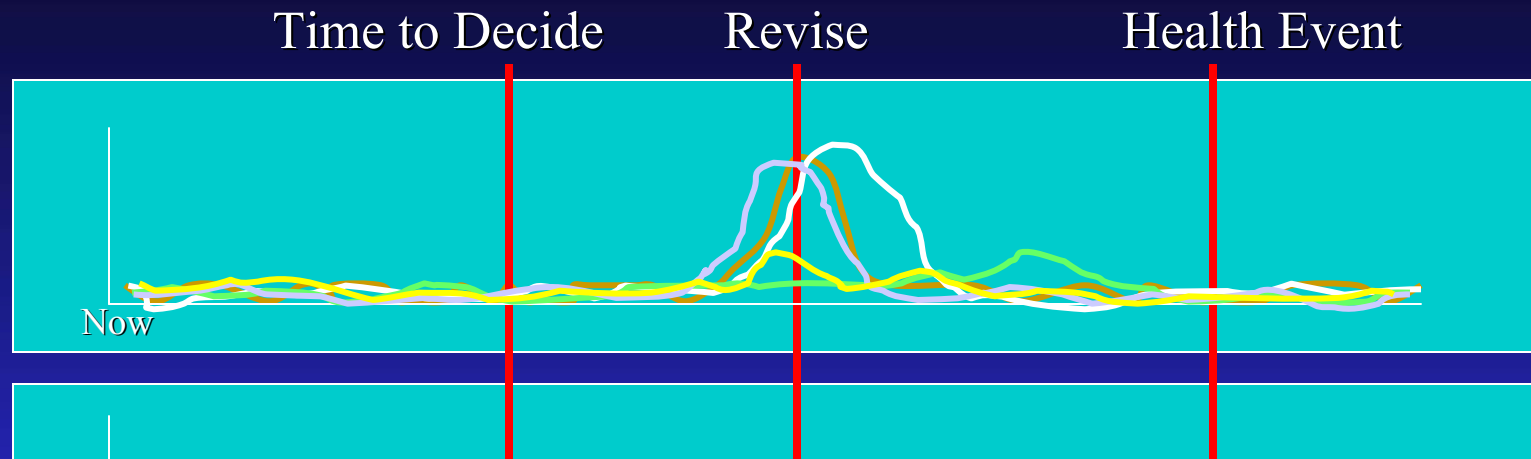
2 Feb 2006

Decision Support and Forecasts



What is the cost of delay?
of revised action?
of getting it wrong?
of a non-event action?

Decision Support and Ensemble Forecasts



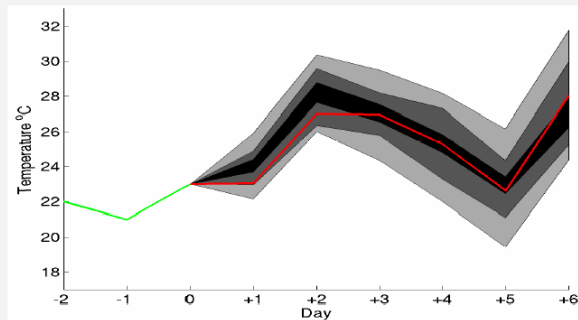
So the ensemble aims to provides information on the reliability of the forecast *given* the information in hand today.

Note that these are still weather forecasts, they must be translated into case loads, which may require more model(s).

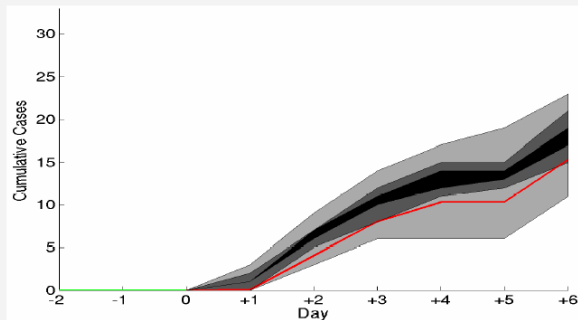
Is the ensemble result better?

- a) The final evaluation must be made in health relevant variables!
- b) Better than what, exactly?

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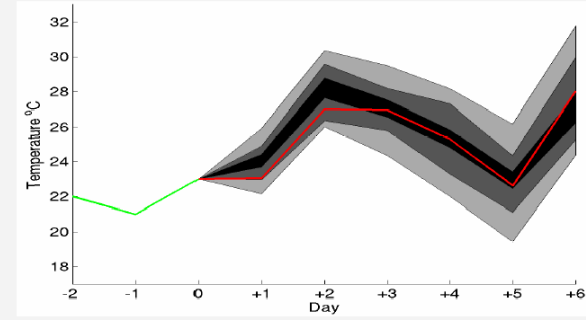
| Day | -2 | -1 | 0 | +1 | +2 | +3 | +4 | +5 | +6 |
|---------------|----|----|----|----|----|----|----|----|----|
| Temp | 21 | 20 | 22 | 21 | 23 | 23 | 27 | 27 | 25 |
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| Cases | 0 | 0 | 0 | - | - | - | - | - | - |
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| Exp Cases | 0 | 0 | 0 | 1 | 5 | 4 | 2 | 1 | 4 |



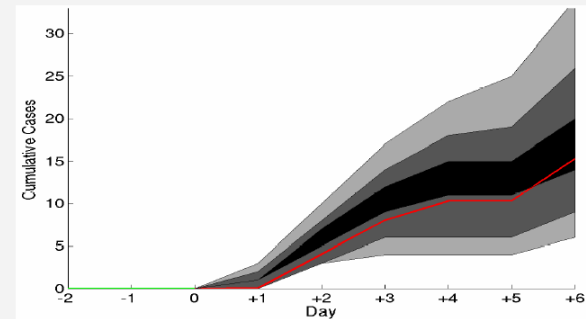
A

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| Day | -2 | -1 | 0 | +1 | +2 | +3 | +4 | +5 | +6 |
|---------------|----|----|----|----|----|----|----|----|----|
| Temp | 21 | 20 | 22 | 21 | 23 | 23 | 27 | 27 | 25 |
| Thresh | 23 | 23 | 23 | 23 | 23 | 23 | 23 | 23 | 23 |
| Cases | 0 | 0 | 0 | - | - | - | - | - | - |
| Max Exp Cases | 0 | 0 | 0 | 3 | 7 | 7 | 6 | 3 | 9 |
| Exp Cases | 0 | 0 | 0 | 1 | 5 | 4 | 2 | 1 | 5 |



B

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In this kind of decision support ensembles can yield:

we see the uncertainty in likely case load in both A & B

but we also see the substantially greater risk in B

This information depends on the full EPS, not just the probability of weather on each day.

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Take Home Messages:

If you have an ensemble, use it.

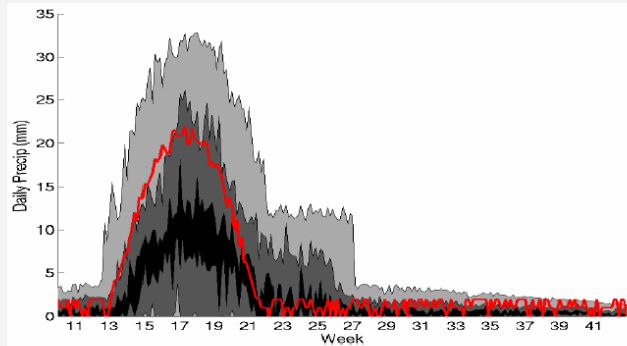
The relevant question is one of decision support, not forecasting.

Ensembles are always valuable in nonlinear models, when they warn you that the model does NOT know what will happen.

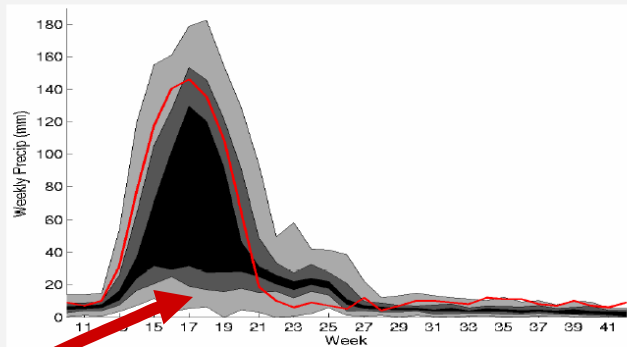
A Schematic Seasonal Example

LSE-CATS Weather-Health Weekly Health Management Page

weather



weather



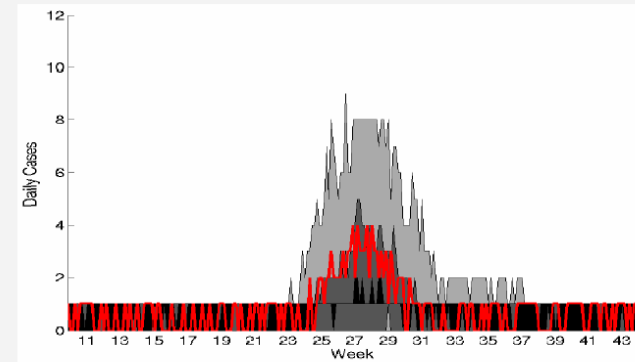
A

Weather
Event

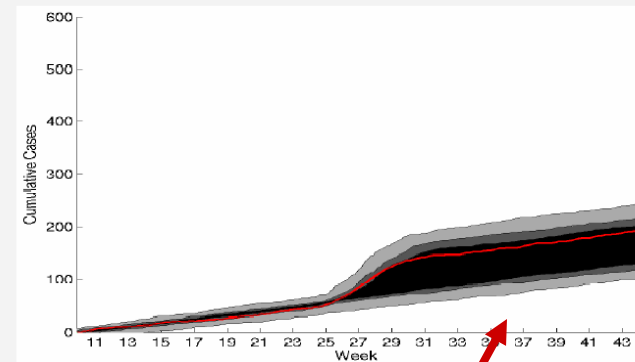
Onset of
health event

©L.A. Smith

health



health



A

Weather
Event

Onset of
health event

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Note the delay between Precip on Onset

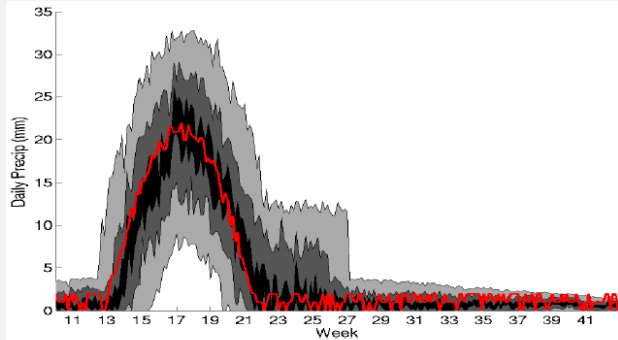
In this case we do not know if there will be on event, but at least we know that we do not know!

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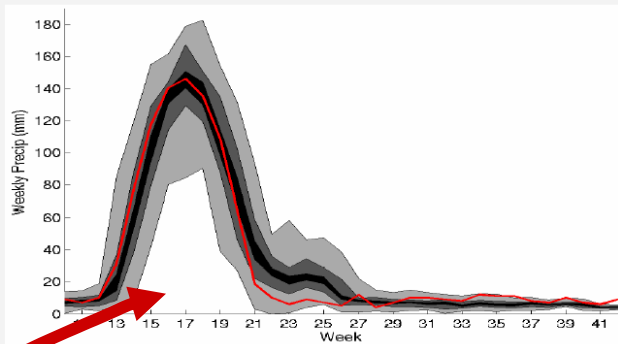
A Schematic Seasonal Example

LSE-CATS Weather-Health Weekly Risk Management Page

weather



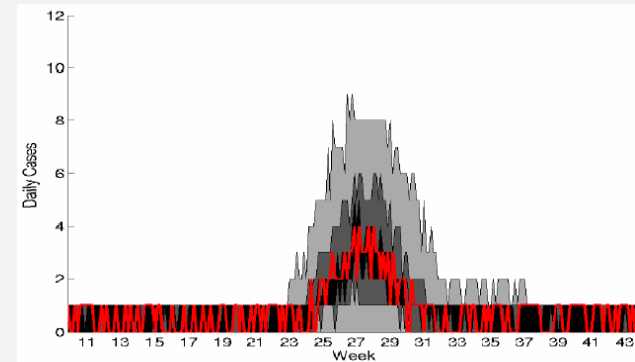
weather



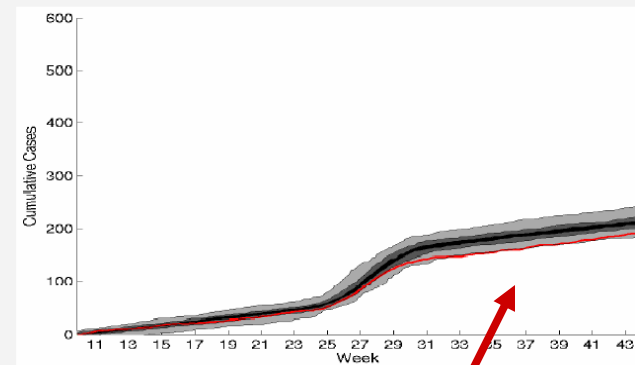
A

©L.A. Smith

health



health



A

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In this case we know *the model* does “expect” an event.

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Take Home Messages:

If you have an ensemble, use it.

The relevant question is one of decision support, not forecasting.

Ensembles are always valuable in nonlinear models, when they warn you that the model does NOT know what will happen.

A good EPS can also indicate what the likely alternatives are, and thus assist in decision support.

Take Home Messages:

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A good EPS can also indicate what the likely alternatives are, and thus assist in decision support.

Focus on information content, *not* on meteorological accuracy.

The proof of the pudding is in the eating.

The proof of predictability is in the utility.

Establishing positive socio-economic benefit from an EPS usually takes four steps.

- Proof of Concept Timescales make sense (re: decision support)
Historical/Theoretical causal connections OK.
Models work on toy targets (internal consistency)
- Proof of Information Forecasts contain relevant information for relevant *empirical* targets.
Risk management scenario viable.
- Proof of Value End-to-end hindcasts on *actual target data*.
Is the insight demonstrated worth more than the full cost of the decision support system?
- **Real-time Demonstration** System deployed and proven in real time.

Scientifically, success at each stage is interesting, valuable, and exciting.
From a users point of view, anything less than PoV is incomplete.

Take Home Messages:

If you have an ensemble, use it.

The relevant question is one of decision support, not forecasting.

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Focus on information content, not on meteorological accuracy.

Require “verification” on relevant, semi-independent, real target, observations!

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The goal is utility, not optimality. (Decision aid, not decision made)

Take Home Messages:

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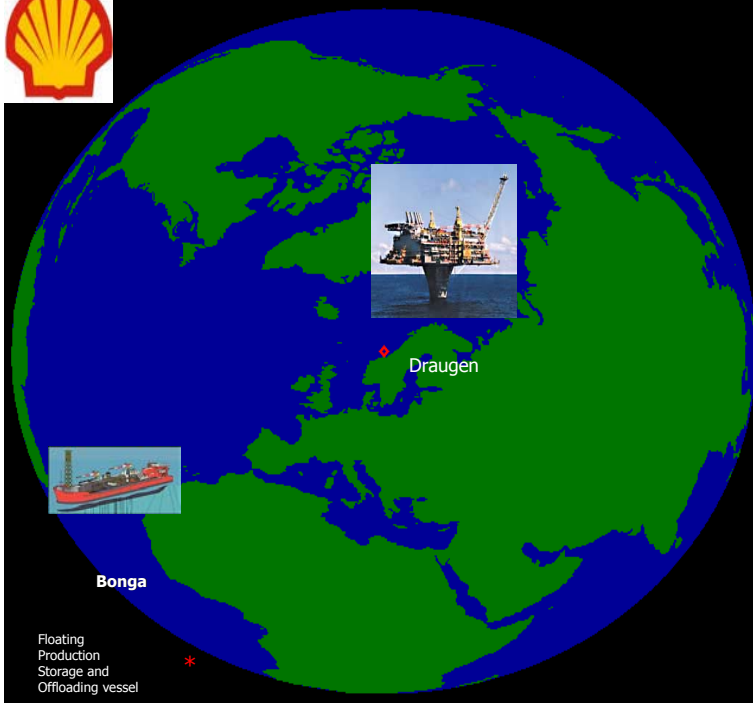
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Focus on information content, not on meteorological accuracy.

Require “verification” on relevant, semi-independent, real target, observations!

The goal is utility, not optimality. (Decision aid, not decision made)

*If one forecast is good, then 50 forecasts will be better!
(but not 50 times better)*



Seeing Through Weather Models



CALIFORNIA ISO



ALSTOM



weather.com



National Grid

Risk Management Solutions



A Few Examples

Charley: Has to make simple binary decisions.

Charles: Simple decisions, but not binary!

Charlotte: Difficult optimization decisions, and real verifications!

Charlemagne: Earth shattering responsibility!

Should I Stay or Should I Go?

A Cost-Loss Example

Charley is a contractor who makes cement patios. Every Saturday he has to decide whether to put in a new patio, or play golf.

If he works and then it freezes overnight, the cement is ruined.

How would Charles use ensemble forecasts?

In theory, he can work out an optimal probability of freezing, above which he plays golf.

In practice, the construction companies often set a threshold for, say, rain without doing the “cost/loss” calculation. Why?

This one you can easily find in books...

Where should I bet?

A Weather Derivatives Example

Charles, a graduate from the LSE; trades weather derivatives.

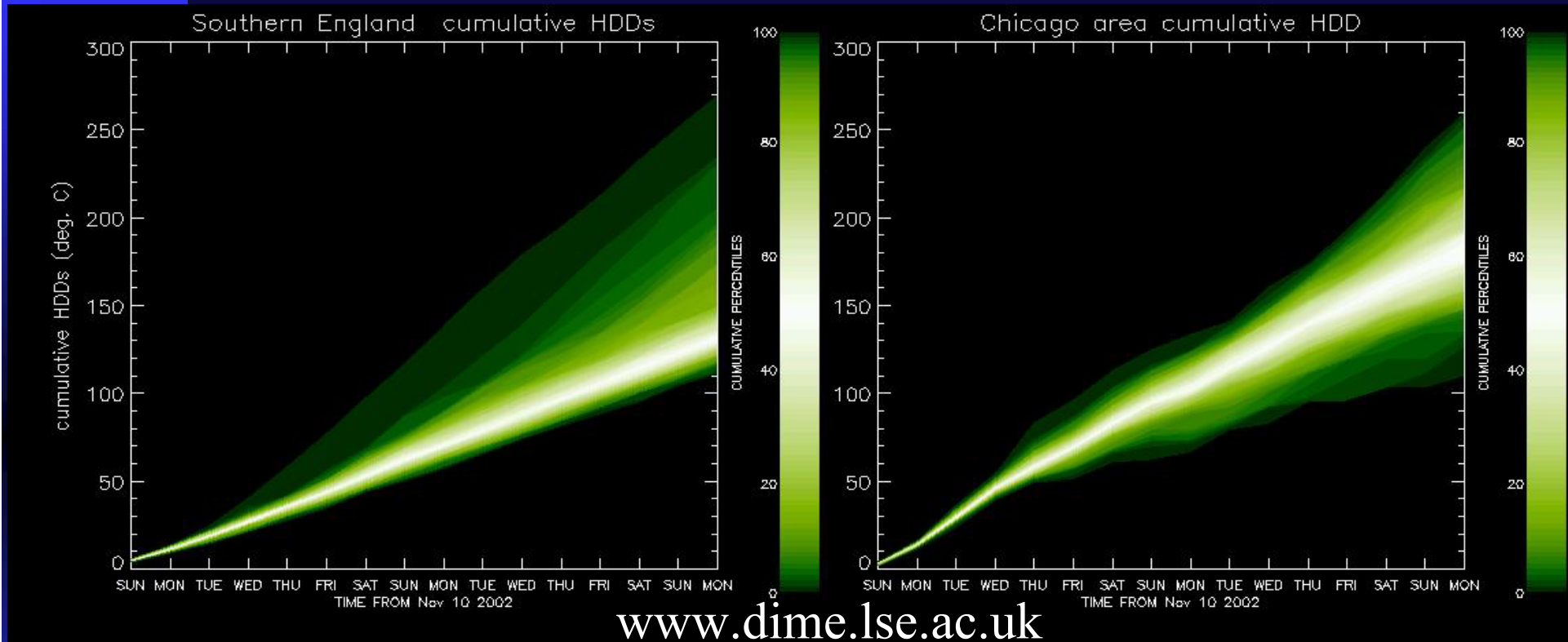
He rather to go home flat (no open risk every night).

He wants life to be interesting (he is NOT risk avoiding).

And he does not really care what the real temperature is, only the official temperature.

How would Charles use ensemble forecasts?

Scenario-based cumulative HDD forecasts.



This cumulative information on total energy requirements is simply not in a single hi-res forecast.

Can I be more efficient?

A Wind Farm Example

Charlotte runs wind farms. She does not have a yes/no decision, but a “how much” decision. How much energy should she contract to sell tomorrow, given that *if* she doesn’t produce that much she will have to buy it on the spot market?

How would Charlotte use ensemble forecasts?



PERGAMON

Renewable Energy 28 (2003) 585–602

**RENEWABLE
ENERGY**

www.elsevier.com/locate/renene

Using medium-range weather forecasts to
improve the value of wind energy production

M.S. Roulston^{a,b,*}, D.T. Kaplan^c, J. Hardenberg^{a,b},
L.A. Smith^{a,b}

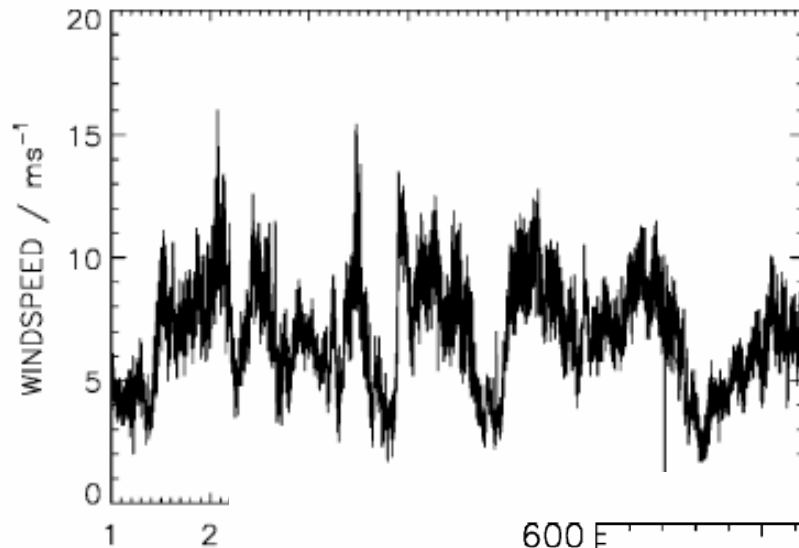


Fig. 3. A one-week sample of the Laboratory Energy Research Unit in Oxford, UK, at 1-m intervals.

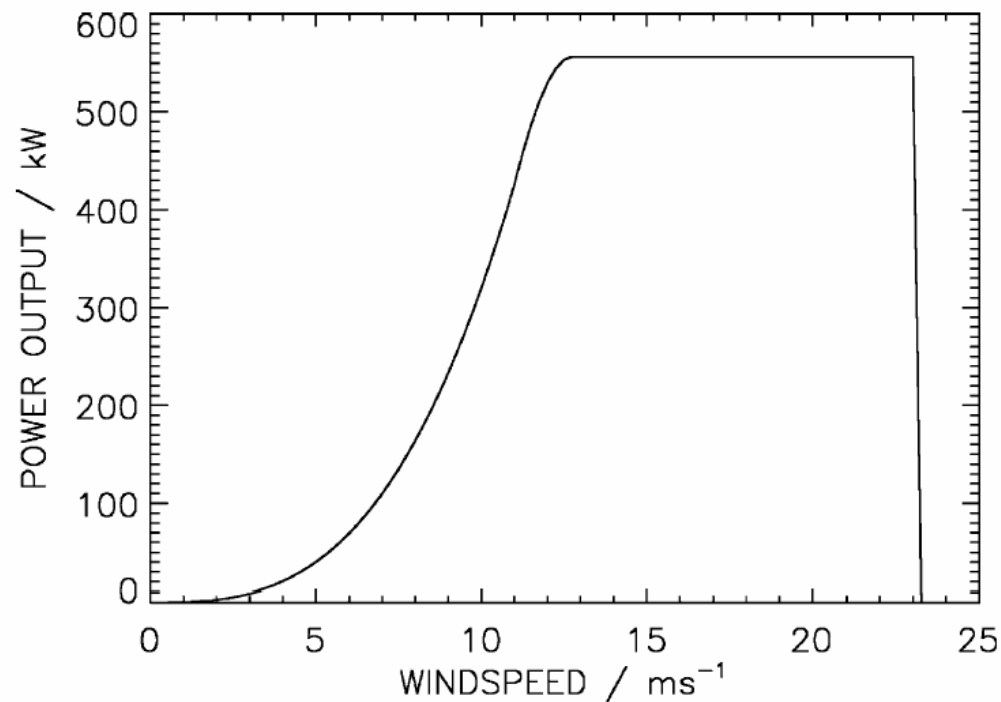


Fig. 5. The profile of wind turbine output as a function of wind speed that was used for the study.

Charlotte is interested in windspeed, but she is more interested in power.

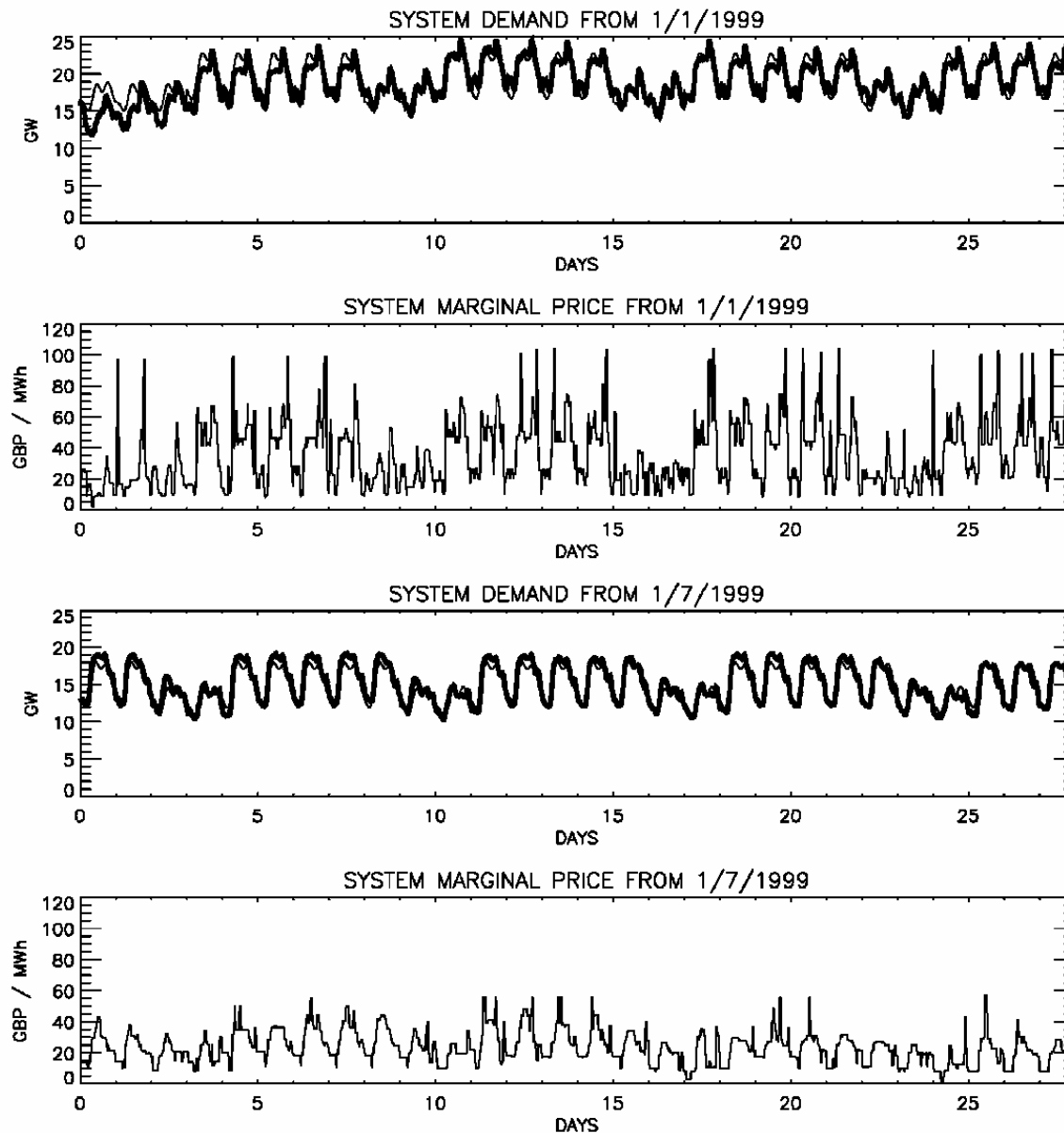


Fig. 6. Samples of UK system demand and the system marginal price for January and July 1999. In the demand panels the thick line is the actual demand and the thin line is the demand predicted using Eq. (A2) described in the Appendix.

In fact, she cares about demand as well as supply!

So how do we evaluate all of this end-to-end?

We take probabilistic wind forecasts, turn them into probabilistic power forecasts, turn that in to bids, and the bids into income based on the observed prices.

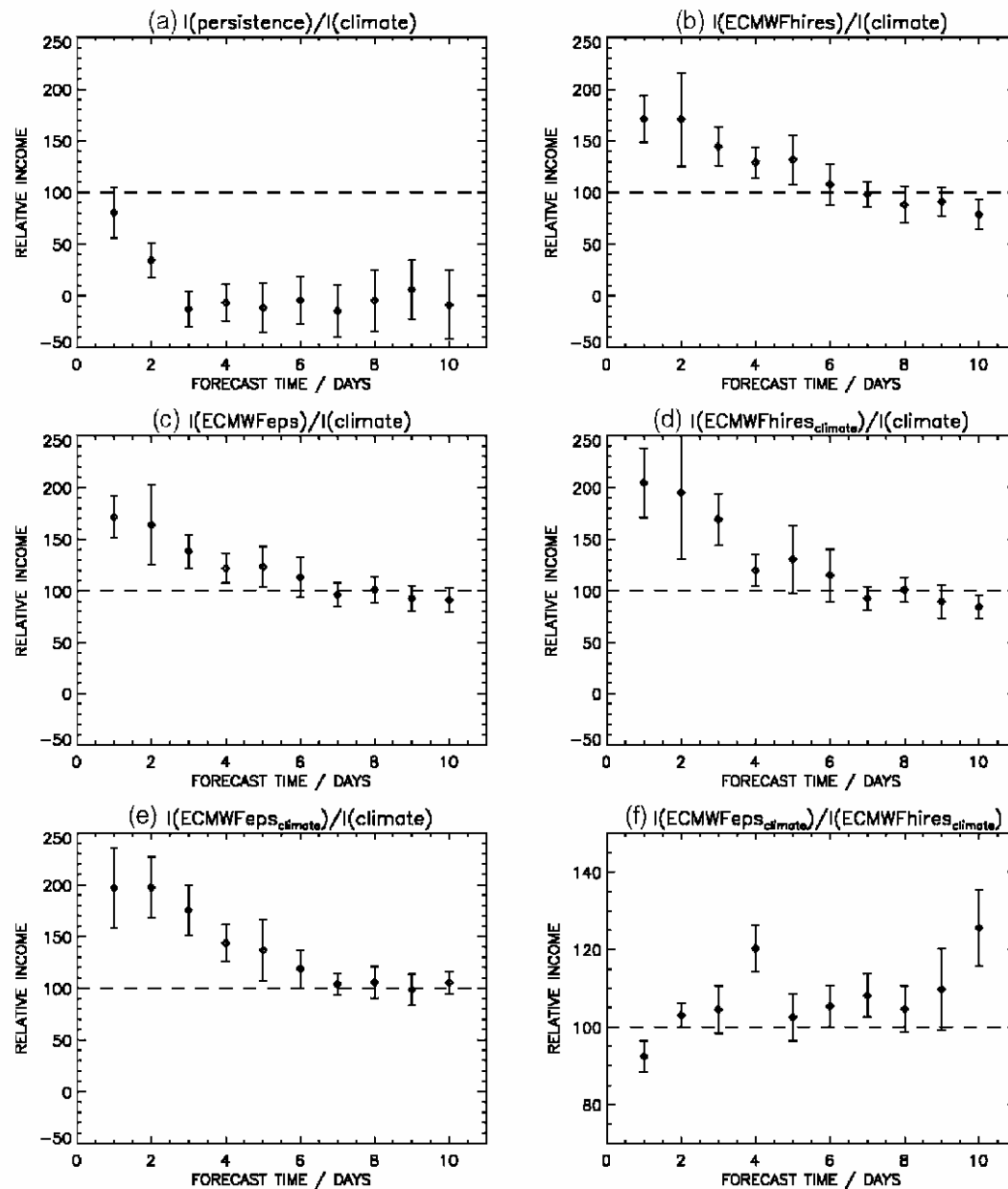


Fig. 7. Relative mean weekly net income as a function of forecast lead time for five different wind forecasting methods described in the text. Panels (a)–(e) are normalized with respect to the profits of a generator using the climatological wind model. Panel (f) compares the climate conditioned on the ensemble forecasts with the climate conditioned on the best-guess forecast. The error bars are the standard errors obtained by resampling with replacement [3].

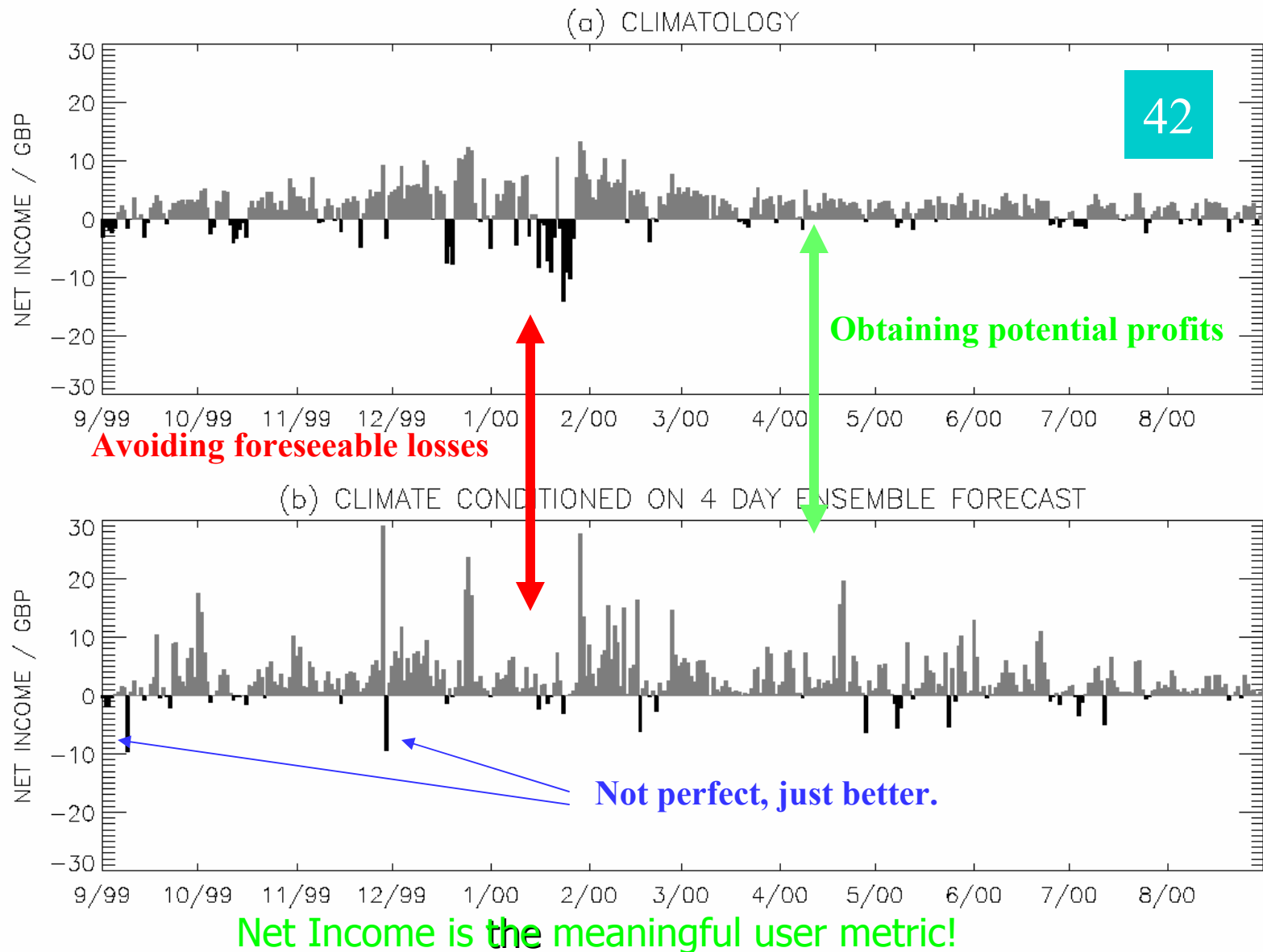
This is a comparison of relative income using strategies based on climatology, the hi-res, and the ensemble.

With bootstrap bars.

Bigger is better!

But what does this really mean?

Charlotte could have run a more profitable UK wind farm in the 1999 under NETA rules.





Could this work in practice?

Case Study: Electricity Demand

SCIENCE APPLICATIONS INTERNATIONAL CORPORATION

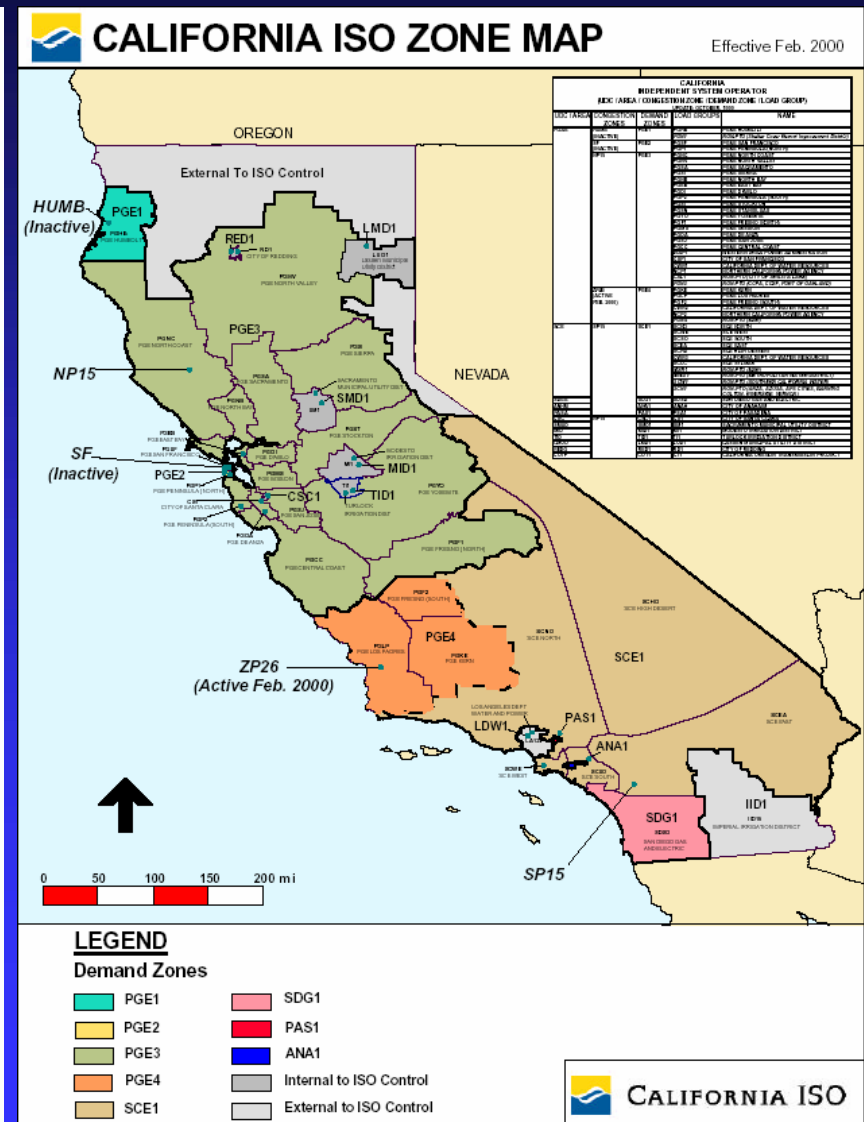
The Economic Benefit of Incorporating Weather and Climate Forecasts Into Western Energy Production Management.

Deliverable 2: Case Study Design and Scenario Report

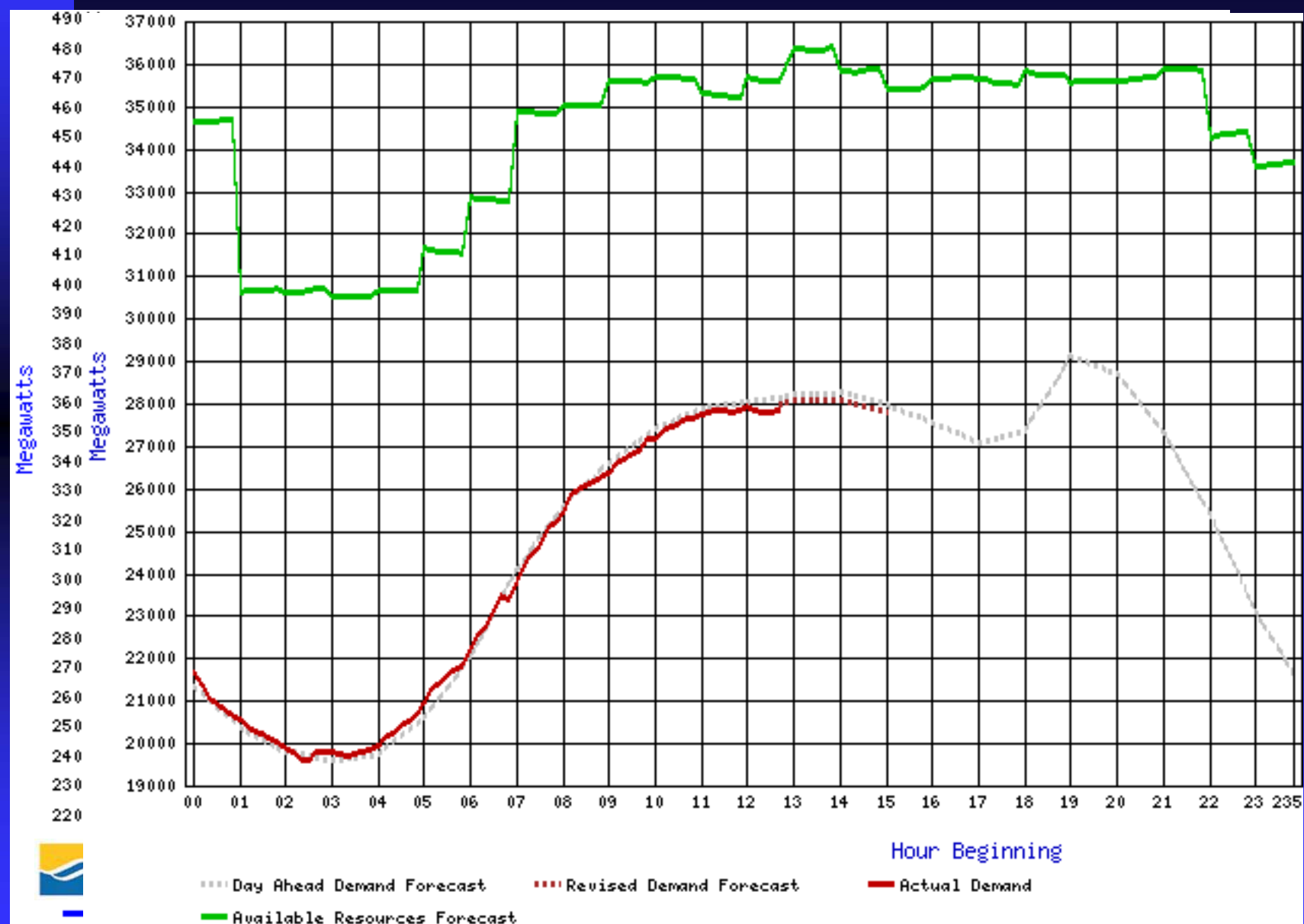
Scripps Institution of Oceanography (SIO)
LA Jolla, CA

December 31, 2003

SAIC
An Employee-Owned Company

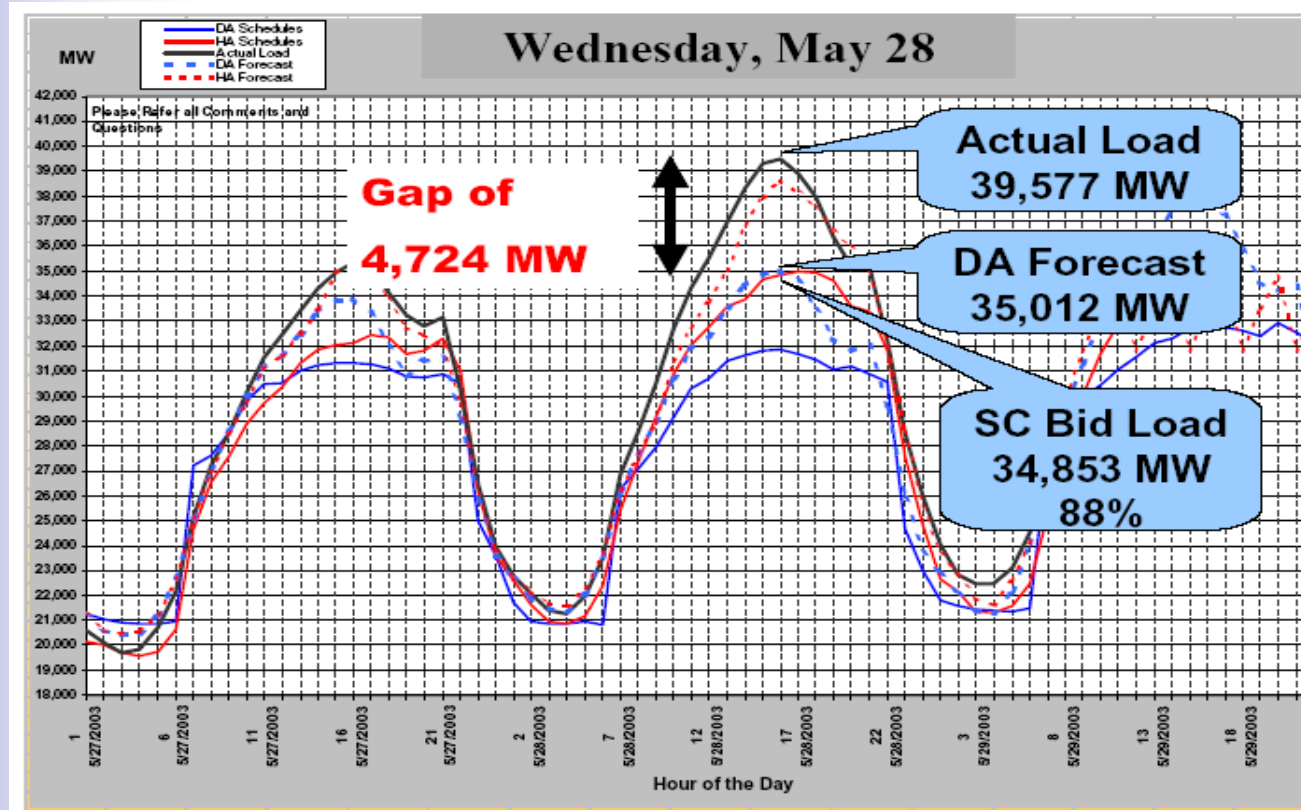


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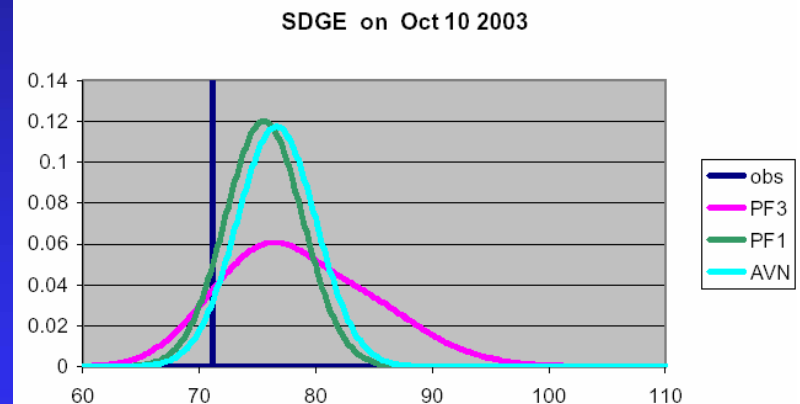
2 Feb 2006

- Case Study 1. Cal ISO Weather Forecast Error and Potential Cost





How should we interpret the forecast distribution?

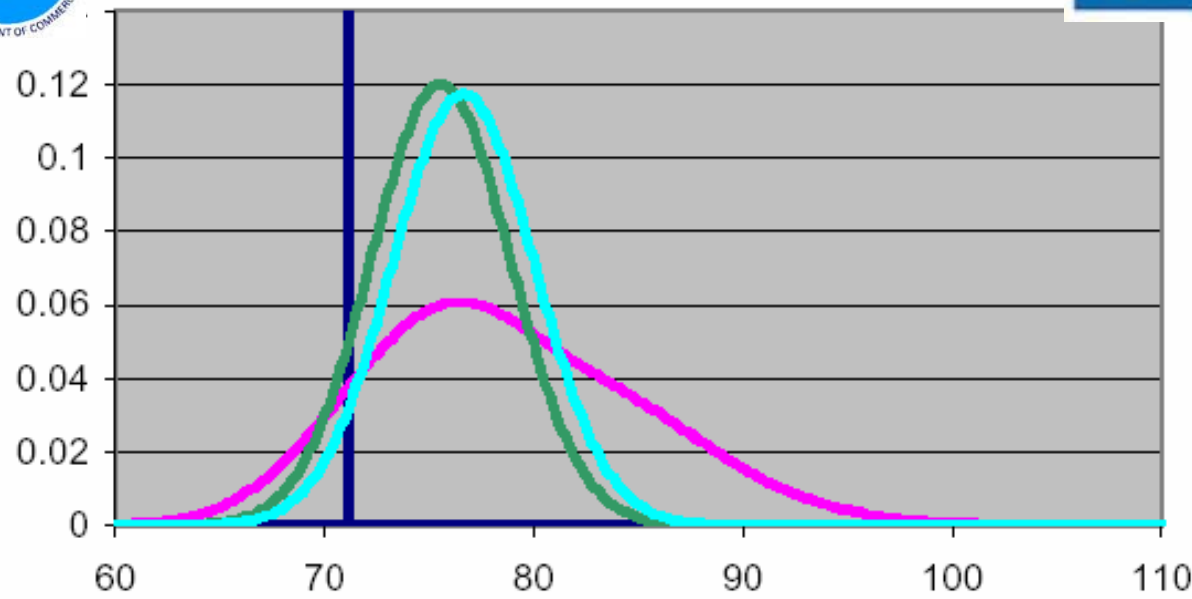




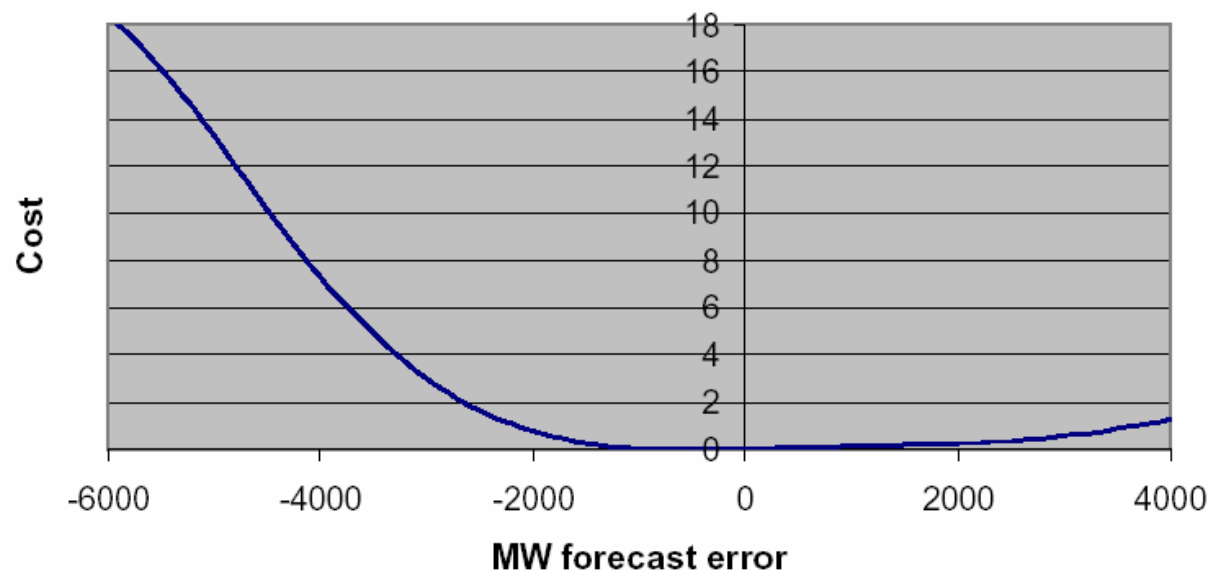
SDGE on Oct 10 2003



CALIFORNIA ISO



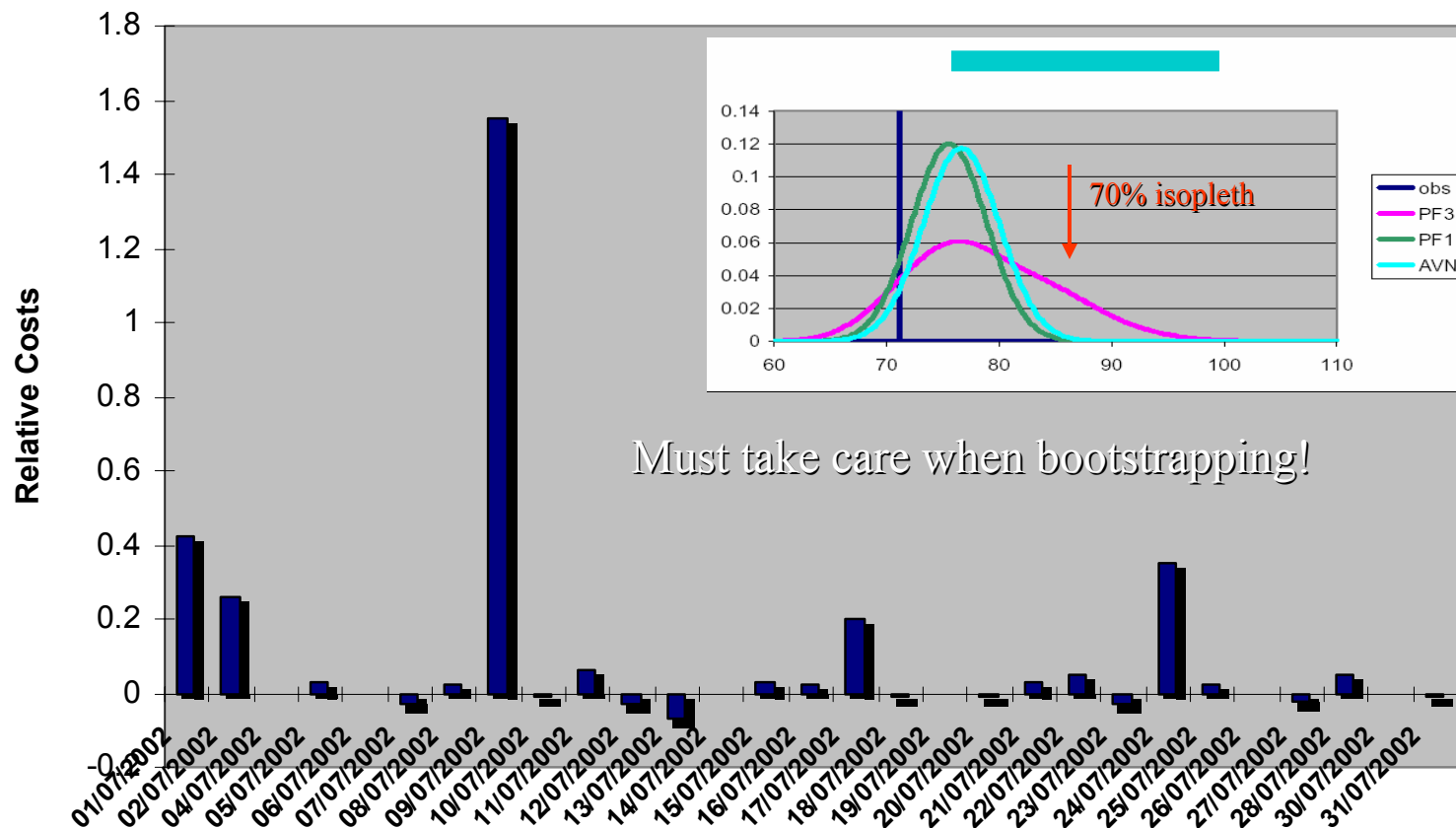
Cost of Over/Under Forecasting



If we really believed that PF3 was a probability forecast, then we would maximise our expected utility (and lose money!).

in 2003

In this case, interpreting the ensemble as a probability (and maximizing Expected Utility) is far from optimal: is it then rational to interpret the forecast distribution as a probability forecast?



From Smith, Altalo & Ziehmann (2004)

Figure 6: Relative costs of PF1 forecasts versus the Cal ISO surrogate forecasts for days in July 2002, a positive value represents a savings of using PF1. Note the significant savings on July 9th

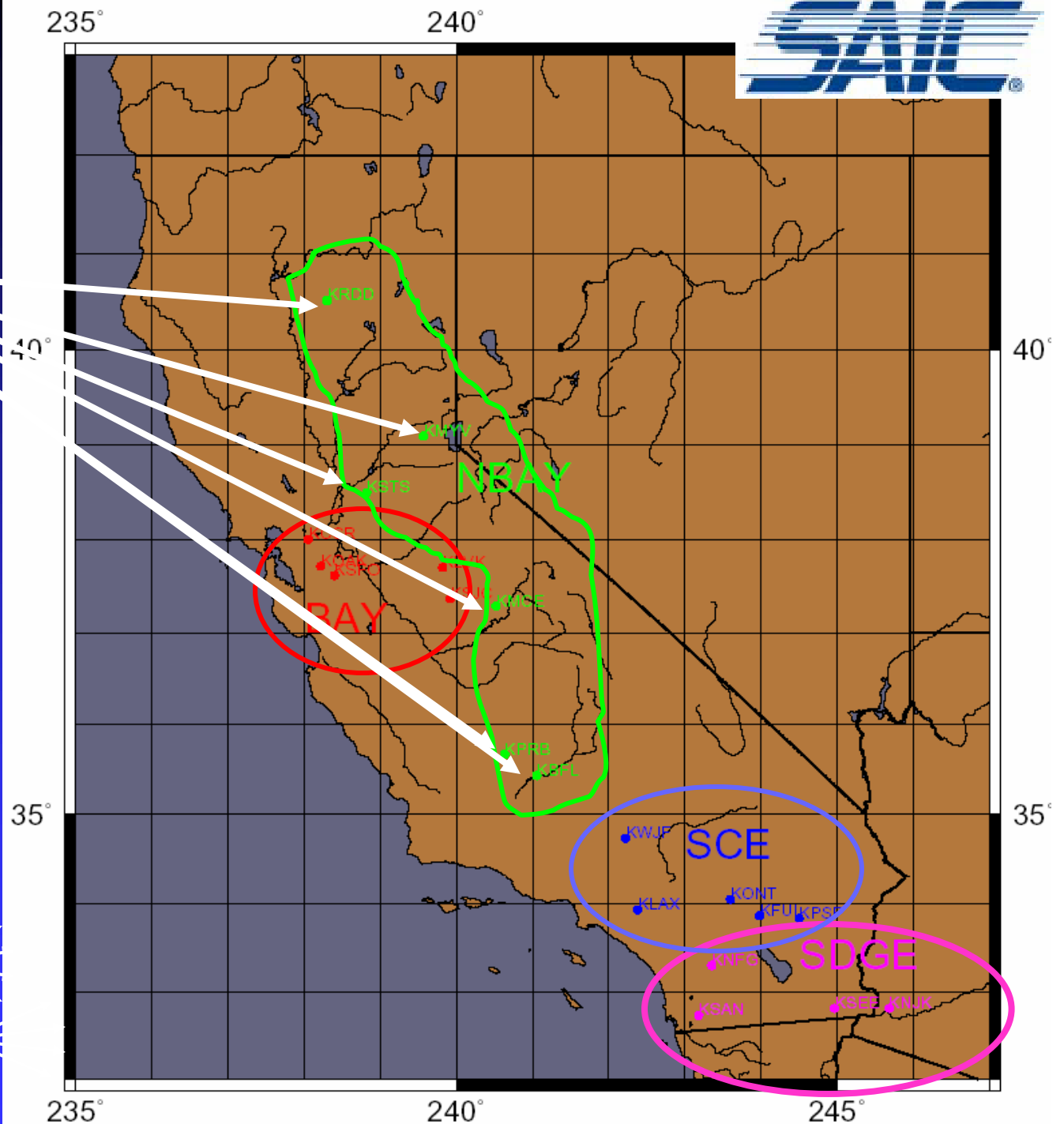
Every model provides a “package” for each station, there is more info than mere model temperature.

AVN_mos

ETA_mos

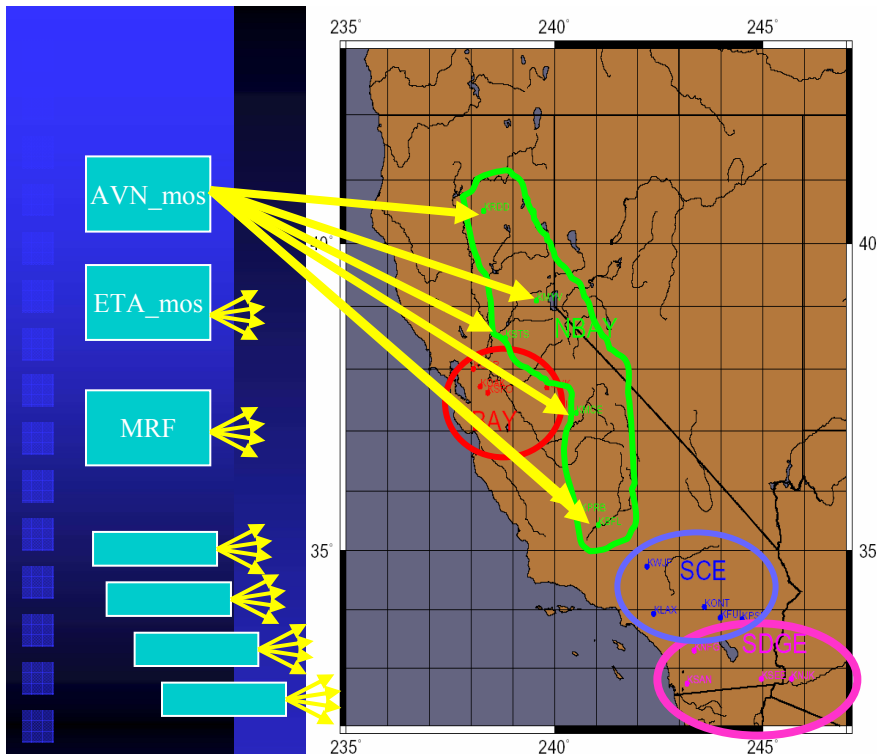
MRF

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From the station forecasts of each model,
make a region temperature forecast for each region

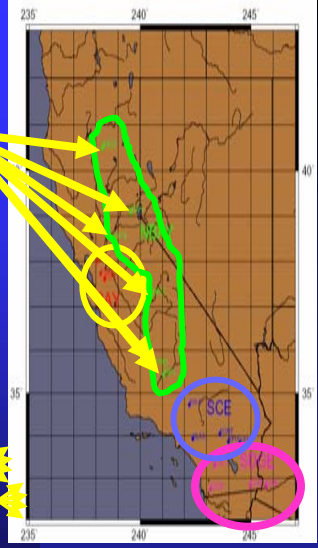
| | T | T | T | T |
|----------|-----|------|-----|------|
| AVN_mos: | BAY | NBAY | SCE | SDGE |
| ETA_mos: | BAY | NBAY | SCE | SDGE |
| MRF: | BAY | NBAY | SCE | SDGE |
| ... | BAY | NBAY | SCE | SDGE |



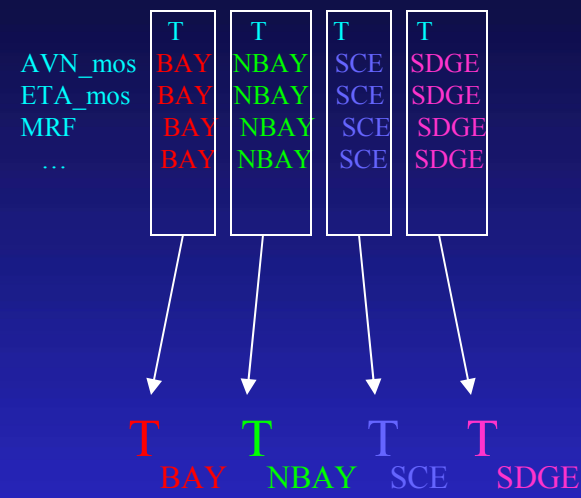
AVN_mos

ETA_mos

MRF



From the station forecasts of each model,
make a region temperature forecast for each region

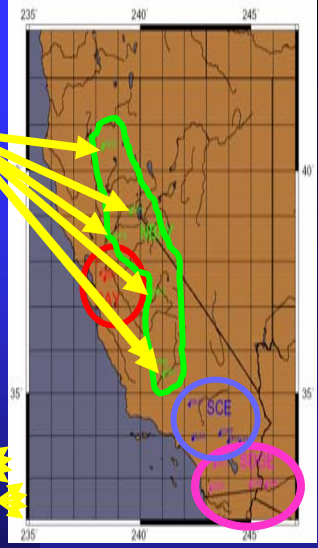


Combine the region temperature
forecasts from each model to a
regional forecast

AVN_mos

ETA_mos

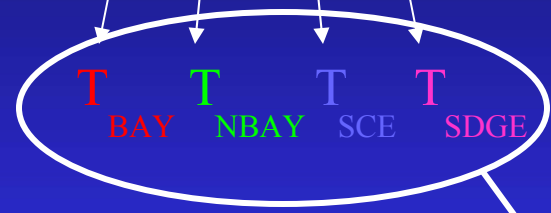
NRF



From the station forecasts of each model,
make a region temperature forecast for each region

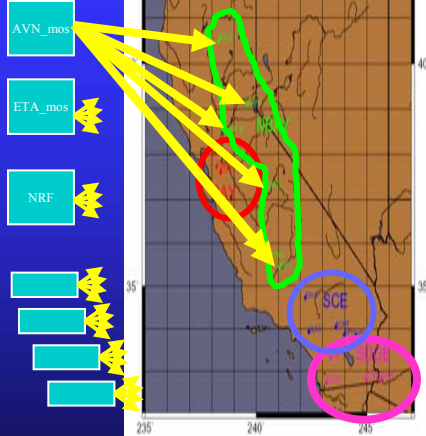
| | | | | |
|---------|-----|------|-----|------|
| AVN_mos | T | T | T | T |
| ETA_mos | BAY | NBAY | SCE | SDGE |
| MRF | BAY | NBAY | SCE | SDGE |
| ... | BAY | NBAY | SCE | SDGE |

Combine the region temperature
forecasts from each model to a
regional forecast



Compute demand from these regional
temperatures. (Cal ISO Demand Model)

MW



From the station forecasts of each model,
make a region temperature forecast for each region

| | | | | |
|---------|-----|------|-----|------|
| AVN_mos | T | T | T | T |
| ETA_mos | BAY | NBAY | SCE | SDGE |
| MRF | BAY | NBAY | SCE | SDGE |
| ... | BAY | NBAY | SCE | SDGE |

Now, combine the region
temperature forecasts from each
model to a regional forecast

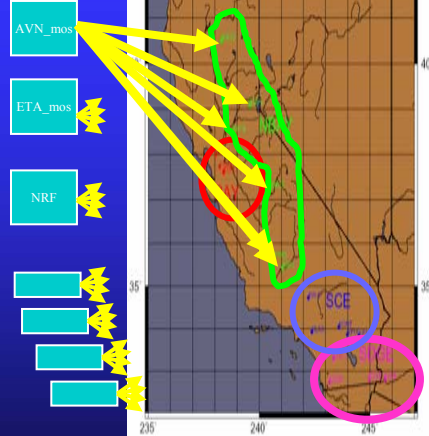


Compute forecast demand from these regional
temperatures. (Cal ISO Demand Model)

MW

Compute the expected cost of
this error in demand forecast
(Cal ISO Cost Function)

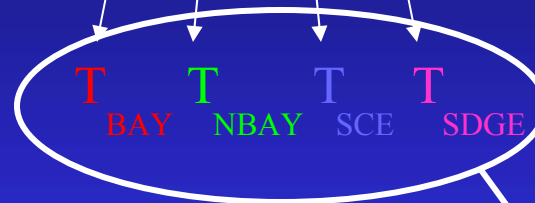
\$\$\$



From the station forecasts of each model,
make a region temperature forecast for each region

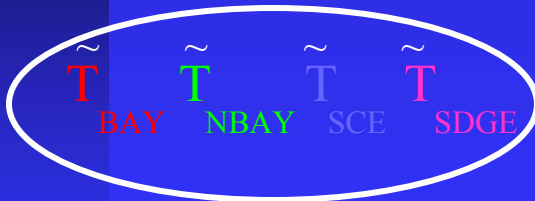
| | T BAY | T NBAY | T SCE | T SDGE |
|---------|----------|-----------|----------|-----------|
| AVN_mos | BAY | NBAY | SCE | SDGE |
| ETA_mos | BAY | NBAY | SCE | SDGE |
| MRF | BAY | NBAY | SCE | SDGE |
| ... | BAY | NBAY | SCE | SDGE |

Now, combine the region
temperature forecasts from each
model to a regional forecast



Compute forecast demand from these regional
temperatures. (Cal ISO Demand Model)

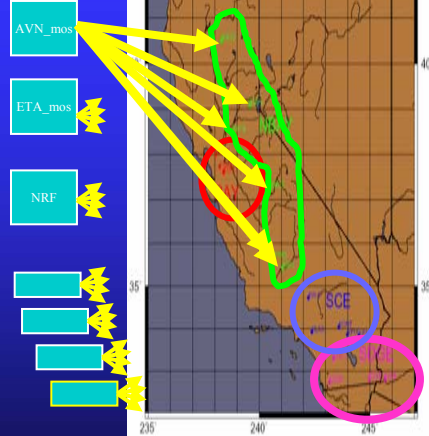
Take regional temperatures computed from the
observed station data



MW

Compute the expected cost of
this error in demand forecast
(Cal ISO Cost Function)

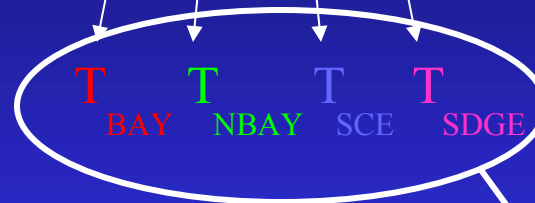
\$\$\$



From the station forecasts of each model,
make a region temperature forecast for each region

| | T BAY | T NBAY | T SCE | T SDGE |
|---------|----------|-----------|----------|-----------|
| AVN_mos | BAY | NBAY | SCE | SDGE |
| ETA_mos | BAY | NBAY | SCE | SDGE |
| MRF | BAY | NBAY | SCE | SDGE |
| ... | BAY | NBAY | SCE | SDGE |

Now, combine the region
temperature forecasts from each
model to a regional forecast



Compute forecast demand from these regional
temperatures. (Cal ISO Demand Model)

Take regional temperatures computed from the
observed station data



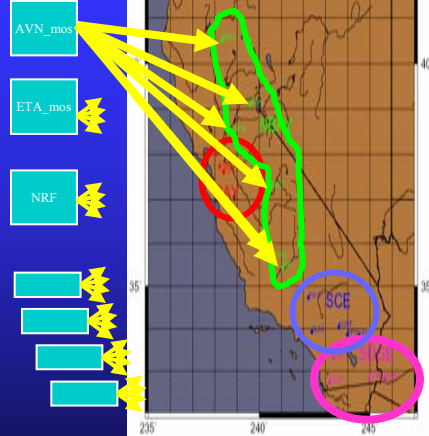
Compute "perfect weather info" demand.
(Cal ISO Demand Model)

MW

MW

Compute cost of error in
demand forecast
(Cal ISO Cost Function)

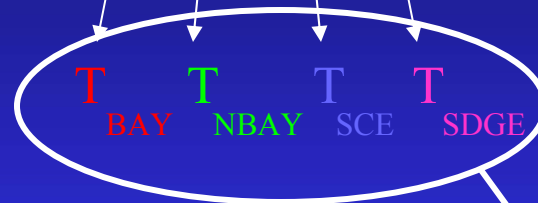
\$\$\$



From the station forecasts of each model,
make a region temperature forecast for each region

| | | | | |
|---------|-----|------|-----|------|
| AVN_mos | T | T | T | T |
| ETA_mos | BAY | NBAY | SCE | SDGE |
| MRF | BAY | NBAY | SCE | SDGE |
| ... | BAY | NBAY | SCE | SDGE |

Now, combine the region
temperature forecasts from each
model to a regional forecast



Compute forecast demand from these regional
temperatures. (Cal ISO Demand Model)

Take regional temperatures computed from the
observed station data



Compute "perfect weather info"
demand. (Cal ISO Demand Model)

MW

MW

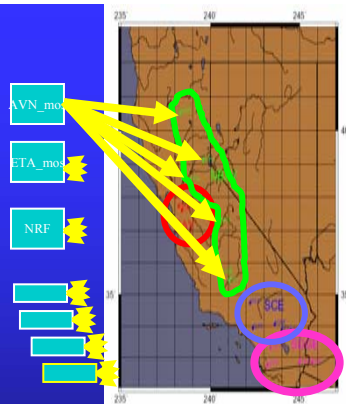
Compute weather forecast
related loss for this day.

(Cal ISO Cost Function)



For details see: Smith Ziehmman & Altalo (2004) Public Utilities Fortnightly (in preparation)

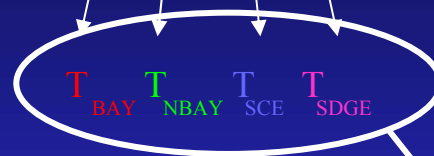
2 Feb 2006



From the station forecasts of each model,
make a region temperature forecast for each region

| | | | | |
|---------|-----|------|-----|------|
| AVN_mos | T | T | T | T |
| ETA_mos | BAY | NBAY | SCE | SDGE |
| NRF | BAY | NBAY | SCE | SDGE |
| ... | BAY | NBAY | SCE | SDGE |

Now, combine the region temperature
forecasts from each model to a regional
forecast



Compute forecast demand from these regional temperatures.
(Cal ISO Demand Model)

Take observed regional temperatures computed from the
observed station data



Compute "perfect weather info" demand.
(Cal ISO Demand Model)



(Cal ISO Cost Function)

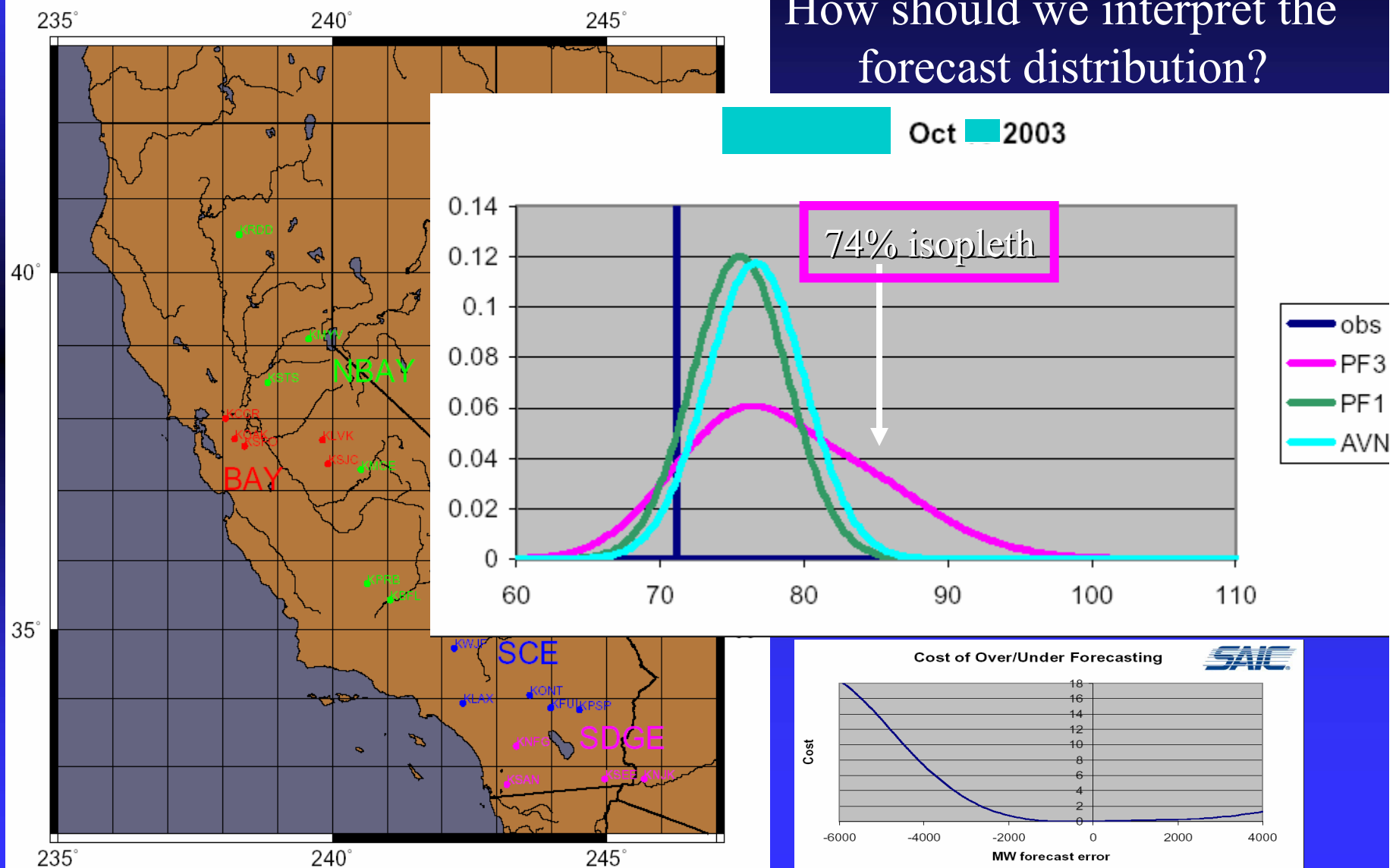
Compute weather forecast
related loss for this day.

All that remains now is to:

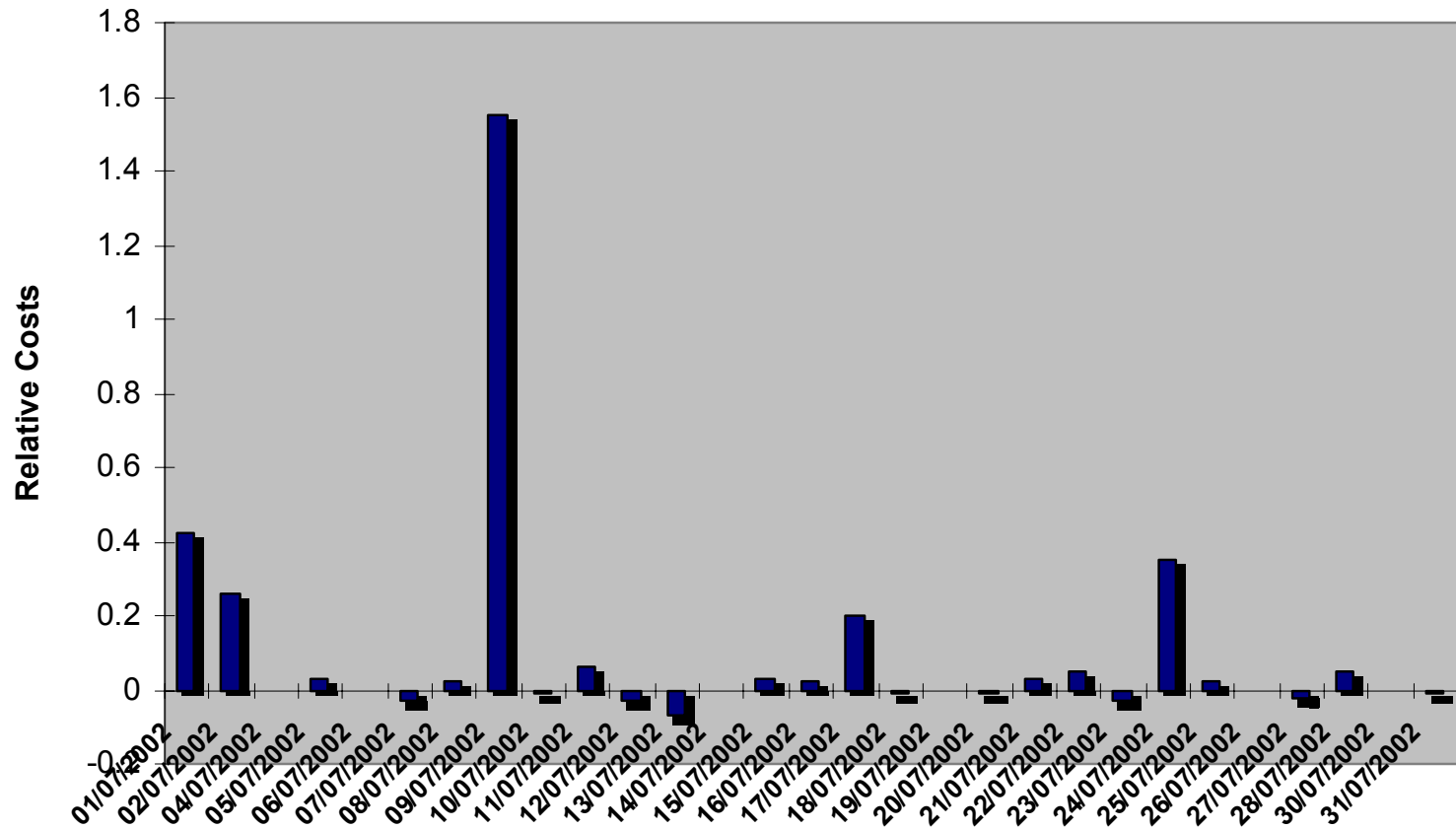
- repeat this on all days in the summer,
- introduce distribution kernels at the right place
 - use expected utility –or- isopleths?
- optimise and (cross-)validate the entire model (on a small data set)
- true out-of-sample testing.

4 regions, 20 stations, one ultimate demand forecast: generation.

How should we interpret the forecast distribution?



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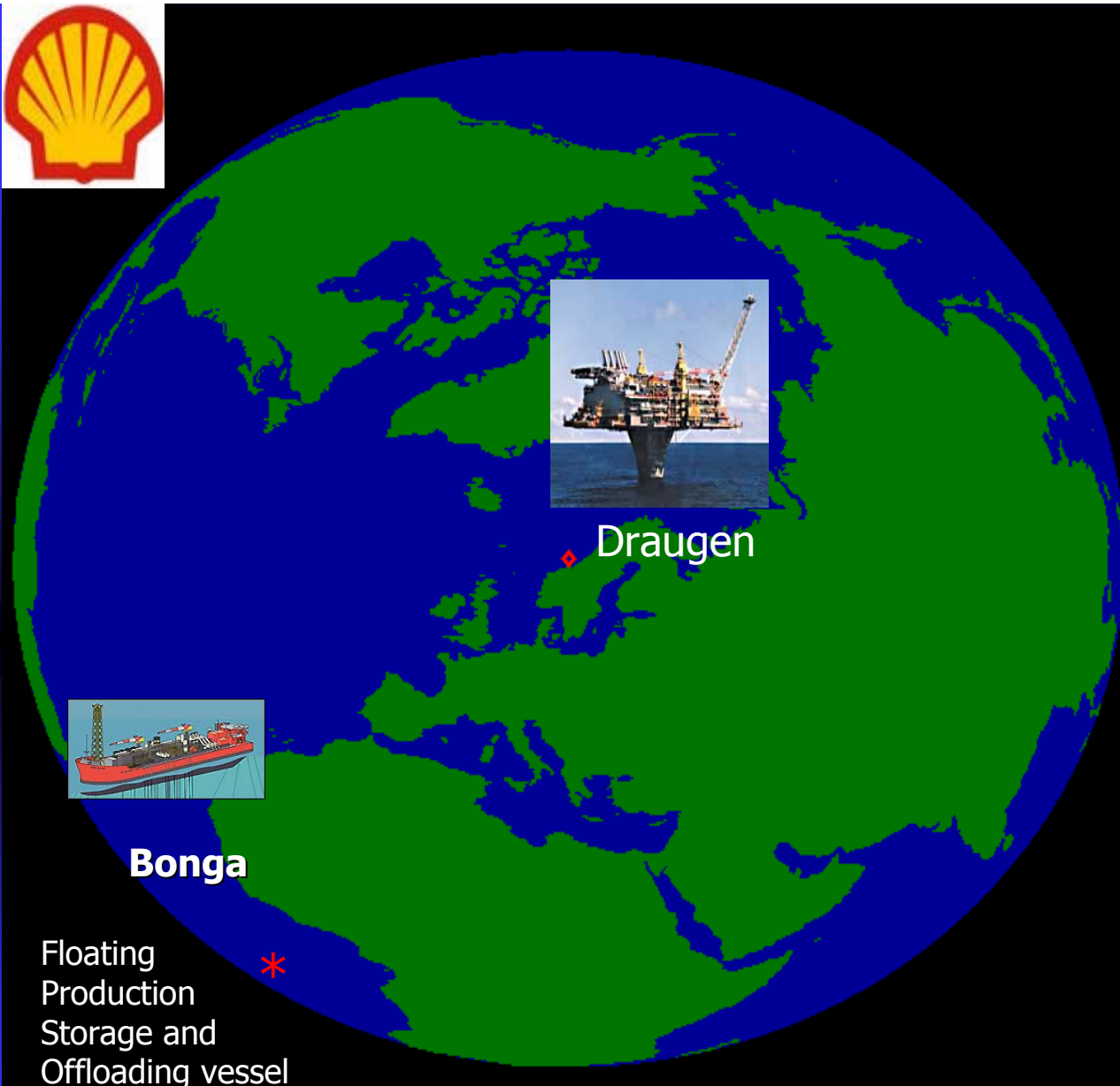


From Smith, Ziehmman & Altalo (2004)

Figure 6: Relative costs of PF1 forecasts versus the Cal ISO surrogate forecasts for days in July 2002, a positive value represents a savings of using PF1. Note the significant savings on July 9th.

Wave Safety-case Example

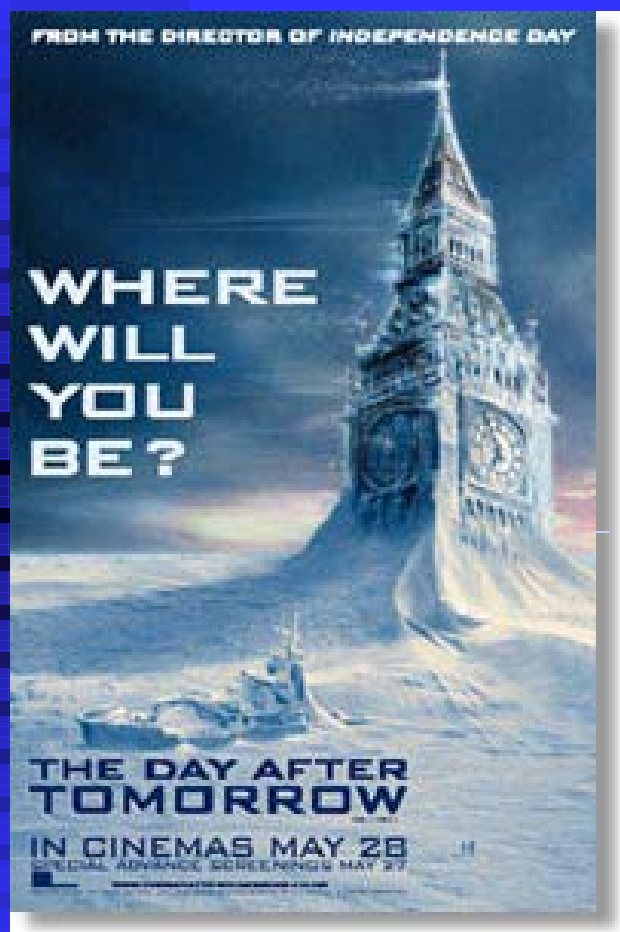
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Shell is incorporating these ideas into their safety forecasts.

2 Feb 2006

How big is a “low probability” to you?



Although we estimate that the chances of a 'Big Chill' in the next hundred years has a *low probability*, we *don't know how low*, and if it happened it would have a very high impact”

UKMO

| | |
|---------|----|
| 60% | 1 |
| 30%-50% | 12 |
| 10%-25% | 8 |
| 0% | 1 |



When is a probabilistic Forecast not a probability forecast?

?Whenever you'd not apply it as a probability forecast?

Numerate user's who have useful utility functions can detect that an operational forecast gives bad decision-support when used to maximise their expected utility!

On the other hand, the ECMWF ensemble is repeatedly found to provide valuable decision support in terms of identifying when a user's bespoke forecast is likely to be unusually poor.

The evaluations above considered ECMWF information as probability forecasts!

If the model is imperfect, there is no deep reason to do this!

What is a Probability Forecast?

Given:

- a complete, finite set of mutually exclusive events
- some symmetry assumptions



Then we can construct (empirically) useful probability forecasts.

What is a Probability Forecast?

These are good assumptions for rolling dice:



Not so good for rolling gold bars!

Probabilities assigned to random events are rather different than probabilities which reflect only our ignorance.

It is best to bet on (or advise regarding) only the former!

An “If I ruled the world” Example

Charlemagne (not her real name) rules the world, he is honestly concerned with the both the short run (social security) and the long run (the state of societies in 2100).

What should s/he do about carbon dioxide emissions?

GOTO LSE STUDENT SLIDES