Combining Physical and Statistical Models in Order to Narrow Uncertainty in Projections of Global Warming



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ARTICLE

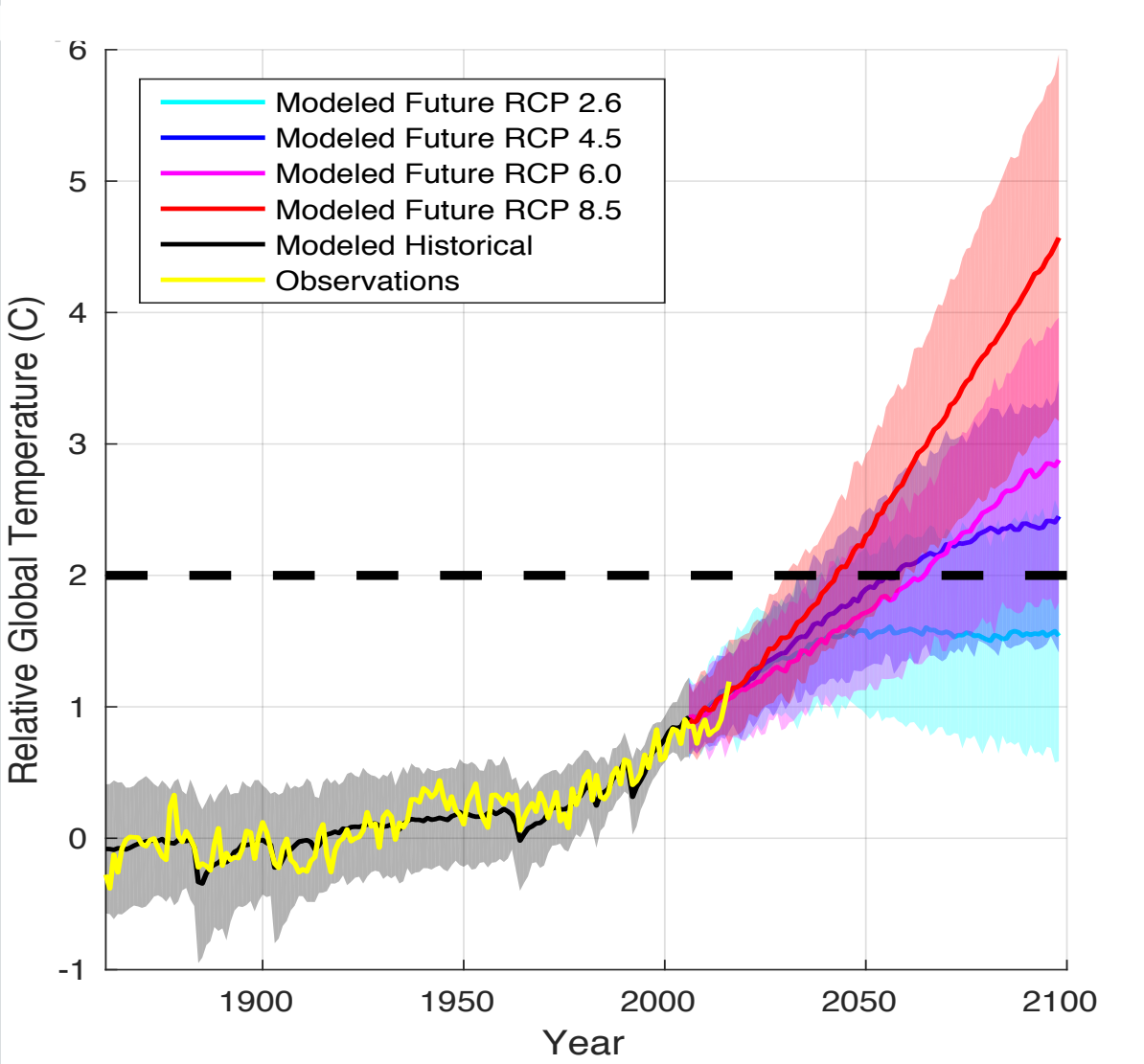
doi:10.1038/nature24672

Greater future global warming inferred from Earth's recent energy budget

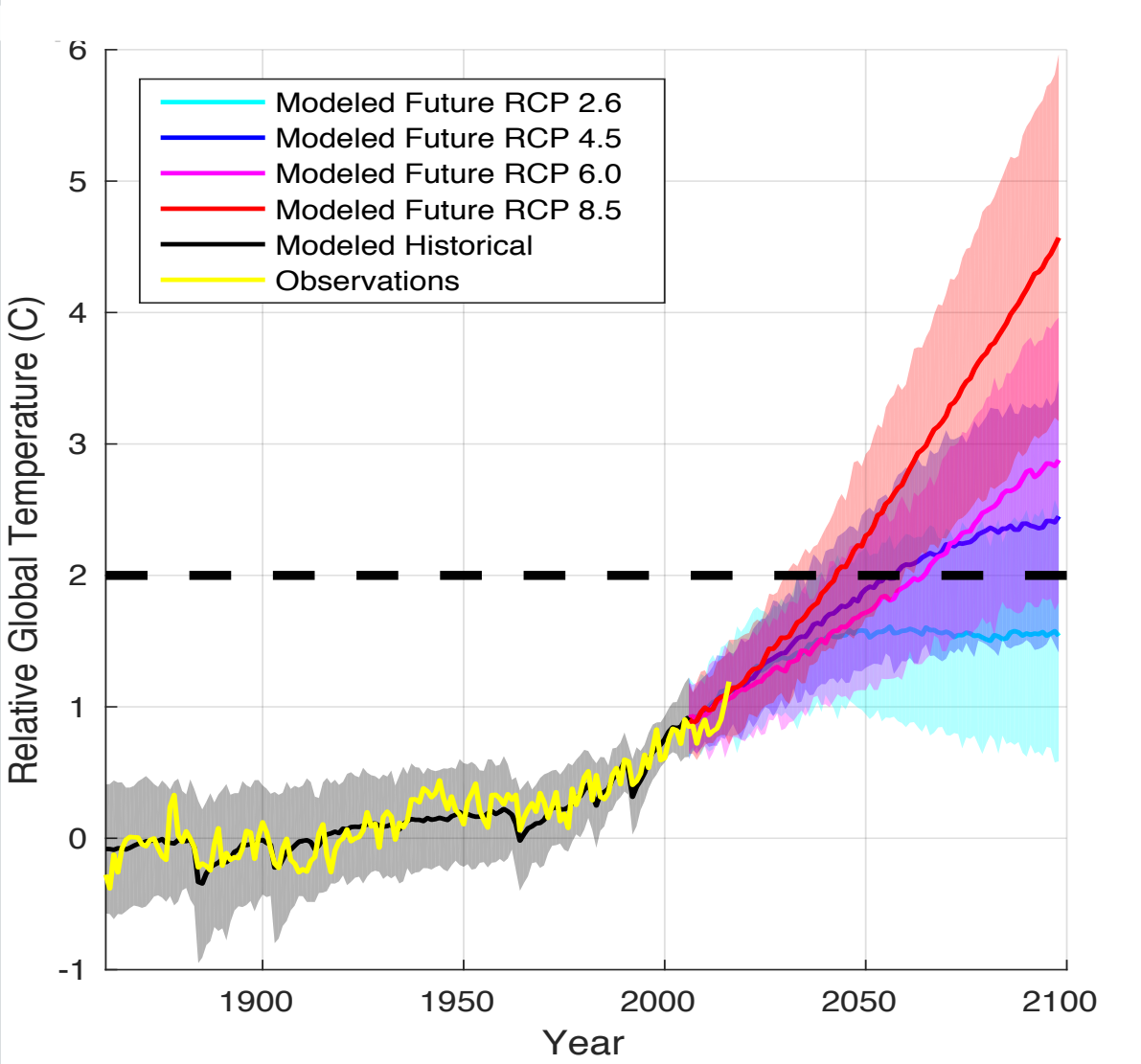
Patrick T. Brown[1] & Ken Caldeira[1]

Combining Physical and Statistical Models in Order to Narrow Uncertainty in Projections of Global Warming

Combining Physical and Statistical Models in Order to Narrow Uncertainty in **Projections of Global Warming**



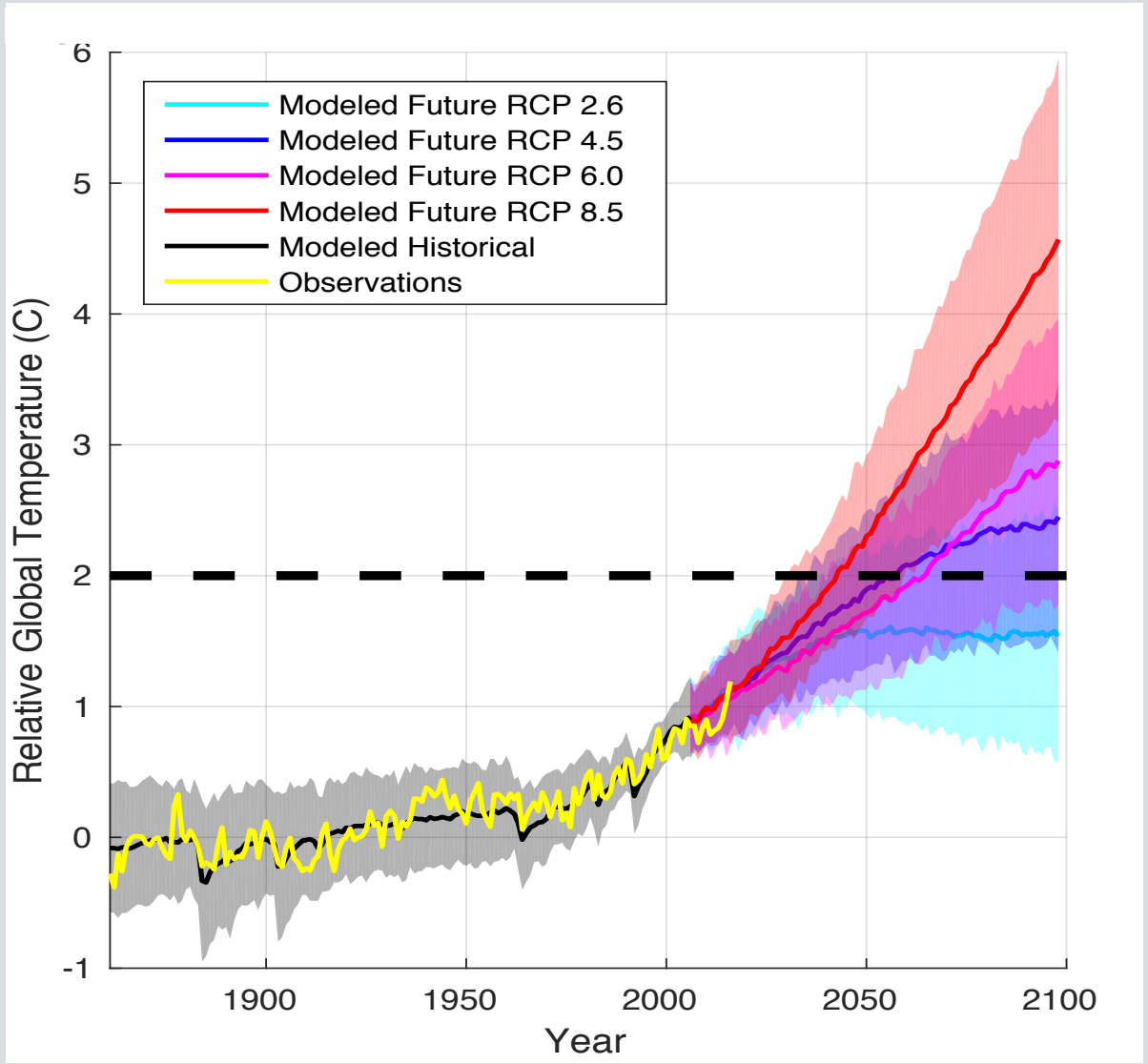
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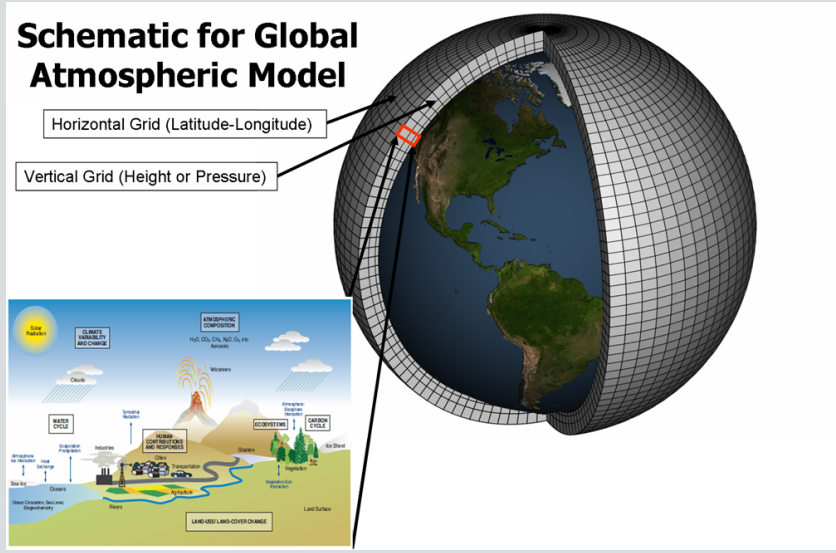




$$C\frac{d[\Delta T]}{dt} = F - \lambda\Delta T$$

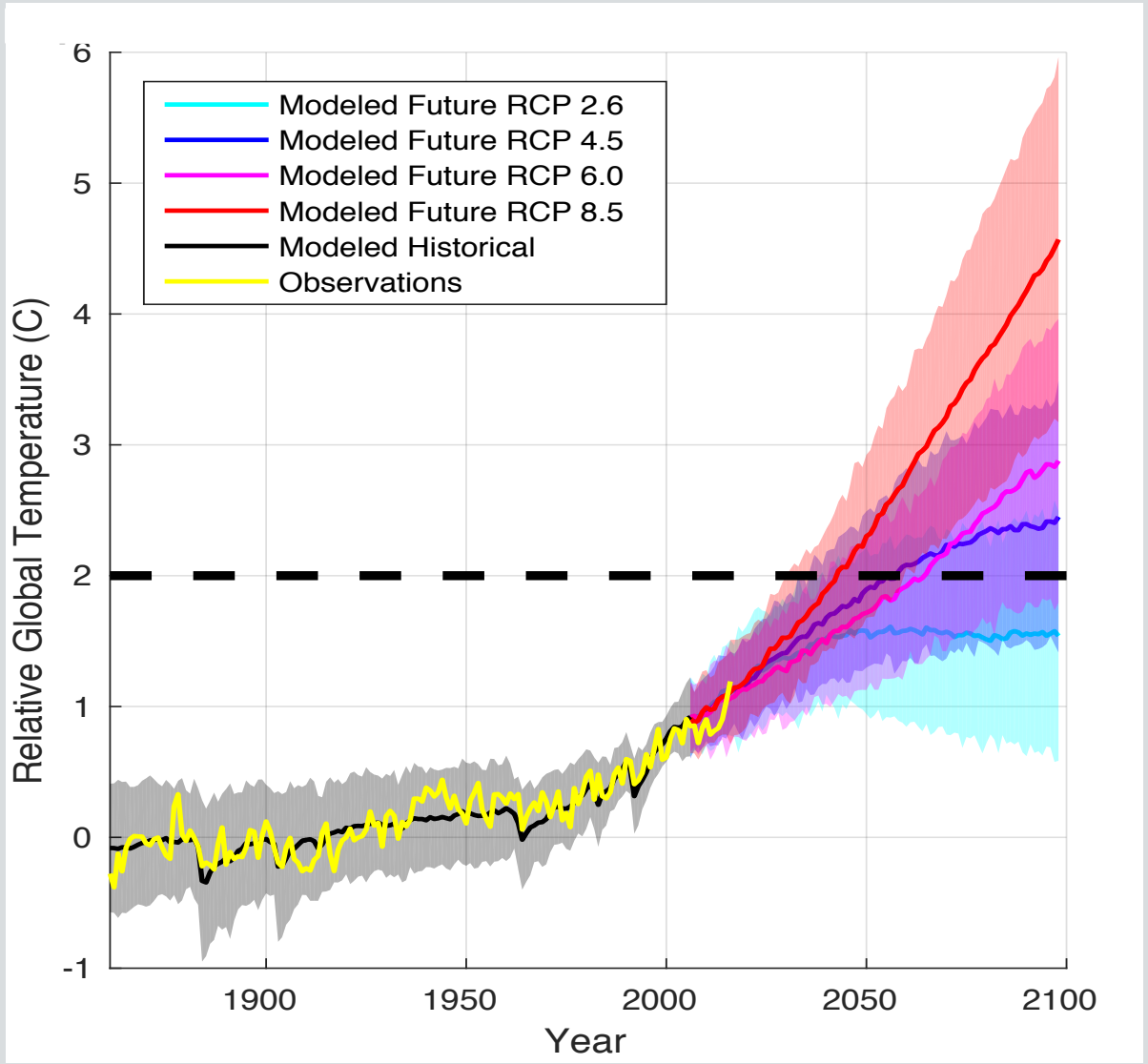
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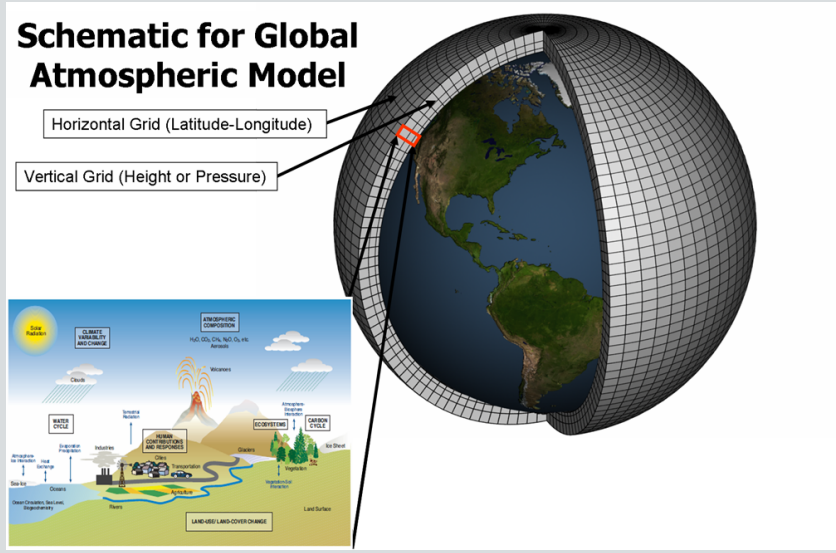




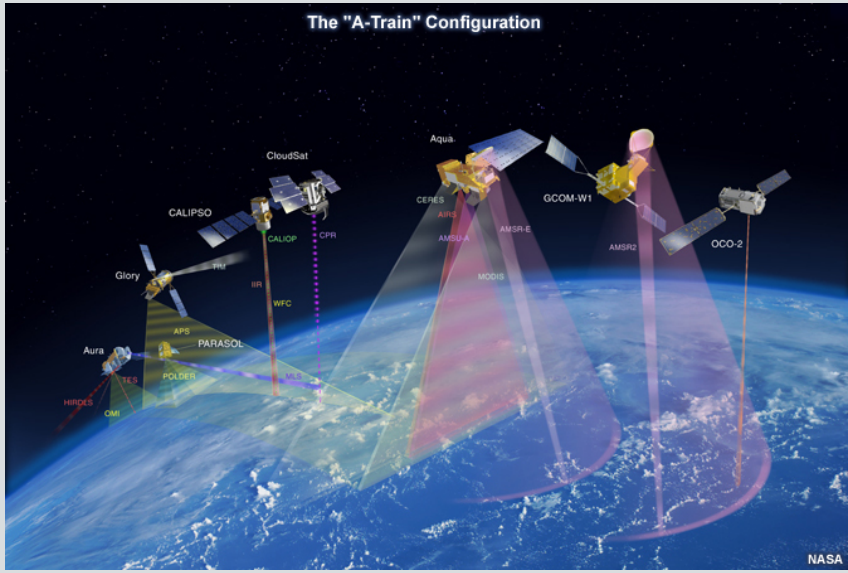


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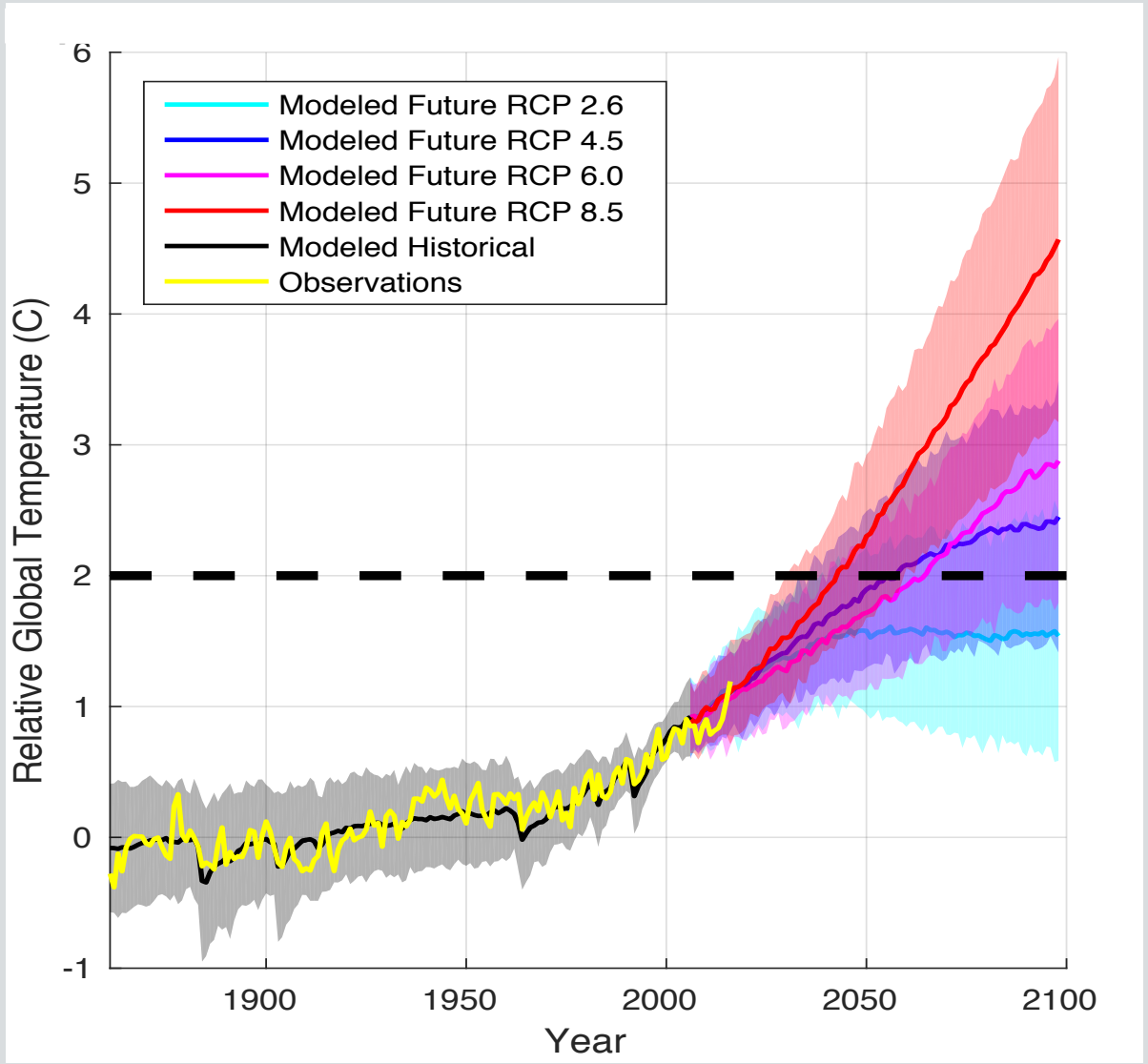


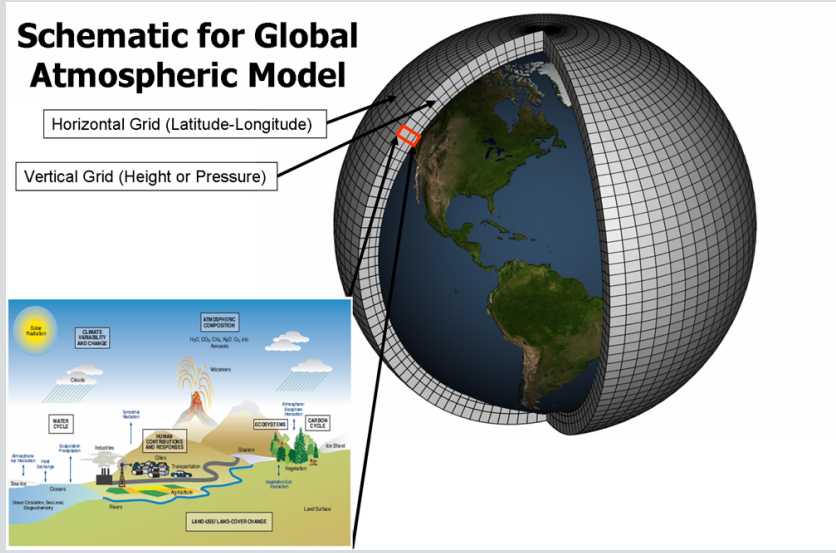


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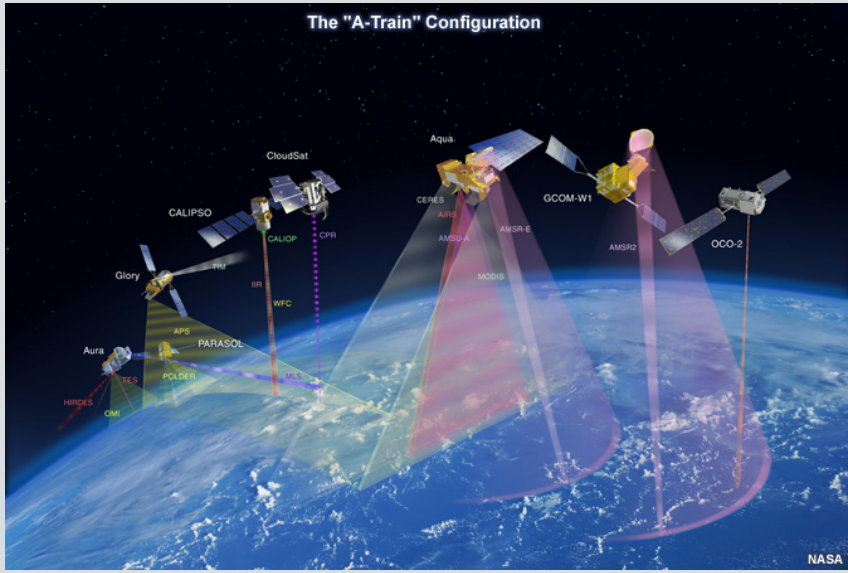


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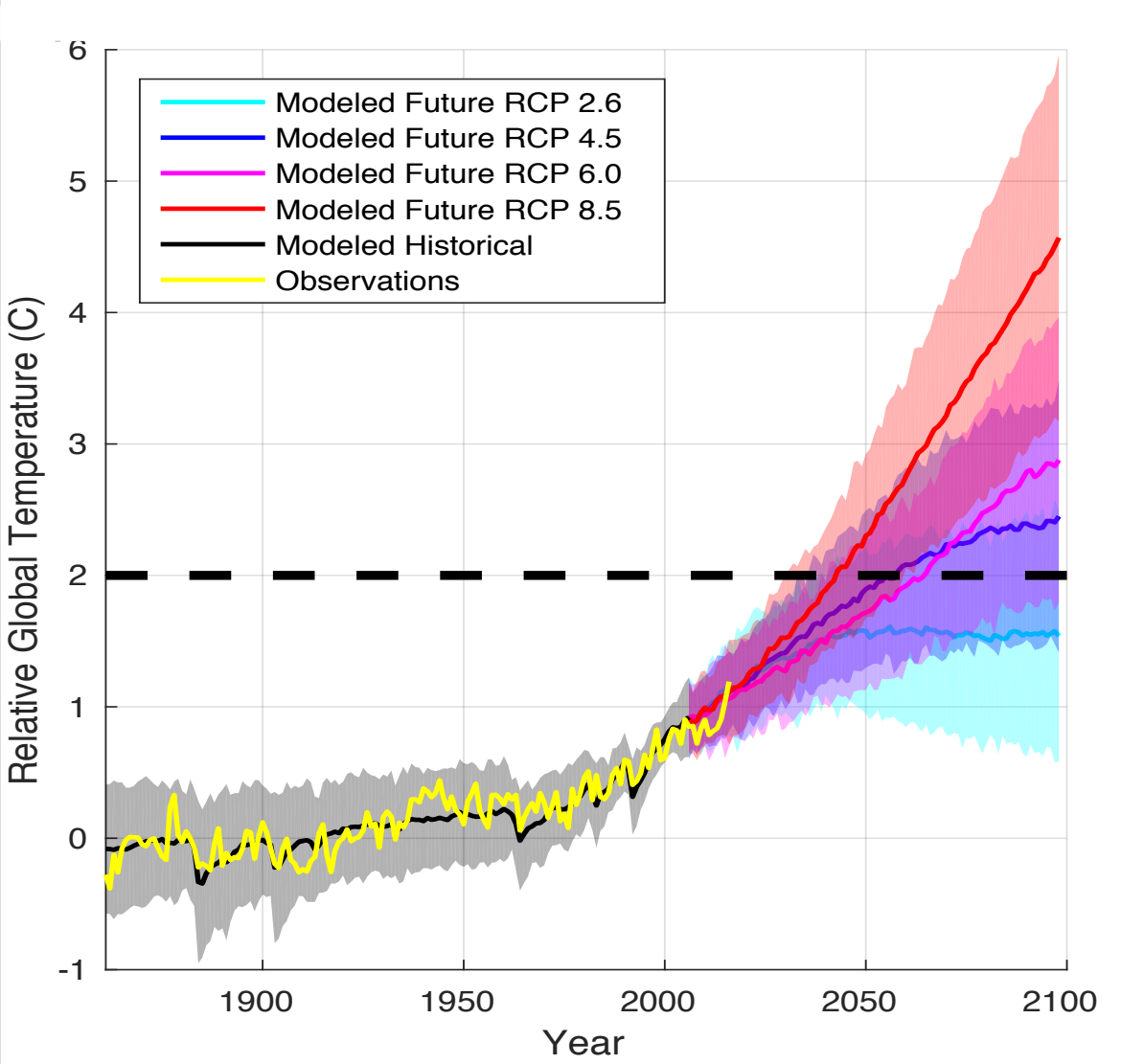




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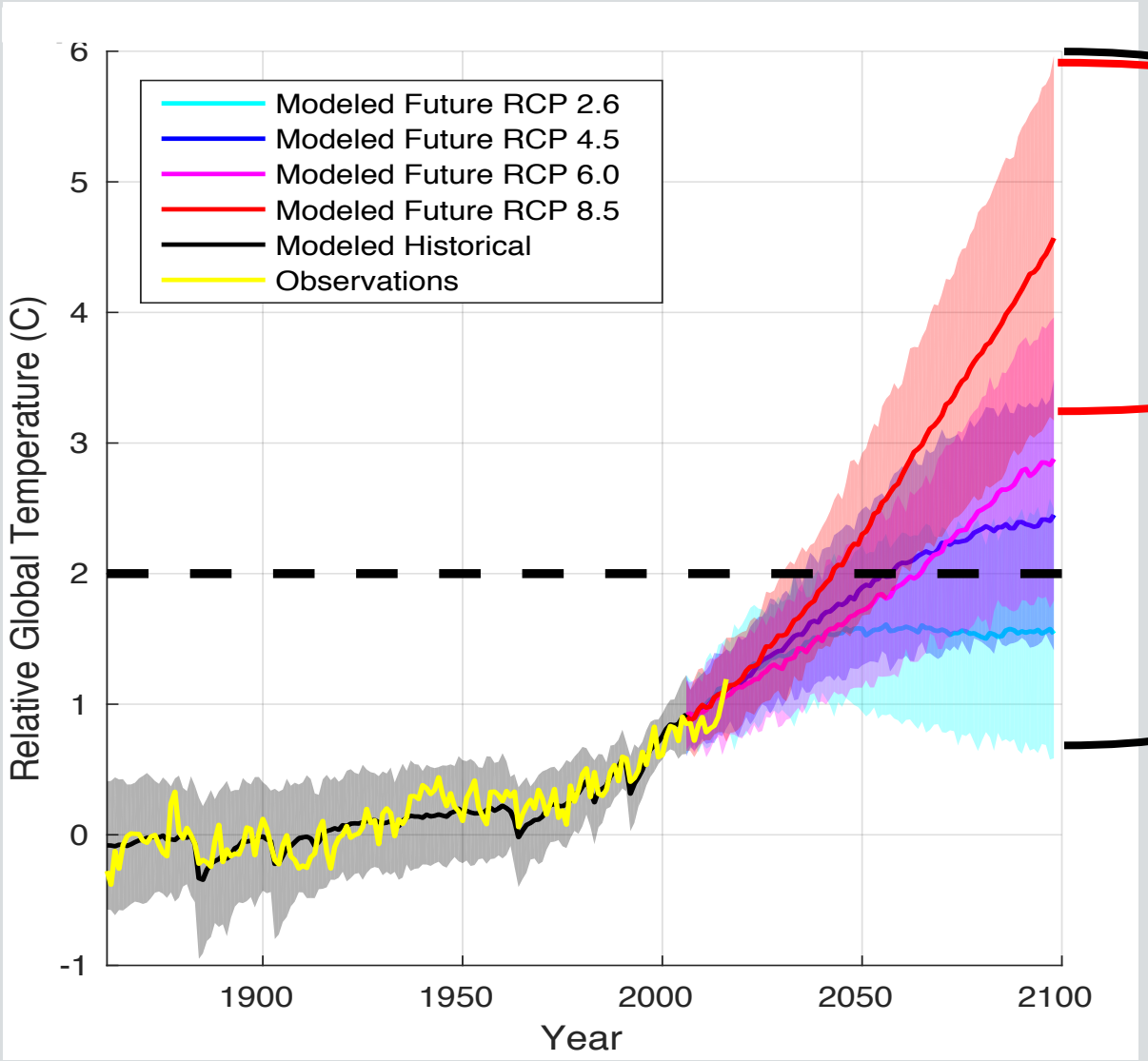
Combining Physical and Statistical Models in Order to Narrow Uncertainty in Projections of Global Warming





"The Agreement aims to respond to the global climate change threat by keeping a global temperature rise this century well below 2 degrees Celsius above pre-industrial levels and to pursue efforts to limit the temperature increase even further to 1.5 degrees Celsius"

Combining Physical and Statistical Models in Order to Narrow Uncertainty in Projections of Global Warming



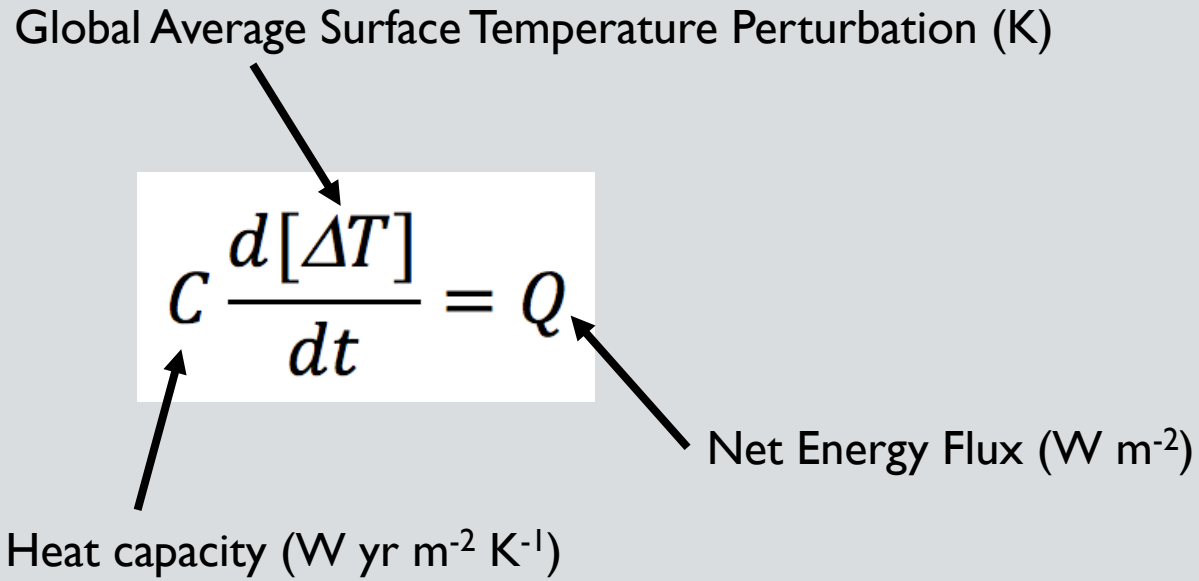
Response Uncertainty

Scenario Uncertainty

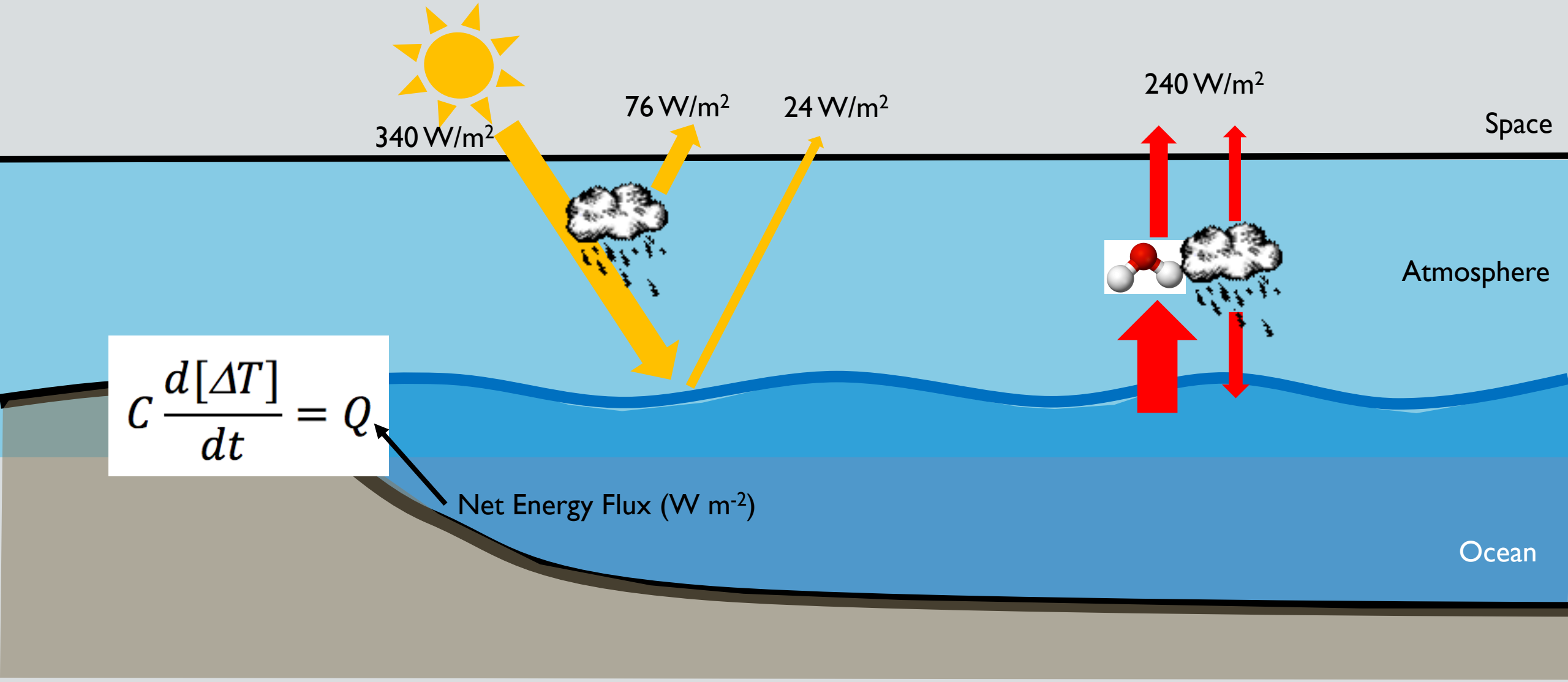
How much global warming should we expect for a given increase in the atmospheric concentration of greenhouse gases?

Projections differ by a factor of 2

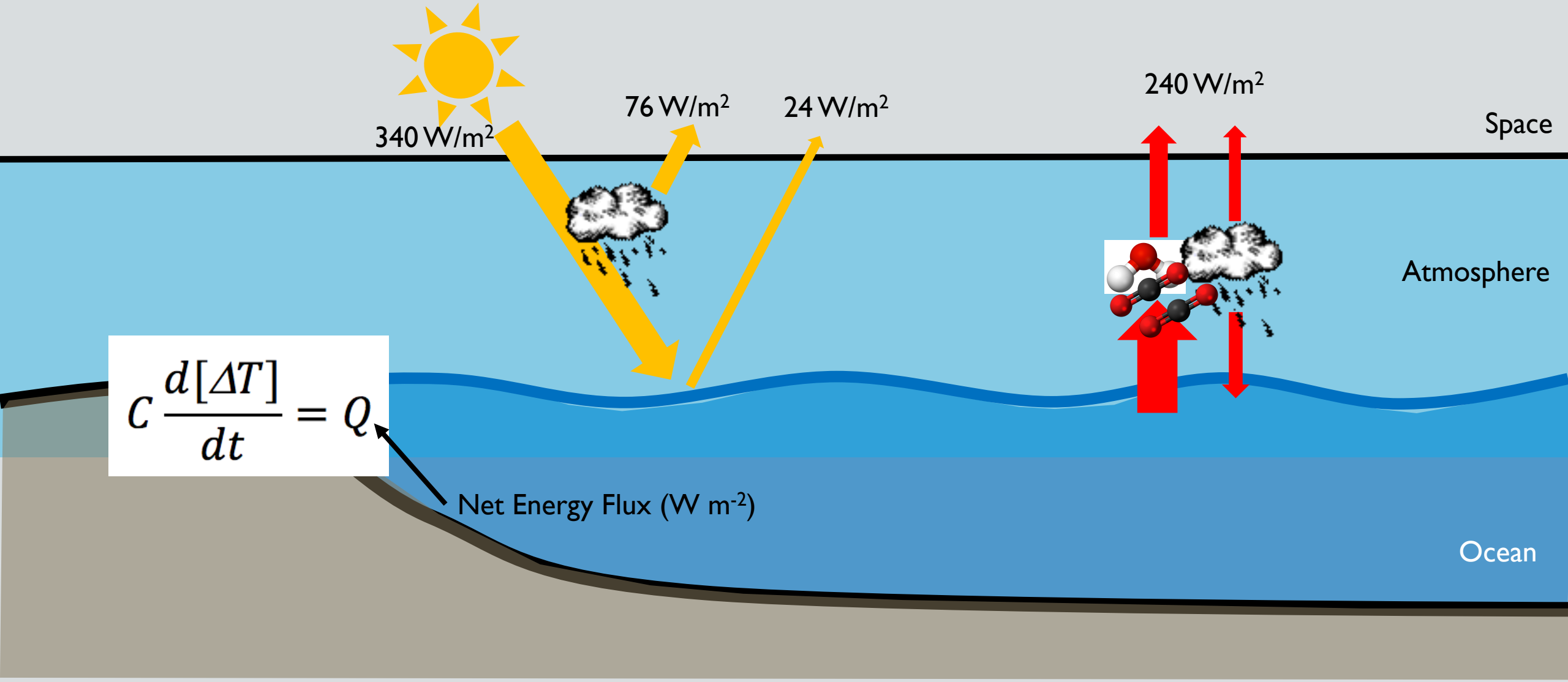
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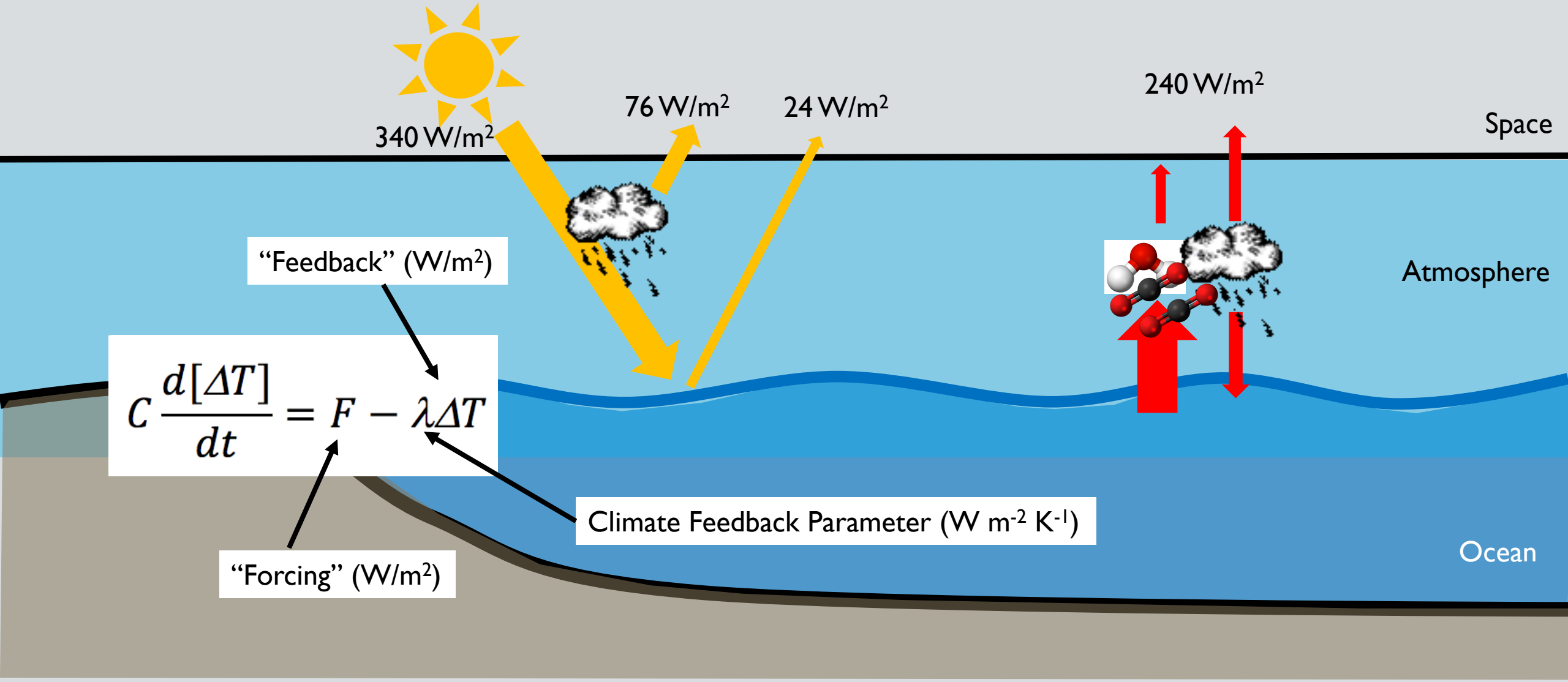
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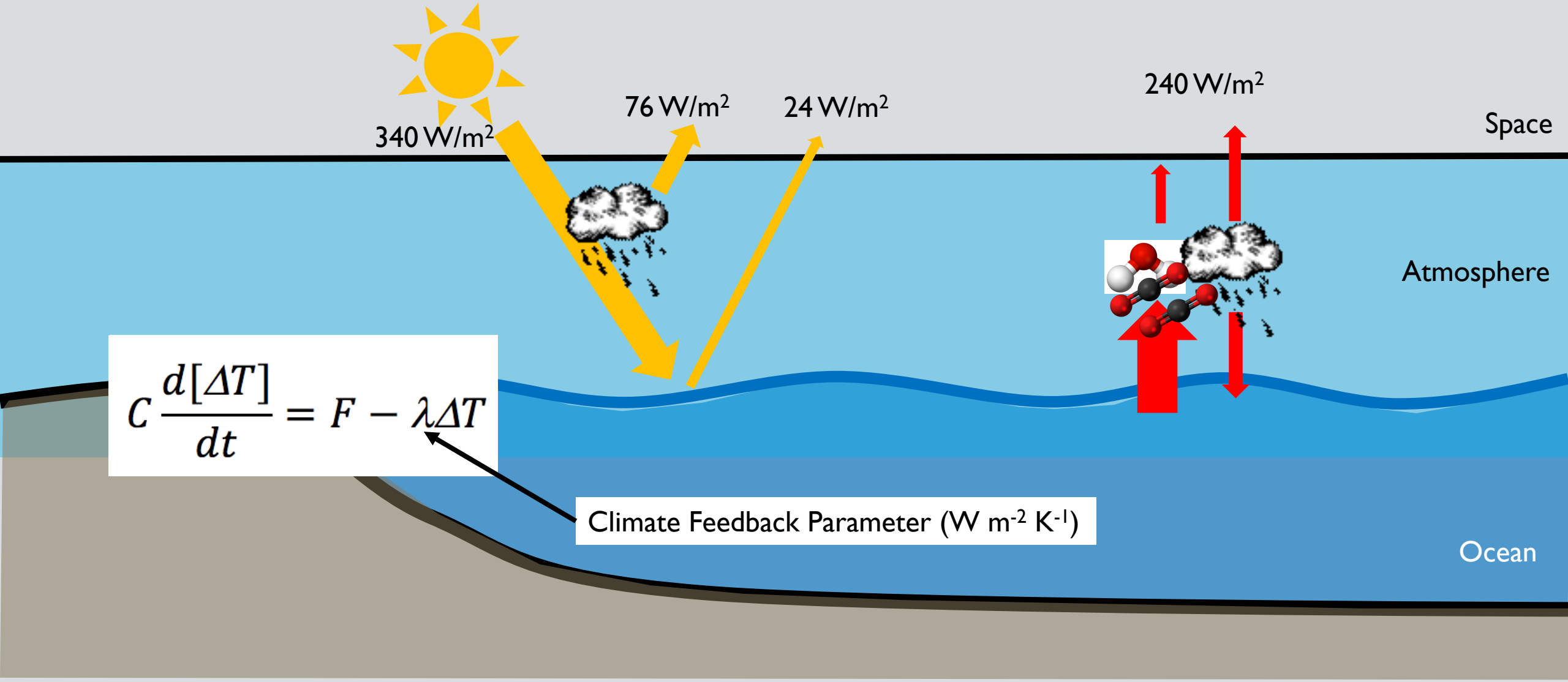
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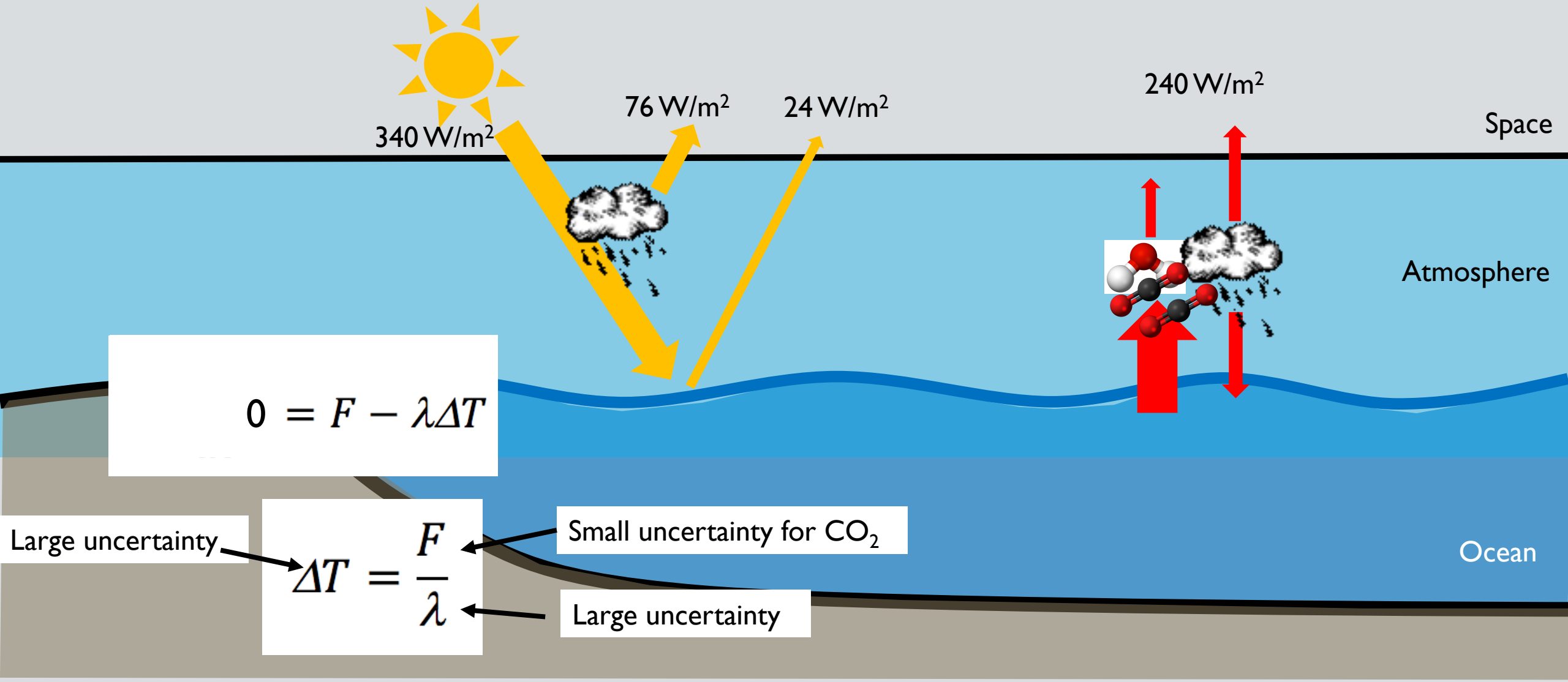
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$$0 = F - \lambda \Delta T$$

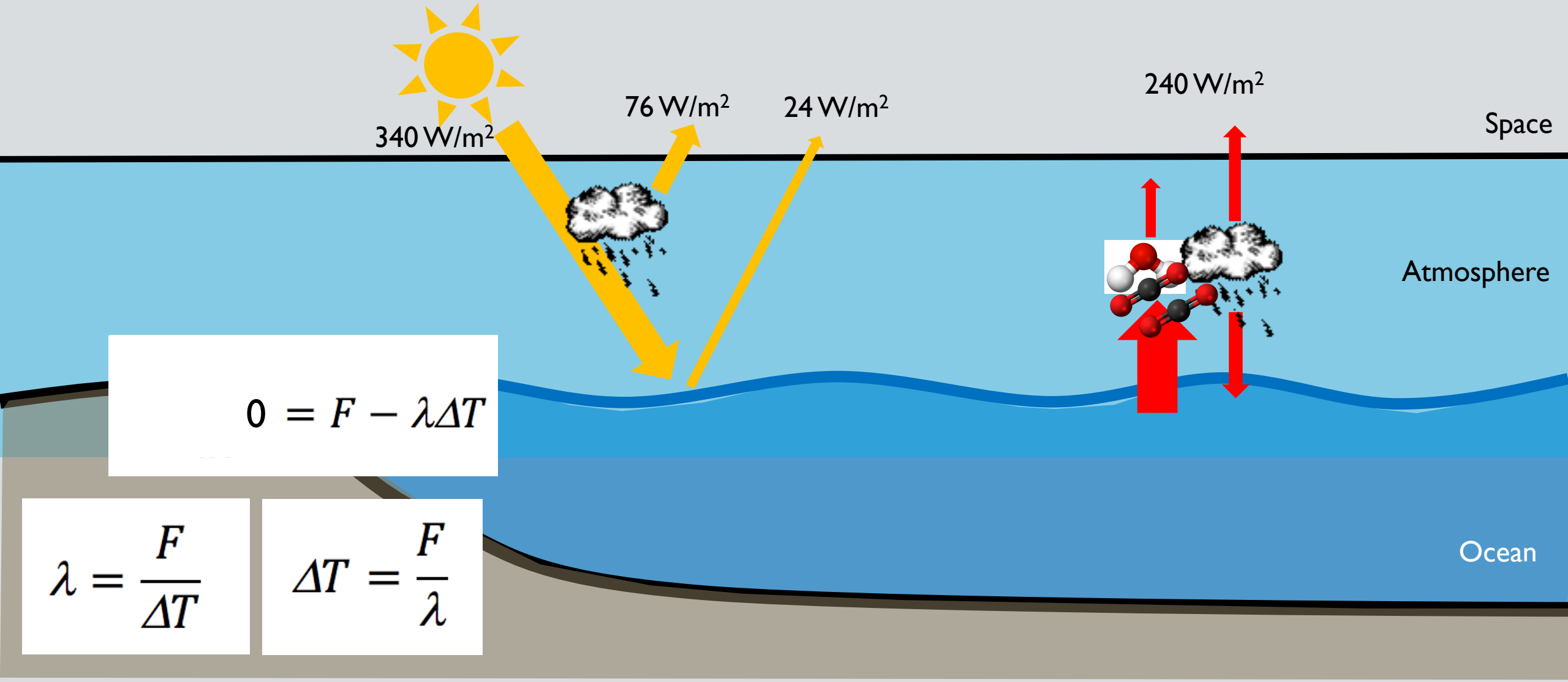
$$\Delta T = \frac{F}{\lambda}$$

Large uncertainty

Small uncertainty for CO_2

Large uncertainty

How much global warming should we expect for a given increase in the atmospheric concentration of greenhouse gases?



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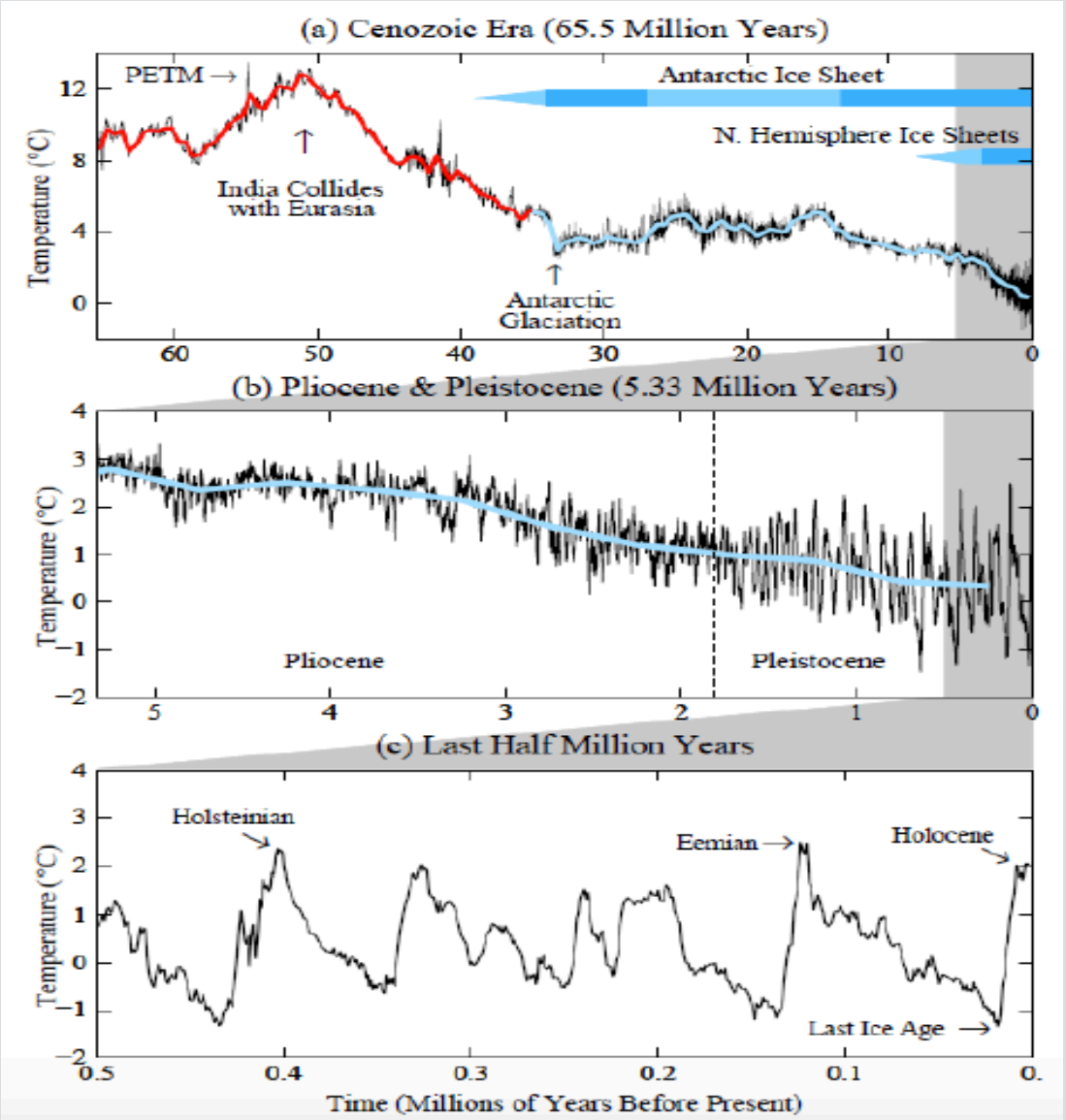
$$\lambda = \frac{F}{\Delta T}$$

$$\Delta T = \frac{F}{\lambda}$$

How much global warming should we expect for a given increase in the atmospheric concentration of greenhouse gases?

Strategy #1:
estimate F and ΔT over some time in the past

$$\lambda = \frac{F}{\Delta T}$$



How much global warming should we expect for a given increase in the atmospheric concentration of greenhouse gases?

Strategy #2:
Increase greenhouse gas concentrations in a **physical** climate model and have it calculate ΔT

$$\lambda = \frac{F}{\Delta T}$$

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Physical Global Climate Models

- **Mathematical / mechanistic models of the entire Earth system run on supercomputers**
- **Typically about a million lines of code**



How much global warming should we expect for a given increase in the atmospheric concentration of greenhouse gases?

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Physical Global Climate Models

- **Developed at many centers around the world**



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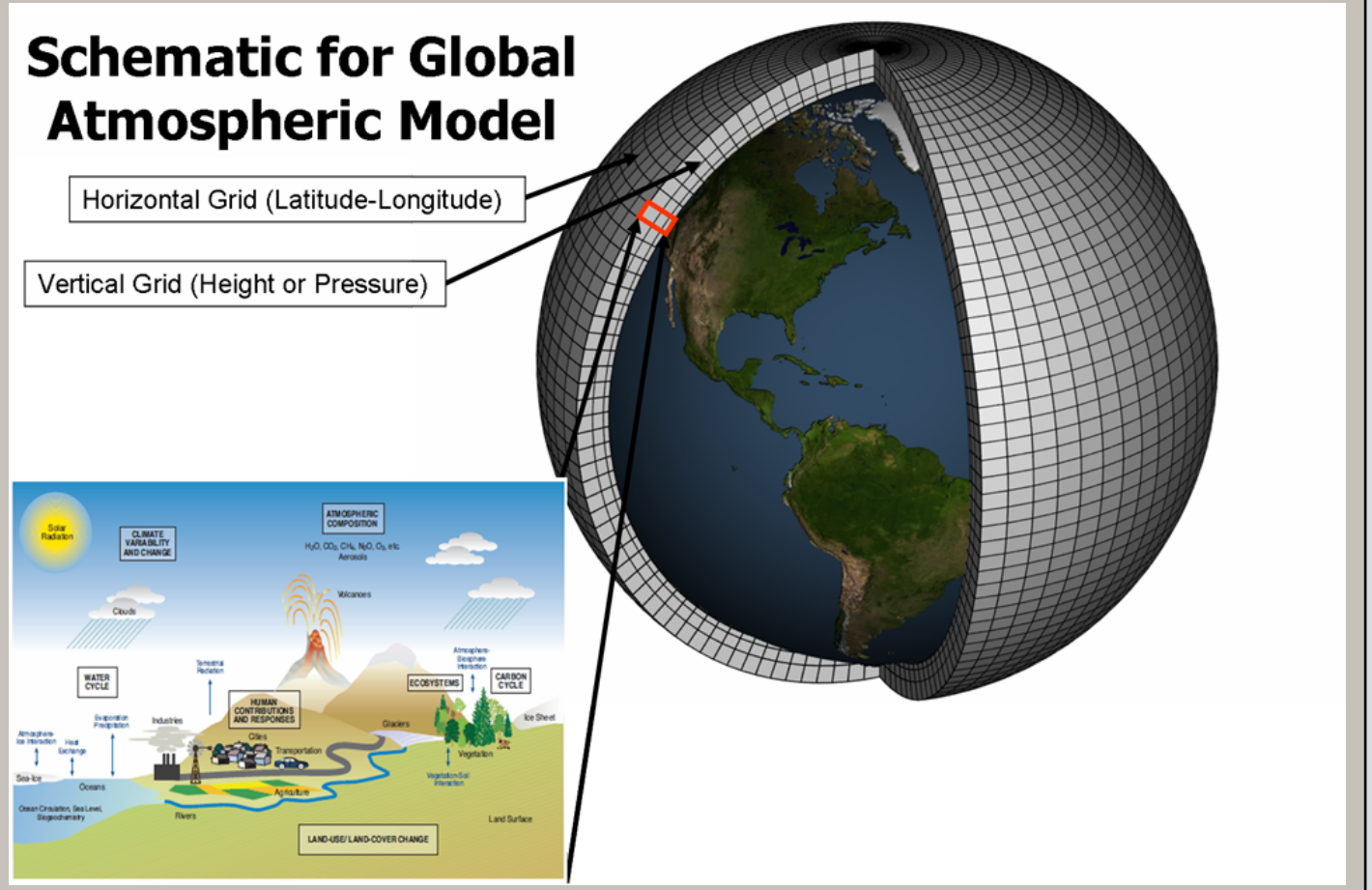
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Physical Global Climate Models

- **Discretize the Earth system in space and time**



How much global warming should we expect for a given increase in the atmospheric concentration of greenhouse gases?

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$$\lambda = \frac{F}{\Delta T}$$

Physical Global Climate Models

- **Use laws of physics to calculate state of Earth system at every 3D location**
- **March forward in time with time steps of ~30 minutes**

At every grid cell GCMs calculate:

- Temperature (T)
- Pressure (P)
- Winds (U, V)
- Humidity (Q)

- Conservation of momentum
  $\frac{\partial \vec{V}}{\partial t} = -(\vec{V} \cdot \nabla)\vec{V} - \frac{1}{\rho}\nabla p - \vec{g} - 2\vec{\Omega} \times \vec{V} + \nabla \cdot (k_m \nabla \vec{V}) - \vec{F}_d$
- Conservation of energy
  $\rho c_{\vec{v}} \frac{\partial T}{\partial t} = -\rho c_{\vec{v}} (\vec{V} \cdot \nabla) T - \nabla \cdot \vec{R} + \nabla \cdot (k_T \nabla T) + C + S$
- Conservation of mass
  $\frac{\partial \rho}{\partial t} = -(\vec{V} \cdot \nabla)\rho - \rho(\nabla \cdot \vec{V})$
- Conservation of H_2O (vapor, liquid, solid)
  $\frac{\partial q}{\partial t} = -(\vec{V} \cdot \nabla) q + \nabla \cdot (k_q \nabla q) + S_q + E$
- Equation of state
  $p = \rho R_d T$

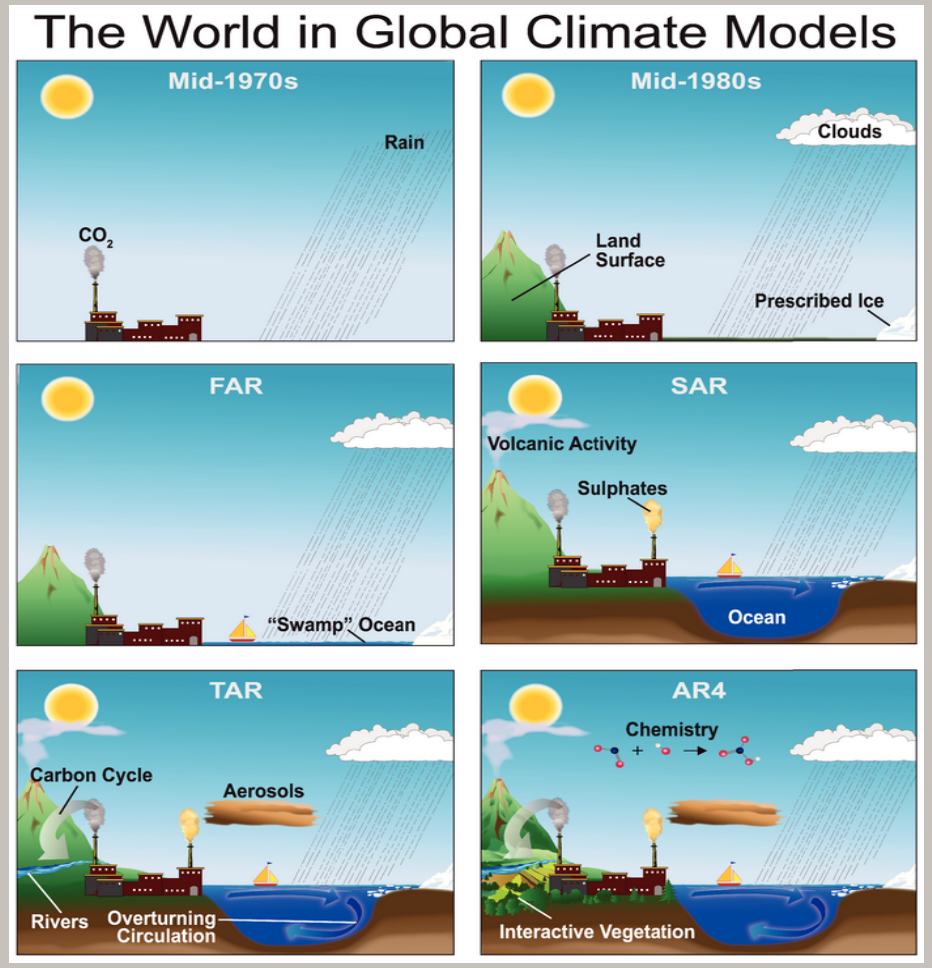
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Physical Global Climate Models

- **Number of processes explicitly represented has increased over time**



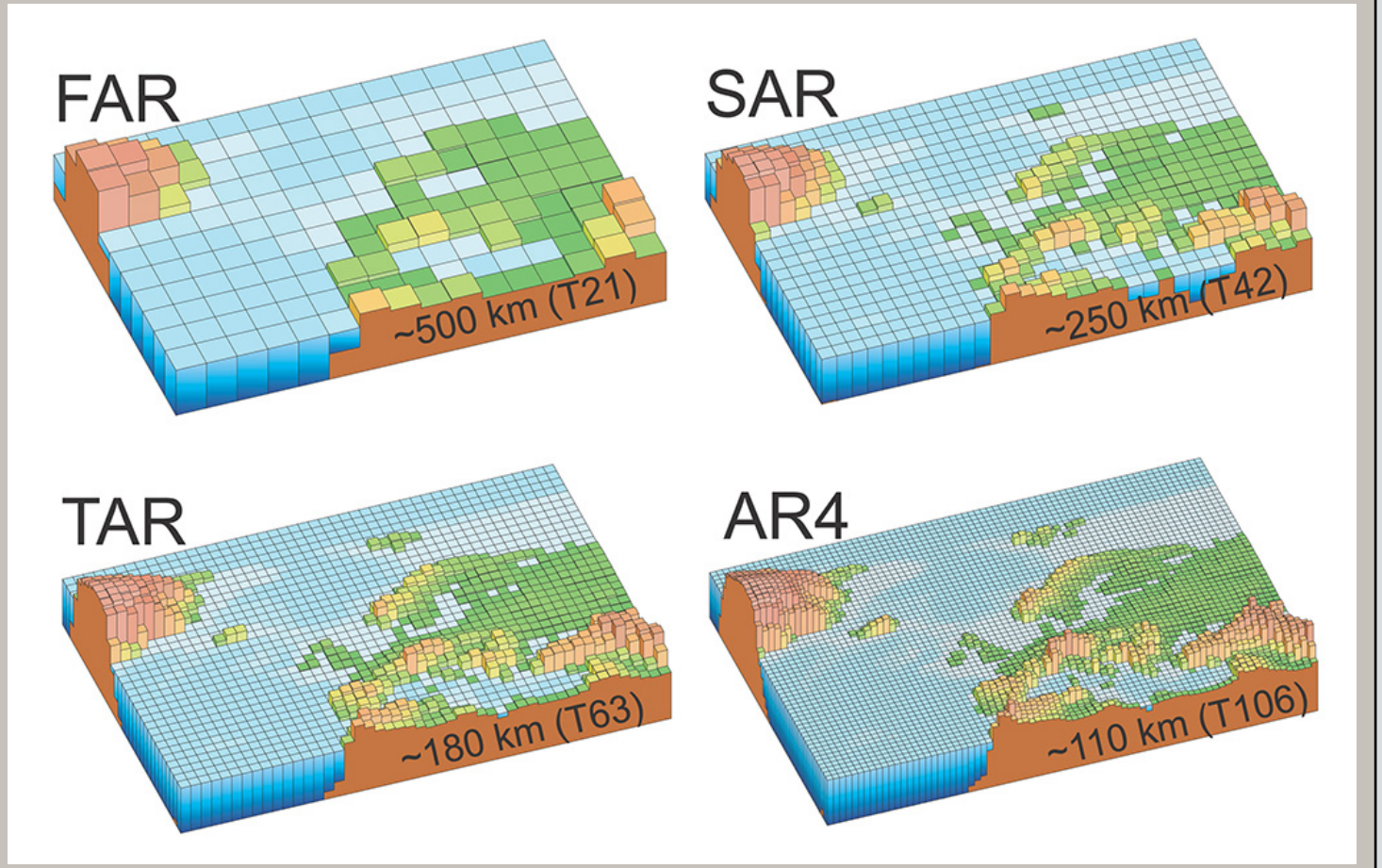
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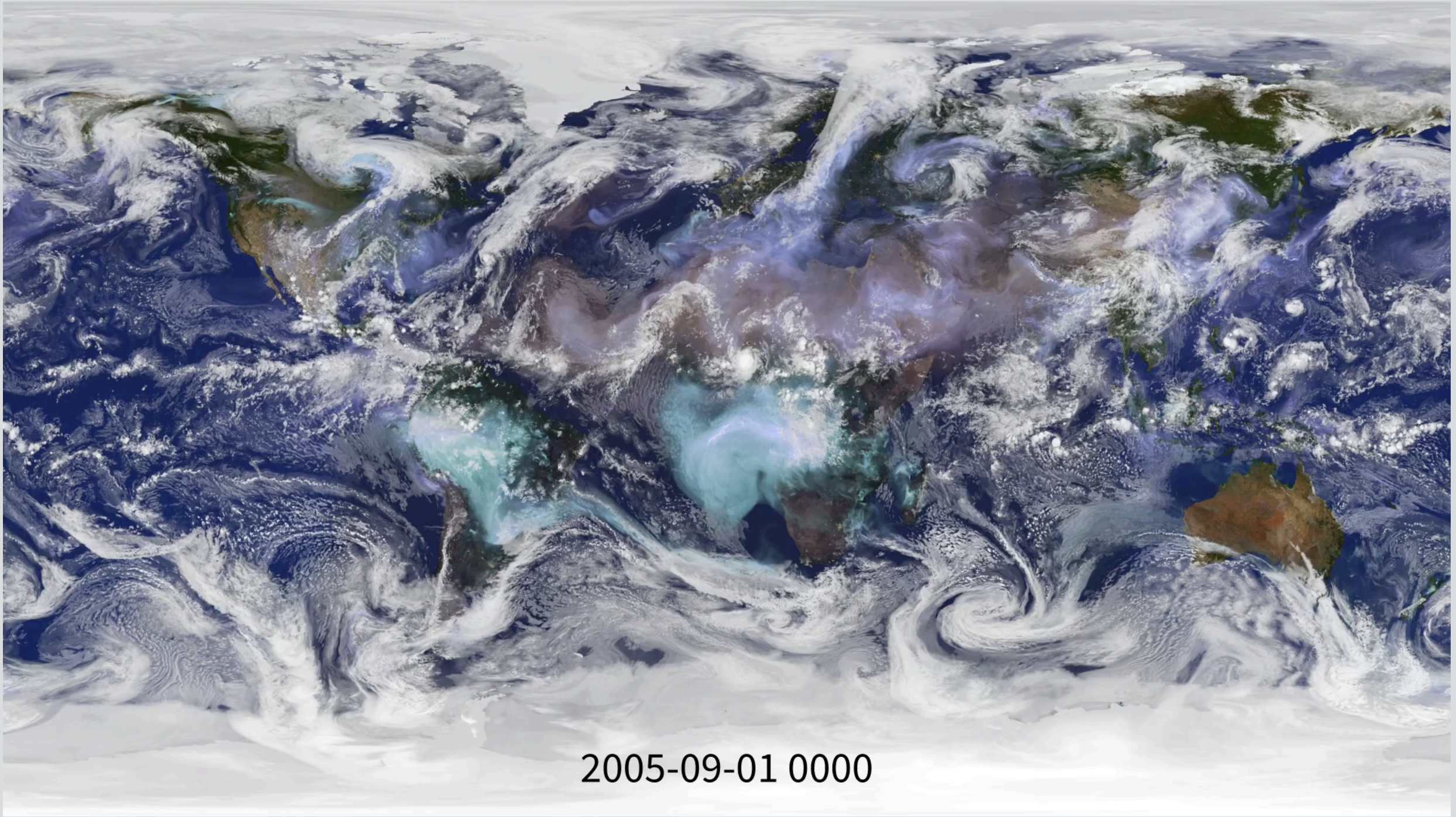
Strategy #2: Increase greenhouse gas concentrations in a **physical** climate model and have it calculate ΔT

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Physical Global Climate Models

- **Spatial resolution has increased over time**




2005-09-01 0000

How much global warming should we expect for a given increase in the atmospheric concentration of greenhouse gases?

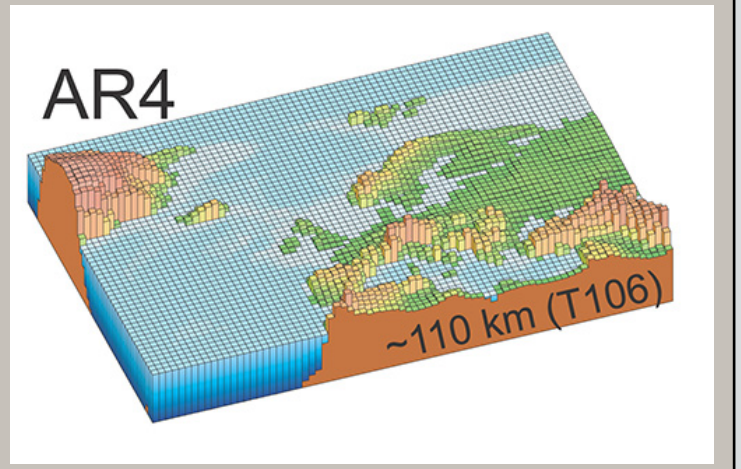
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Physical Global Climate Models

- **Spatial resolution not sufficient to represent many important processes**
- **These processes must be 'parameterized'**
- **Calculated based on a formula that is only semi-physical and has tunable parameters that are poorly constrained**
- **Example: Cloud fraction**





How much global warming should we expect for a given increase in the atmospheric concentration of greenhouse gases?

Strategy #2: Increase greenhouse gas concentrations in a **physical** climate model and have it calculate ΔT

$$\lambda = \frac{F}{\Delta T}$$

Physical Global Climate Models

```
subroutine cldfrc(lchnk   ,ncol    , pbuf, & 4,15
     pmid    ,temp    ,q       ,omga    , phis, &
     shfrc   ,use_shfrc, &
     cloud   ,rhcloud, clc     ,pdel    , &
     cmfmc   ,cmfmc2  ,landfrac,snowh   ,concld  ,cldst   , &
     ts      ,sst     ,ps      ,zdu     ,ocnfrac ,&
     rhu00   ,cldice  ,icecldf ,liqcldf ,relhum  ,dindex )
  !-------------------------------------------------------------------------
  !
  ! Purpose:
  ! Compute cloud fraction
  !
  !
  ! Method:
  ! This calculate cloud fraction using a relative humidity threshold
  ! The threshold depends upon pressure, and upon the presence or absence
  ! of convection as defined by a reasonably large vertical mass flux
  ! entering that layer from below.
  !
  ! Author: Many. Last modified by Jim McCaa
  !
  !-------------------------------------------------------------------------
  use ppgrid
  use physconst,      only: cappa, gravit, rair, tmelt
  use cldconst
  use wv_saturation, only: aqsat, aqsat_water, polysvp
  use phys_grid,      only: get_rlat_all_p, get_rlon_all_p
  use dycore,         only: dycore_is, get_resolution
```

```
!set Wang and Sassen IWC paramters
a=26.87_r8
b=0.569_r8
c=0.002892_r8
!set schiller parameters
as=-68.4202_r8
bs=0.983917_r8
cs=2.81795_r8
!set wood and field paramters...
Kc=75._r8

! Evaluate potential temperature and relative humidity
! If not computing ice cloud fraction then hybrid RH, if MG then water RH
if ( .not. cldfrc_ice ) then
   call aqsat(temp, pmid, es, qs, pcols, &
              ncol, pver, 1, pver)
else
   call aqsat_water(temp, pmid, es, qs, pcols, &
                    ncol, pver, 1, pver)
endif

do k=1,pver
   do i=1,ncol

      if (cldfrc_ice) then
         !++ag calculate qsat ice from qsatw
         esl(i,k)=polysvp(temp(i,k),0)
         esi(i,k)=polysvp(temp(i,k),1)
```

```
   !
   ! Estimate of local convective cloud cover based on convective mass flux
   ! Modify local large-scale relative humidity to account for presence of
   ! convective cloud when evaluating relative humidity based layered cloud amount
   !
   do k=1,pver
      do i=1,ncol
         concld(i,k) = 0.0_r8
      end do
   end do
   !
   ! cloud mass flux in SI units of kg/m2/s; should produce typical numbers of 20%
   ! shallow and deep convective cloudiness are evaluated separately (since processes
   ! are evaluated separately) and summed
   !
#ifndef PERGRO
   do k=1,pver-1
      do i=1,ncol
         if ( .not. use_shfrc ) then
            shallowcu(i,k) = max(0.0_r8,min(sh1*log(1.0_r8+sh2*cmfmc2(i,k+1)),0.30_r8))
         else
            shallowcu(i,k) = shfrc(i,k)
         endif
         deepcu(i,k) = max(0.0_r8,min(dp1*log(1.0_r8+dp2*(cmfmc(i,k+1)-cmfmc2(i,k+1))),0.60_r8))
         concld(i,k) = min(shallowcu(i,k) + deepcu(i,k),0.80_r8)
         rh(i,k) = (rh(i,k) - concld(i,k))/(1.0_r8 - concld(i,k))
      end do
   end do
#endif
```

```
   ! Evaluate ice cloud fraction based on in-cloud ice content

   !--------ICE CLOUD OPTION 1--------Wang & Sassen 2002
   !         Evaluate desired in-cloud water content
   !              icival = f(temp,cldice,numice)
   !         Start with a function of temperature.
   !         Wang & Sassen 2002 (JAS), based on ARM site MMCR (midlat cirrus)
   !           parameterization valid for 203-253K
   !           icival > 0 for t>195K
   if (iceopt.lt.3) then
      if (iceopt.eq.1) then
         ttmp=max(195._r8,min(temp(i,k),253._r8)) - 273.16_r8
         icicval=a + b * ttmp + c * ttmp**2._r8
         !convert units
         rho=pmid(i,k)/(rair*temp(i,k))
         icicval= icicval * 1.e-6_r8 / rho
      else
         !--------ICE CLOUD OPTION 2--------Schiller 2008 (JGR)
         !          Use a curve based on FISH measurements in
         !          tropics, mid-lats and arctic. Curve is for 180-250K (raise to 273K?)
         !          use median all flights

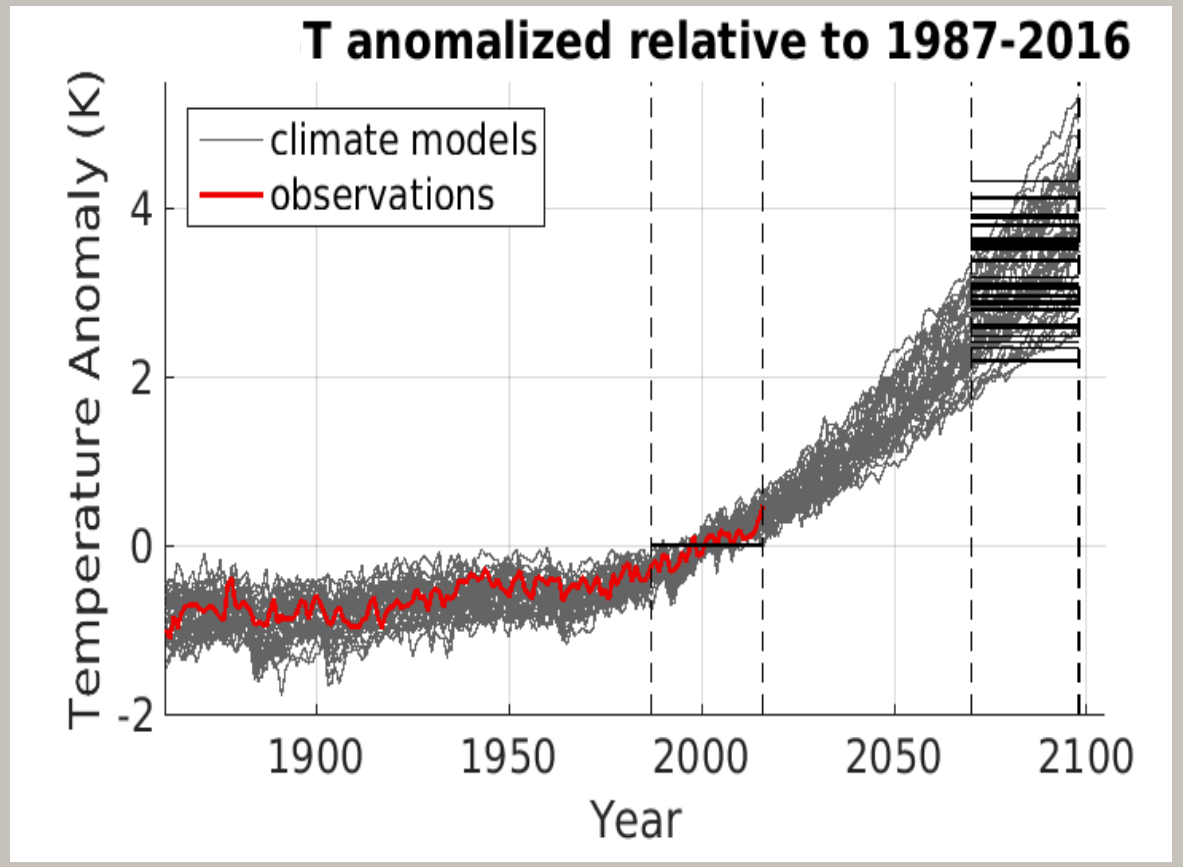
         ttmp=max(190._r8,min(temp(i,k),273.16_r8))
         icicval = 10._r8 **(as * bs**ttmp + cs)
         !convert units from ppmv to kg/kg
         icicval= icicval * 1.e-6_r8 * 18._r8 / 28.97_r8
      endif
      !set icecldfraction  for OPTION 1 or OPTION2
      icecldf(i,k) =  max(0._r8,min(cldice(i,k)/icicval,1._r8))
```

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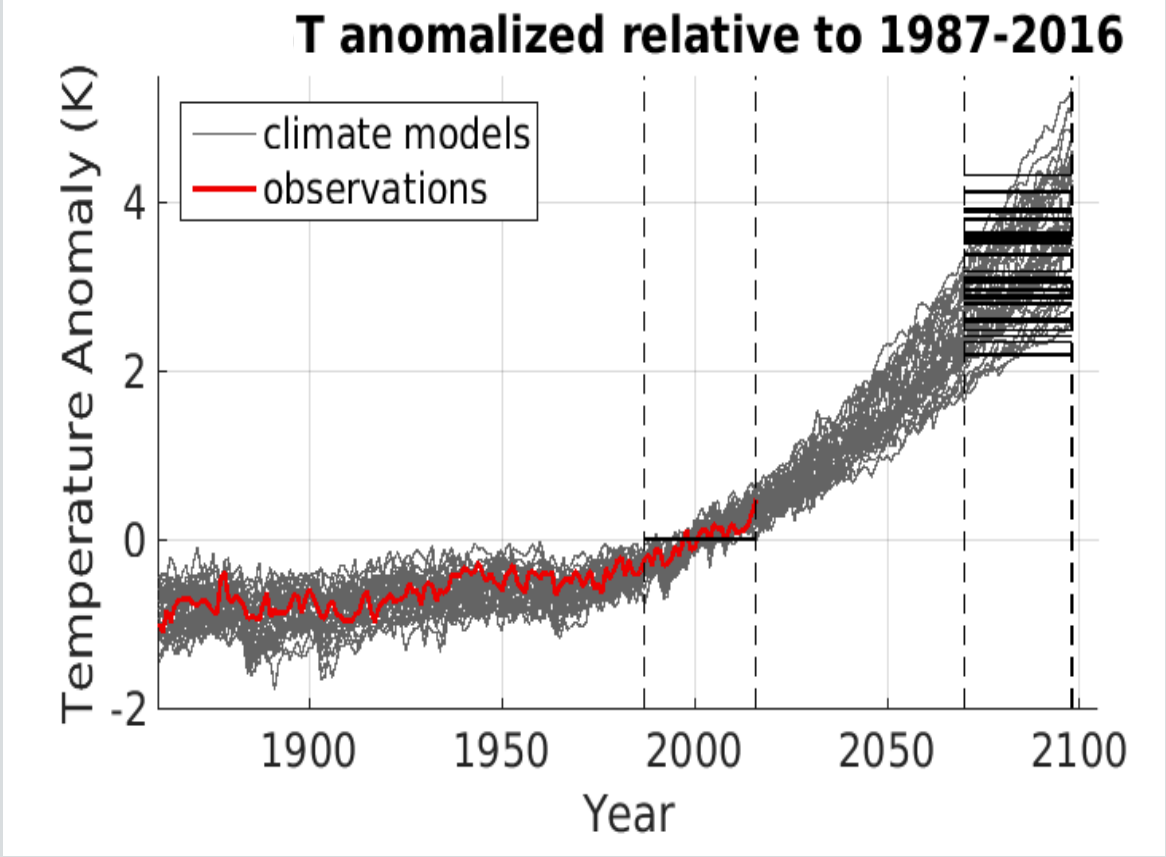
$$\Delta T = \frac{F}{\lambda}$$

Physical Global Climate Models

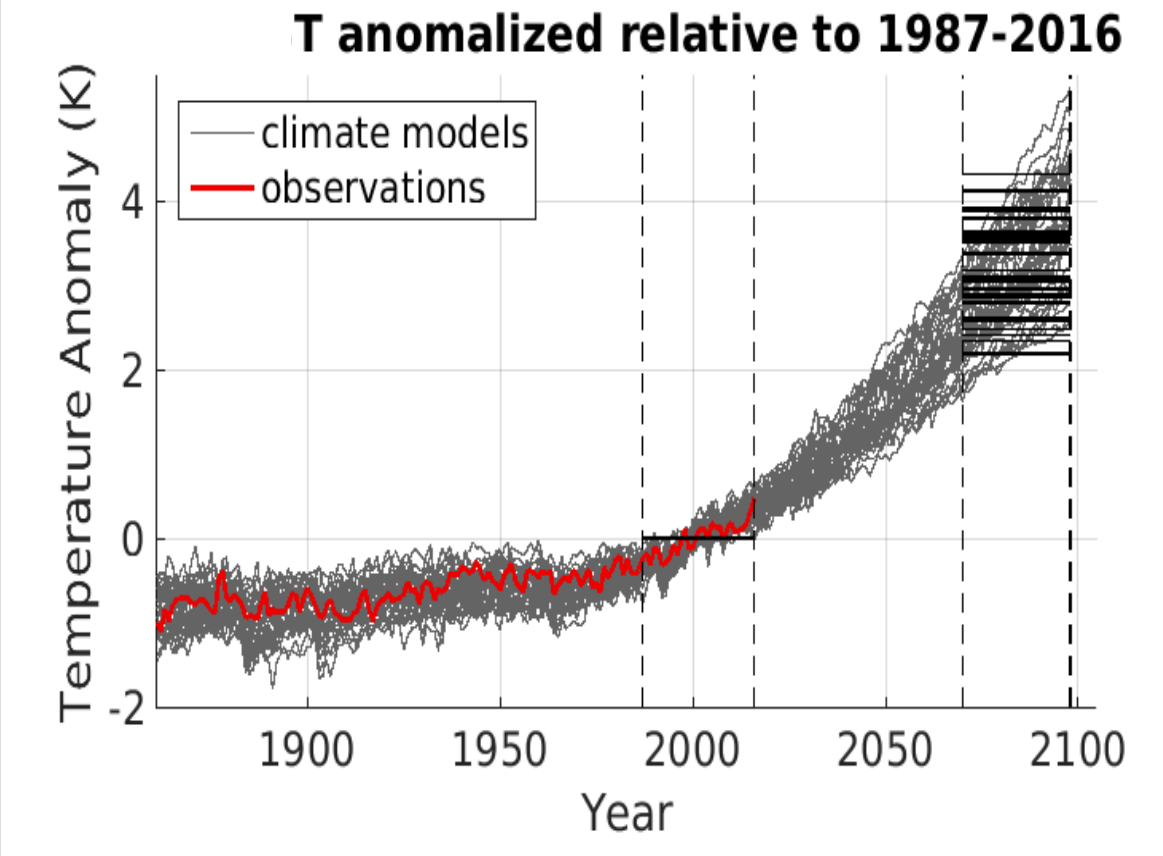


- Most of uncertainty in future warming comes from uncertainty in feedbacks (λ) that stems from important processes being 'parameterized'
- The primary goal of **our study** was to narrow this range of model uncertainty and to assess whether the upper or lower end of the range is more likely.

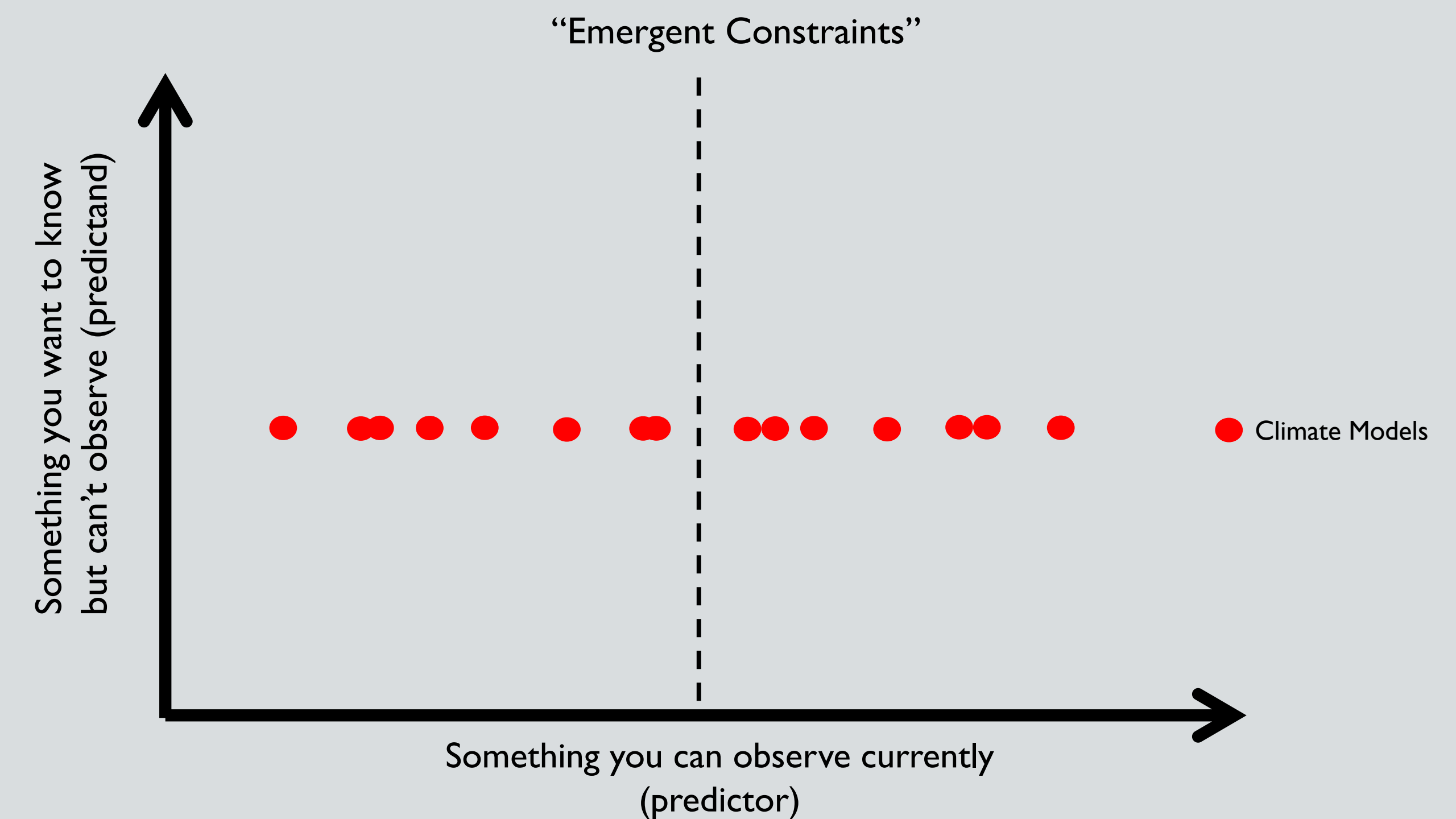
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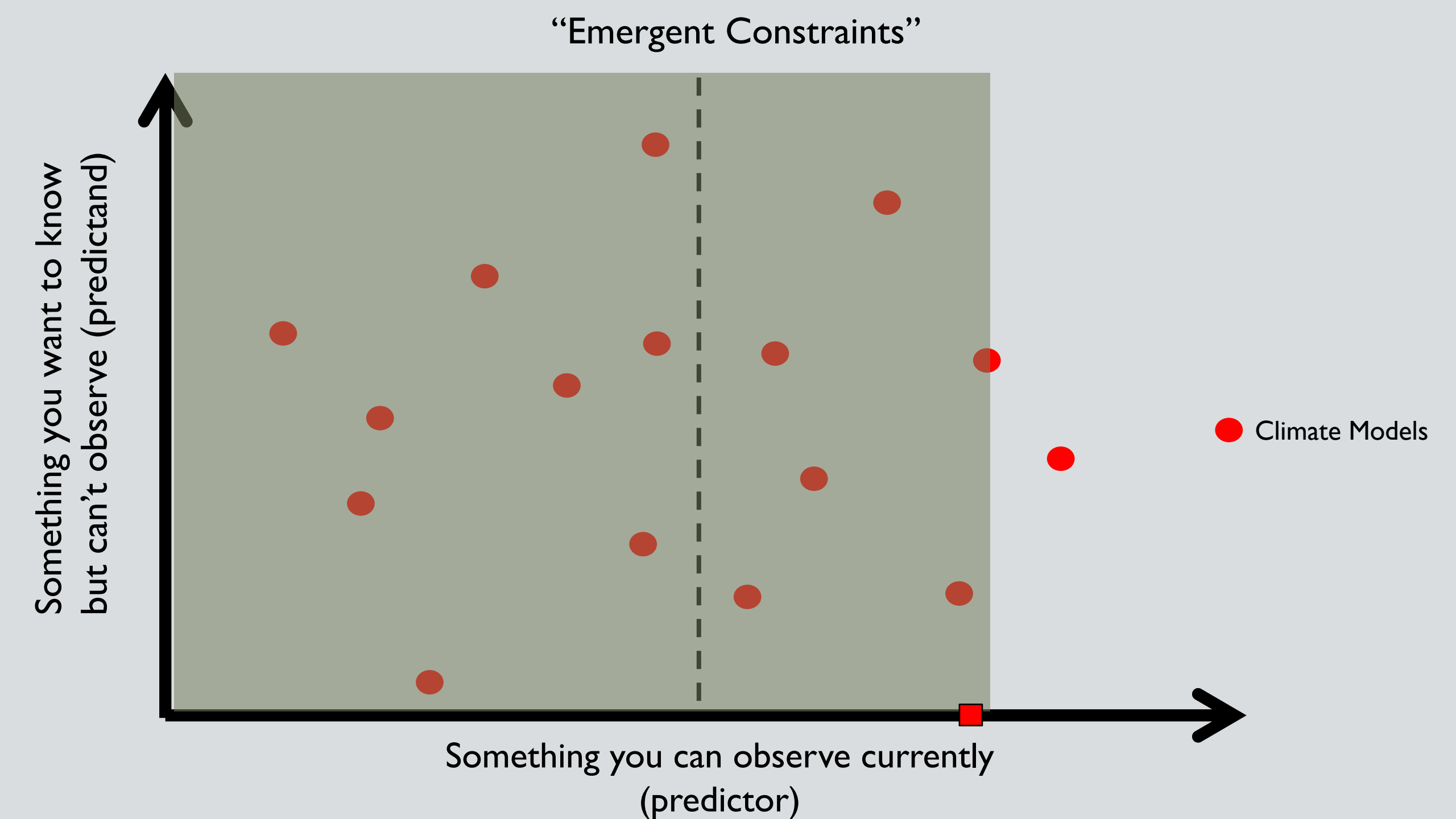


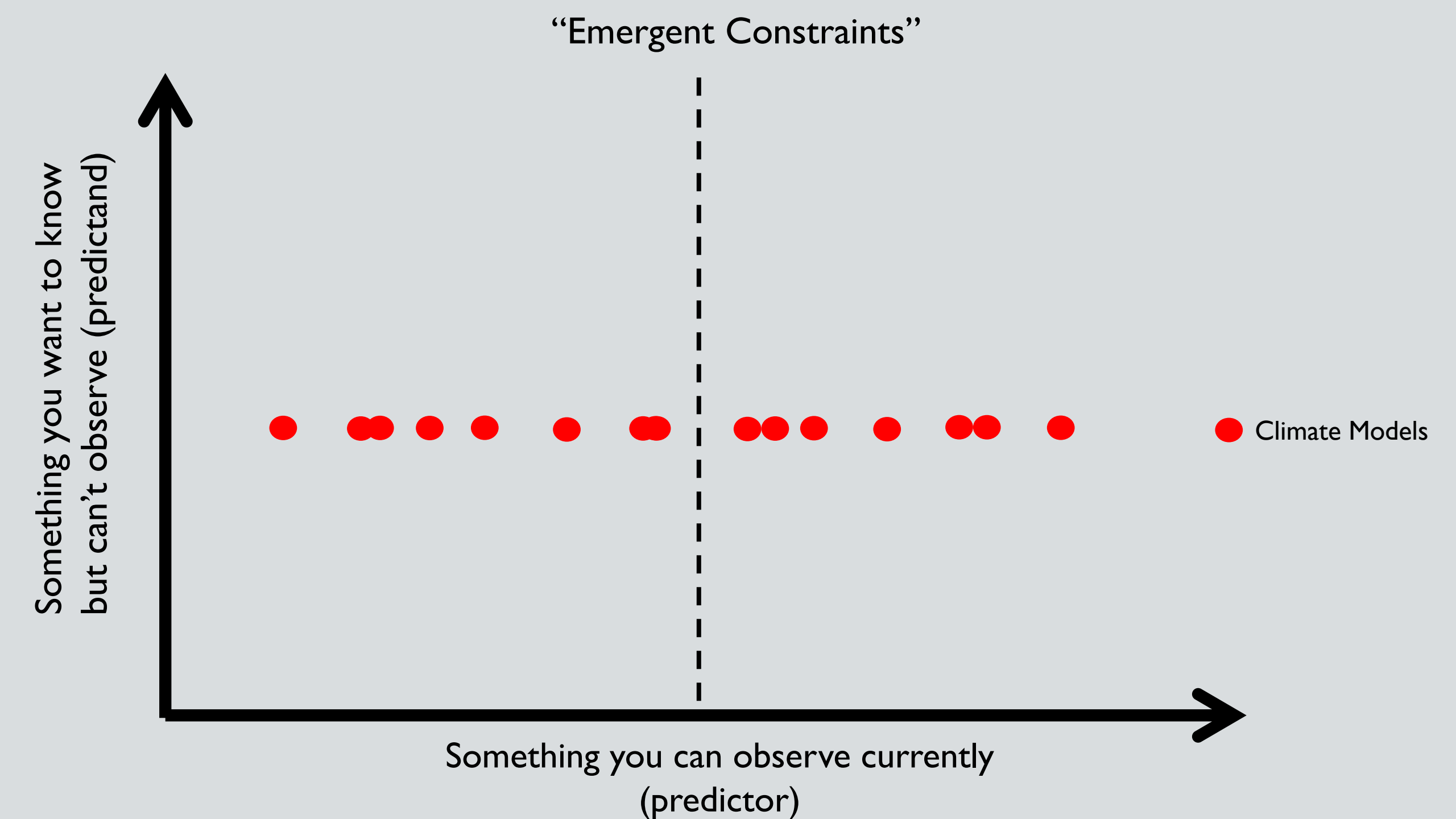
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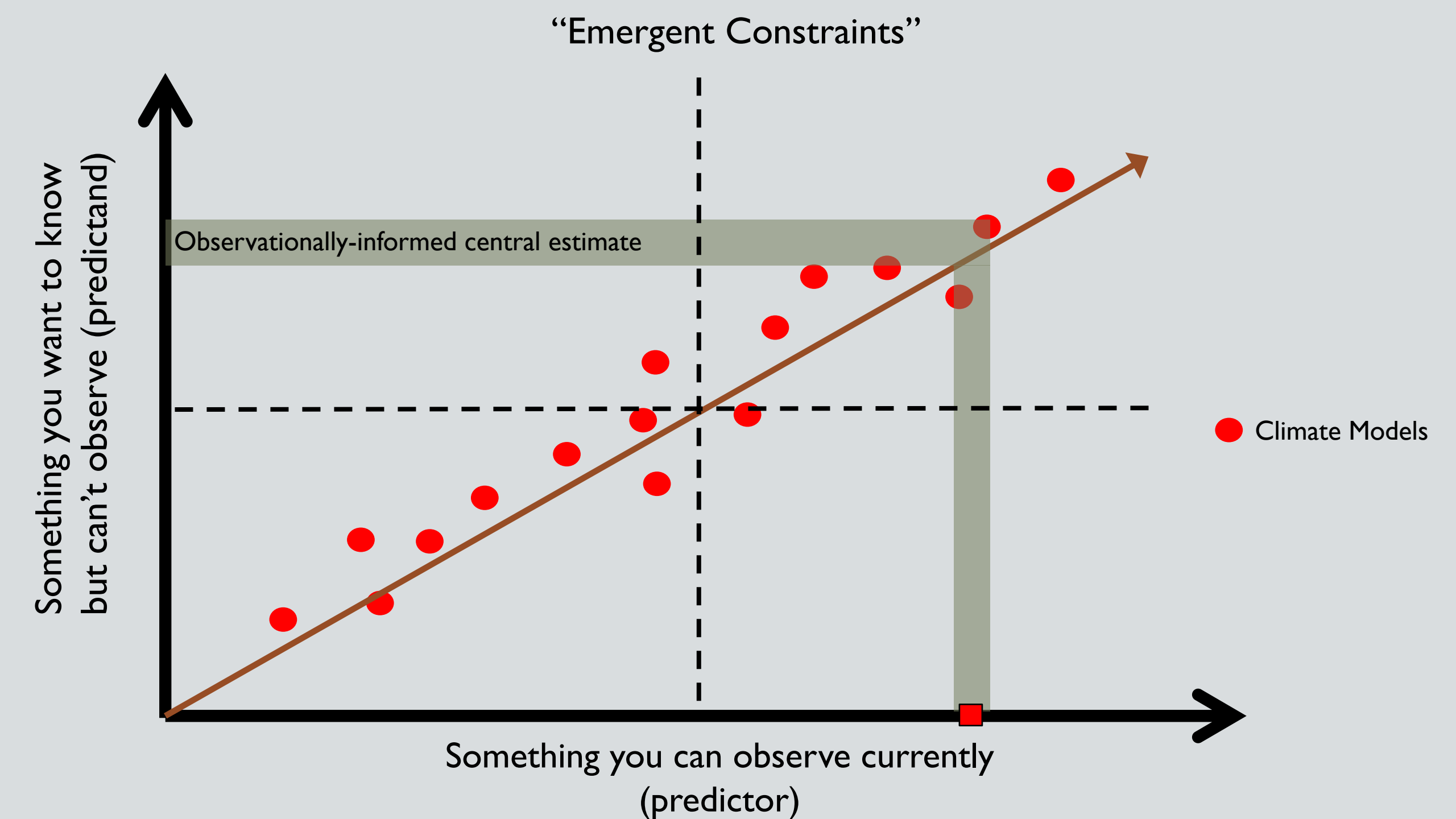


- We utilize the idea that the physical models that are going to be the most skillful in their projections of future warming (and thus have the most accurate parameterizations) should also be the most skillful in other contexts like simulating the recent past.
- **Emergent Constraints:** If there is a relationship between how physical models simulate the recent past and how much warming they simulate in the future, then we should be able to use this statistical relationship, along with observations of the recent past, to statistically narrow the range of future warming projections

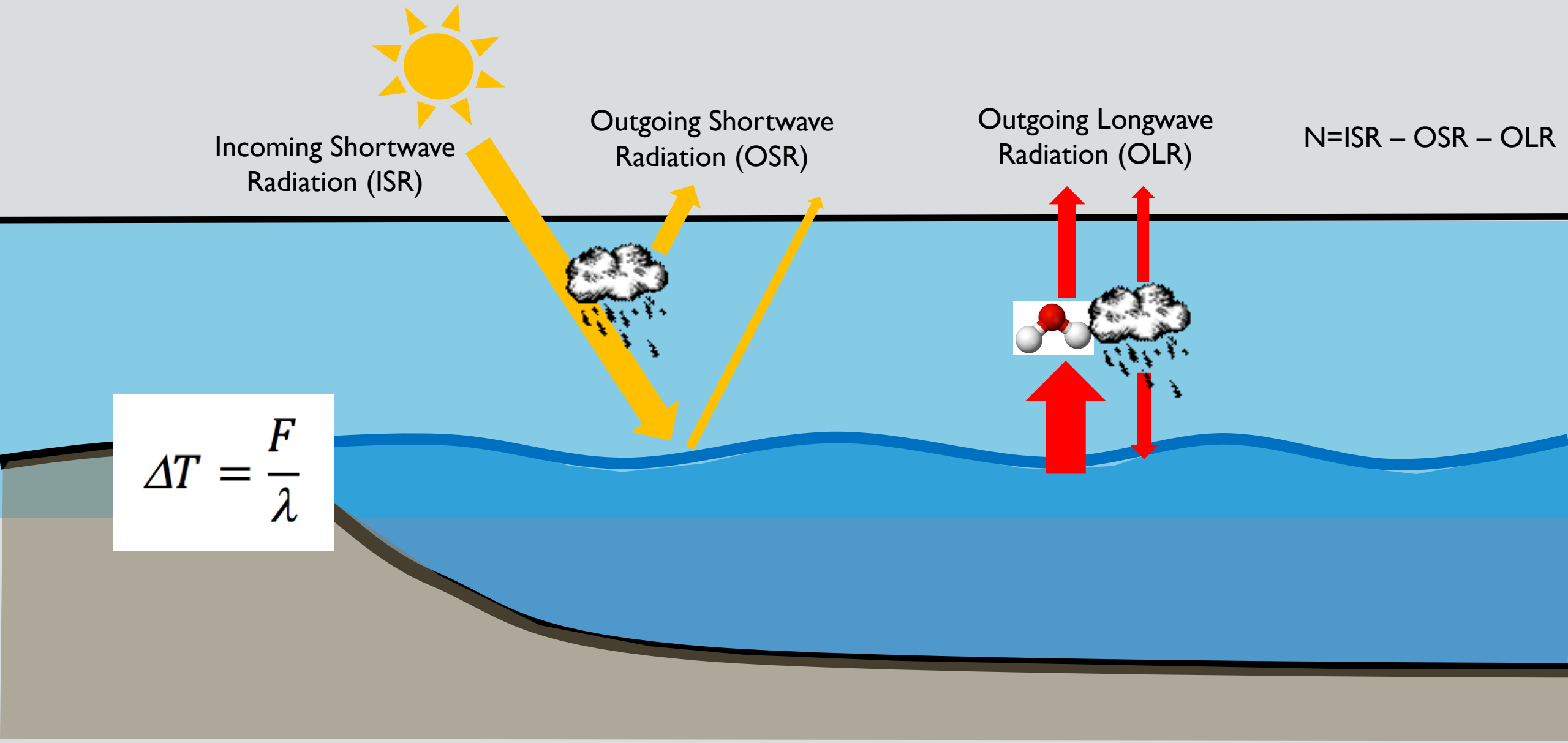

"Emergent Constraints"
Something you want to know
but can't observe (predictand)
Climate Models
Something you can observe currently
(predictor)


"Emergent Constraints"
Something you want to know
but can't observe (predictand)
Climate Models
Something you can observe currently
(predictor)

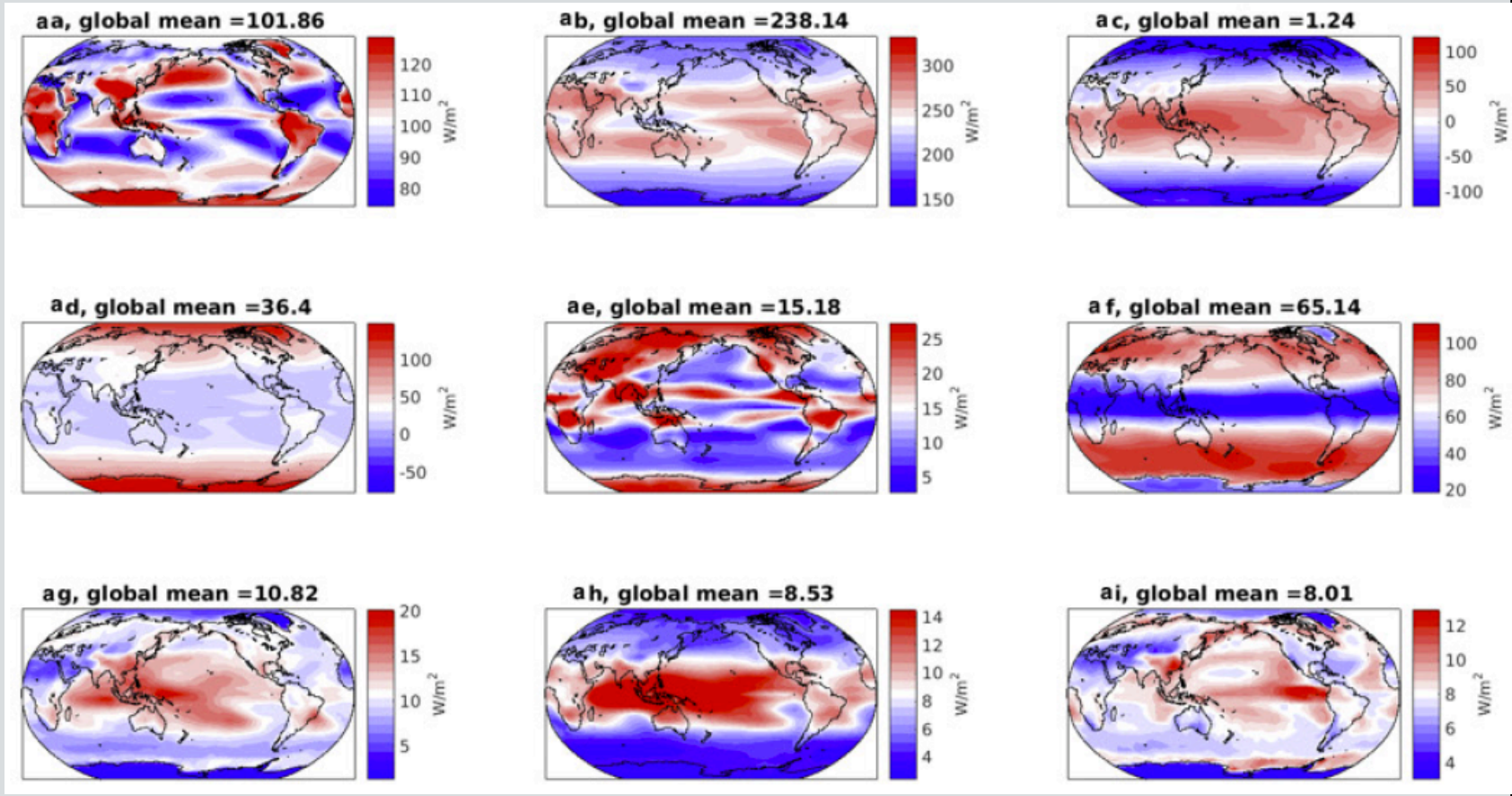

"Emergent Constraints"
Something you want to know
but can't observe (predictand)
Climate Models
Something you can observe currently
(predictor)


"Emergent Constraints"
Something you want to know
but can't observe (predictand)
Observationally-informed central estimate
Climate Models
Something you can observe currently
(predictor)

What variables are most appropriate to use as predictors ?



What variables are most appropriate to use as predictors ?

	Outgoing Shortwave Radiation (OSR)	Outgoing Longwave Radiation (OLR)	N=ISR – OSR – OLR
Mean climatology (Local average)			
Magnitude of the seasonal cycle (Local standard deviation of average seasonal cycle)			
Magnitude of monthly variability (Local standard deviation monthly variability apart from seasonal cycle)			

What variables are most appropriate to use as predictors ?

Outgoing Shortwave Radiation (OSR)

Outgoing Longwave Radiation (OLR)

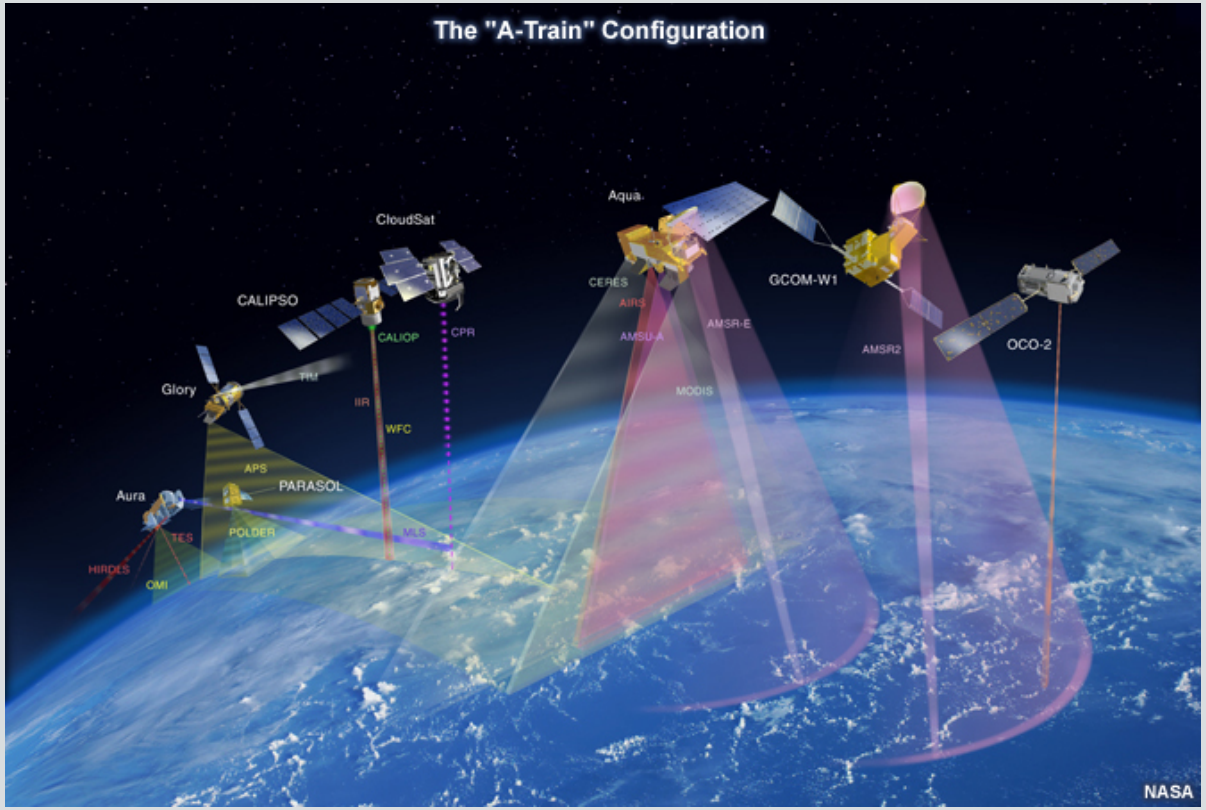
N=ISR – OSR – OLR

Mean climatology

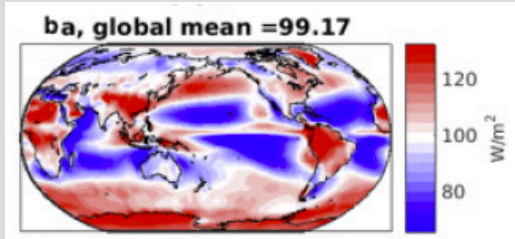
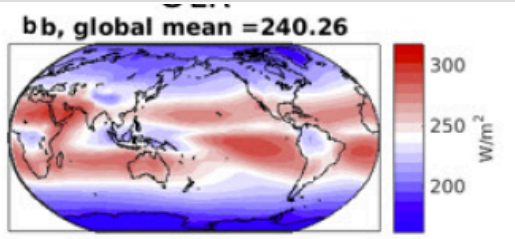
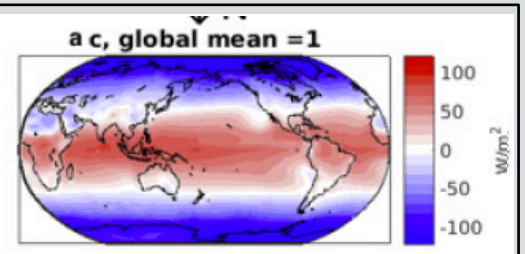
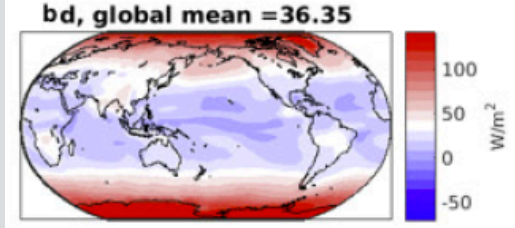
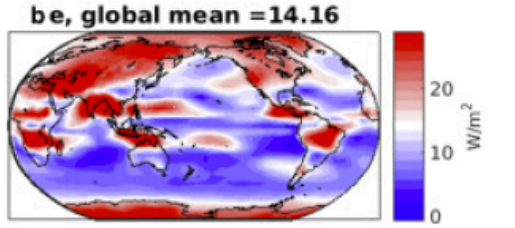
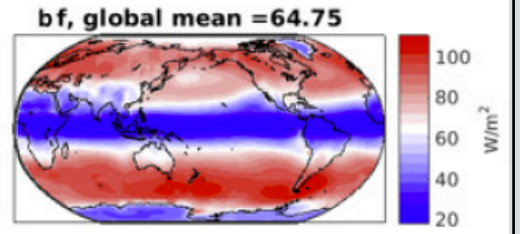
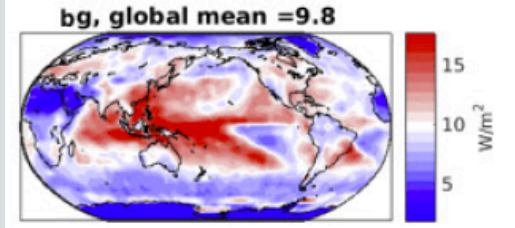
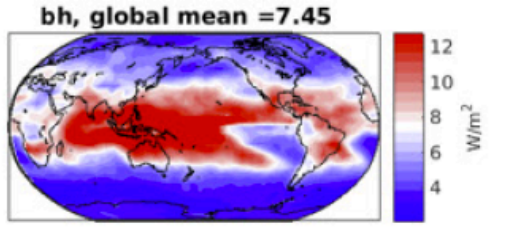
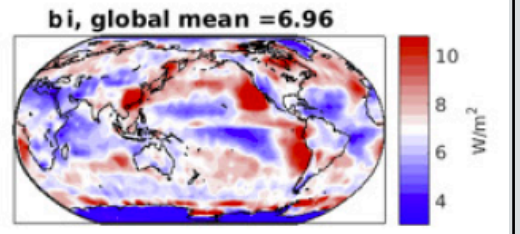
Magnitude of the seasonal cycle

Magnitude of monthly variability

CERES Satellite Record (2001-2015)



What variables are most appropriate to use as predictors ?

	Outgoing Shortwave Radiation (OSR)	Outgoing Longwave Radiation (OLR)	N=ISR – OSR – OLR
Mean climatology			
Magnitude of the seasonal cycle			
Magnitude of monthly variability			

What variables are most appropriate to use as predictors ?

	Outgoing Shortwave Radiation (OSR)	Outgoing Longwave Radiation (OLR)	N=ISR – OSR – OLR
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Magnitude of the seasonal cycle			
Magnitude of monthly variability			

What method is appropriate to statistically relate the predictor to the predictand?

	Outgoing Shortwave Radiation (OSR)	Outgoing Longwave Radiation (OLR)	N=ISR – OSR – OLR
Mean climatology			
Magnitude of the seasonal cycle			
Magnitude of monthly variability			

What method is appropriate to statistically relate the predictor to the predictand?

(Predictor Variable, [x])

Outgoing Shortwave Radiation (OSR)

Mean climatology

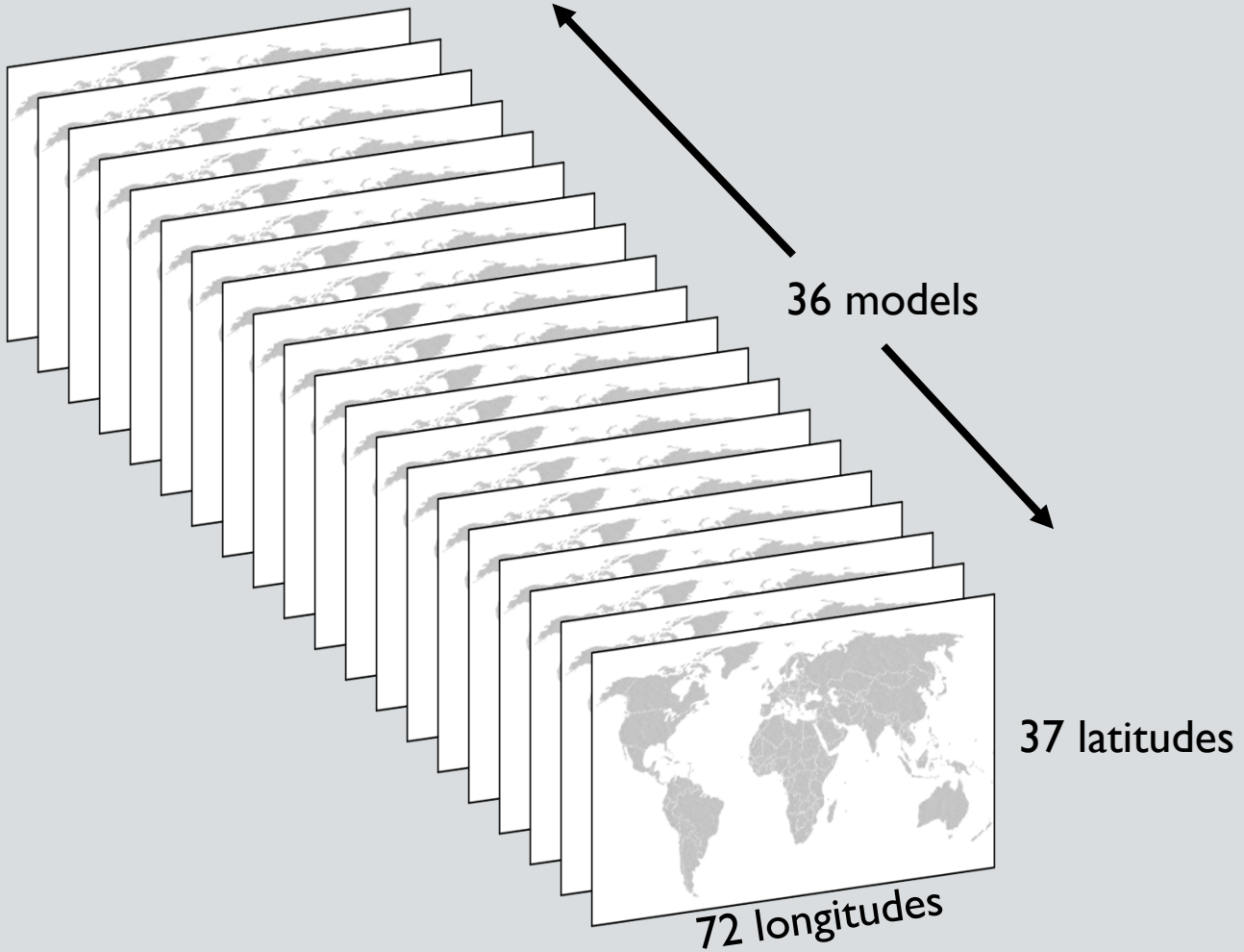


What method is appropriate to statistically relate the predictor to the predictand?

Mean climatology

Outgoing Shortwave Radiation (OSR)

(Predictor Variable, [x])



(Predictand Variable, y)

ΔT
2.0
3.2
4.4
2.1
2.6
3.6
3.2
2.2
4.8
3.9
3.0
3.3

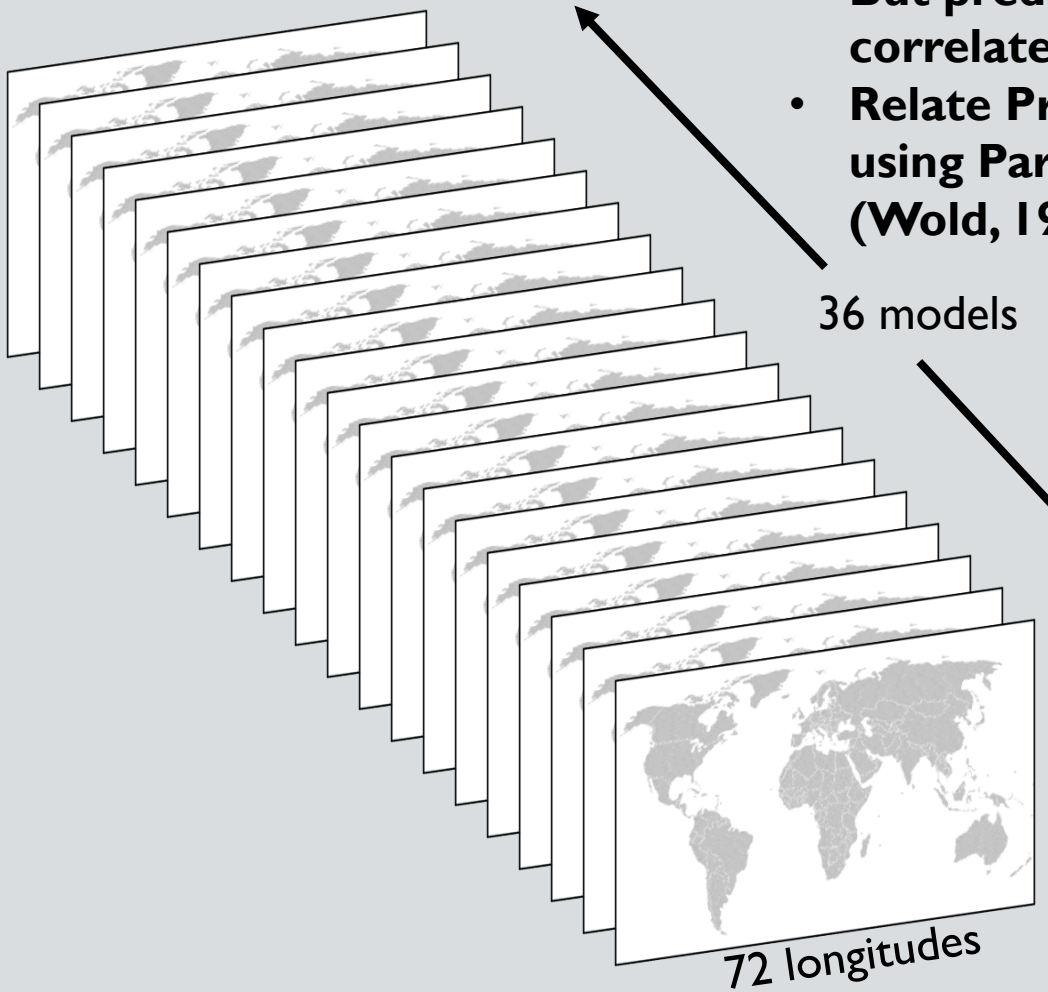
36 models

What method is appropriate to statistically relate the predictor to the predictand?

Mean climatology

Outgoing Shortwave Radiation (OSR)

(Predictor Variable, [x])



- **There are many more predictors than variables to predict**
- **But predictors themselves are correlated with each other**
- **Relate Predictor Field to Predictand using Partial Least Squares Regression (Wold, 1966)**

(Predictand Variable, y)

ΔT
2.0
3.2
4.4
2.1
2.6
3.6
3.2
2.2
4.8
3.9
3.0
3.3

36 models

Partial Least Squares Regression

- Could think of this in terms of Multiple Linear Regression

$$[X]\vec{b} + \vec{r} = \vec{y}$$

2664 Locations→

$$\leftarrow 36\ \text{Models} \begin{bmatrix} 1 & OSW_{model_1,location_1} & OSW_{model_1,location_2} & \cdots & OSW_{model_1,location_{2664}} \\ 1 & OSW_{model_2,location_1} & OSW_{model_2,location_2} & \cdots & OSW_{model_2,location_{2664}} \\ 1 & OSW_{model_3,location_1} & OSW_{model_3,location_2} & \cdots & OSW_{model_2,location_{2664}} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ 1 & OSW_{model_{36},location_1} & OSW_{model_{36},location_2} & \cdots & OSW_{model_{36},location_{2664}} \end{bmatrix} \begin{bmatrix} b_0 \\ b_{location_1} \\ b_{location_2} \\ \cdots \\ b_{location_{2664}} \end{bmatrix} + \begin{bmatrix} r_{model_1} \\ r_{model_2} \\ r_{model_3} \\ \cdots \\ r_{model_{36}} \end{bmatrix} =$$

(Predictand Variable, y)

ΔT
2.0
3.2
4.4
2.1
2.6
3.6
3.2
2.2
4.8
3.9
3.0
3.3

36 models

- System is underdetermined (more unknowns than equations)
- Because of the high degree of spatial autocorrelation in the predictor fields used here, the columns in [X] will be highly collinear, and thus [X] will be well below full rank.
- PLS creates a small number of 'PLS components' or 'latent vectors' that are:
  - Linear combinations of the original original columns
  - Uncorrelated with each other
  - Explain as much of the variability in the predictand as possible

Partial Least Squares Regression

- Could think of this in terms of Multiple Linear Regression

$$[Z]\vec{\boldsymbol{\beta}} + \vec{r} = \vec{y}$$

7 Components →

$$\leftarrow 36\ \text{Models}\begin{bmatrix} 1 & OSW_{model_1,component_1} & OSW_{model_1,component_2} & \cdots & OSW_{model_1,component_7} \\ 1 & OSW_{model_2,component_1} & OSW_{model_2,component_2} & \cdots & OSW_{model_2,component_7} \\ 1 & OSW_{model_3,component_1} & OSW_{model_3,component_2} & \cdots & OSW_{model_2,component_7} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ 1 & OSW_{model_{36},location_1} & OSW_{model_{36},component_2} & \cdots & OSW_{model_{36},component_7} \end{bmatrix} \begin{bmatrix} \boldsymbol{\beta}_0 \\ \boldsymbol{\beta}_{component_1} \\ \boldsymbol{\beta}_{component_2} \\ \cdots \\ \boldsymbol{\beta}_{component_7} \end{bmatrix} + \begin{bmatrix} r_{model_1} \\ r_{model_2} \\ r_{model_3} \\ \cdots \\ r_{model_{36}} \end{bmatrix} =$$

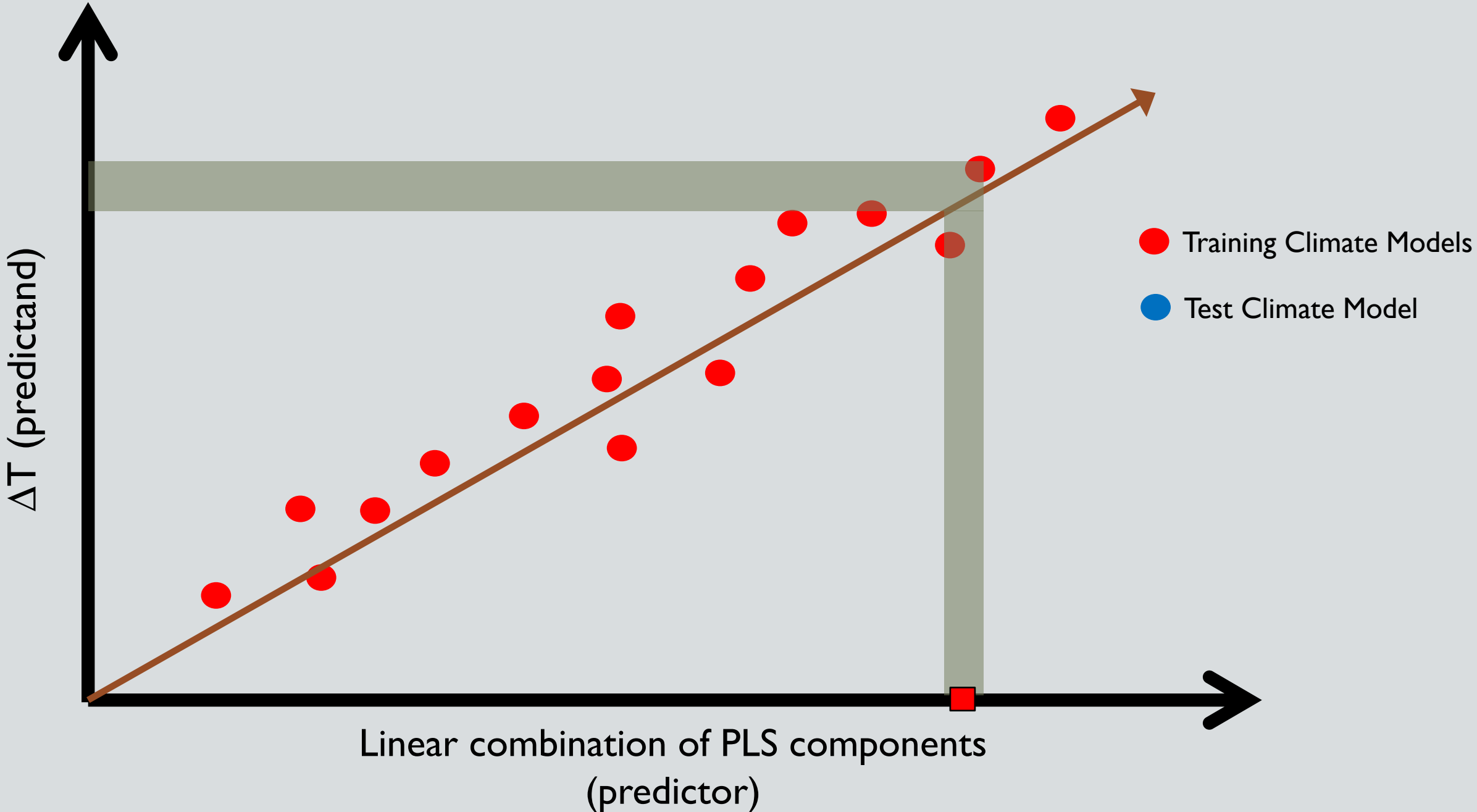
(Predictand Variable, y)

ΔT
2.0
3.2
4.4
2.1
2.6
3.6
3.2
2.2
4.8
3.9
3.0
3.3

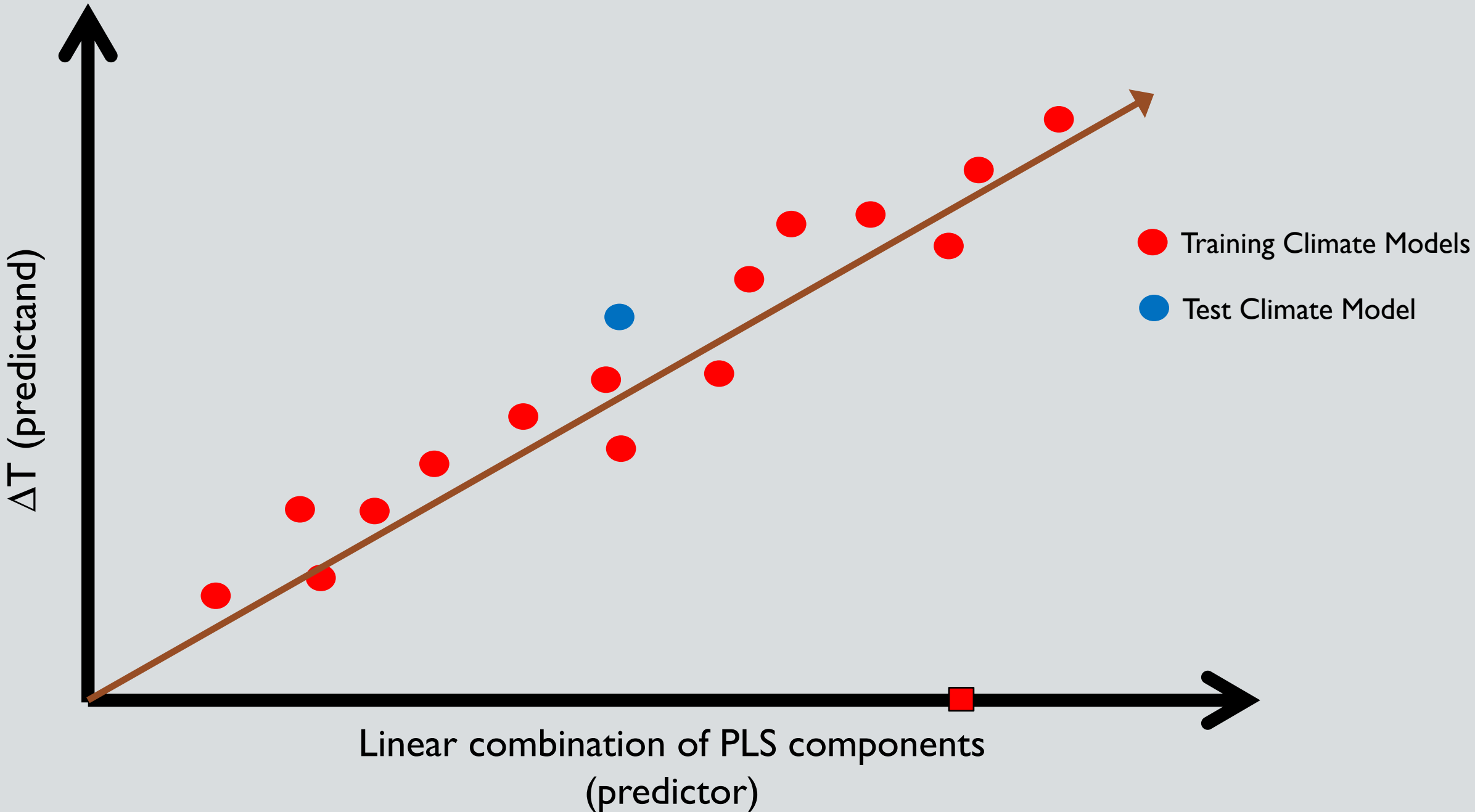
36 models

- Must guard against over-fitting
- PLS procedure is more than capable of overfitting predictors to predictands.
- We evaluated the predictive skill of the predictors (and thus the constrained warming uncertainty) using leave-one-out cross-validation.

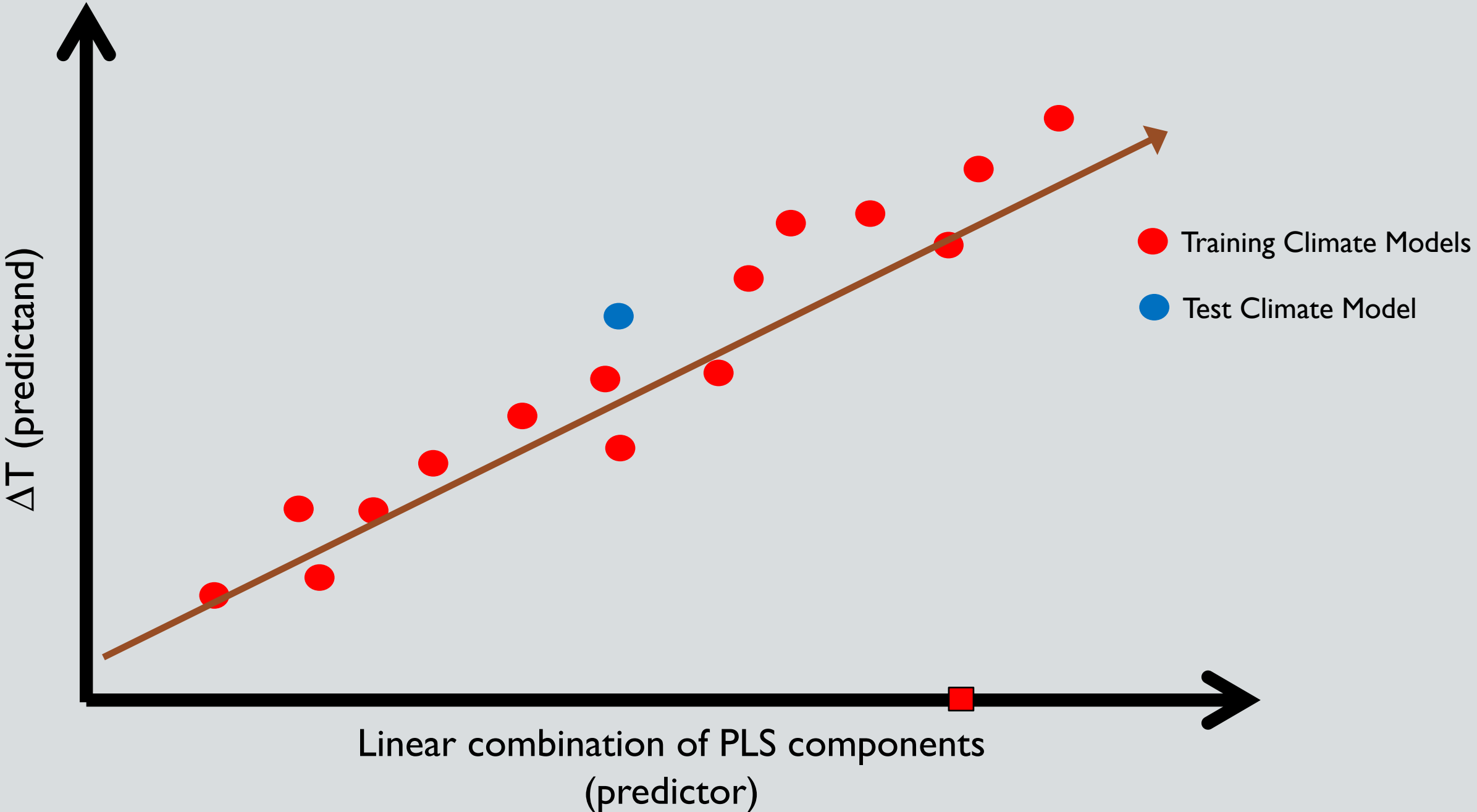
Cross-validation



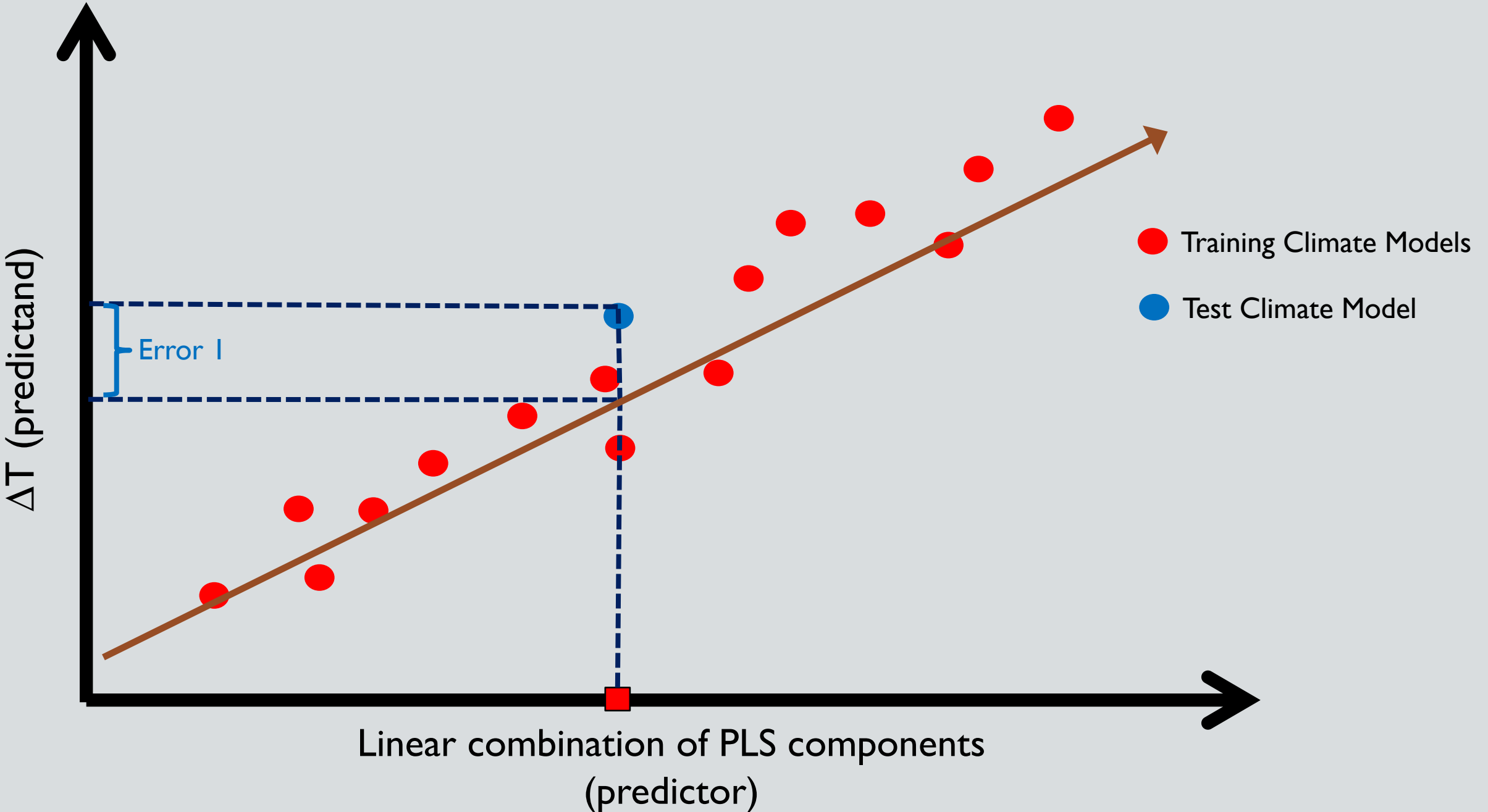
Cross-validation

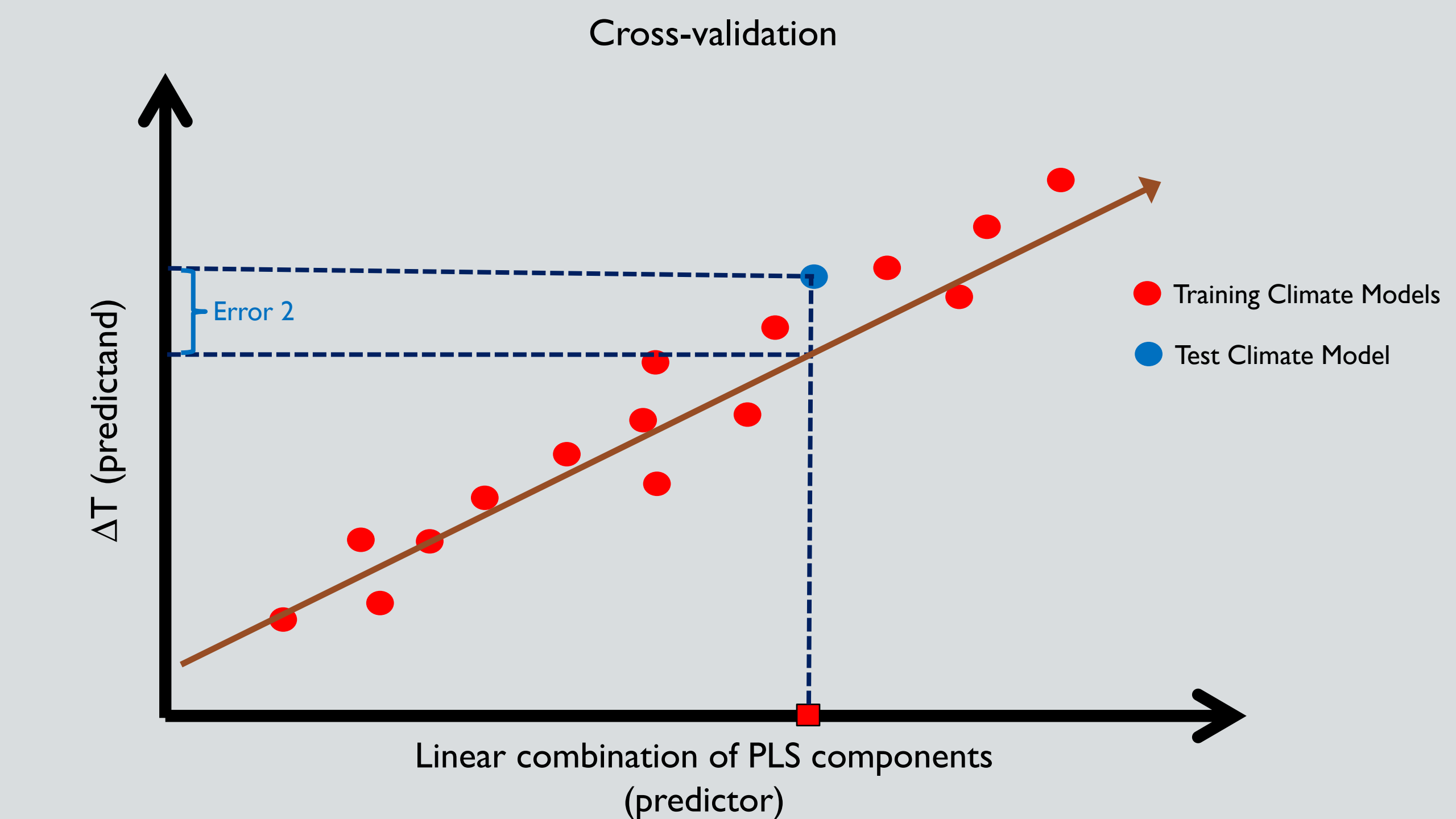


Cross-validation

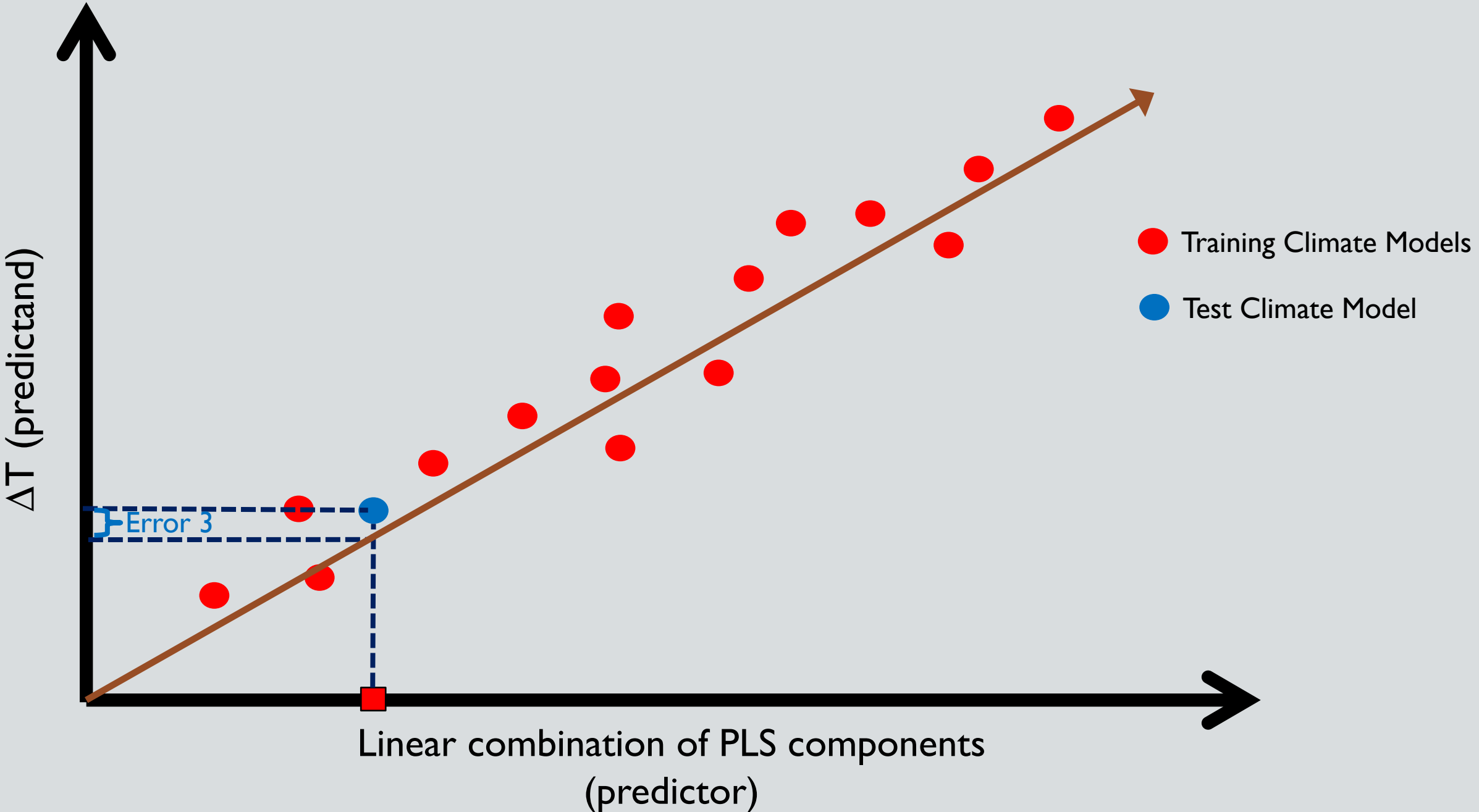


Cross-validation

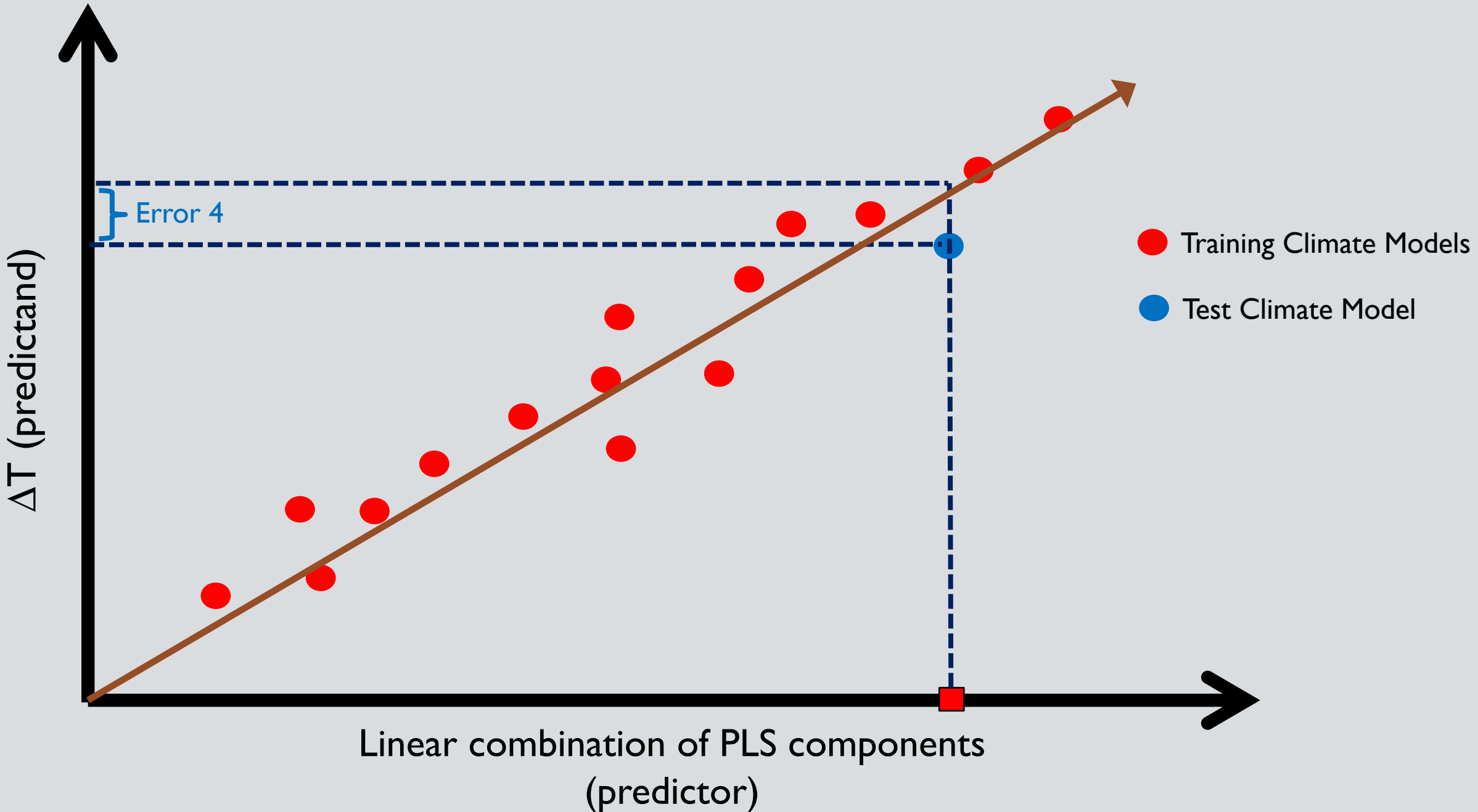



Cross-validation
ΔT (predictand)
Error 2
Training Climate Models
Test Climate Model
Linear combination of PLS components
(predictor)

Cross-validation

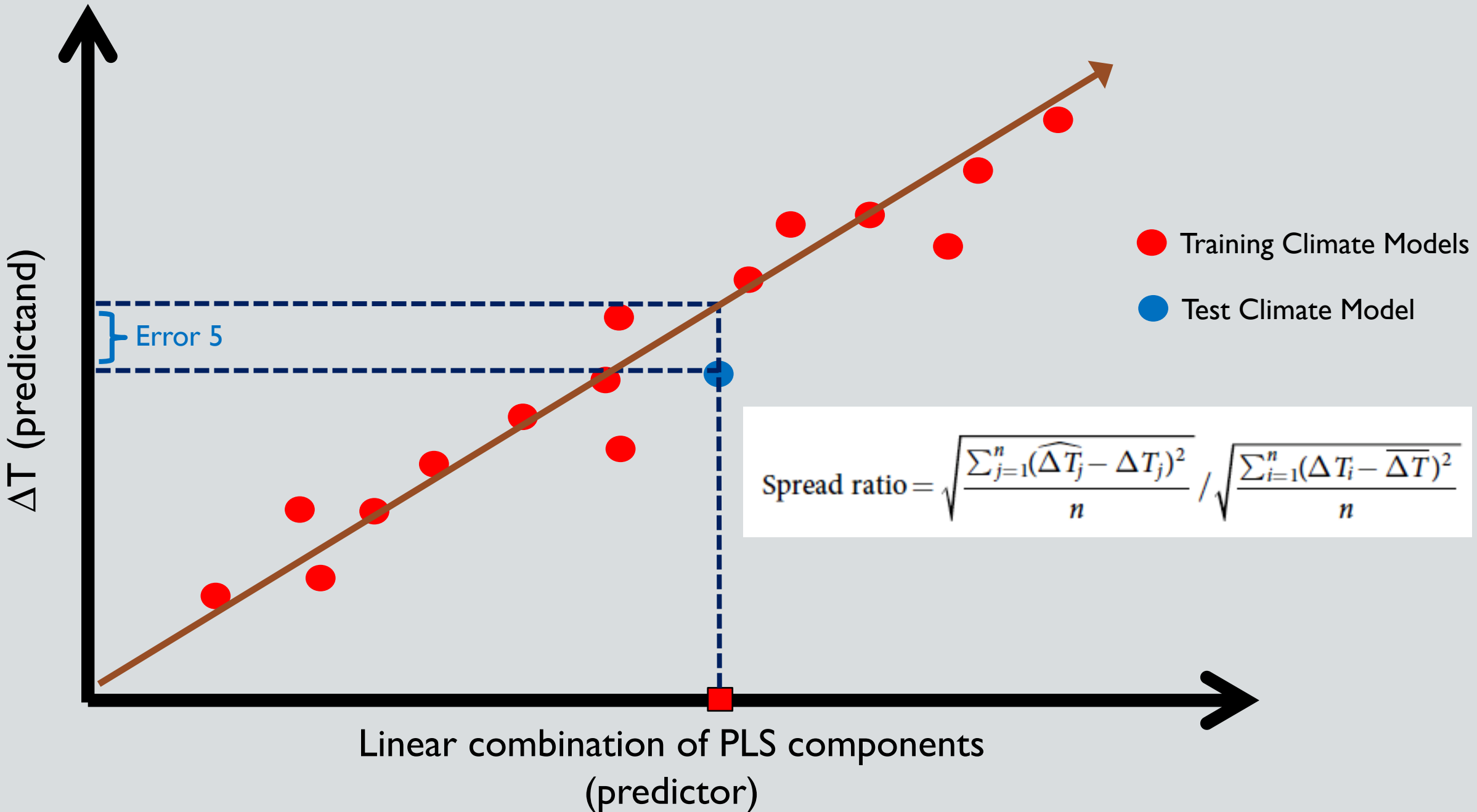


Cross-validation



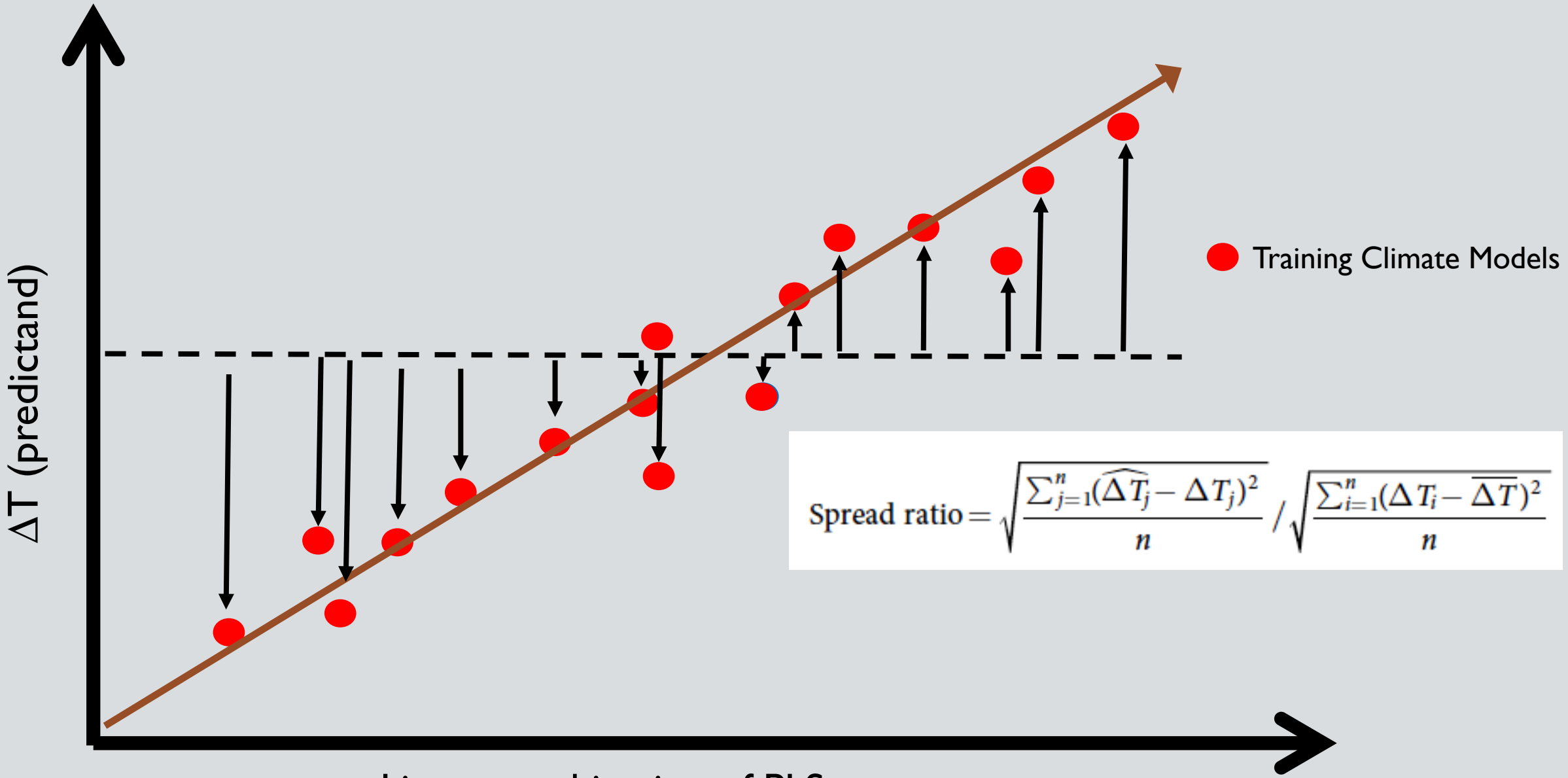
Results

Cross-validation



$$\text{Spread ratio} = \sqrt{\frac{\sum_{j=1}^{n}(\widehat{\Delta T_j} - \Delta T_j)^2}{n}} \Big/ \sqrt{\frac{\sum_{i=1}^{n}(\Delta T_i - \overline{\Delta T})^2}{n}}$$

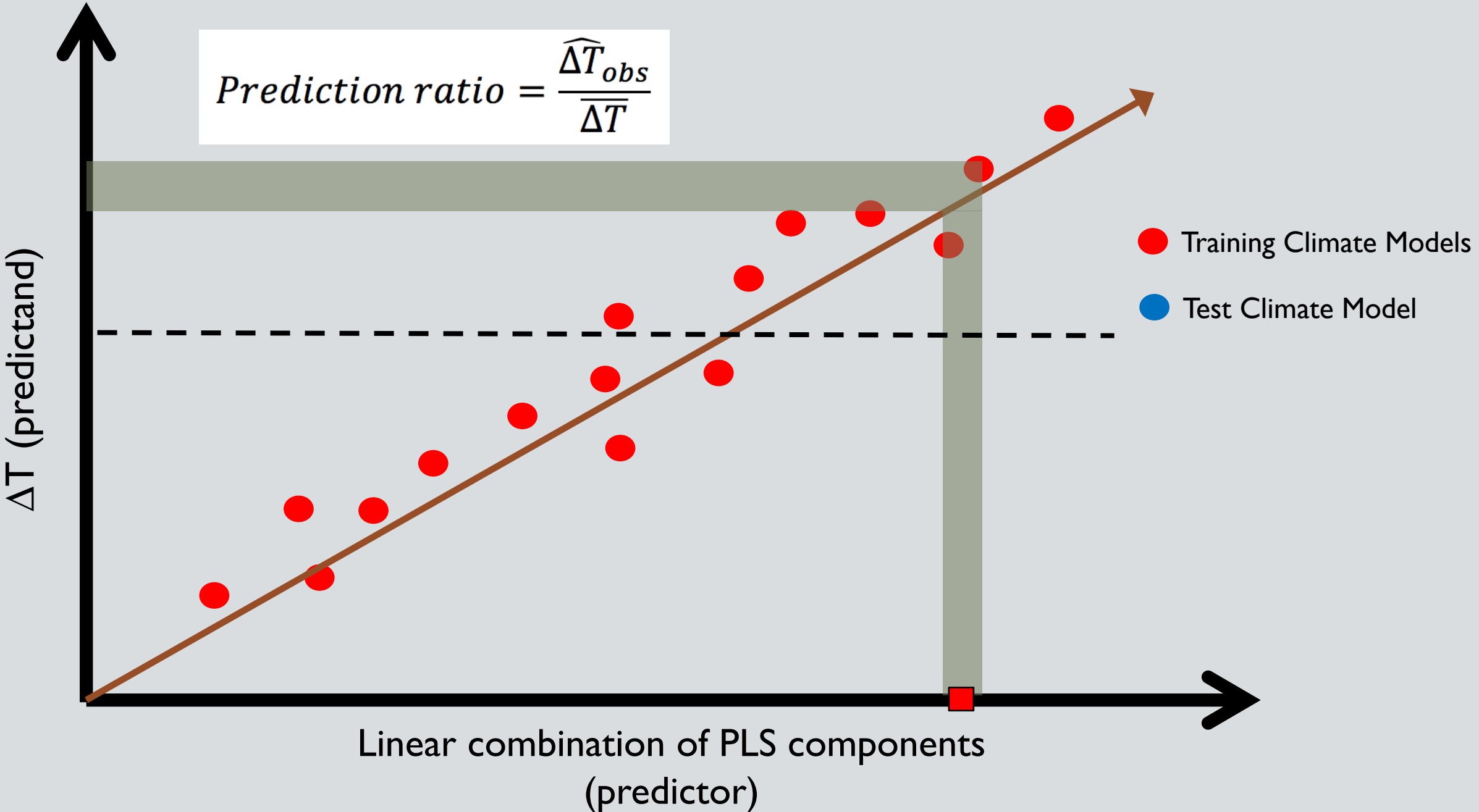
Cross-validation



$$\text{Spread ratio} = \sqrt{\frac{\sum_{j=1}^{n}(\widehat{\Delta T_j} - \Delta T_j)^2}{n}} \Big/ \sqrt{\frac{\sum_{i=1}^{n}(\Delta T_i - \overline{\Delta T})^2}{n}}$$

Results

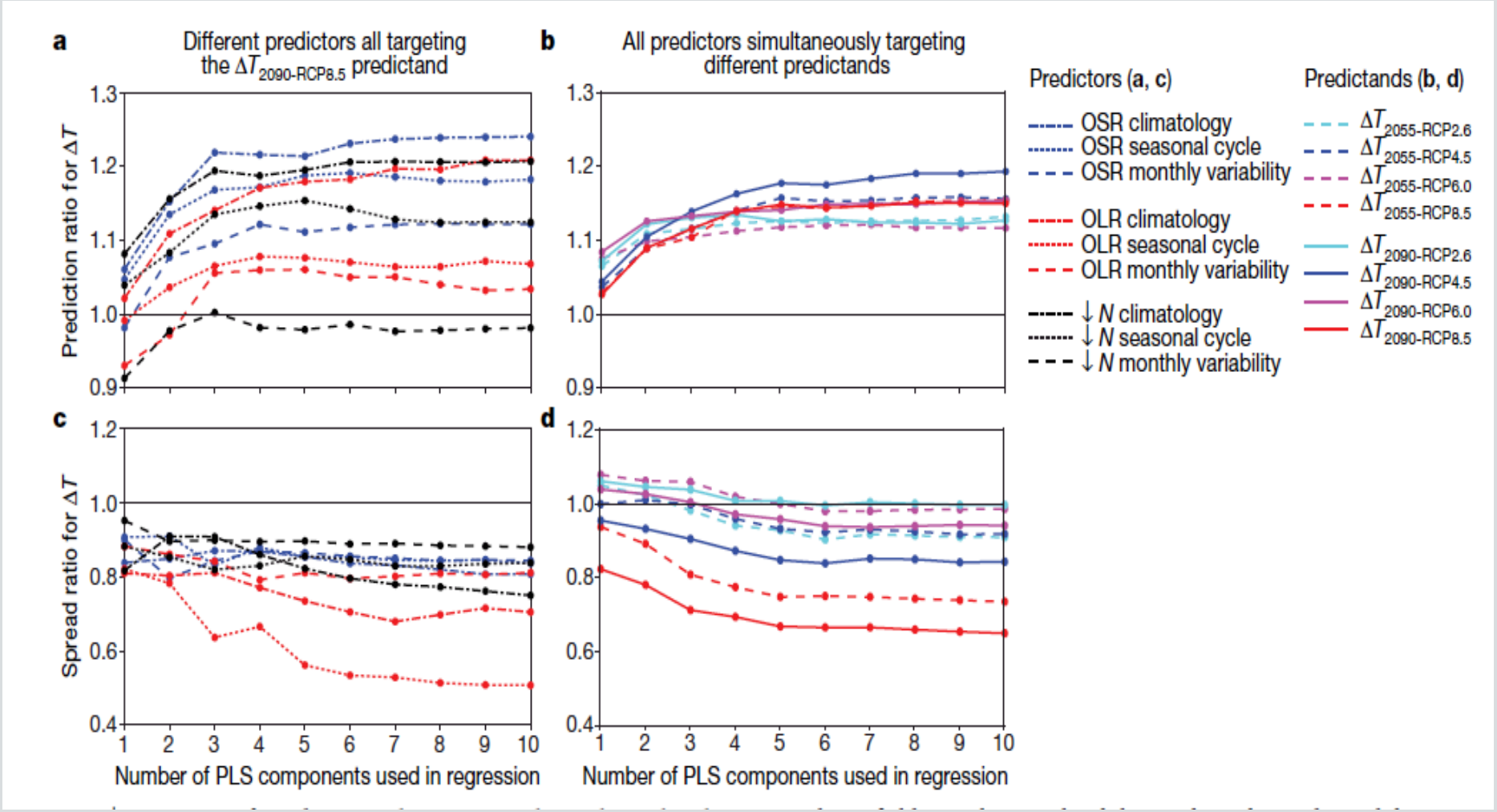
$$Prediction\ ratio = \frac{\widehat{\Delta T}_{obs}}{\overline{\Delta T}}$$



Results

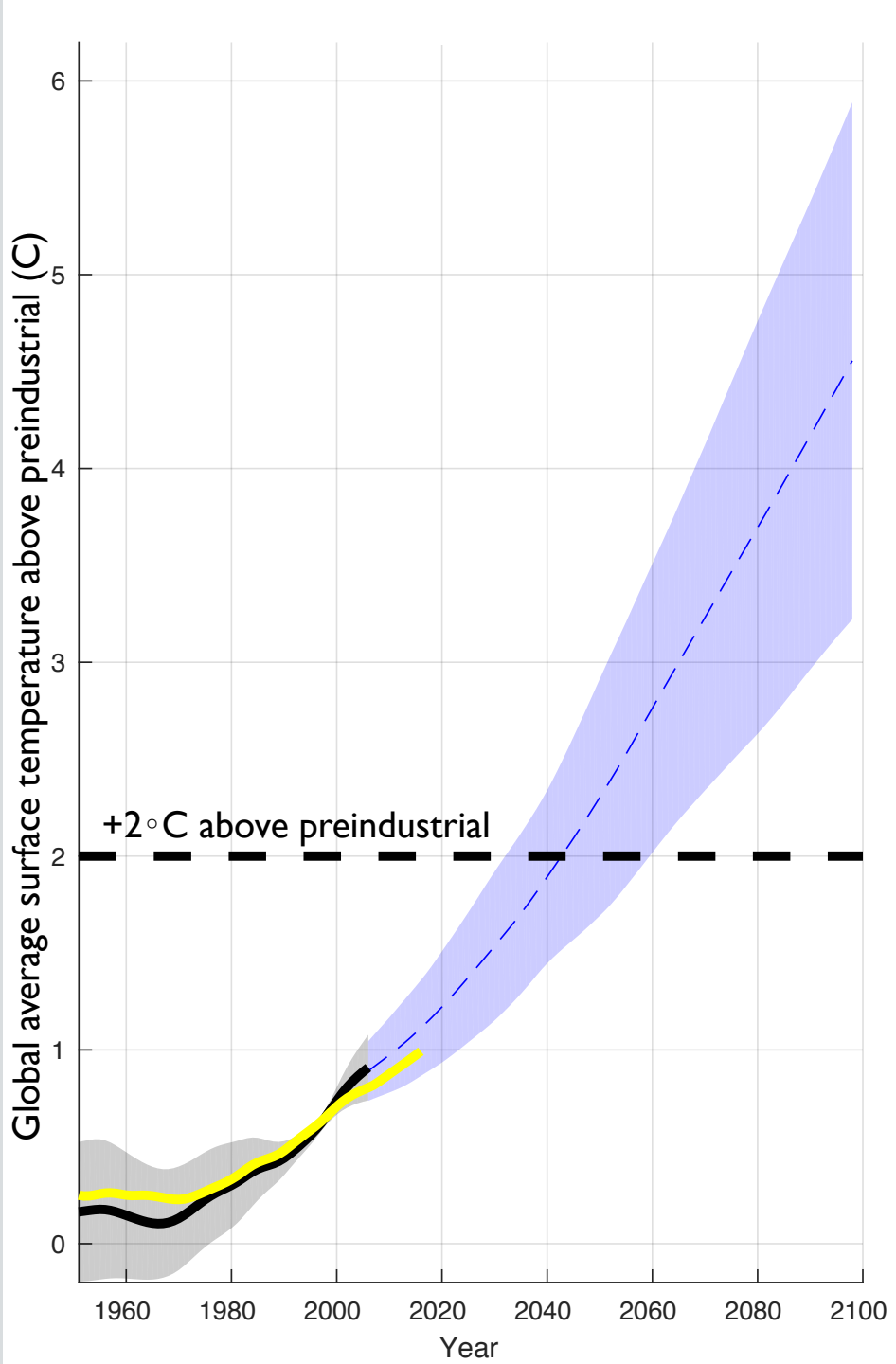
$$Prediction\ ratio = \frac{\widehat{\Delta T}_{obs}}{\overline{\Delta T}}$$

$$\text{Spread ratio} = \sqrt{\frac{\sum_{j=1}^{n}(\widehat{\Delta T_j} - \Delta T_j)^2}{n}} \Big/ \sqrt{\frac{\sum_{i=1}^{n}(\Delta T_i - \overline{\Delta T})^2}{n}}$$

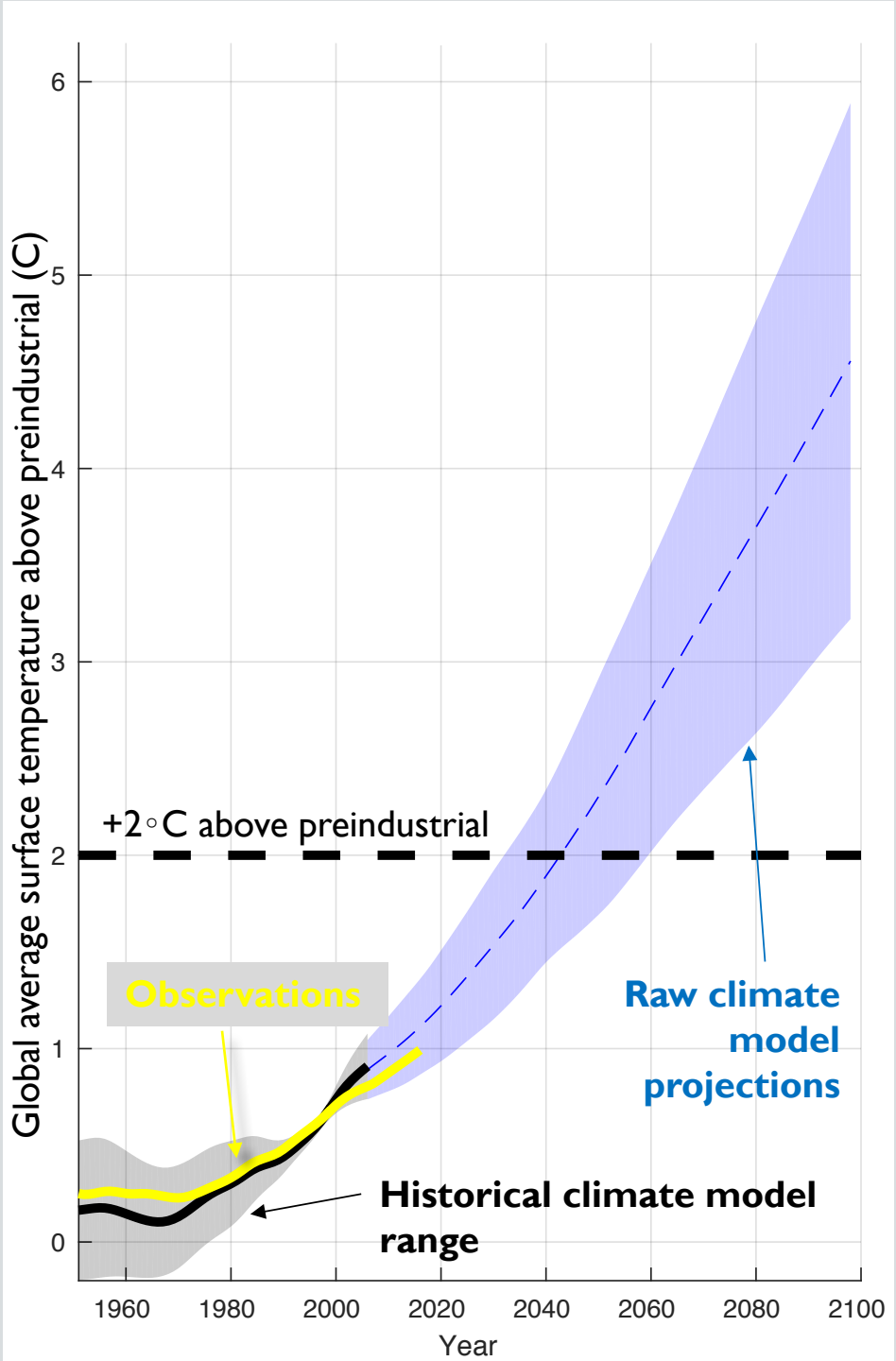


Observations of several diverse attributes of Earth's global energy budget indicate both individually and collectively that global warming is likely to be greater than that suggested by the unconstrained model suite.

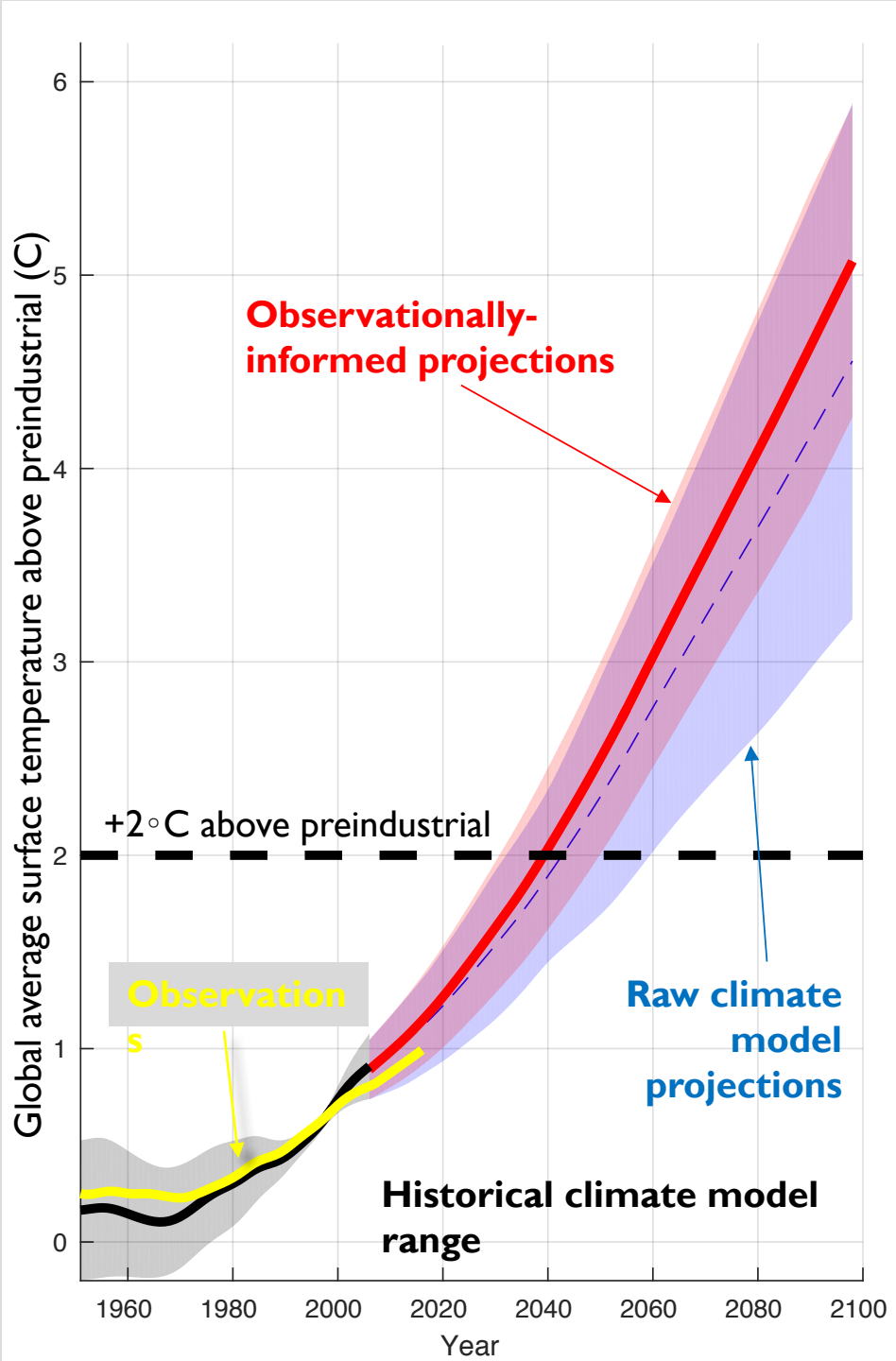
Results


Global average surface temperature above preindustrial (C)
6
5
4
3
2
1
0
+2◦C above preindustrial
1960
1980
2000
2020
2040
2060
2080
2100
Year

Results

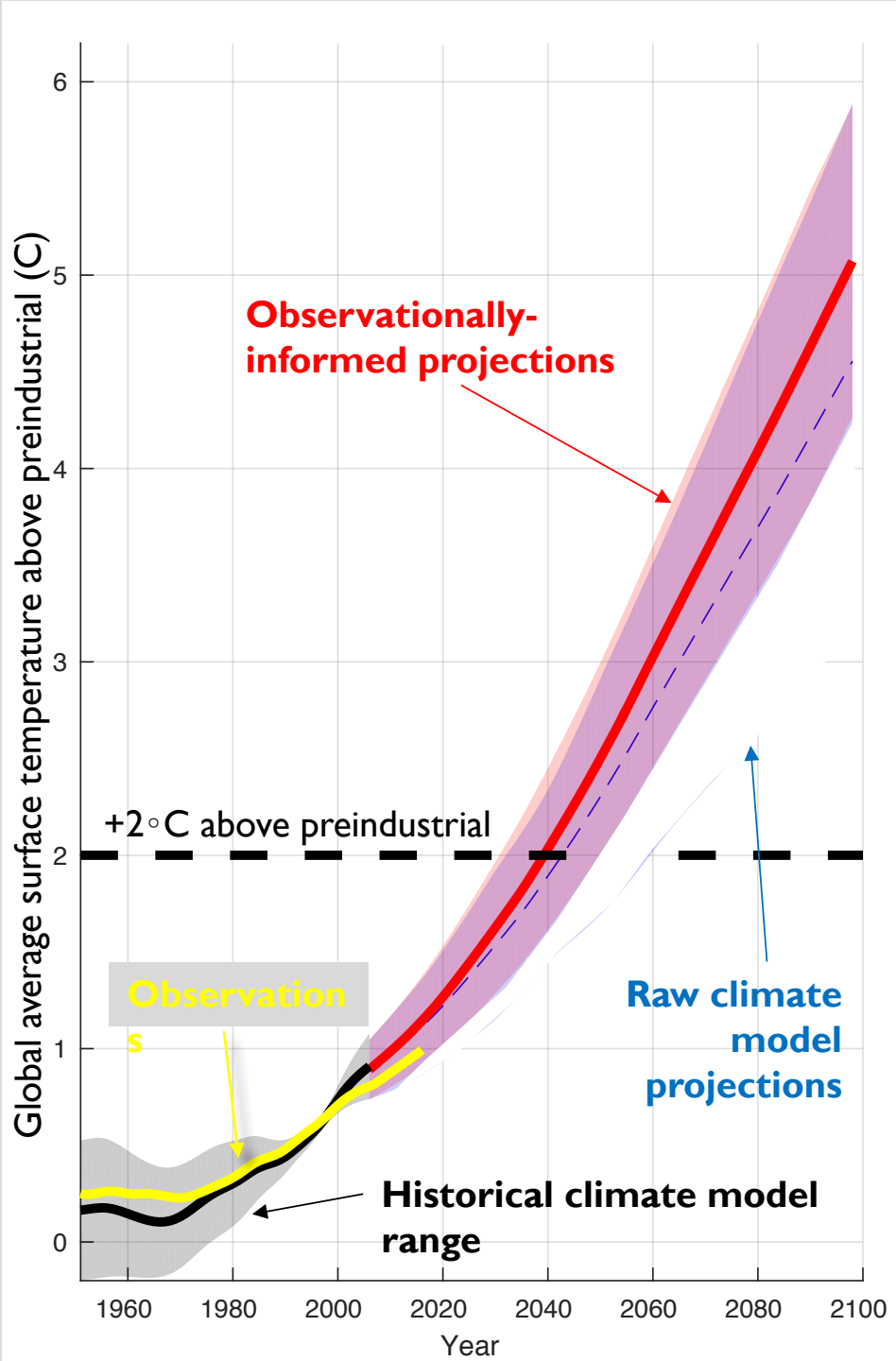

Global average surface temperature above preindustrial (C)
6
5
4
3
2
1
0
+2◦C above preindustrial
Observations
Raw climate model projections
Historical climate model range
1960
1980
2000
2020
2040
2060
2080
2100
Year

Results


Global average surface temperature above preindustrial (C)
Year
0
1
2
3
4
5
6
1960
1980
2000
2020
2040
2060
2080
2100
Observationally-informed projections
+2◦C above preindustrial
Observations
Raw climate model projections
Historical climate model range

Results

- It is sometimes argued that climate model-projected global warming should be taken less seriously on the grounds that climate models are imperfect in their simulation of the current climate.

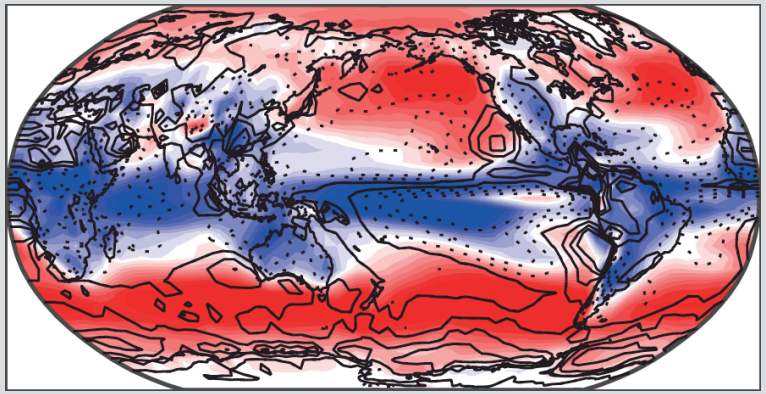


- Our results suggest that model shortcomings can likely be used to dismiss the *least* severe projections, rather than the *most* severe projections

Results - Physical Mechanisms

	Outgoing Shortwave Radiation (OSR)	Outgoing Longwave Radiation (OLR)	N=ISR – OSR – OLR
Mean climatology	1	2	3
Magnitude of the seasonal cycle	4	5	6
Magnitude of monthly variability	7	8	9

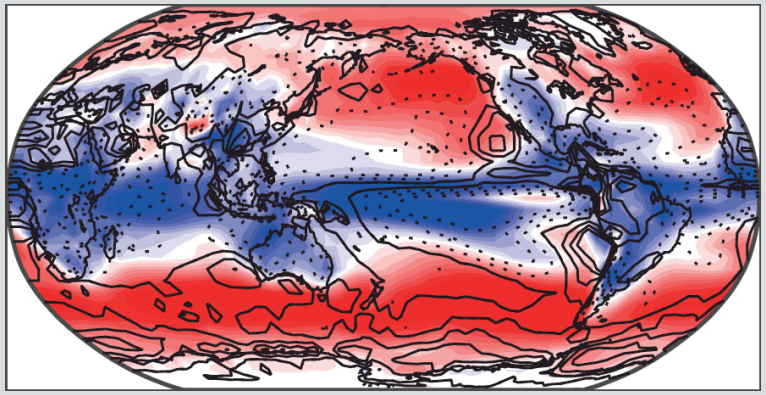
Results - Physical Mechanisms

	Outgoing Shortwave Radiation (OSR)	Outgoing Longwave Radiation (OLR)	N=ISR – OSR – OLR
Mean climatology		2	3
Magnitude of the seasonal cycle	4	5	6
Magnitude of monthly variability	7	8	9

Results - Physical Mechanisms

Outgoing Shortwave Radiation (OSR)

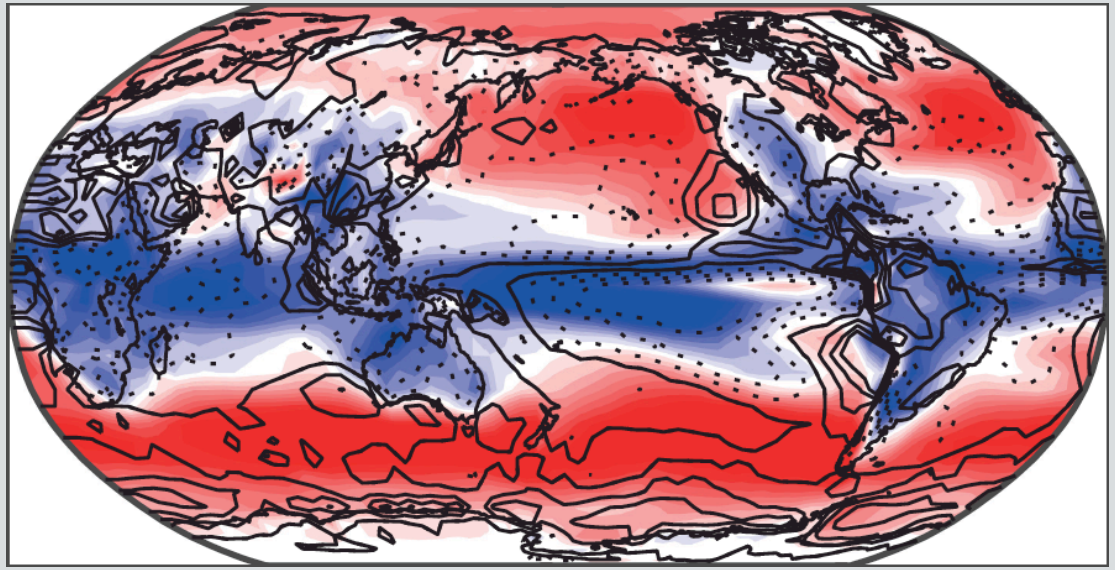
Mean climatology



Results - Physical Mechanisms

Outgoing Shortwave Radiation (OSR)

Mean climatology



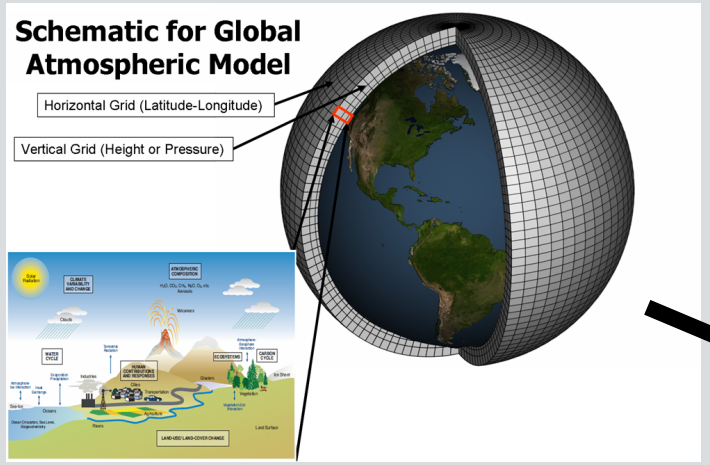
Positive = Models with more OSR in this location, warm more in the future

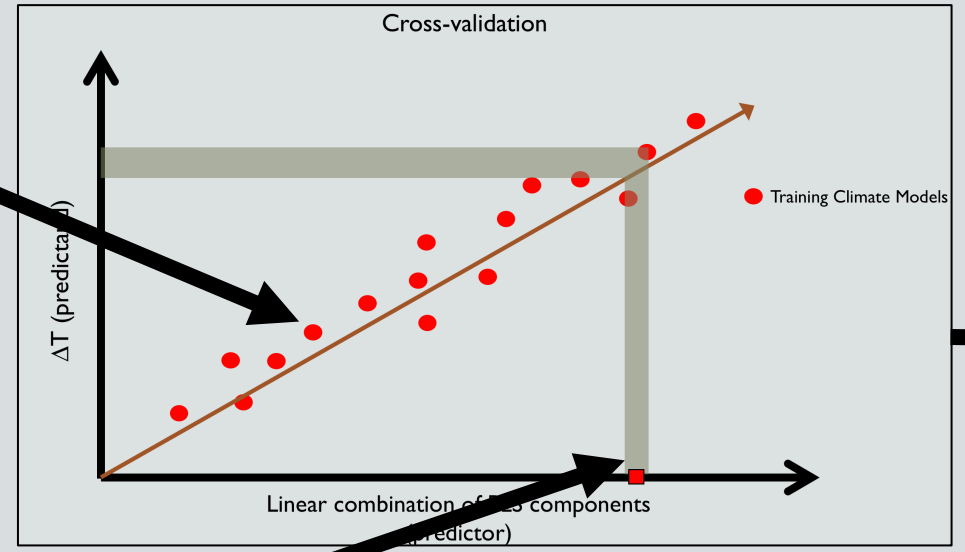
Negative = Models with more OSR in this location, warm less in the future

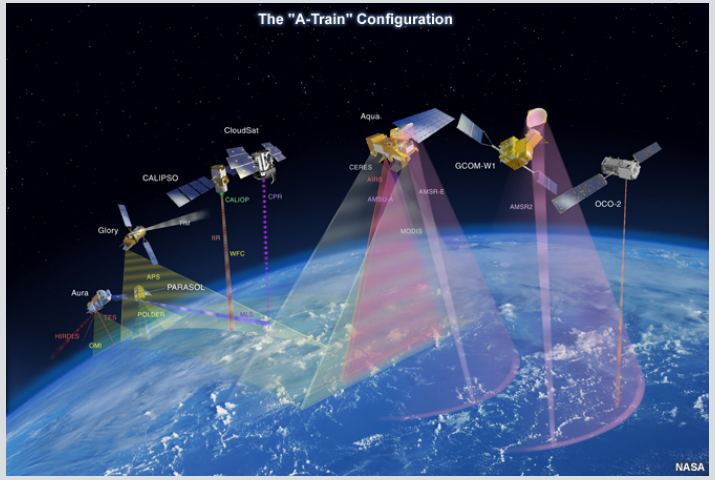
Contours = Satellite observations relative to model mean

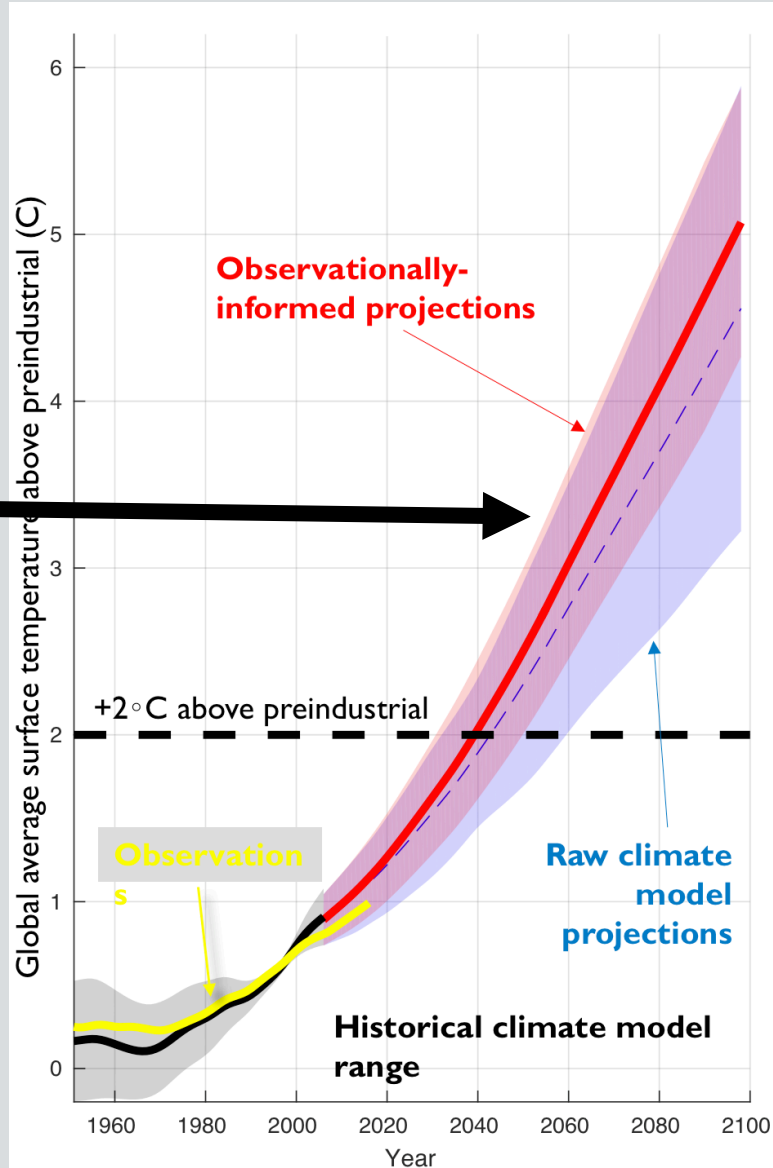
- Models with more average reflected sunlight from clouds and sea ice over the the southern ocean, warm more in the future
- More potential for positive shortwave sea-ice feedbacks
- Less potential for negative shortwave cloud feedbacks
- Observations tell us that models with more OSR are correct

Combining Physical and Statistical Models in Order to Narrow Uncertainty in Projections of Global Warming









Combining Physical and Statistical Models in Order to Narrow Uncertainty in Projections of Global Warming



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Stanford EE Computer Systems Colloquium

January 17, 2018



ARTICLE

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Greater future global warming inferred from Earth's recent energy budget

Patrick T. Brown[1] & Ken Caldeira[1]