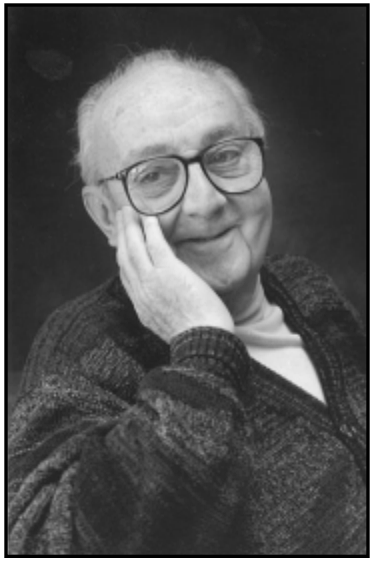
# Modeling Species and Ecosystem Responses

> Essentially, all models are wrong, but some are useful.
>
> \- George E.P. Box

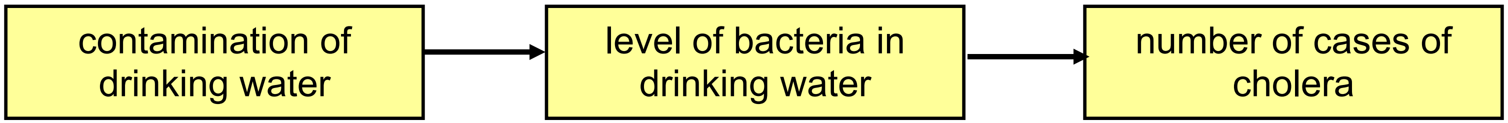


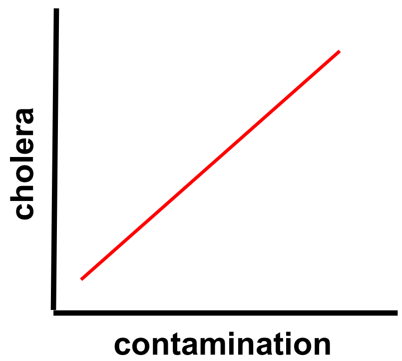
*Structural models* project state variable through time based on some understanding of the way factors affecting the variables interact with each other and respond to external forcings.

*Statistical models* project state variables through time using associations between jointly sampled measures of variables.

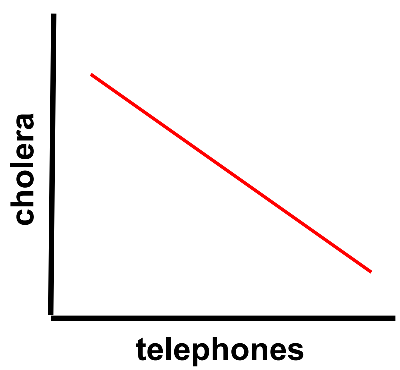
# Types of Models

## Structural Model for Cholera




Understanding the way the variables affecting cholera  operate allows us to generate a predicted increase in cholera as the level of contamination increases.




## Statistical Model for Cholera

Data were collected showing that as the number of telephones increased the incidence of cholera went down.

The statistical association can be used to project cholera levels given the number of telephones.

# Types of Climate Impact Models

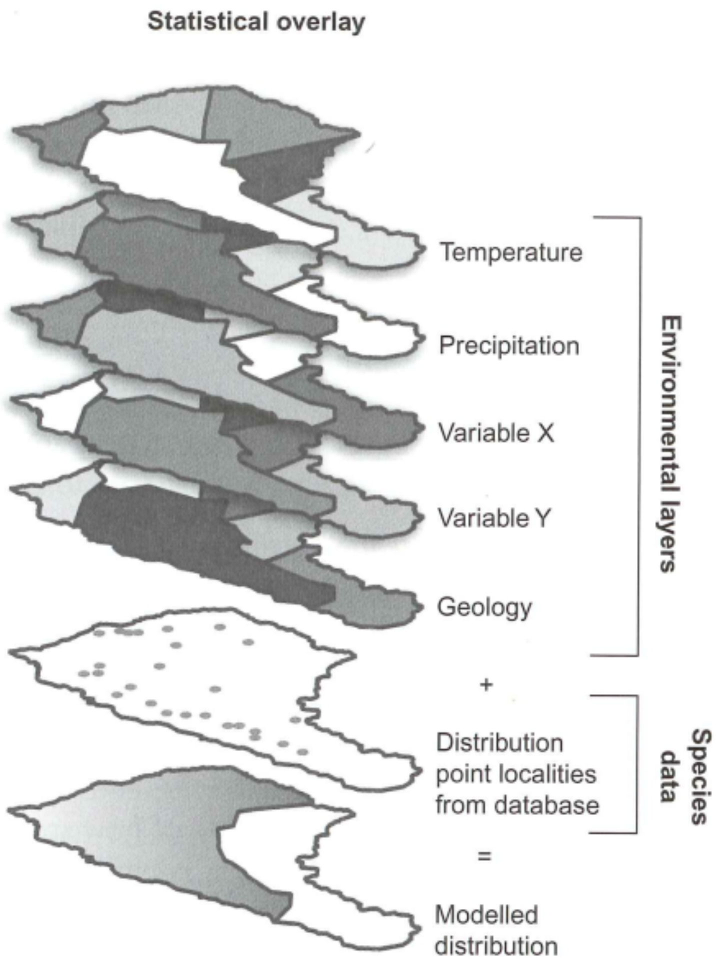
| Model | Domain | Spatial Resolution | Output Unit | Output Format | $CO_2$ |
|---|---|---|---|---|---|
| SDM | species range | 1 km | species | map | no |
| GAP | point | point | species | chart or map | no |
| DGVM | global / regional | 10 km | plant functional type | map | yes |

SDM – Species Distribution Models are statistically based.

GAP – Gap analysis models are hybrids.

DGVM – Dynamic Global Vegetation Models are structurally based.

# Species Distribution Models

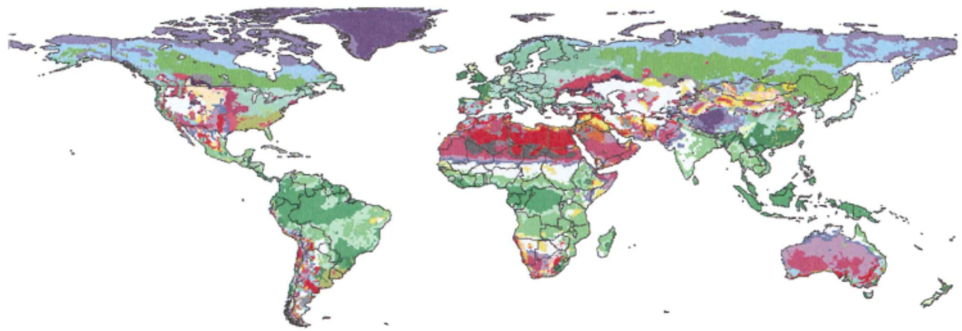


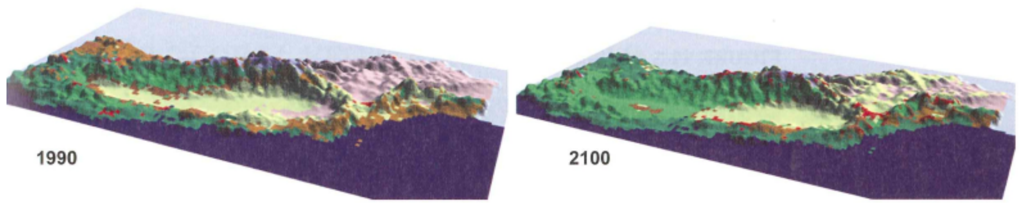

SDM's attempt to develop a statistical relationship between the geographic distribution of a set of environmental variables and the geographic distribution of a species.

They are often used in attempts to map the distribution of poorly known species.

Once the relationship between species and environmental variables is established, future distributions can be projected as a function of changes in the modeled environmental variables.

# Dynamic Global Vegetation Models





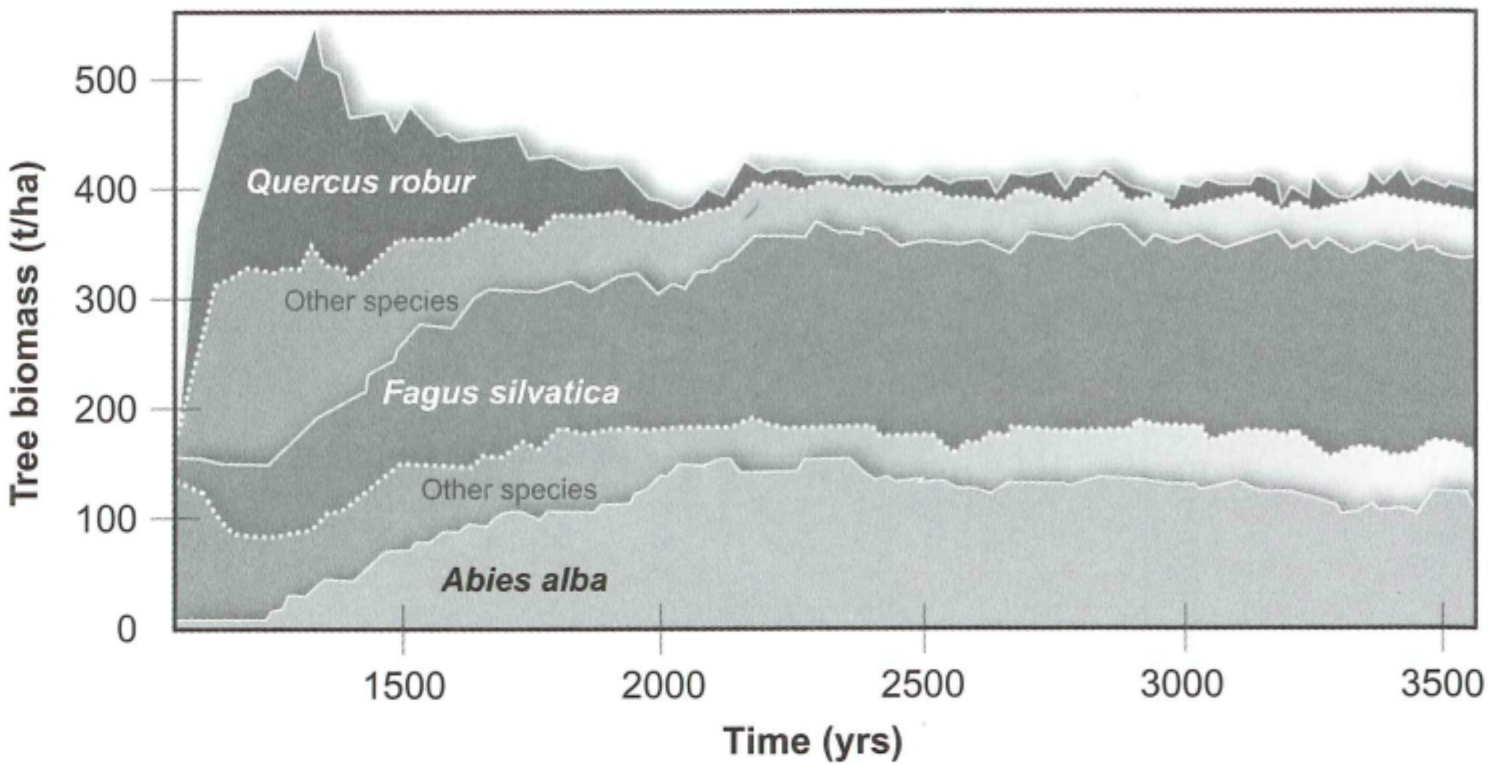

These models use first principle equations relating *plant functional types* to levels of $CO_2$ and climate via photosynthesis, respiration and geological processes.

Plant functional types are guilds of plants that respond in similar ways (e.g. grasses, shrubs, coniferous trees).

These models can be applied at global or regional scales and are based on processes occurring within geographic “cells” of appropriate size.

They are often linked with General Circulation Models to project the effect of climate change.

# GAP Models




GAP models are structurally based and simulate what happens in forest gaps after a tree fall.

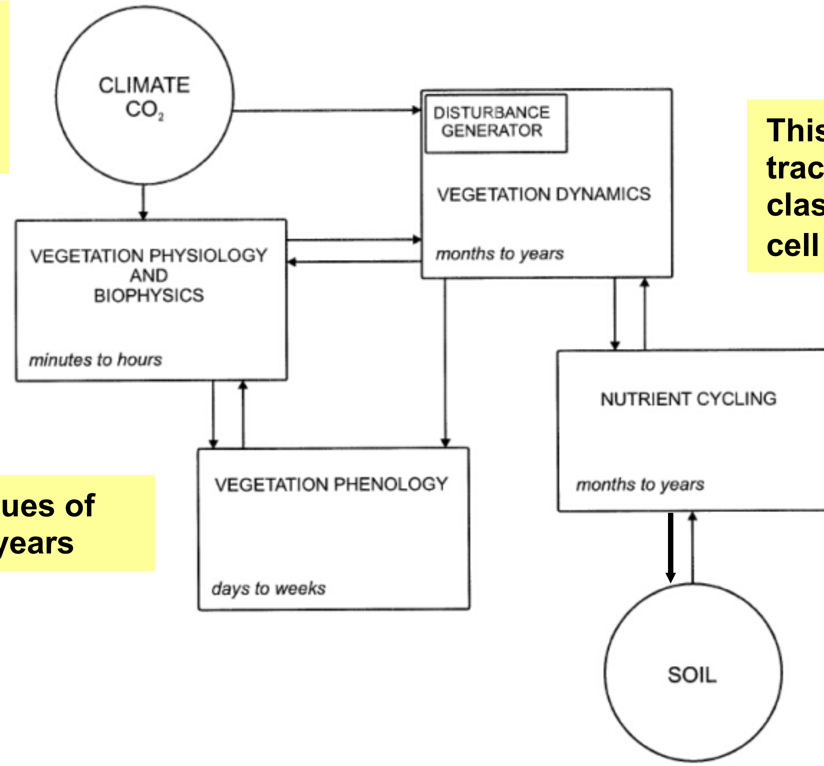
The parameters of the model are the relative growth and competitive rates of the various tree species that occur in a particular habitat under a given set of climate conditions.

# Dynamic Global Vegetation Models – General Structure

**Climate and $CO_2$ can each be held constant or varied using output from a GCM.**

**This generates and tracks NPP, NEP, biomass and respiration.**

**Addresses issues of timing within years**




**This generates and tracks the vegetation class occupying each cell at each time step.**

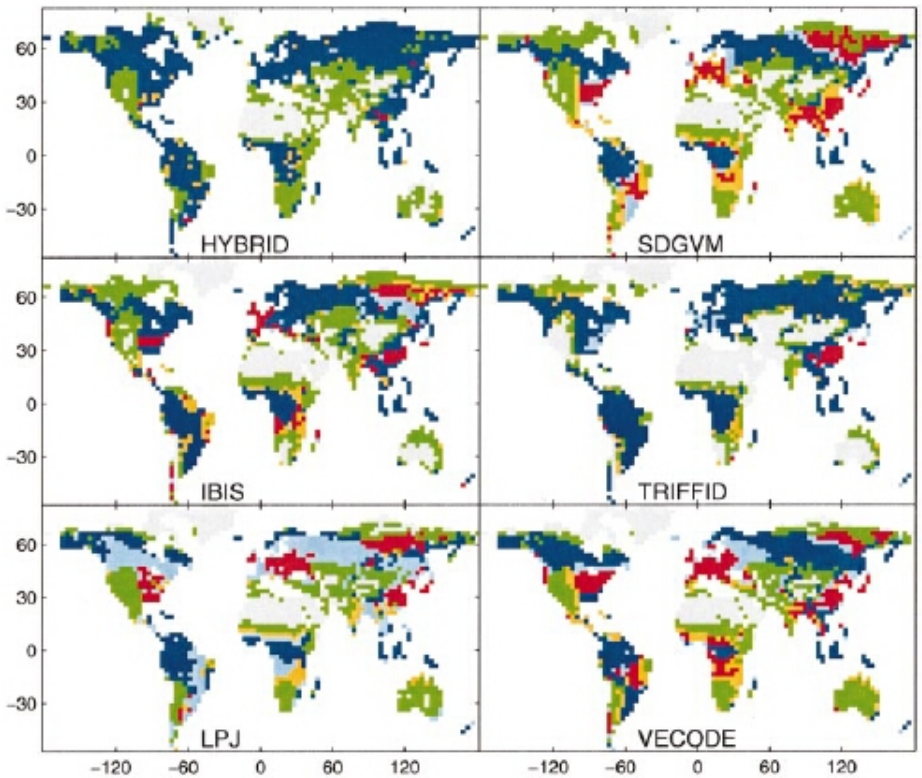
**Generates and monitors soil carbon and runoff**

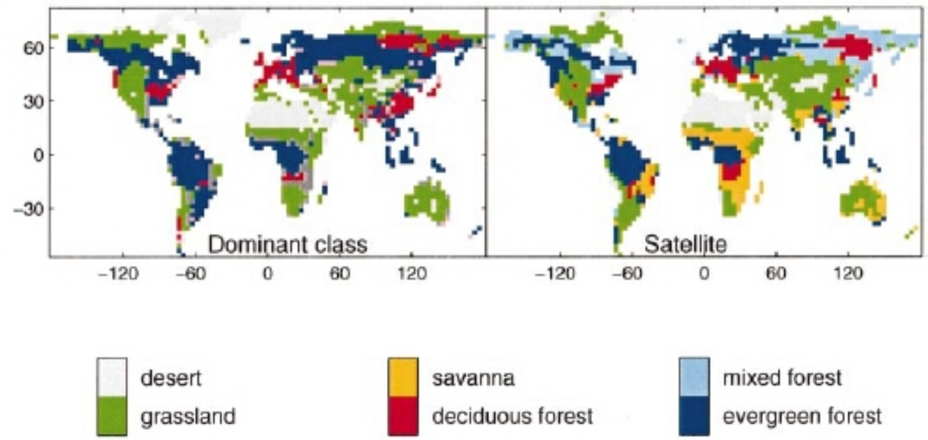
Different implementations use different equations and algorithms to compute the values of *state variables* such as NPP, biomass, vegetation class, etc. at each time step.

*Forcings*, such as $CO_2$ and Climate can be held constant or vary according to a times series generated by a linked *GCM*.

# Projecting the Present – Model Evaluation

**output of 6 models** **model average** **present status**




All models initiated with bare ground.

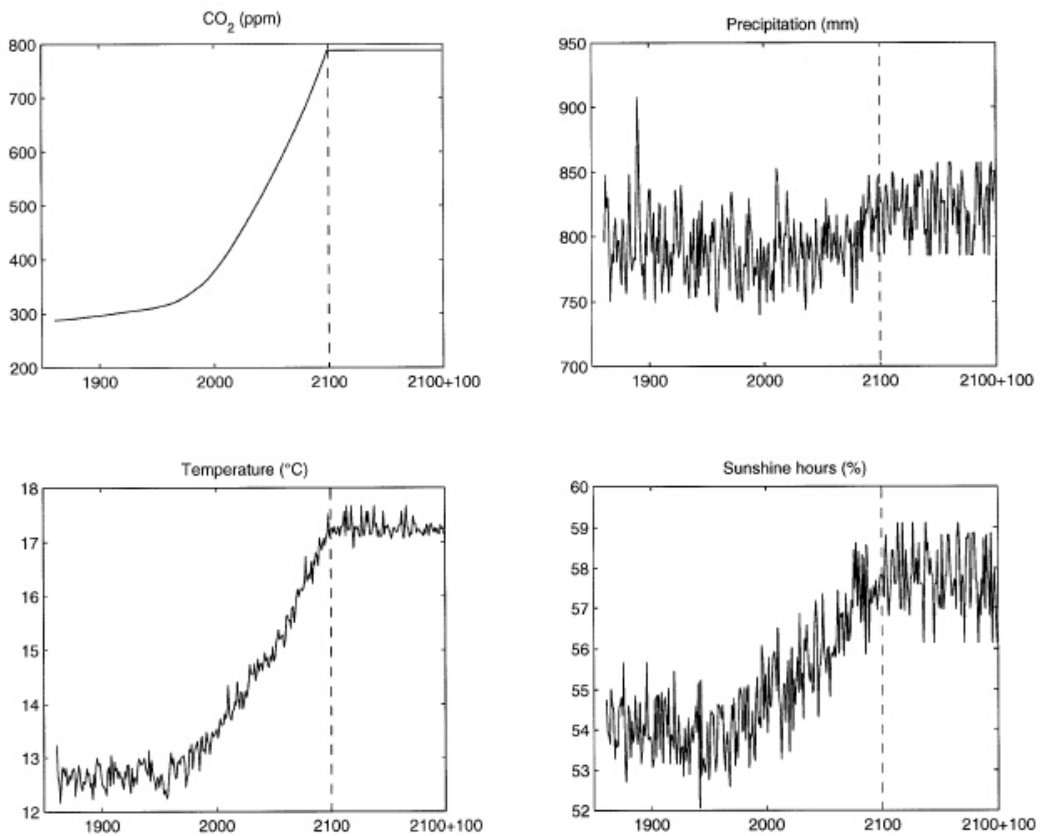
All models had constant $CO_2$ and Climate set at “pre-industrial age” values.

All models run to equilibrium.

There are differences in model output but those differences are not extreme: e.g. more mixed rather than evergreen forest.

They all overestimate forested habitat – failing to account for human activity.

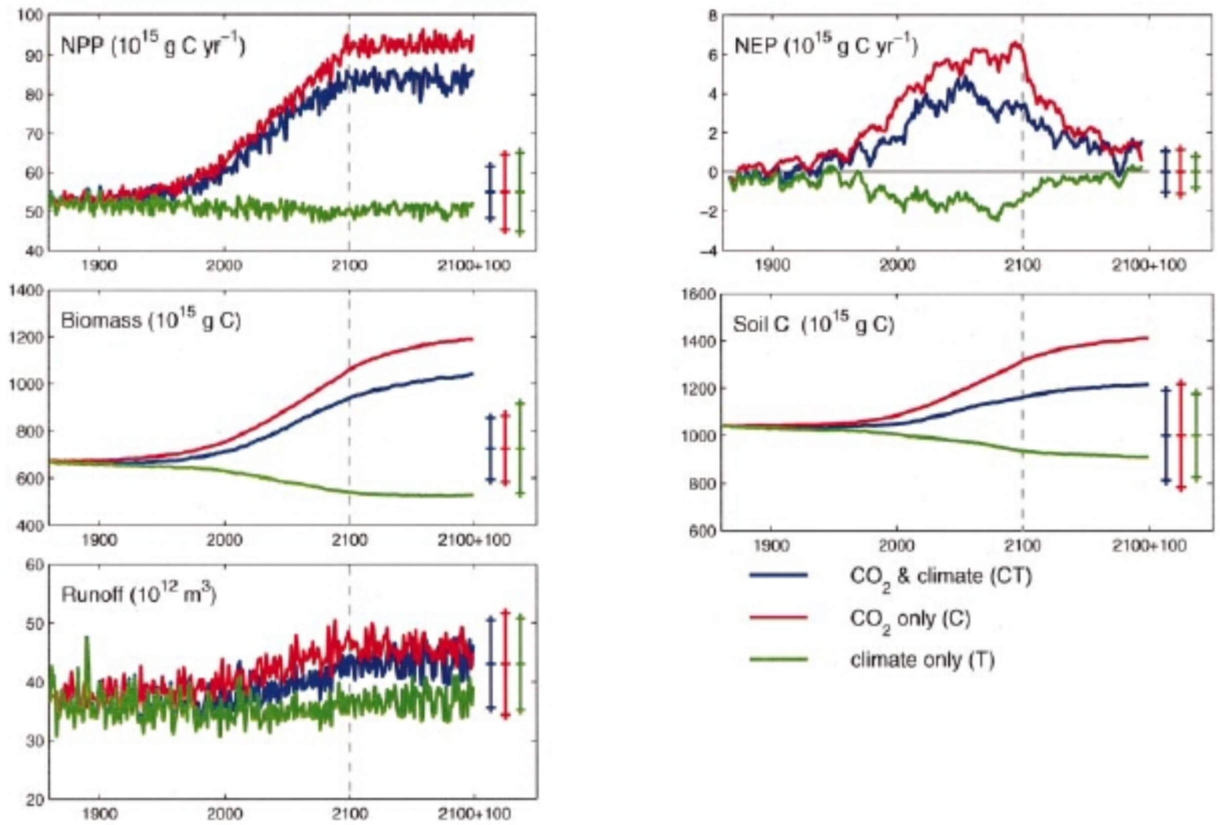
# Time Trends of CO2 and Climate Forcings




Output is from GCM HadCM2SUL with IPCC scenario IS92a.

Series runs from 1861 to 2100 and then holds values constant for 100 years to (2100+100).

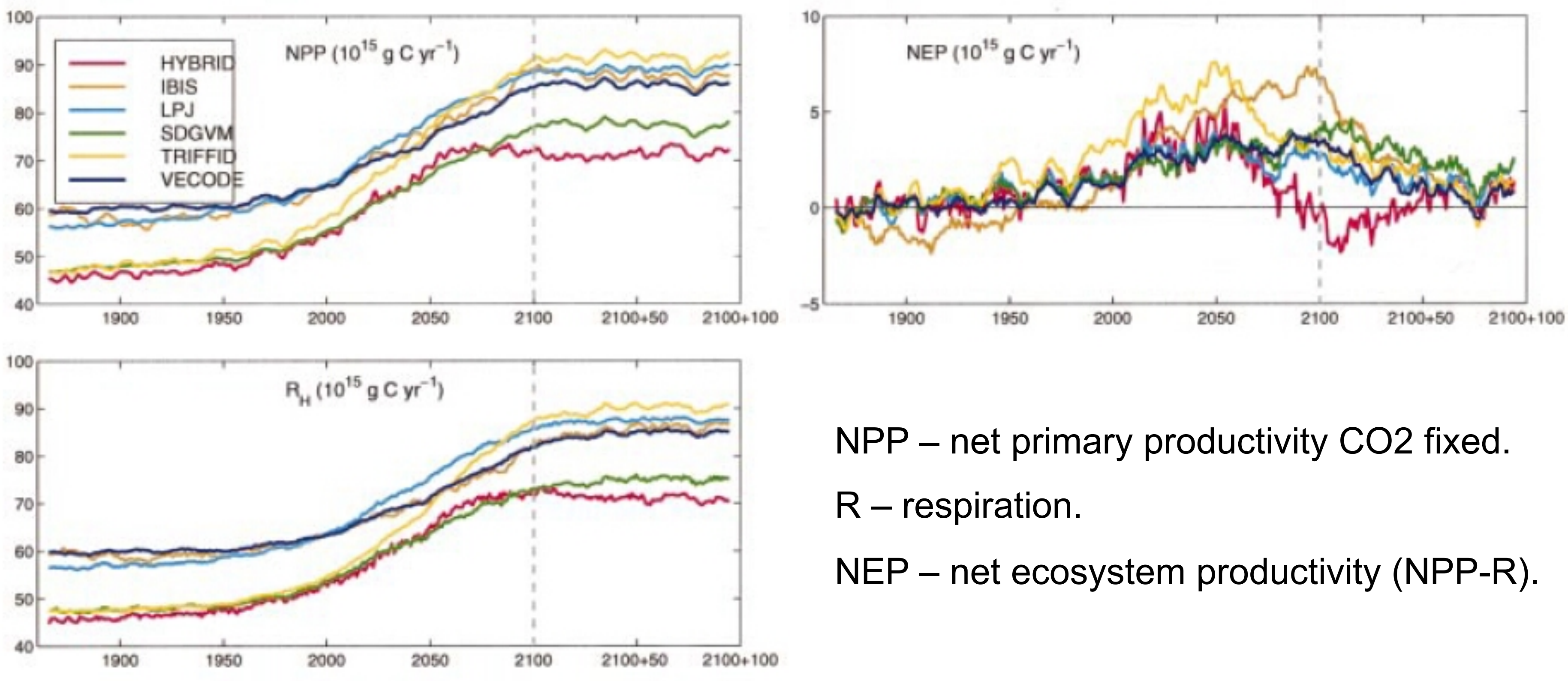
# State Variable Outputs of Model Averages under 3 Time Series




Realizations with changing $CO_2$ differ substantially from those with climate alone.

This indicates that $CO_2$ level rather than $CO_2$-induced temperature change will be the primary driver of climate change effects.

# Model Outputs for Ecosystem State Variables




NPP – net primary productivity CO2 fixed.

R – respiration.

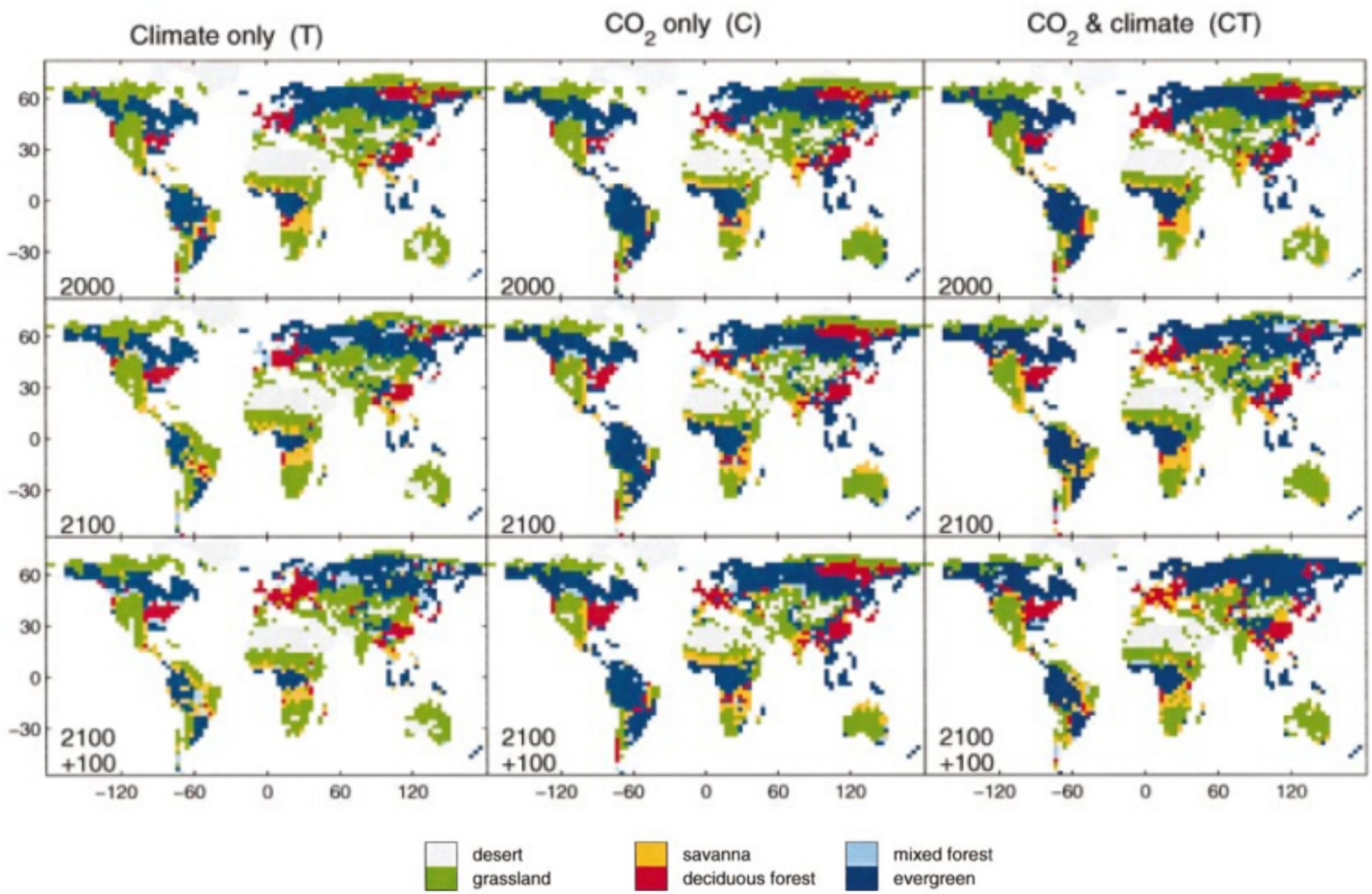
NEP – net ecosystem productivity (NPP-R).

Each model was run from bare earth under the changing $CO_2$ and climate time series.

Basic pattern of the models is the same.

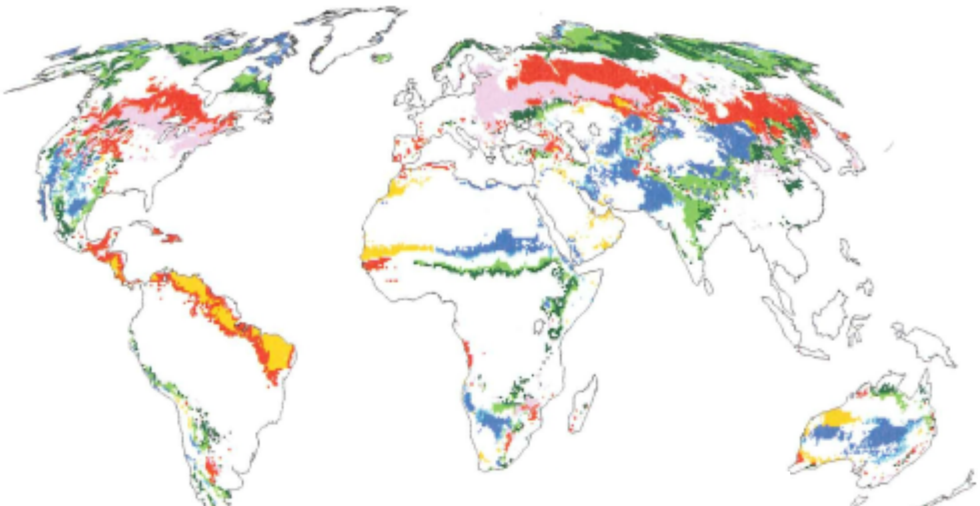
Careful examination shows a lag for all in R relative to NPP which results in NEP ultimately declining – an effect exacerbated when $CO_2$ and climate become constant in 2100.

# Vegetation State Outputs of Model Averages under 3 Time Series

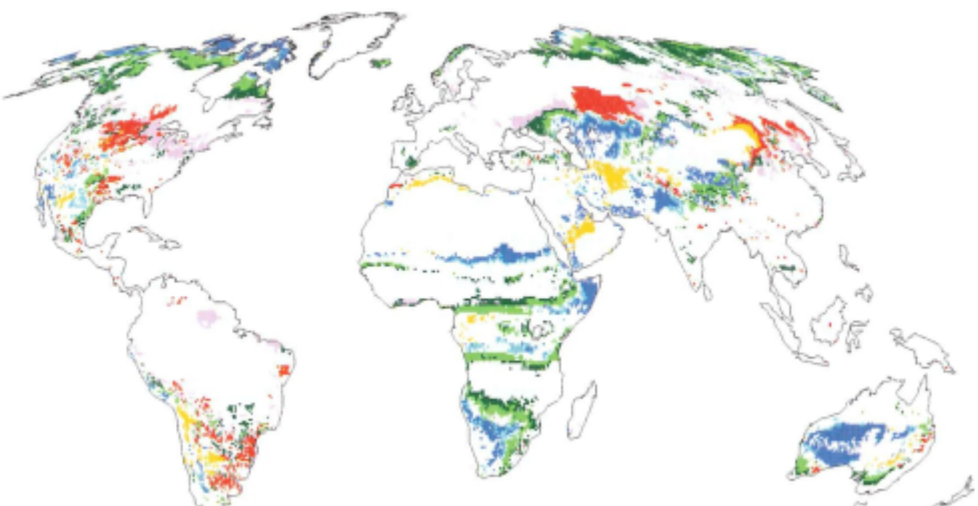



Clearly $CO_2$ has a much larger direct effect than through its indirect climate effect.

# DGVM under Different Climate Scenarios



scenario A1



scenario B2

Projected vegetation changes under high $CO_2$ emissions (IPCC scenario A1) and lower $CO_2$ emissions (IPCC scenario B2).

The maps depict change in various Plant Functional Types.

Higher emissions not only have a more extreme effect but the pattern is quite different (e.g. northeastern South America).

# Species Distribution Models

These models are sometimes referred to as “niche” or “envelope “ models as they attempt to define the set of habitat and environmental conditions consistent.

The standard approach uses values for one or more climate variable at points where the species was observed.

Assume a species has been observed at 50 locations and the lowest mean temperature of the 50 sites was 20°C and the highest was 30°C.

The temperature “envelope” for the species is thus 20-30°C and the SDM would project that the species should be found at any location within that envelope.

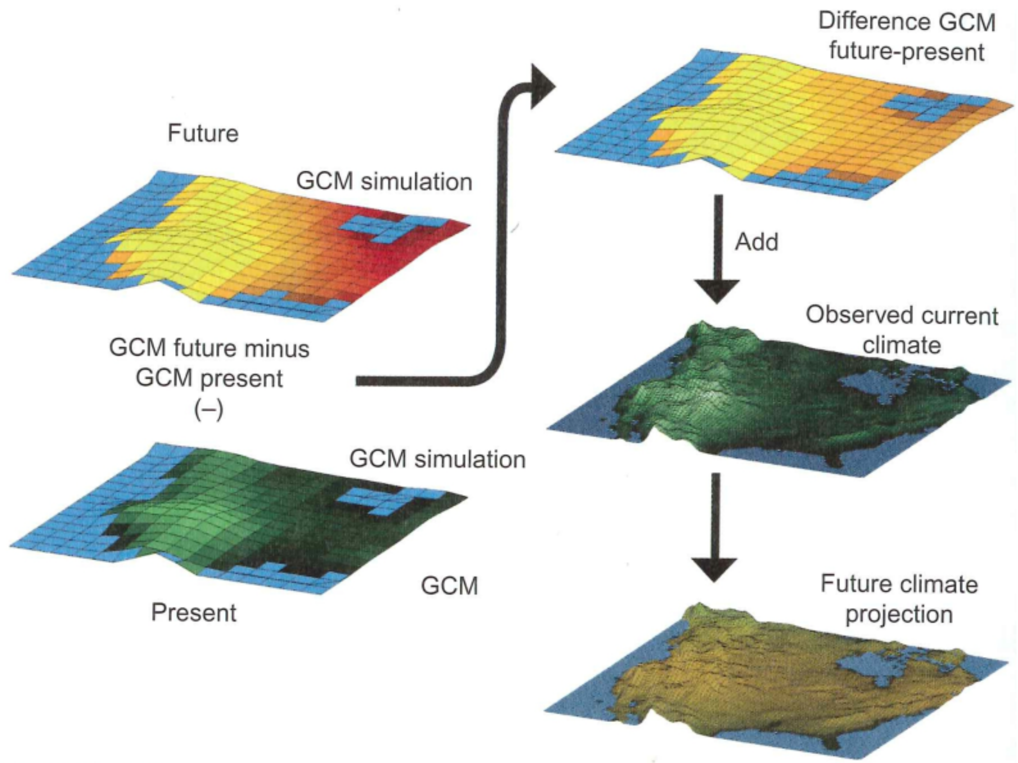
This would likely overestimate the geographic range since there are likely other variables (e.g. moisture) that are important.

The more variables that are included the more realistic the SDM becomes.

There is one problem with this to which we will return later – the sampling in this case is biased.

It would be more correct to assess 50 (or more) sites and ask the questions: *Is the species here?* and *What is the temperature?*

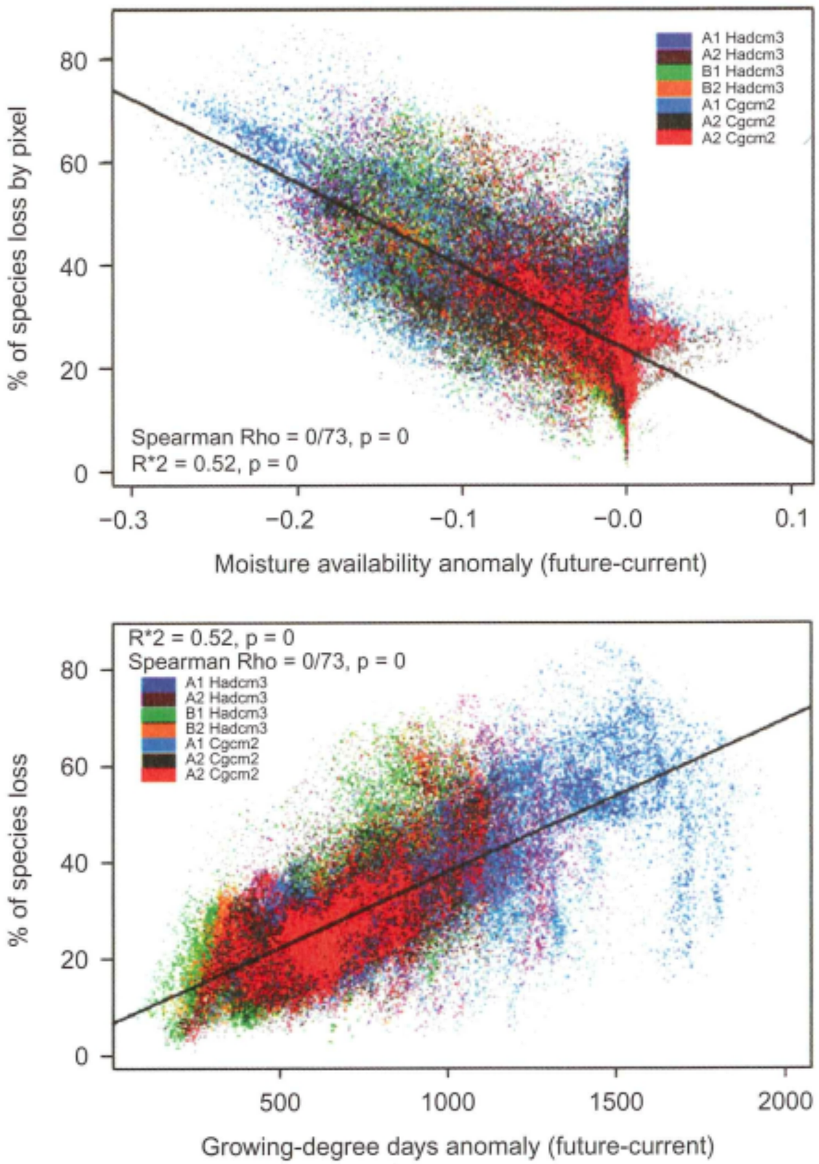
# SDM – Future Climatology




Most SDM's use a spatial scale finer than GCM's can produce so a differential is used.

The differential generated from GCM's produces a more global trend that is used to "project" a finer scale climate scenario.

# SDM – Relation to Climate Variables

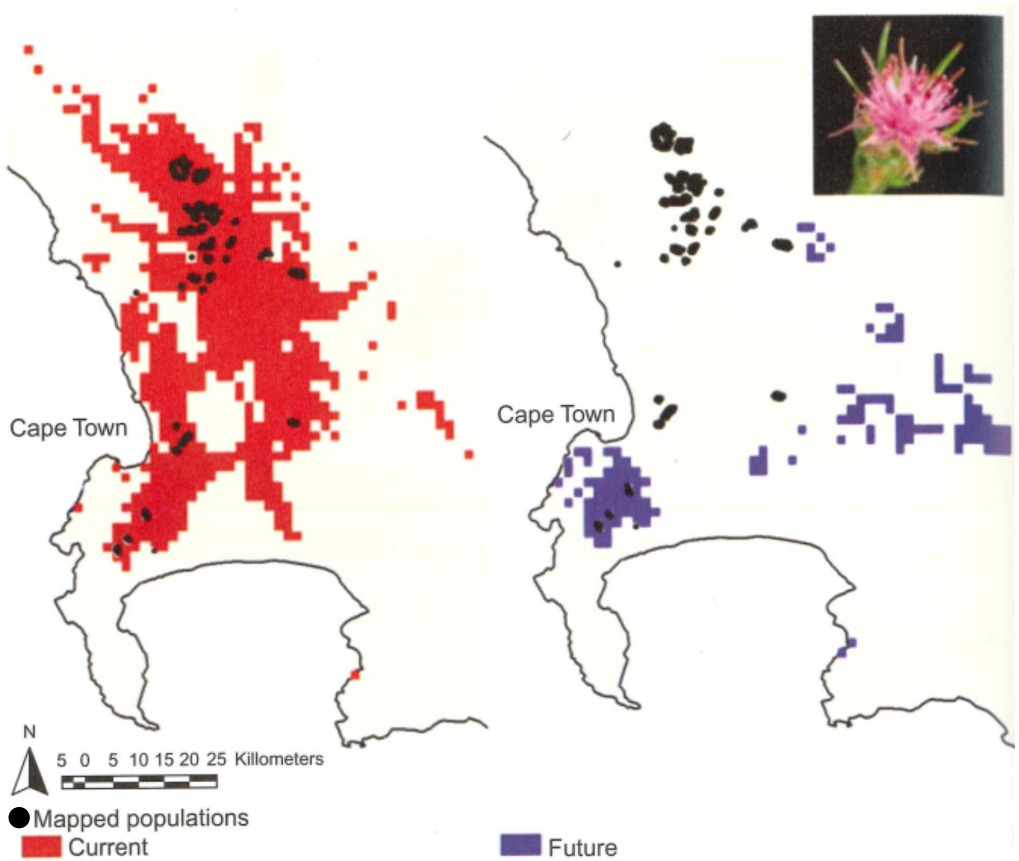



Statistical associations are established for the presence of a species (and perhaps the species' abundance) and the climate variables of interest using current limits of the climate variables.

Changes in presence (or abundance) are then projected for values of the climate variables that are anticipated under climate change.

These projections are *extrapolations* that assume the relationship that exists for known levels of the climate variables hold for extralimital levels of those variables.

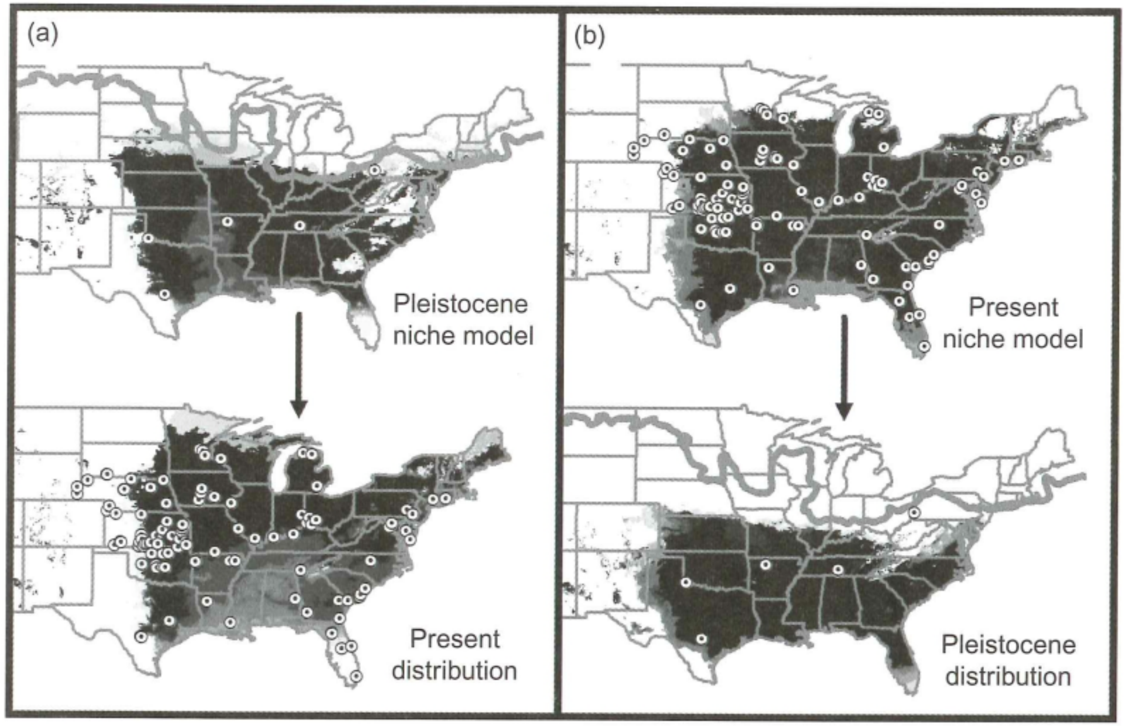
# SDM – Integration and Output




The left figure shows the projected current envelope of *Protea cyneroides* based on SDM of the sampled points and current climate.

The right figure depicts the projected envelope under climate change.

# SDM – Foreword and Backward Projection

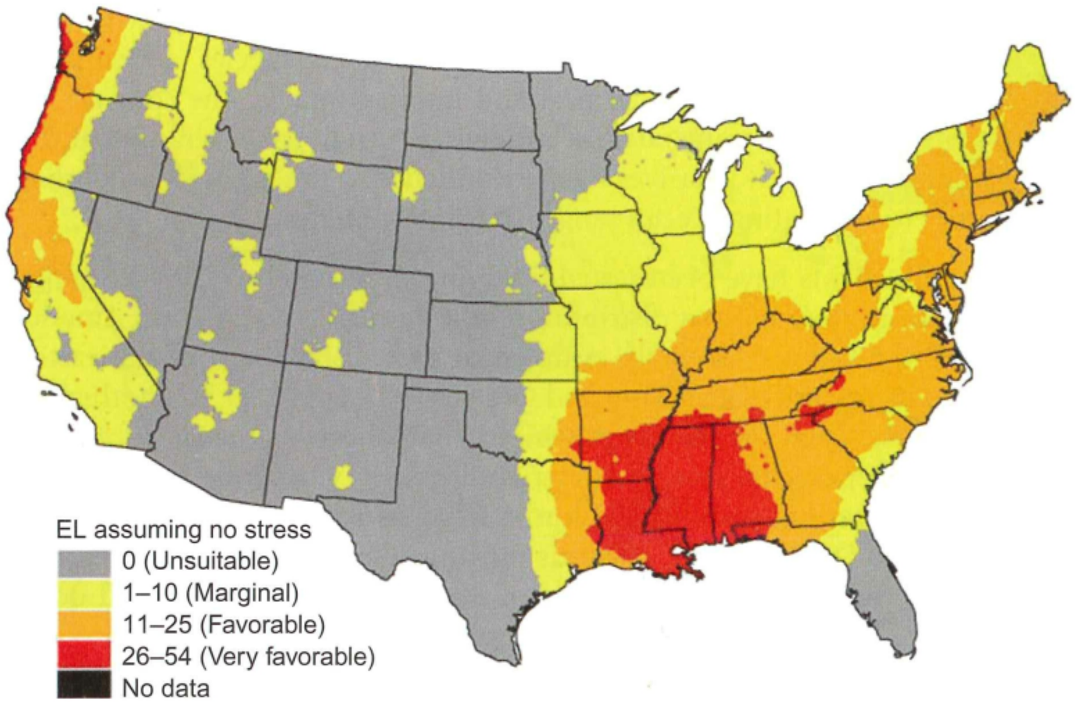



Given sufficient spatial information on species' presence and climate, SDM's can be used to project current distributions from prehistoric data.

Similarly, prehistoric distributions can be projected from current data.

The latter can actually be tested by searching for fossils in projected areas of occurrence – a form of *model validation*.

# SDM – Shorter Term Pest Management

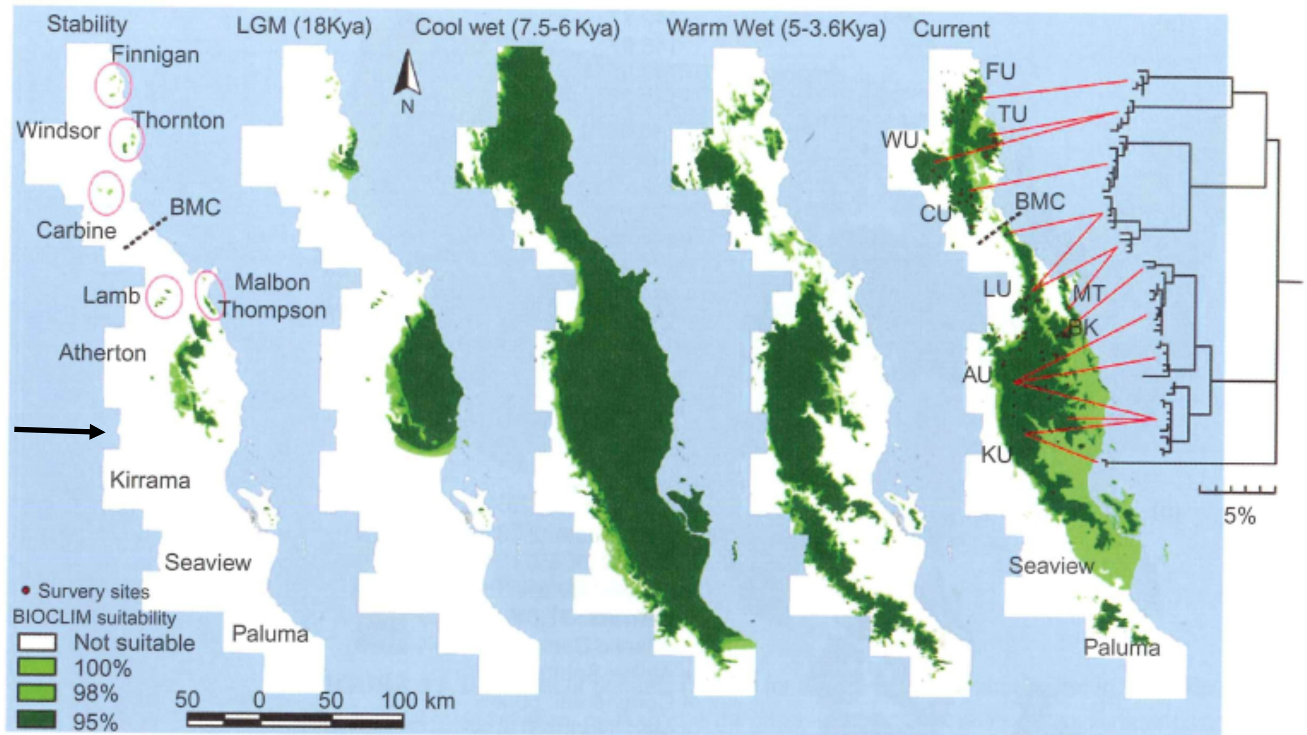



Increasingly, SDM's are linking presence of pest species and associated climate and habitat variables to project areas of potential outbreak.

early preparation and detection can often prevent catastrophic invasions.

# SDM – Biome Modeling

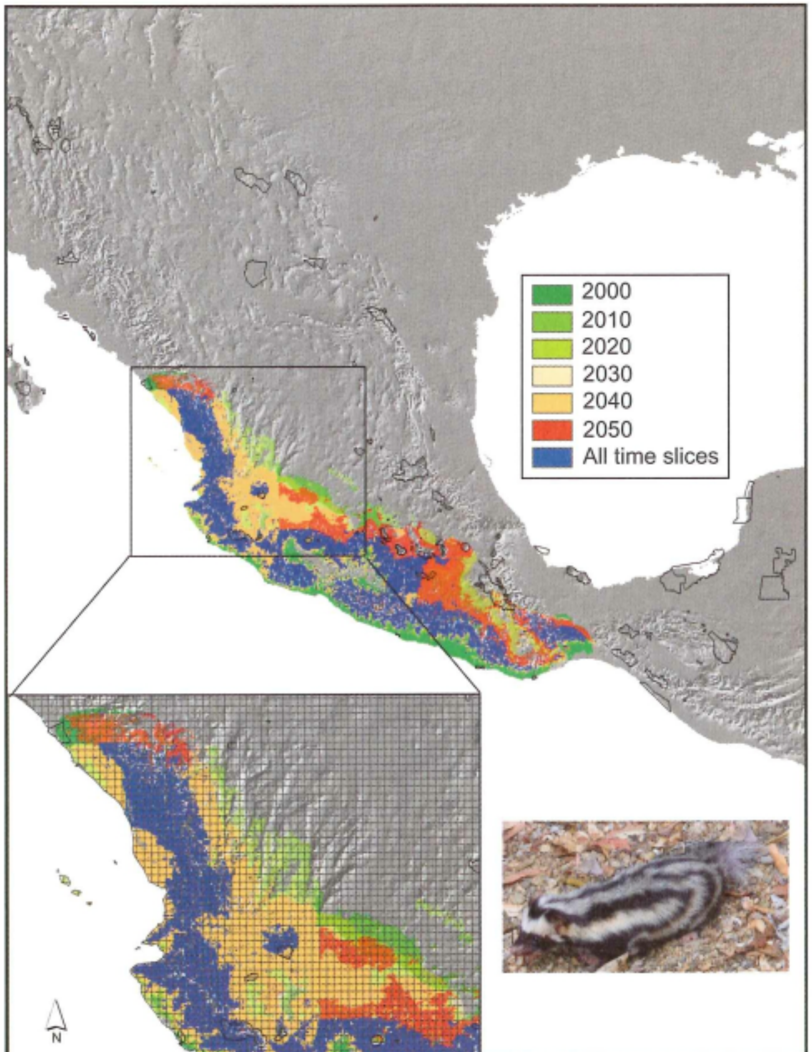
map of consistently suitable areas




genetic relatedness

Treating a biome as a “species” or integrating several species-level SDM’s allows construction of biome level projections.

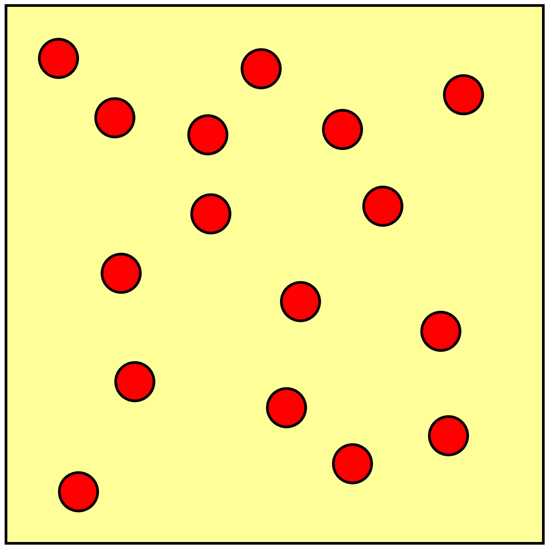
# SDM – Fine Level Time Steps



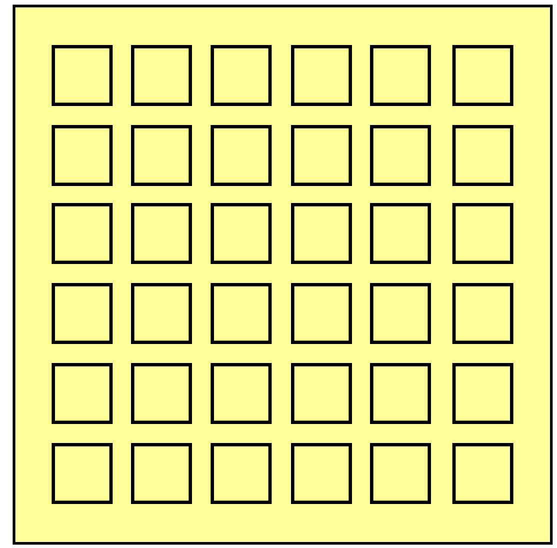

By projecting the species distribution over short time steps, it is possible to construct the precise pattern of distributional change.

This can be very useful in management situations where there is concern about dispersal corridors.

# SDM – A Sampling Problem



Measure climate at those sites where the species is found.



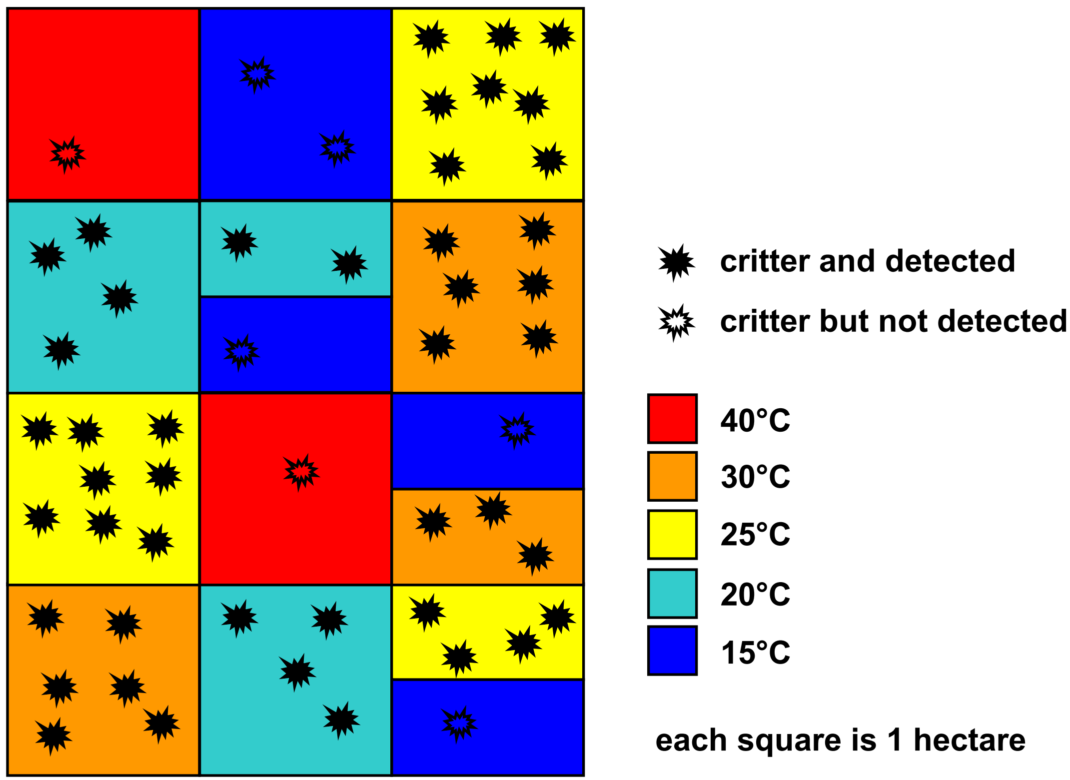
Assess species presence and measure climate at sampling sites.

The left panel is the standard approach used in establishing the association between species presence and climate.

It is the same as establishing the relation between smoking and lung cancer by only asking victims of lung cancer if they smoked or not.

The right panel is the correct approach but is seldom used since studies are usually based on pre-existing specimen locations.

# SDM – A Detection Problem



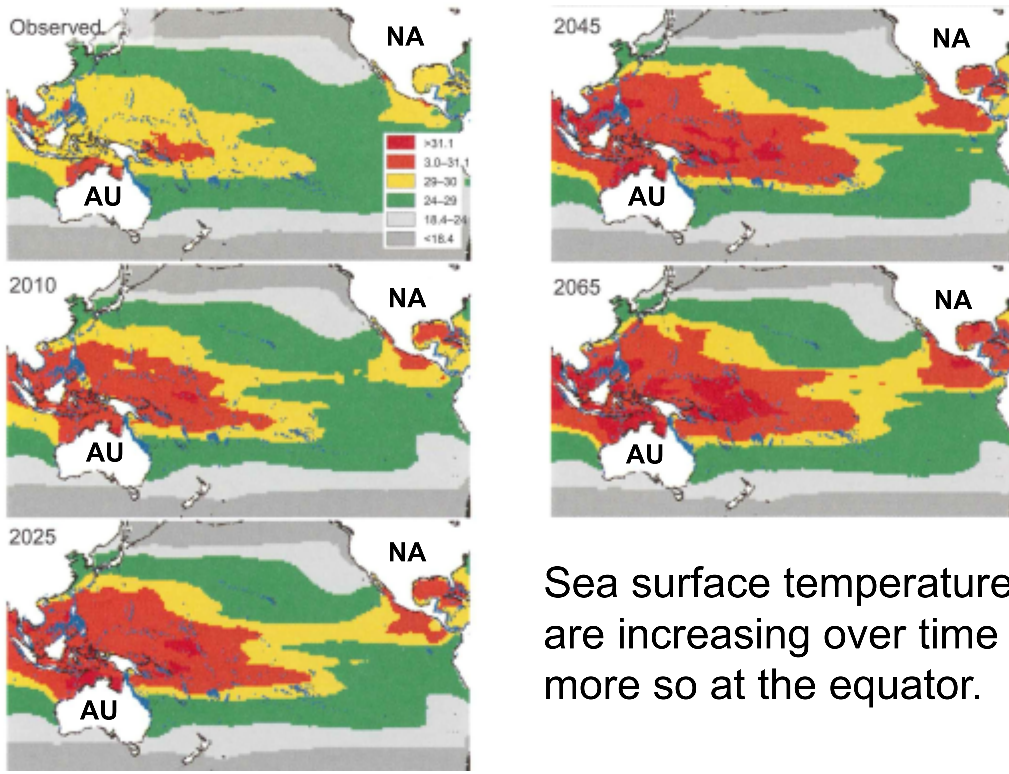

| temperature | density |
|---|---|
| 15 | 0 |
| 20 | 4 |
| 25 | 8 |
| 30 | 6 |
| 40 | 0 |

Envelope is 20-30°C with maximum at 25°C based on detected critters.

But truth is a wider envelope once detection problem is accounted for.

Without accounting for detection probability, projections from SDM would be wrong.

# Modeling Aquatic Systems

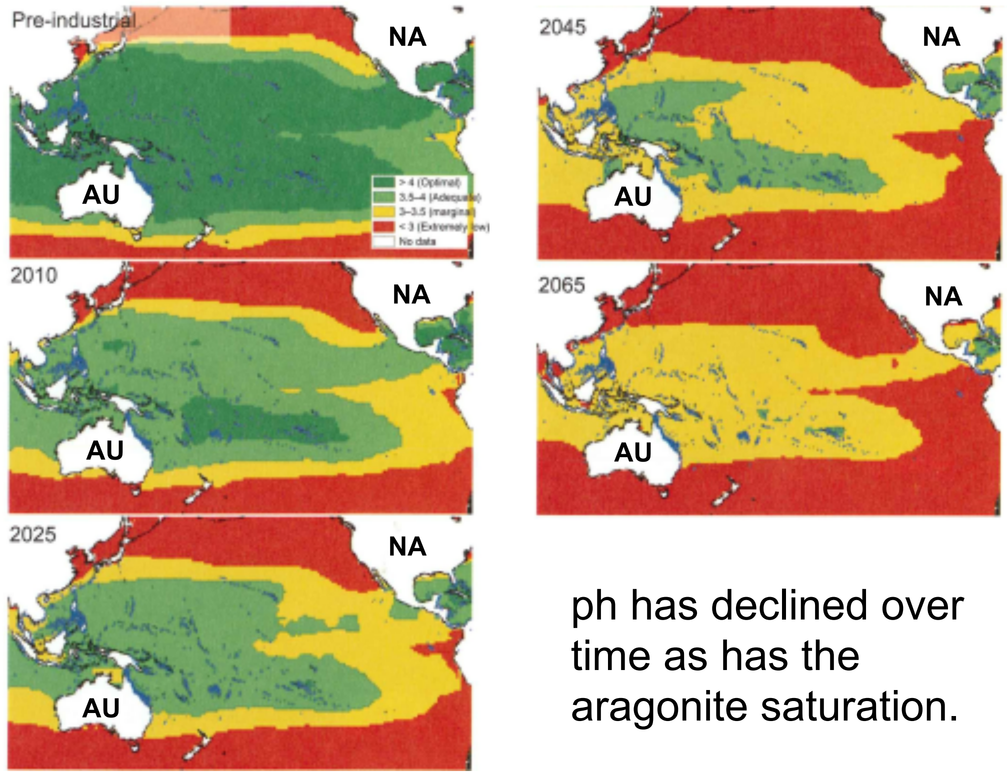



Sea surface temperatures are increasing over time – more so at the equator.

Most aquatic modeling has centered on modeling physical changes in the habitat.

Climate change is resulting in an increase in sea surface temperatures making equatorial regions less hospitable to coral reefs (increased bleaching).

# Modeling Aquatic Systems

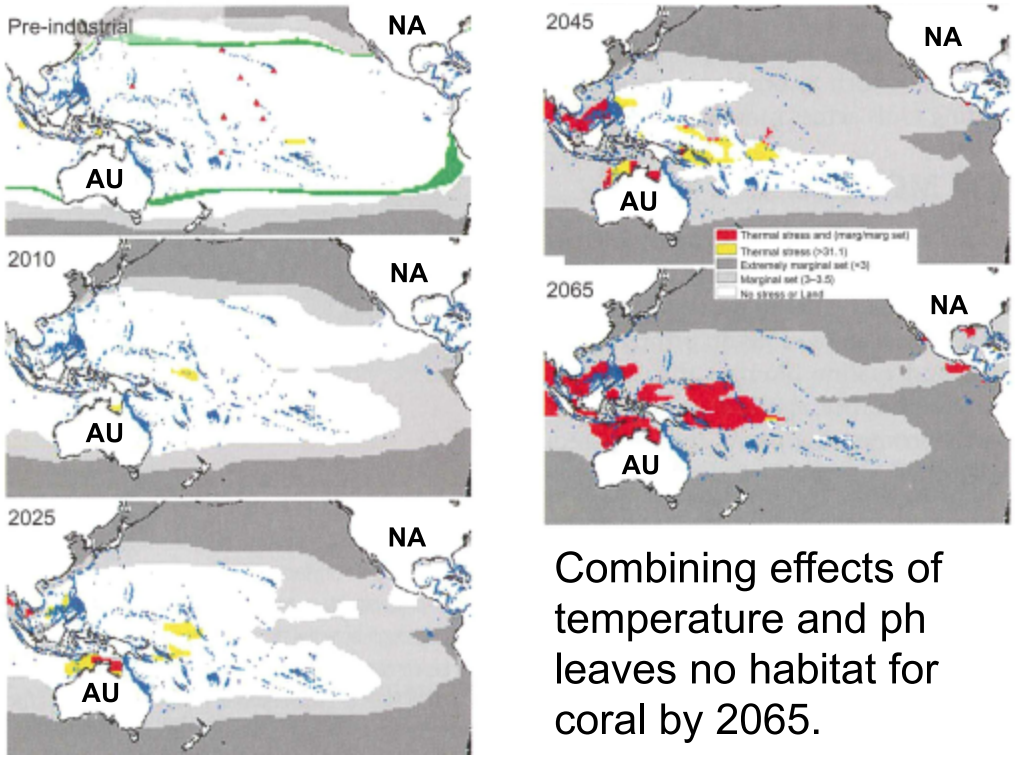



ph has declined over time as has the aragonite saturation.

Increasing $CO_2$ increases the acidity of sea water over time and makes the habitat less hospitable to coral reefs.

The effect is more extreme at the poles.

# Modeling Aquatic Systems



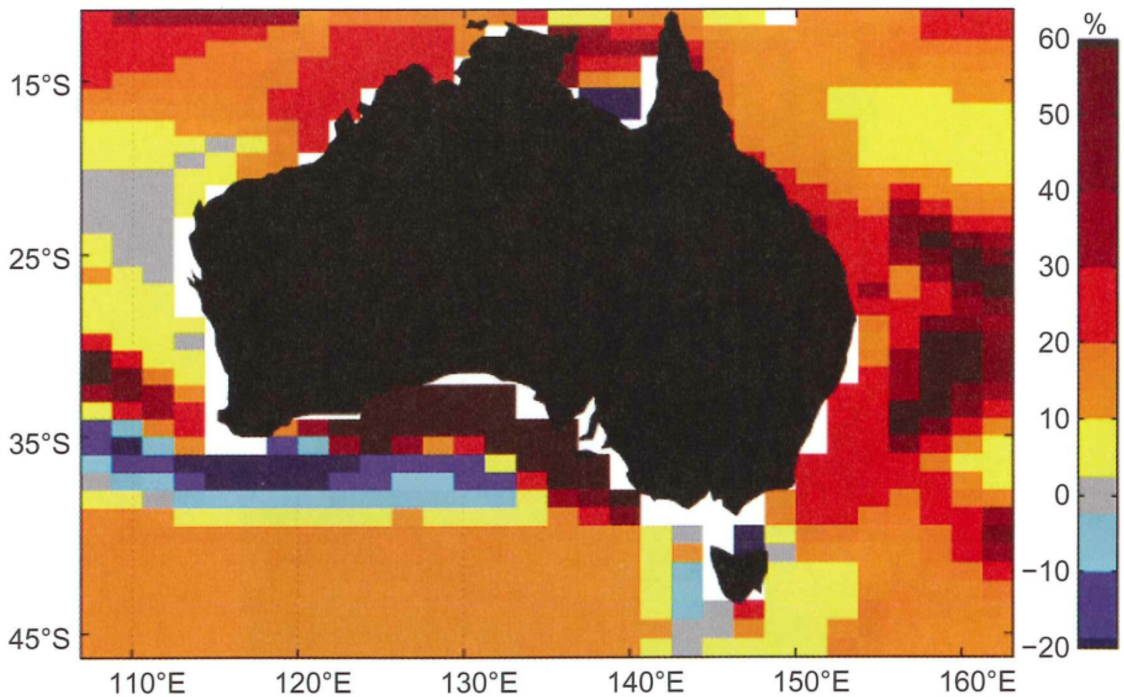

Combining effects of temperature and ph leaves no habitat for coral by 2065.

Temperature should shift coral poleward but ph conditions there are inhospitable.

Acidity should shift coral equatorial but temperature increases are inhospitable.

And then there is the human overharvesting of coral!!!

# Modeling Aquatic Systems

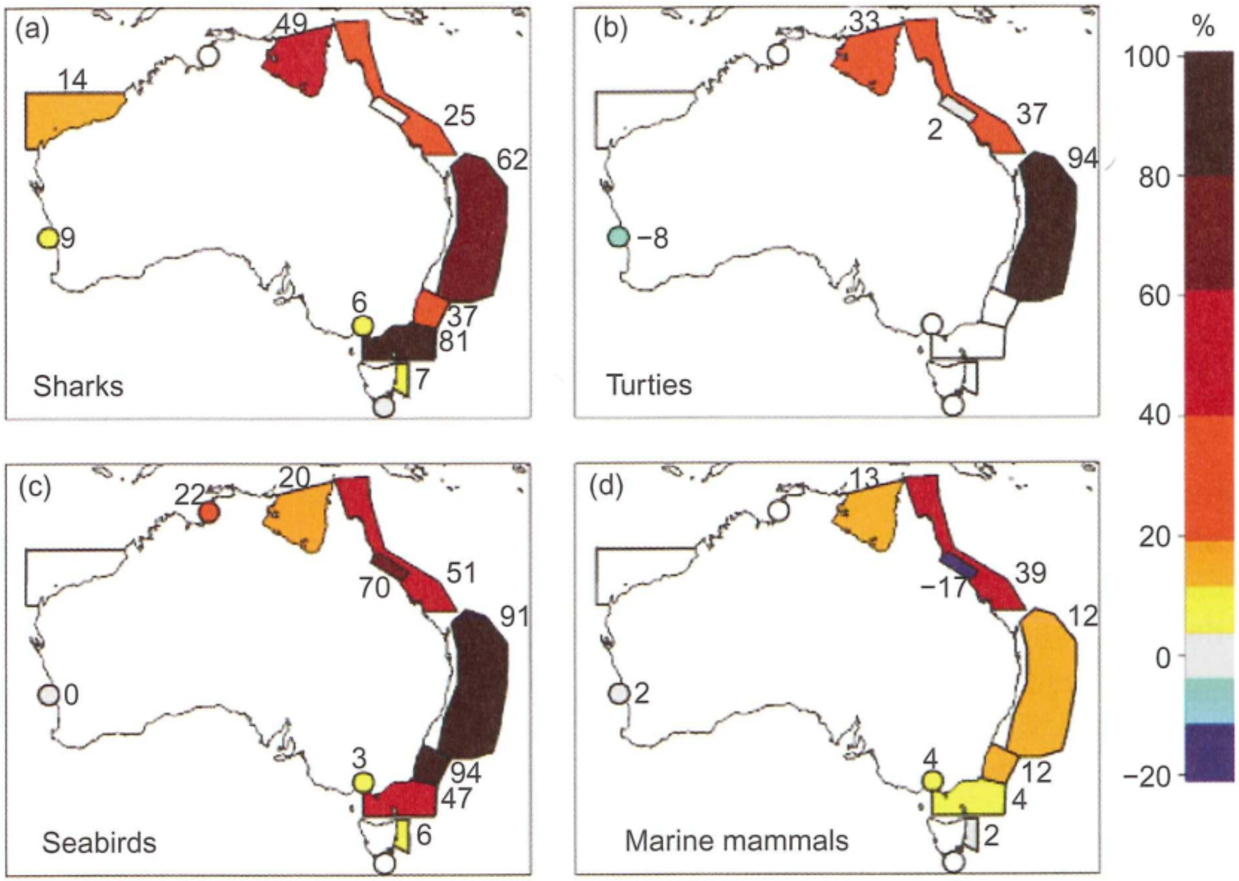



There have been some attempts to generate DGVM-style models for aquatic systems using changes in $CO_2$ to drive altered productivity by phytoplankton.

This productivity is linked via food-webs to higher trophic levels.

The graphic depicts changes in net ecosystem productivity (NEP) over 50 years.

# Modeling Aquatic Systems




Using food web links, climate based changes in productivity can be translated into projected changes in other groups.

Climate change increases levels of these various apex members of the ecosystem.

# Earth System Models

Dynamic Global Vegetation Models project the effects of climate change by using a time series of changing environmental variables such as $CO_2$ as input.

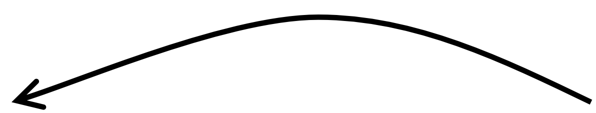
This assumes that climate changes independently of any feedback from global ecosystems and belies a simplistic serial and linear arrangement.

GCM → DGVM → Plant Functional Types

We know, however, that the collection of plant functional types present at any point in time have effects on the climate by modifying climate forcing such as CO2, atmospheric and soil moisture, etc.

As such, a more realistic general arrangement would be one that allows feedback and likely one that operates in a parallel rather than serial fashion.

A better depiction might be:



GCM → DGVM → Plant Functional Types

# Estimating Extinction Risk from Climate Change


**Science**

How Di made us into conspiracy theorists
Catherine Bennett in G2

Last act
The inside story of a stage flop
In G2

Craig Johnston
Footballer to design genius
In G2

2004 – a hectic year in space
In Life
Plus Online & jobs

The Guardian

An unnatural disaster

- Global warming to kill off 1m species
- Scientists shocked by results of research
- 1 in 10 animals and plants extinct by 2050

Under threat

Europe
25%

Central America
Golden toad

Brazil
4,400

South Africa
30%

Australia
54%

**Sensationalism**

In 2004, a group of scientists who had been building regional SDM's met.

They compared their data and concluded that with mid-range climate change through 2050 that18-34% of species were at risk of extinction.

They multiplied this by the 5-10 million species estimated to exist and concluded that 1 million species were at risk of extinction from climate change.

# Estimating Extinction Risk from Climate Change


USA TODAY

Cost of global warming: 1 million species

The Washington Post

Warming May Threaten 37% of Species by 2050

San Jose Mercury News

Study: Global warming to doom many species

IT MAY BE WORSE THREAT THAN HABITAT LOSS

THE SUN

Broad study on climate envisions extinctions

San Francisco Chronicle

Dire warming warning for Earth's species

Scientists need to learn to be more circumspect when reporting findings lest they be used to sell newspapers and magazines.

Even the scientists involved in that paper knew there were unlikely assumptions under the estimates.

Those assumptions are seldom mentioned nor are the caveats that apply to any pronouncement of this type.

# Estimating Extinction Risk from Climate Change

The estimate was made from a single approach and science is done better when multiple approaches are taken.

Can we learn anything about estimates from the past?

The 5 mass extinctions can likely be related in some fashion to climate change.

But, there have been other instances of climate change for which there were no mass extinctions.

We are left with a sampling problem, much like asking how many lung cancer victims smoked.

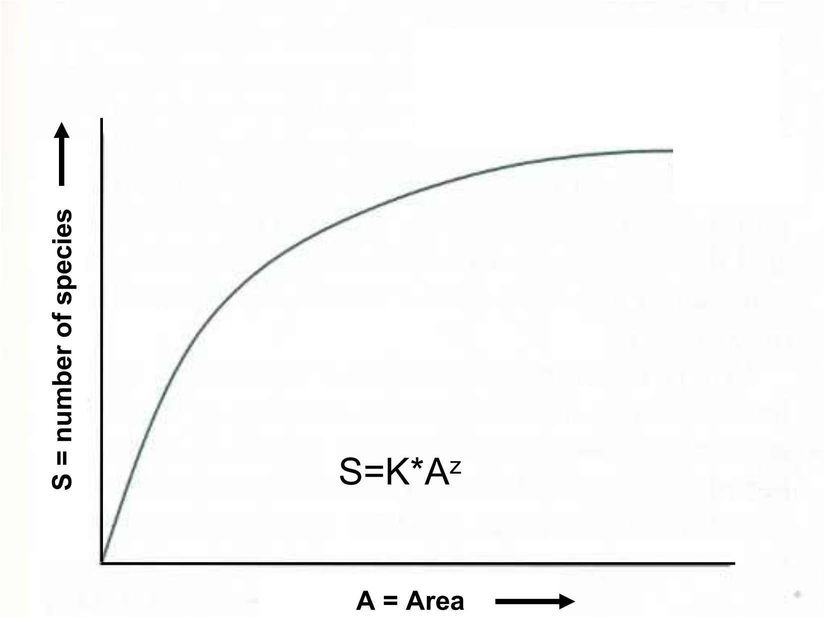
There is also no really relevant period in earth history that has had a long period of cooling followed by rapid warming.

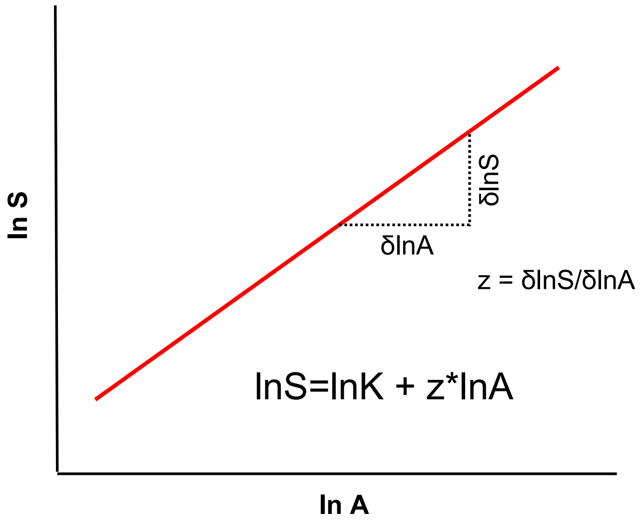
The only close analogy is the last interglacial and that led to no mass extinctions.

The current interglacial (since the glaciers retreated) has extinctions but they are more likely caused directly by man and not indirectly by our impact on climate.

# Estimating Extinction Risk from Climate Change

The approach that led to the prediction of a million extinctions in 50 years combined species distribution models with species area relationships.

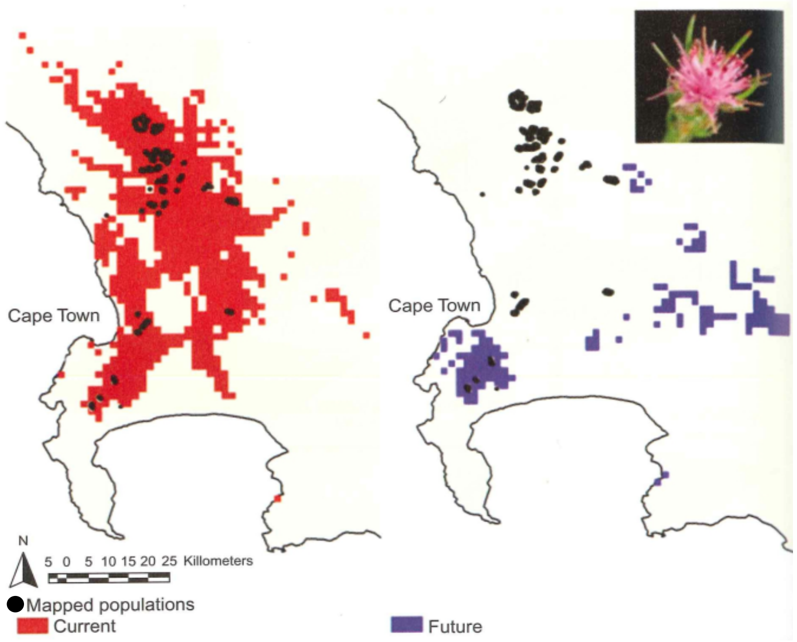



Species area relationships (SAR) were originally based on an empirical data on the number of species occurring on oceanic islands and the size of those islands.

It is generally true that larger "islands" (surrounded by water or other inhospitable habitat) host more species than smaller islands, all else being equal.

# Estimating Extinction Risk from Climate Change




SDM's can be used to project the distribution (and hence Area occupied) by a species under climate change.

The area for *Protea cyneroides* will be less in the future.

The same calculation can be done for a number of species in the same region and an "average" can be formed across the species.

Assuming there is a SAR for that region, it can be used to estimate the probability of extinction.

The logic is simply that if the number of species increases with area then the number should go down as the area declines.

Formally the relationship is $Pr(extinction) = 1 - (E(A_{new})/E(A_{old}))$

# Extinction Probabilities Estimated from Proportionate Habitat Loss

| taxon | region | dispersal | | | no dispersal | | |
|---|---|---|---|---|---|---|---|
| | | minimum | median | maximum | minimum | median | maximum |
| mammals | mexico | .05 | .08 | | .24 | .25 | |
| | australia | .16 | | .77 | | | |
| | s. africa | | 0 | | | .69 | |
| birds | mexico | .04 | .05 | | .09 | .08 | |
| | europe | | | .07 | | | .48 |
| | australia | .12 | | .85 | | | |
| | s. africa | | 0 | | | .51 | |
| frogs | australis | .13 | | .68 | | | |
| reptiles | australia | .09 | | .76 | | | |
| | s. africa | | 0 | | | .59 | |
| butterflies | mexico | .07 | .07 | | .13 | .19 | |
| | australia | .07 | .23 | .33 | .16 | .35 | .54 |
| | s. africa | | 0 | | | .78 | |
| inverts | s. africa | | 0 | | | .85 | |
| plants | amazonia | | | .69 | | | .87 |
| | europe | .06 | .07 | .08 | .18 | .22 | .29 |
| | cerrado | | | | | .66 | .75 |
| | s. africa | | .38 | | | .52 | |
| **all species** | | **.11** | **.19** | **.33** | **.34** | **.45** | **.56** |

There is substantial variation among the taxa and across the geographic regions but there are patterns

# Extinction Probabilities Estimated from Proportionate Habitat Loss

| taxon | region | dispersal | | | no dispersal | | |
|---|---|---|---|---|---|---|---|
| | | minimum | median | maximum | minimum | median | maximum |
| **average** | | **.11** | **.19** | **.33** | **.34** | **.45** | **.56** |

We can explore some of those patterns by examining the averages taken across taxa and region.

Minimum, median and maximum refer to the extent of climate change used in the SDM's and it seems reasonable that extinction probability should increase as climate change becomes more drastic, assuming it happens too fast for species to adapt.

It also seems reasonable that species that can disperse to track their optimal conditions will have a lower extinction probability as climate change makes the current location less hospitable.

On a technical note, forming an average across taxa and regions is statistically inappropriate in light of the extent of differences they found.

# Species Area Relationships – Assumptions and Issues

Species area curves are primarily based on the accumulation of species on islands from a continental source and are the result of interplay of immigration and extinction.

Persistence of a species is based on adaptedness to the habitat and competitive ability since it has to interact with the other species present.

It is generally thought that larger areas have more habitat options and represent a larger initial “target” for immigrants.

It is reasonable to assume that species numbers increase over time and that on average more of the interacting species persist.

However, when SAR’s are used to estimate the reduction in species number as the Area declines, the time relationships are effectively being “played backwards”.

In doing this one has to either assume that there were no interactions during the accumulation process or the interactions can be ignored when playing the process in reverse.

Neither of these assumptions is likely correct.

# Localized Habitat and Endemism

Species Distribution Models are generally designed for a restricted range of habitat.

They are not usually applied to species that use several different habitat types over the year (migrants) nor to species capable of using varying habitat types.

As such, they are most accurately applied to endemic species or populations that have easily defined habitat characteristics.

This leads to a critical problem when SDM's are linked to SAR's since the latter almost always include non-endemics.

As a consequence, the slope of the relationship between species and area is biased high.

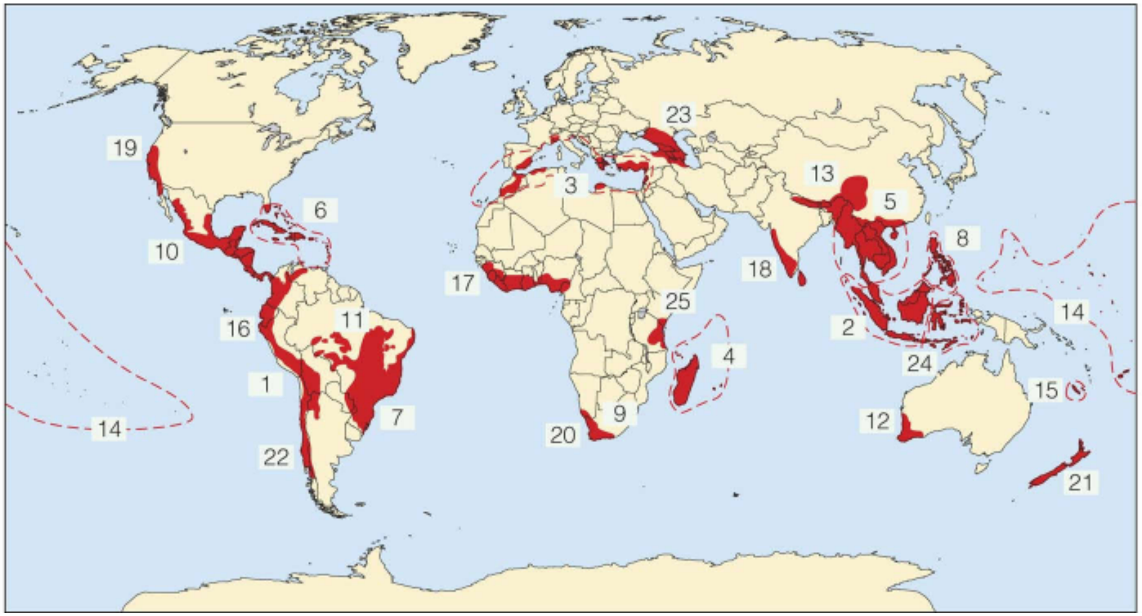
When the SAR is "played backward" the probability of extinction is also inflated.

What is needed is a species area relationship for endemics that share a common and somewhat limited habitat.

These are being and have recently been developed and are referred to as EAR's.

It is still questionable to run these backwards as you have to assume independence.

# Endemism, Hotspots and Dynamic Global Vegetation Models




Areas of high endemism are distributed globally but south of the northern temperate zone.

Fortunately, the species are tightly adapted to the local plant community that can be modeled with regional DGVM's.

These allow an assessment of potential reduction in biotic habitat under climate change that is not as fraught with problems as estimates from SDM's.

These can then be paired with EAR's for the regions to estimate extinction probabilities.

# Projected Extinction Risks for Hot Spots

| hotspot | broad biome definition | | narrow biome definition | |
|---|---|---|---|---|
| | broad specificity | narrow specificity | broad specificity | narrow specificity |
| california floristic province | .05 | .46 | .05 | .42 |
| cape floristic region | .03 | .03 | .08 | .08 |
| caribbean | .04 | .04 | .04 | .04 |
| indo-burma | .03 | .27 | .07 | .31 |
| mediterranean basin | .04 | .16 | .06 | .25 |
| new zealand | .03 | .06 | .03 | .06 |
| polynesia and micronesia | .02 | .17 | .04 | .28 |
| succulent karoo | .03 | .28 | .04 | .30 |
| southwest australia | .03 | .10 | .07 | .23 |
| tropical andes | .06 | .31 | .11 | .32 |

A broad biome would be “forest” while a narrow one would be tropical angiosperm forest and this would affect the overall functioning of the DGVM’s.

Specificity refers to the width of tolerance allowed in species within the EAR.

In general, these estimates of extinction probability are smaller than those from the SDM/SAR approach but they are not zero.

# The Key Assumption


A key assumption to all the projections is that the plants and animals can not “adapt” to habitat conditions altered by climate change.

Many think that polar bears can only persist by hunting seals from a sea ice platform.

# The Key Assumption

seal

caribou

Our work shows that polar bears are increasingly catching seals along the shore and successfully hunting more terrestrial prey.

Such shifts can be the result of phenotypic plasticity where confronted by an altered environment, a genotype expresses an altered phenotype.

If there is sufficient time and underlying genetic variation, adaptations to altered habitat can evolve.