

# When do “the details” matter?

*The promise of DEB for climate change adaptation*

Brian Helmuth

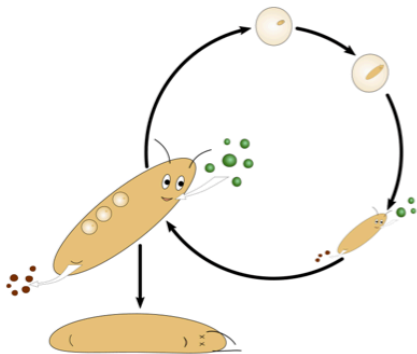
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**DEB2019** 1-12 April 2019 / Brest (France)

Sixth International Symposium and Thematic School  
on DEB theory for metabolic organization

$$|O(T, \varepsilon, a, b)| \leq 2$$

$$\varphi(\sigma_1 t) \varphi(\sigma_2 t) = \varphi(\sqrt{\sigma_1^2 + \sigma_2^2} t)$$

$$\sum_{k=1}^r \int_{b_k}^{x+b_{k+1}} \left( \int_0^t \Psi_k^*(\tau) d\tau \right) dt - x \int_0^{b_k} \Psi_k^*(\tau) d\tau = \frac{x^2}{2} B(x) + \int_0^x (x-u) \sum_{k=1}^r \Psi_k^*(u) du \quad A(x) = \sum_{k=1}^r b_k \Psi^*(b_k)$$

$$p(x) = \frac{\sum_{k=1}^r p_k^* \log_2 \frac{1}{p_k}}{\sum_{k=1}^r p_k^*}$$

$$(i_k \sigma_k^2 = \lambda_i; c_i k) \quad y = \phi(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{+\infty} e^{-\frac{t^2}{2}} dt$$

$$\eta_1 = \sum_{k=1}^n a_k \xi_k \quad \log \varphi(u) = -\frac{\sigma^2 u^2}{2}$$

$$S(\alpha, \bar{t}) = \frac{2}{\pi} \int_0^{\pi} \frac{\sin \alpha t}{t} dt \quad P(\eta_{\infty} < x) = F(x)$$

$$i^2 = -1; j^2 = -1; k^2 = -1 \quad \lim_{n \rightarrow \infty} \frac{\binom{2n}{n+c}}{\binom{2n}{n}} = e^{-2c}$$

$$S_n = A_n U \Pi A_n$$

$$W_k = \binom{n}{k} p^k (1-p)^{n-k}$$

$$P(\eta < y | \xi = x) = \sup_{y' < y, y' \in R} P(\eta < y' | \xi = x)$$

$$|A_n| = \frac{n!}{2} \left| \int_{|x| > A} f(x) \log_2 \frac{1}{f(x)} dx \right| < \varepsilon \quad g^{-1} \cdot g = e$$

$$y = \sqrt{\frac{\lambda u}{\lambda_n}} \left( \frac{\eta_{2n}}{\sqrt{\lambda_n}} + \frac{\eta_{2n} - \eta_{2n}}{\sqrt{\lambda_n}} \right)$$

$$f(t|y) = \frac{2e^{-\frac{y^2}{2}}}{\sqrt{2\pi}} \int_{\frac{y}{t}}^{+\infty} \frac{e^{-\frac{u^2}{2}} du}{\left(1 - \frac{y^2}{u^2}\right)^{3/2}} \quad \Delta N = \sum_{k=1}^N \frac{\varepsilon_k}{u}$$

$$\int dG_k(x) \geq \frac{1}{2} \sum_{k \rightarrow \infty} e^{-\frac{k^2 \pi^2}{x^2}} = H(k)$$

$$\prod_{k \leq b} \prod_{i=1}^{n-1} M_{i,j} \prod_{n=0}^{\infty} X_n$$

$$f_n(t) = \frac{2^{-n} t^{n-1} e^{-2t}}{(n-1)!}$$

$$H_r(x) = \frac{G_r(x)}{1 + G_r(x)}$$

$$U_{n,c}^+ = \binom{2n}{n} - \binom{2n}{n-c}$$

$$f_{n-1}(t) = \int_0^1 f_n(u) f_1(t-u) du = \frac{2^{n+1} t^n e^{-2t}}{n!}$$

$$\lim_{t \rightarrow 0} (c t) = 0$$

$$\lim_{n \rightarrow +\infty} \frac{f(u)}{u} = P_e$$

$$R = \int_{-\infty}^{+\infty} \varphi(t) dt$$

$$\frac{\sinh t}{t} [\varphi(t) e^{-itx} + \varphi(-t) e^{itx}]$$

$$\log \varphi(t) = i \gamma t - c |t|^\alpha \left[ 1 + i \beta \frac{t}{|t|} \omega(t, \alpha) \right] \quad B(x) = \sum_{k=1}^r \Psi^*(b_k x)$$

$$c_{iv} = \sum_{j=1}^n a_{ij} b_{jv}$$

$$\lim_{n \rightarrow \infty} P \left( \frac{\ln_{n+1} - \ln_n - \log \frac{1}{q}}{\sqrt{\frac{1-q}{q}}} \right) C_n(\alpha) \geq \frac{n!}{\prod_{k=1}^n n_k(\alpha)!}$$

$$\frac{u}{m} \varphi(t) = \varphi\left(c \left(\frac{u}{m}\right) t\right)$$

$$\int_{-\infty}^{+\infty} e^{-\frac{u^2}{2}} du = F(x) \left(\frac{1}{\sqrt{2\pi}}\right)^{-1} \quad |\Psi_{\xi}(t)| = \left| \int_{-\infty}^{+\infty} e^{itx} dF(x) \right| \leq \int_{-\infty}^{+\infty} e^{-\nu x} dF(x) = \varphi_{\xi}(i\nu)$$

$$g^{-1} N g = \{g^{-1} n_g | n \in N\}$$

$$Q = F^{-1}(q)$$

$$q_n(\alpha) = \frac{p_k^*}{\sum_{j=1}^n p_j^*} \quad PCT_2 =$$

$$|X \cup Y| = |X| + |Y| - |X \cap Y|$$

$$\lim_{n \rightarrow \infty} \frac{1}{n} \ln \binom{x}{\sqrt{n}} = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}$$

$$P_n(k) = P_j^k$$

$$P(\lim_{n \rightarrow \infty} \sup \frac{|h_n|}{\sqrt{2n \log \log n}} \leq 1) = 1 \quad \varphi(t) = 1 - \sqrt{1 - e^{2it}}$$

$$f: X \rightarrow X \cap W$$

$$Q(\alpha) = \int_A \lambda(\omega) dP \quad l'(\alpha) = -\log_2 \left( \frac{\sum_{k=1}^r p_k^* \log_2 \frac{1}{p_k}}{\sum_{k=1}^r p_k^*} - \left( \frac{\sum_{k=1}^r p_k^* \log_2 \frac{1}{p_k}}{\sum_{k=1}^r p_k^*} \right)^2 \right)$$

$$fg(u_i) = f \left( \sum_{j=1}^{\dim V} a_{ji} v_j \right) = \sum_{j=1}^{\dim V} a_{ji} \left( \sum_{k=1}^{\dim V} b_{kj} w_k \right) \frac{\binom{2k}{k}}{2^{2k}} \approx \frac{1}{\sqrt{\pi k}}$$

$$P_{j,k}^{(m)} = \sum_{e=0}^{\infty} P_j^e P_k^{(m-r)} \frac{1}{2\pi} \int_{-\infty}^{+\infty} \operatorname{Re} \left\{ \varphi(t) \frac{e^{-ita} - e^{-itb}}{it} \right\} dt$$

$$q \left( c^{-x} \sqrt{\frac{1-q}{nq}} - 1 \right) = -x \sqrt{\frac{q(1-q)}{n}} + o\left(\frac{1}{n}\right)$$

$$\prod_{k=1}^r \left[ g_k \left( \frac{t}{\sqrt{N_0}} \right) \right]^{N_0 \alpha_k} = e^{-\frac{t^2}{2}}$$

$$\liminf_{N \rightarrow \infty} \int_{-\infty}^{+\infty} f_N(x)^\alpha dx \geq \int_{-\infty}^{+\infty} f(x)^\alpha dx$$

$$M(1/\delta_j - 1/\delta) = \int_0^{\infty} |x-1|^\delta e^{-x} dx$$

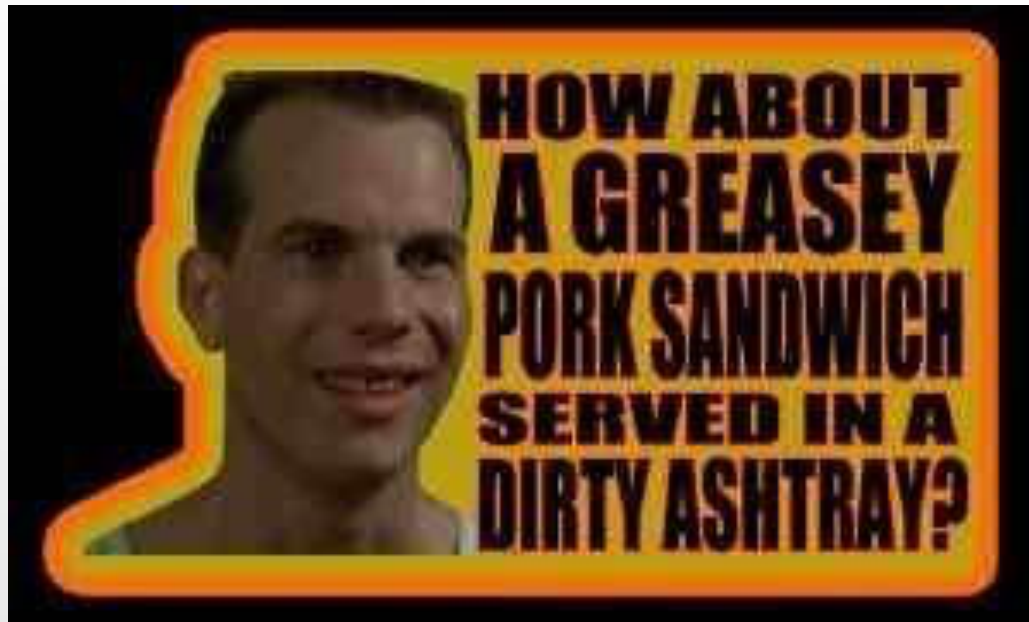
$$\lim_{N \rightarrow \infty} \int_{-A}^{+A} f_N(x) \log_2 \frac{1}{f_N(x)} dx = \int_{-A}^{+A} f(x) \log_2 \frac{1}{f(x)} dx$$

$$P(|\omega_n| \geq \varepsilon) \leq \frac{C_\varphi}{\log N}$$

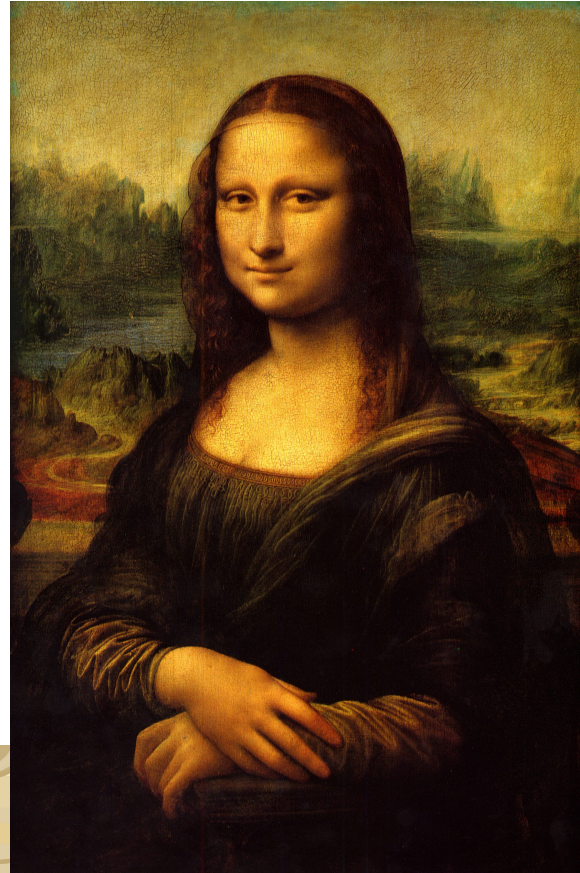
$$D^2(J_n) \leq \frac{k}{n} + 2k \left( \frac{1}{2} \sum_{k=1}^n R(k) \right)$$

$$\det(M') = \det(M) + \det(M^*) = \det(M)$$

$$h(x,y) = \frac{1}{2\pi} \left[ \sqrt{2} e^{-\frac{x^2}{2}} - e^{-x^2} \right] \quad |M(\varepsilon_n, \varepsilon_m)| \leq C_2 \sqrt{\frac{n}{m-n}}$$



# Pattern Recognition



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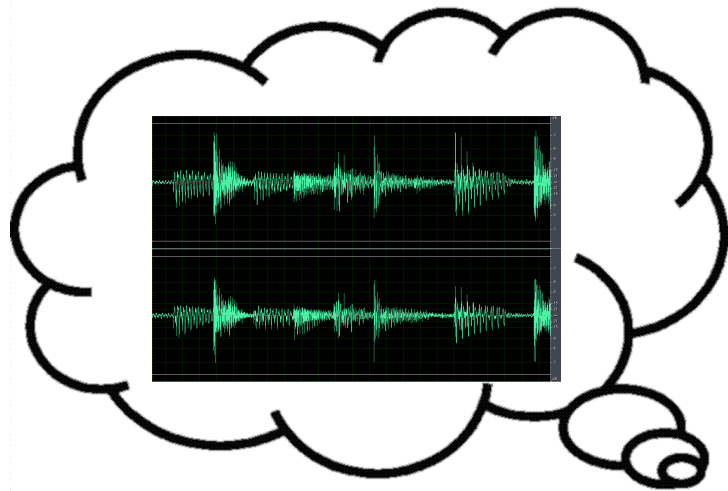
wishURhere

STAR WARS

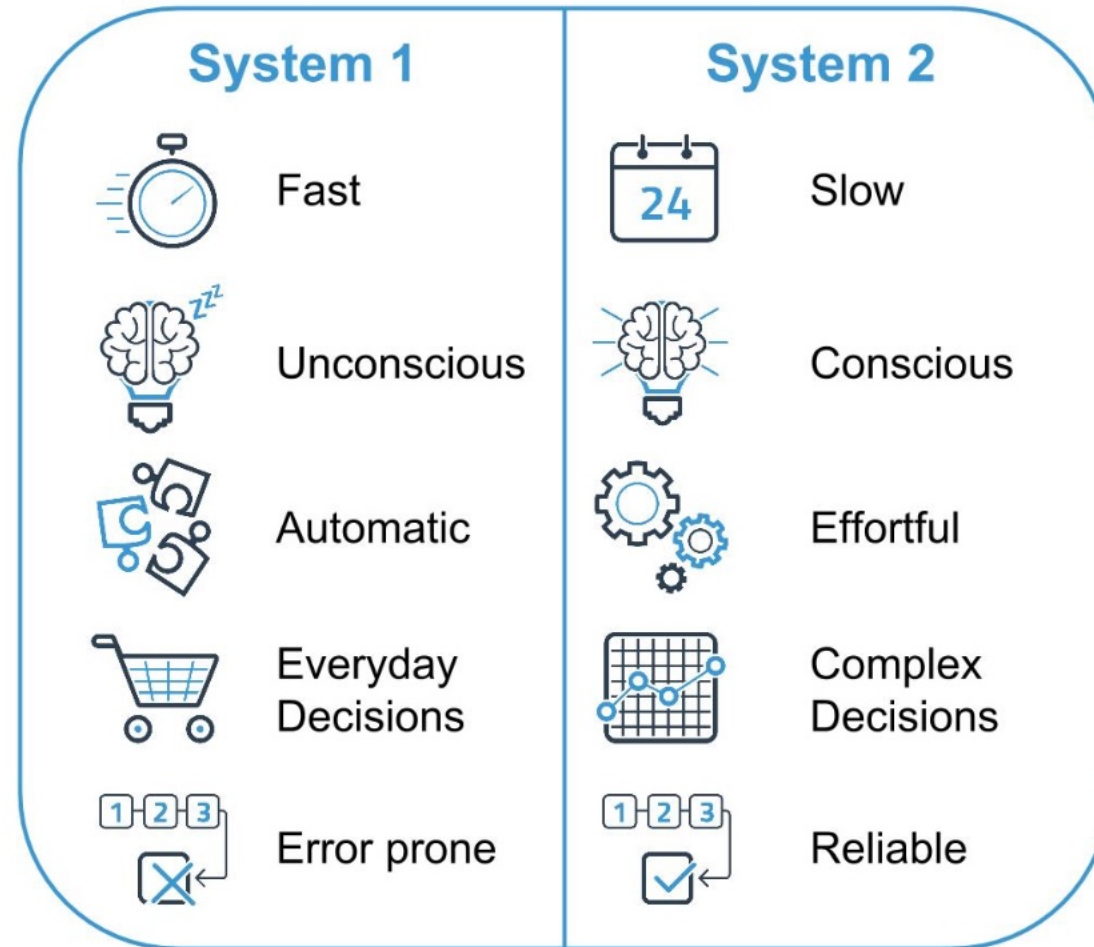
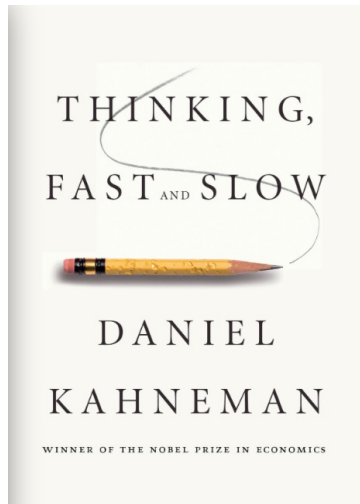


Frutkin/News.com

EMMA G. HARRISON



# "Fast" (system 1) and "slow" (system 2) decision-making responses

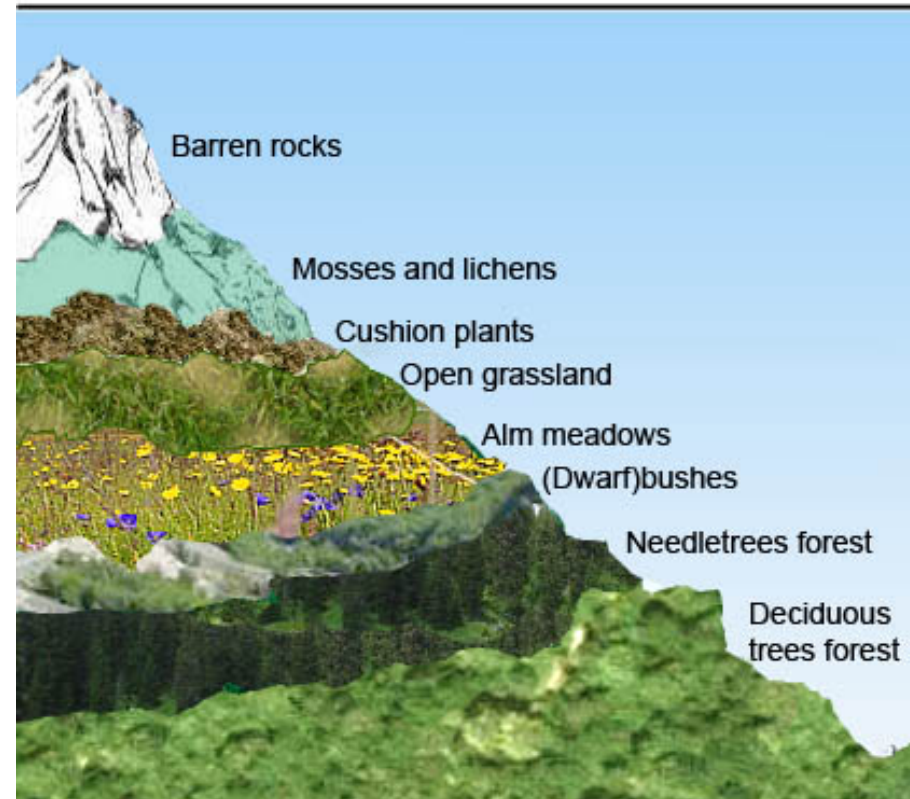


# Seeing patterns in nature

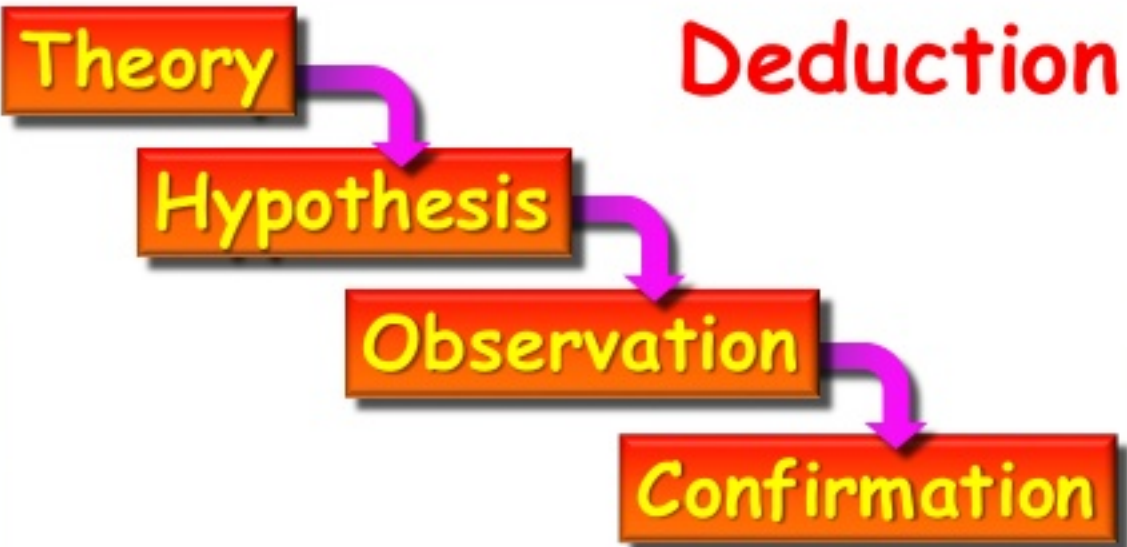


<http://www.ecosystema.ru/08nature/world/75abh/18.jpg>

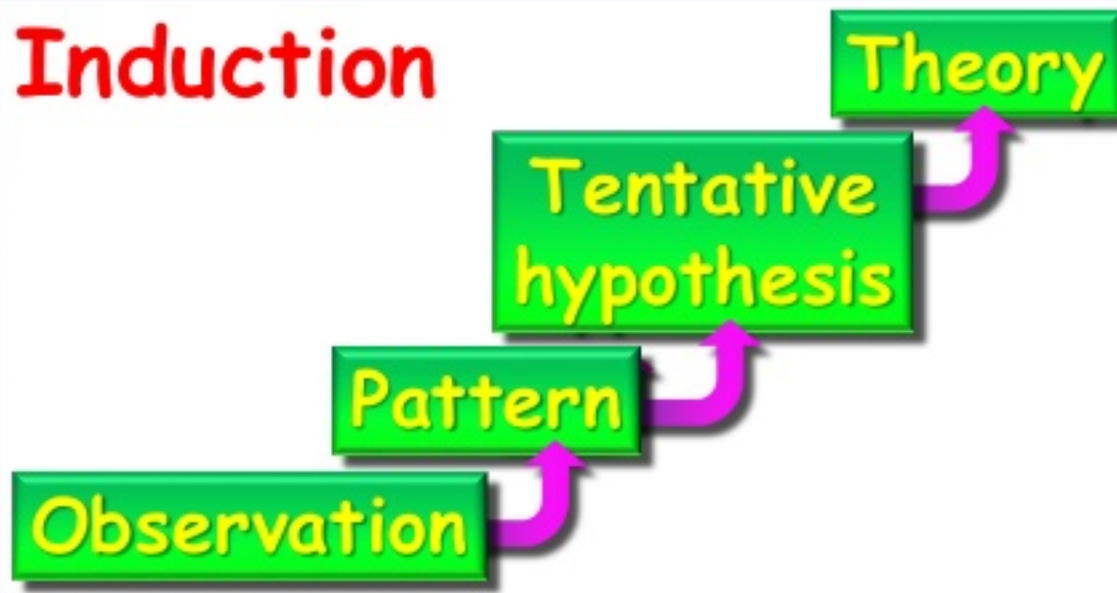
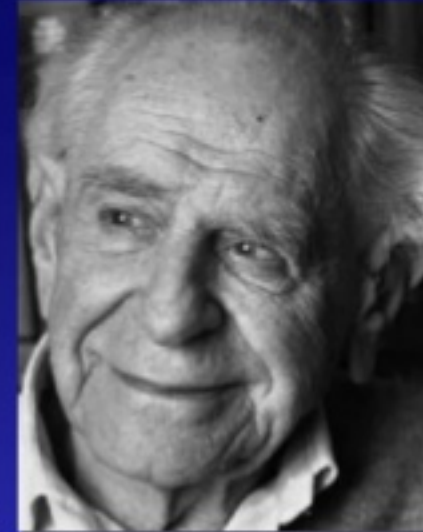
## VEGETATION ZONATION IN MOUNTAINS



[http://www.vcbio.science.ru.nl/images/landscape/landscape-vertical\\_zonation\\_eng.jpg](http://www.vcbio.science.ru.nl/images/landscape/landscape-vertical_zonation_eng.jpg)



Karl Popper




Carl Hempel





# CLIMATE CHANGE

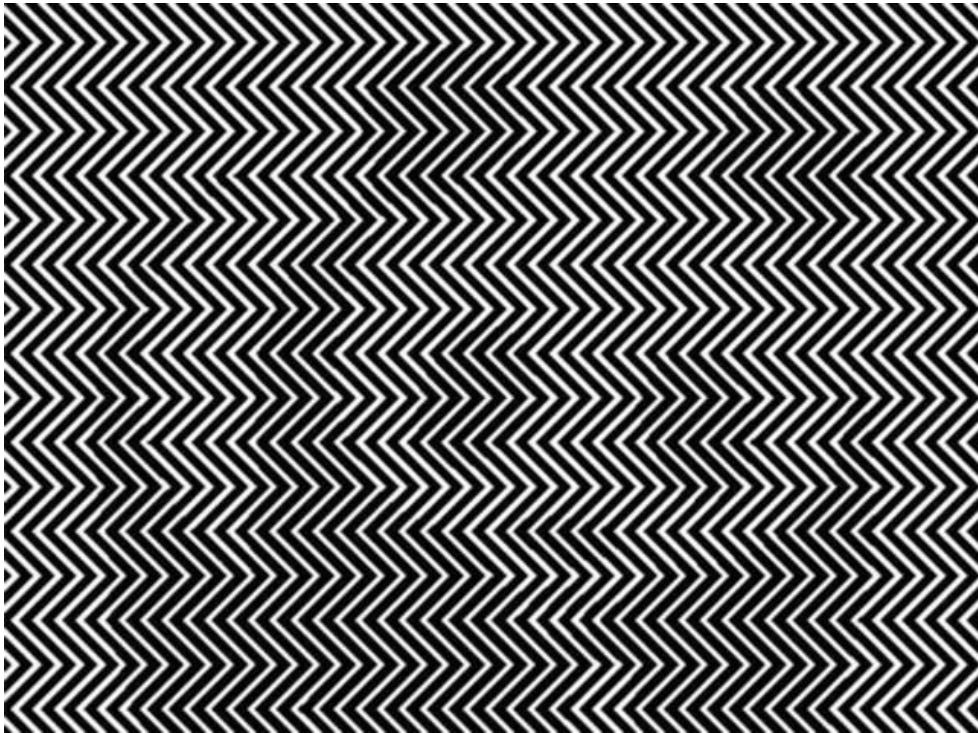
- PATTERNS IN NATURE ARE CHANGING, SOMETIMES QUICKLY
  - WE WANT TO KNOW HOW MUCH TO ATTRIBUTE TO CLIMATE CHANGE, AND WHAT TO DO ABOUT IT
  - WE MUST BASE FUTURE PREDICTIONS OF CLIMATE CHANGE IMPACTS ON WHAT WE OBSERVE TODAY AND IN THE PAST
- 

# ECOLOGICAL IMPACTS OF CLIMATE CHANGE: HOW DO WE TEST OUR ABILITY TO PREDICT THE FUTURE?

- WE ARE USING MODELS “TRAINED” WITH CURRENT CONDITIONS TO PREDICT RESPONSES UNDER NOVEL CONDITIONS
- HOW DO WE “KNOW WHAT WE DON’T KNOW”? AND HOW DO WE INCREASE OUR ABILITY TO PREDICT (AND PREVENT) NASTY “SURPRISES” SUCH AS TIPPING POINTS?
- ARE WE MEASURING THE RIGHT THINGS AT THE RIGHT SCALES?



*Are we looking so hard for  
pattern that we miss  
important mechanisms?*

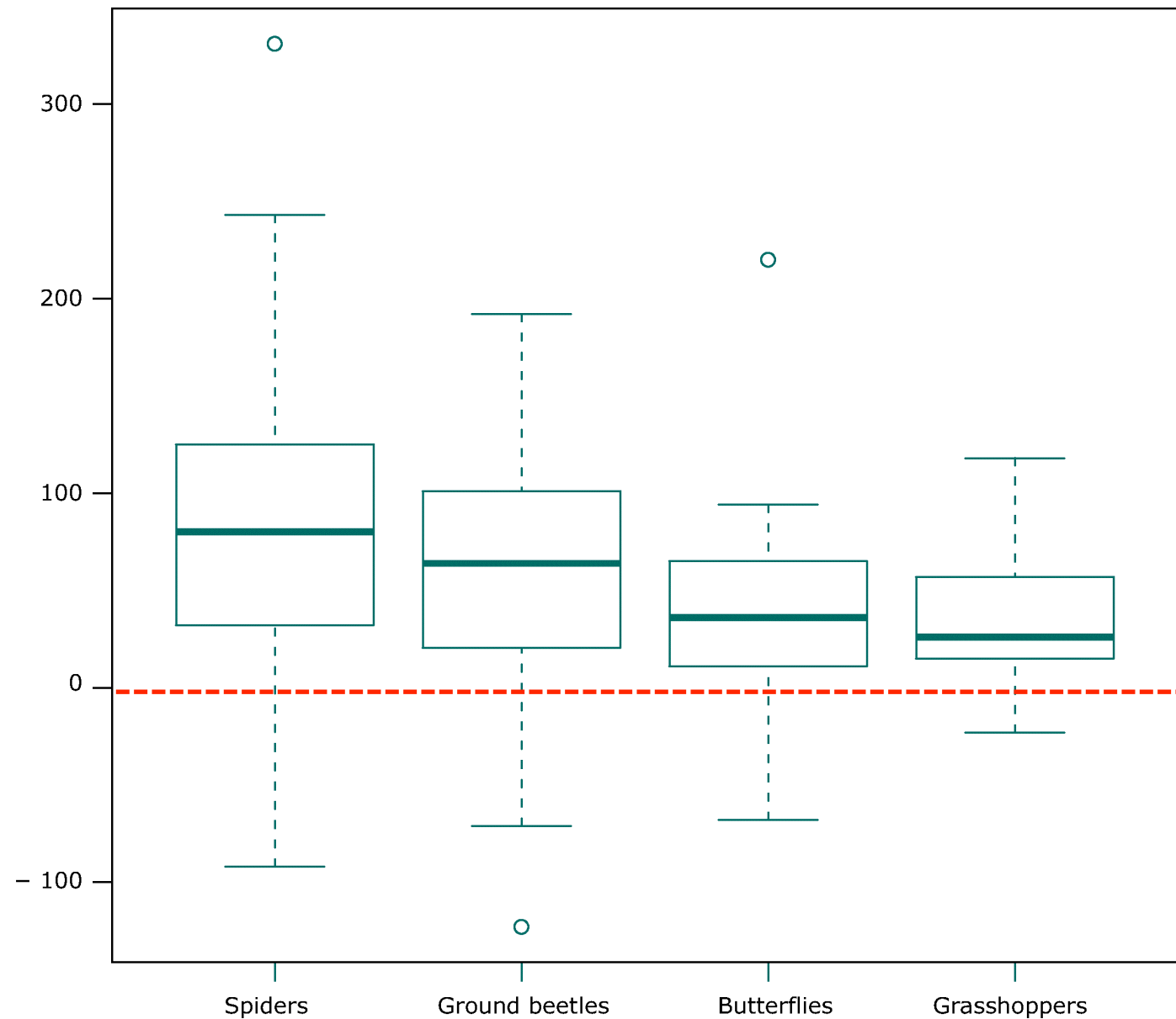


<http://www.telegraph.co.uk/news/2017/02/02/levitation-optical-illusion-confuses-internet/>

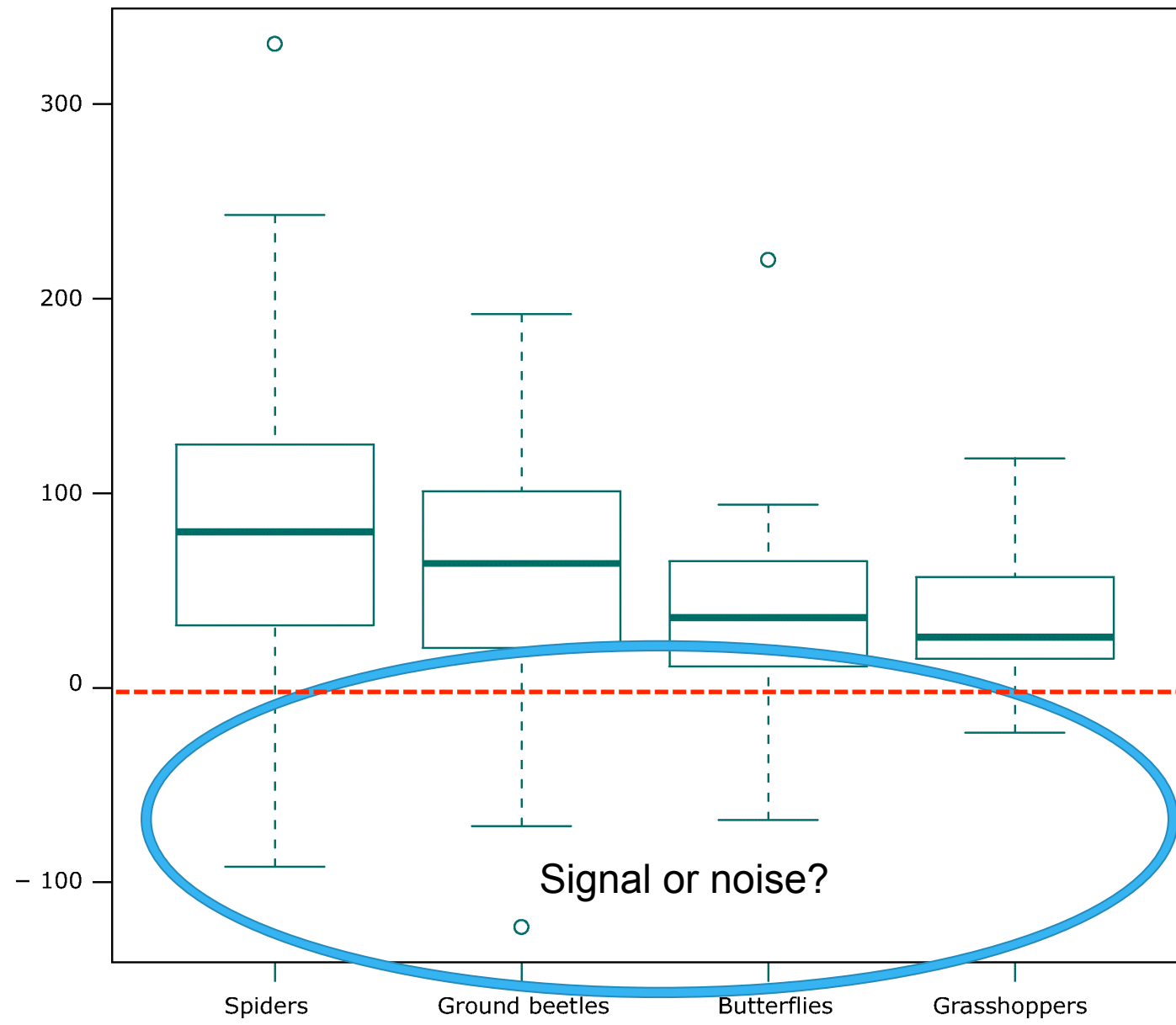


Source: [cns-alumni.bu.edu](http://cns-alumni.bu.edu)

Kilometres moved northwards



Kilometres moved northwards



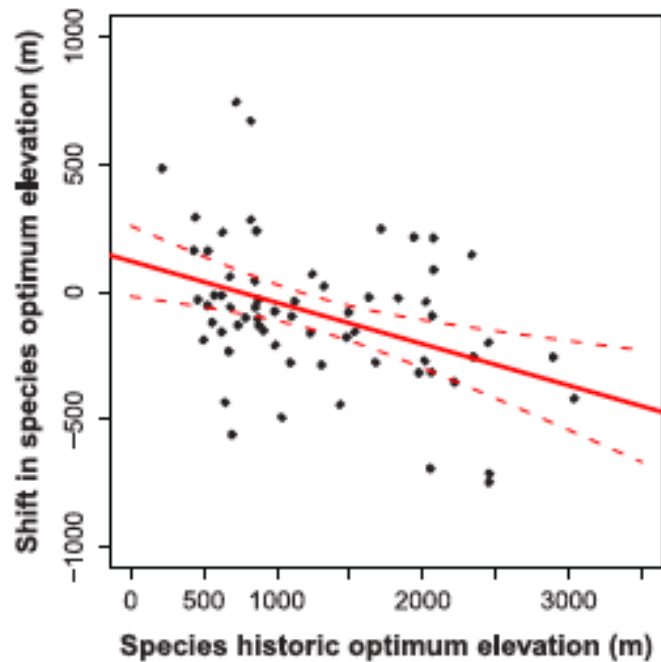


## Changes in Climatic Water Balance Drive Downhill Shifts in Plant Species' Optimum Elevations

Shawn M. Crimmins, *et al.*

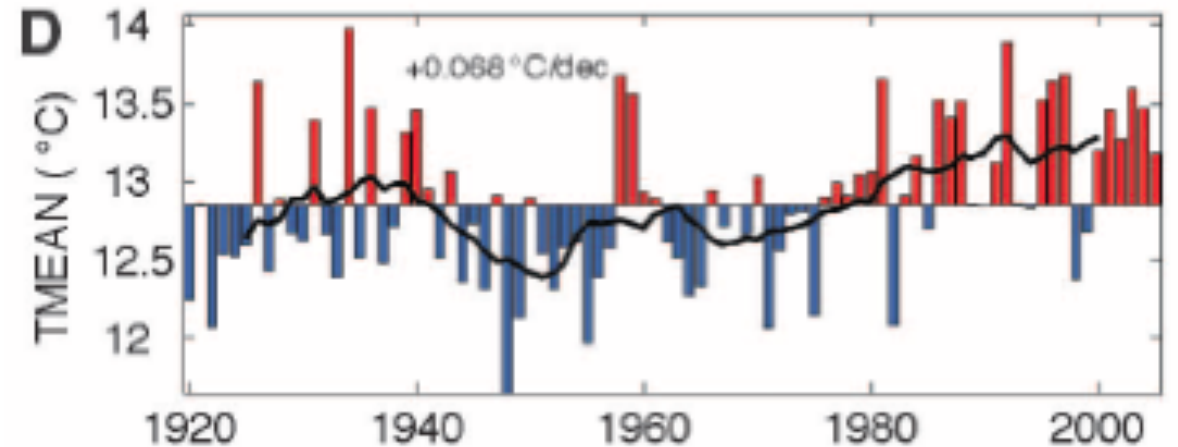
*Science* **331**, 324 (2011);

DOI: 10.1126/science.1199040



**Fig. 4.** Scatterplot of shift in optimum elevation (m) versus historical (circa 1935) altitudinal position (m) for plant species in California. Solid line represents linear regression model with 95% CI bands (as dashed lines).

Sixty four species of plants shifted downslope over last 75 years, despite increasing temperatures



# Watts Up With That?



Getty



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← Surface temperature uncertainty, quantified

WMO: 2010 warmest, but no statistically significant difference between global temperatures in 2010, 2005 and 1998 →

## Another IPCC claim contradicted with new science

Posted on [January 20, 2011](#) by [Anthony Watts](#)

Remember [this story](#) bandied all over the press from 2008?

"...the world's most viewed climate website"

- Fred Pearce *The Climate Files: The Battle for the Truth about Global Warming*

### Blog Stats

■ 85,668,176 views

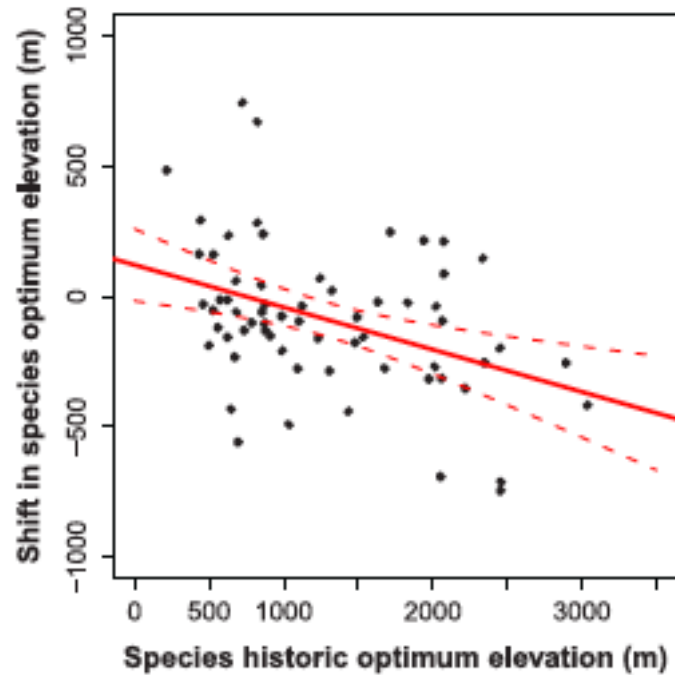


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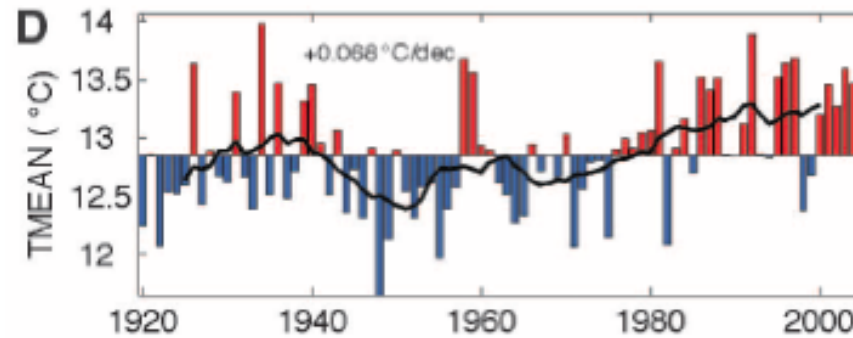
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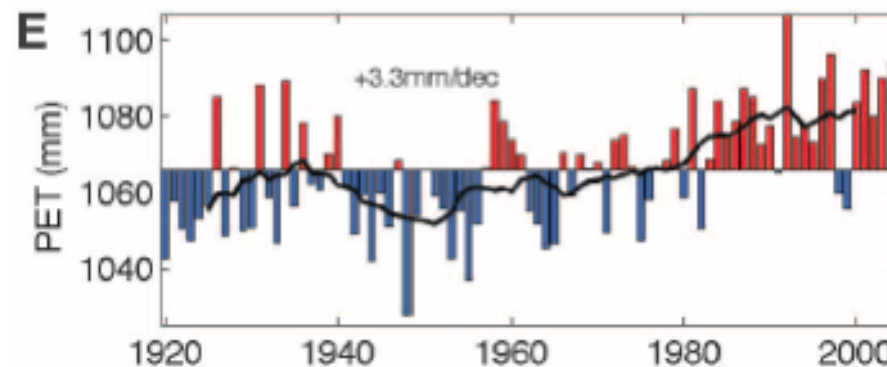


**Fig. 4.** Scatterplot of shift in optimum elevation (m) versus historical (circa 1935) altitudinal position (m) for plant species in California. Solid line represents linear regression model with 95% CI bands (as dashed lines).

Sixty four species of plants shifted downslope over last 75 years, despite increasing temperatures



Why? Precipitation also increased





GIBSON-REINEMER AND RAHEL 2015. *INCONSISTENT RANGE SHIFTS WITHIN SPECIES HIGHLIGHT IDIOSYNCRATIC RESPONSES TO CLIMATE WARMING* PLOS ONE

- ANALYZED PUBLISHED STUDIES THAT DOCUMENTED RANGE SHIFTS OF 273 SPECIES OF PLANTS, BIRDS, MAMMALS AND MARINE INVERTEBRATES. 42-50% SHOW “INCONSISTENCY IN THE DIRECTION OF THEIR RANGE SHIFTS, DESPITE EXPERIENCING SIMILAR WARMING TRENDS.”

PRZESLAWSKI ET AL. 2012. *USING RIGOROUS SELECTION CRITERIA TO INVESTIGATE MARINE RANGE SHIFTS* ESTUARINE COASTAL AND SHELF SCIENCE

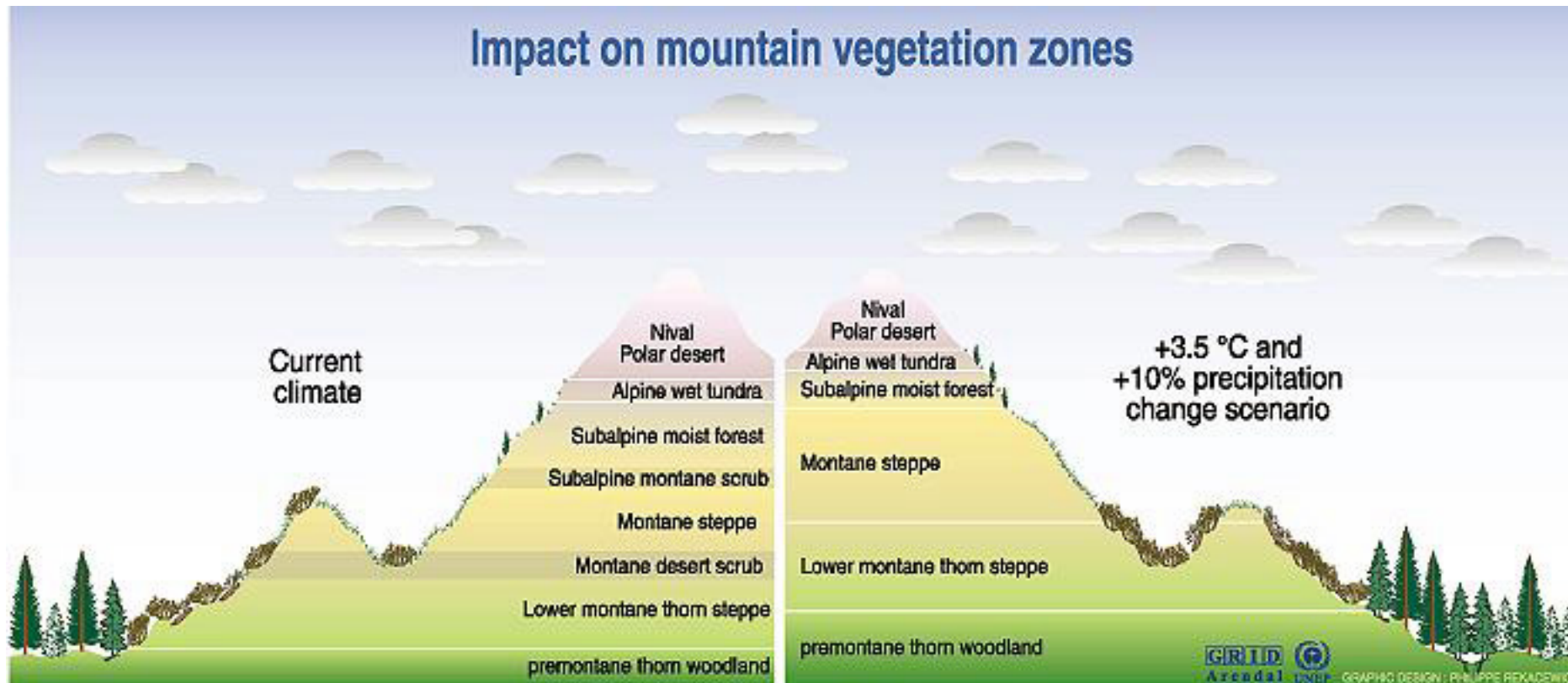
LOOKED AT 311 SPECIES FROM 13 STUDIES AND APPLIED RIGOROUS STANDARDS TO DETERMINE IF POLEWARD SHIFTS HAD OCCURRED-> SUGGESTED THAT AVERAGE RANGE SHIFT IS ORDER OF MAGNITUDE SLOWER THAN PREDICTED USING META-ANALYSIS

ARE EQUATORIAL SHIFTS (OR STASIS) IN  
RANGE BOUNDARIES, INCREASES IN  
PRODUCTIVITY OR IN BIODIVERSITY  
REALLY *INCONSISTENT* WITH WARMING?

..OR SHOULD WE BE MORE SOPHISTICATED IN  
HOW WE FRAME OUR HYPOTHESES AND  
COMMUNICATE EXPECTATIONS?

# GENERALIZATIONS AREN'T VERY USEFUL WHEN PREPARING FOR CLIMATE CHANGE IMPACTS.... OR FOR FRAMING HYPOTHESES ABOUT CLIMATE CHANGE

- E.G., POLEWARD AND ALTITUDINAL RANGE SHIFTS

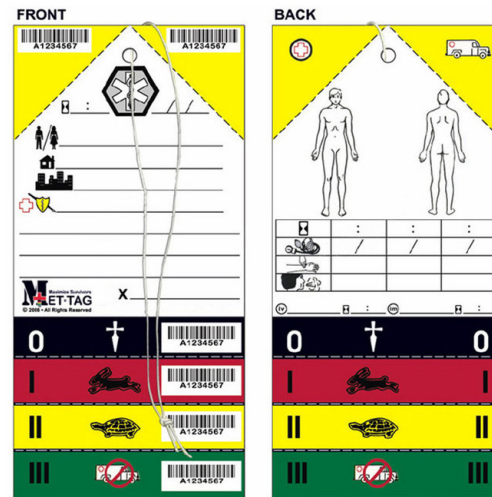


Sources: Martin Beniston, Mountain environments in changing climates, Routledge, London, 1994; Climate change 1995, Impacts, adaptations and migration of climate change, contribution of working group 2 to the second assessment report of the Intergovernmental panel on climate change (IPCC), UNEP and WMO, Cambridge press university, 1996.

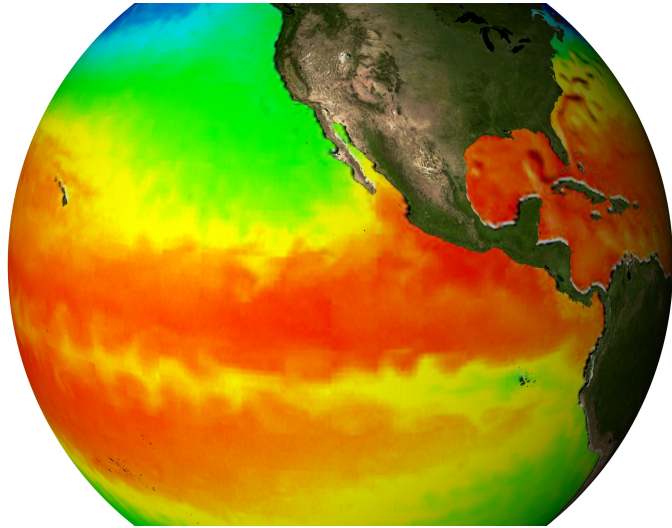
# ECOLOGICAL FORECASTING

## *SCIENCE IN SERVICE OF SOCIETY*

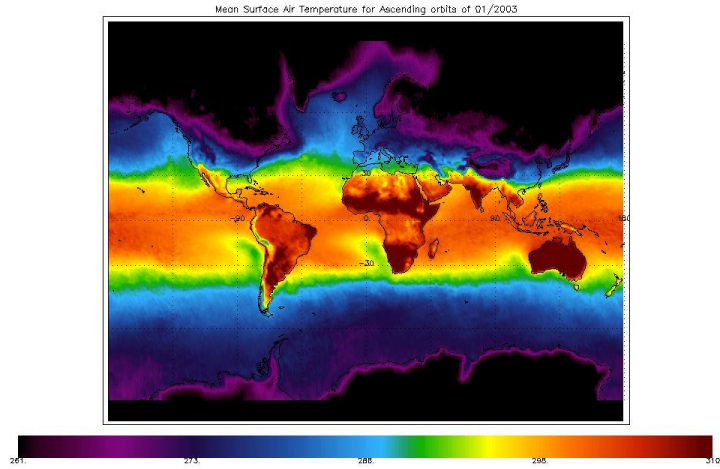
- Ecological forecasting informs  
and is a form of triage:  
how do we decide where to focus our efforts?



# ECOLOGICAL FORECASTING

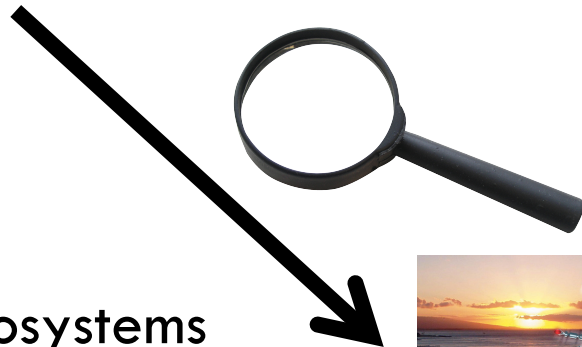


Weather Data and Forecasts



Risk maps and "what if" scenarios

Downscale to organisms, ecosystems and ecosystem services



Models and sensors

Scale up to ecological and societal impacts

# WHAT CAN DEB THEORY TELL US ABOUT THE IMPORTANCE OF UNDERSTANDING “DETAILS” OF CLIMATE CHANGE IMPACTS AS PART OF ECOLOGICAL FORECASTING APPROACHES?

- SUBLETHAL RESPONSES TO ENVIRONMENTAL CHANGE THAT ULTIMATELY DRIVE ECOLOGICAL PROCESSES
- IDENTIFICATION OF HOTSPOTS, STEPPING STONES AND CLIMATE REFUGIA (MARINE SPATIAL PLANNING) AND THE POTENTIAL ROLE OF SMALL-SCALE PROCESSES



**Kearney, M., S. J. Simpson, D. Raubenheimer, and B. Helmuth. 2010. Modelling the ecological niche from functional traits. Philosophical Transactions of the Royal Society B **365**:3469-3483.**

**Kearney, M. R., A. Matzelle, and B. Helmuth. 2012. Biomechanics meets the ecological niche: the importance of temporal data resolution. Journal of Experimental Biology **215**:922-933.**





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Montalto, V., B. Helmuth, P. M. Ruti, A. Dell'Aquila, A. Rinaldi, and G. **Sàra**. 2016. A mechanistic approach reveals non linear effects of climate warming on mussels throughout the Mediterranean sea. *Climatic Change* **139**:293-306.

Montalto, V., G. **Sarà**, P. Ruti, A. Dell'Aquila, and B. Helmuth. 2014. Testing the effects of temporal data resolution on predictions of bivalve growth and reproduction in the context of global warming. *Ecological Modelling* **278**:1-8.

**Sarà**, G., M. Kearney, and B. Helmuth. 2011. Combining heat-transfer and energy budget models to predict thermal stress in Mediterranean intertidal mussels. *Chemistry and Ecology* **27**:135-145.







**Kearney**, M., S. J. Simpson, D. Raubenheimer, and B. Helmuth. 2010. Modelling the ecological niche from functional traits. *Philosophical Transactions of the Royal Society B* **365**:3469-3483.

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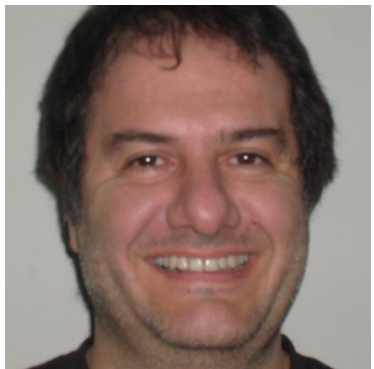
Montalto, V., G. **Sarà**, P. Ruti, A. Dell'Aquila, and B. Helmuth. 2014. Testing the effects of temporal data resolution on predictions of bivalve growth and reproduction in the context of global warming. *Ecological Modelling* **278**:1-8.

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**Matzelle**, A., V. Montalto, G. Sarà, M. L. Zippay, and B. Helmuth. 2014. Dynamic energy budget model parameter estimation for the bivalve *Mytilus californianus*: Application of the covariation method. *Journal of Sea Research* **S1**:105-110.

**Matzelle**, A. J., G. Sarà, V. Montalto, M. Zippay, G. C. Trussell, and B. Helmuth. 2015. A bioenergetics framework for integrating the effects of multiple stressors: Opening a 'black box' in climate change research. *American Malacological Bulletin* **33**:150-160.

**Monaco**, C. J., D. S. Wetthey, and B. Helmuth. 2014. A Dynamic Energy Budget (DEB) model for the keystone predator *Pisaster ochraceus*. *PLoS ONE* **9**:e104658.



# WHAT DEB THEORY CAN TELL US ABOUT CLIMATE CHANGE IMPACTS

- **THE ROLE OF SUBLETHAL PROCESSES, AND CAUTIONS AGAINST USING AVERAGED ENVIRONMENTAL DATA**

# MODEL SKILL AND STATIONARITY

- *MODEL SKILL* = DEGREE OF CORRESPONDENCE BETWEEN MODEL PREDICTIONS AND FIELD OBSERVATIONS
- *MODEL STATIONARITY* = ABILITY OF A MODEL GENERATED FROM DATA COLLECTED AT ONE PLACE/TIME TO PREDICT PROCESSES AT ANOTHER PLACE/TIME

# MODEL SKILL AND STATIONARITY

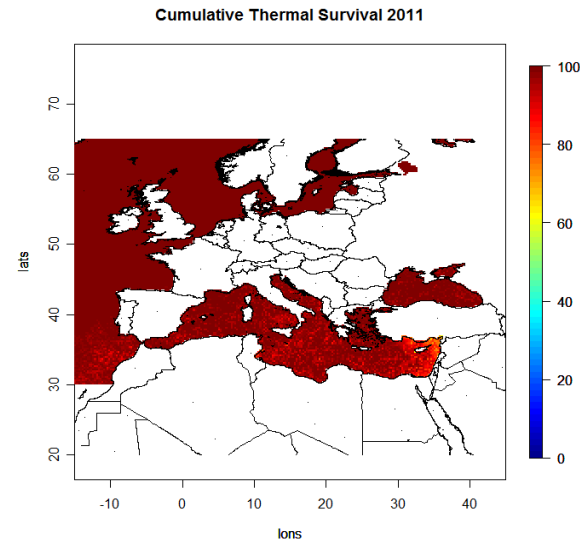
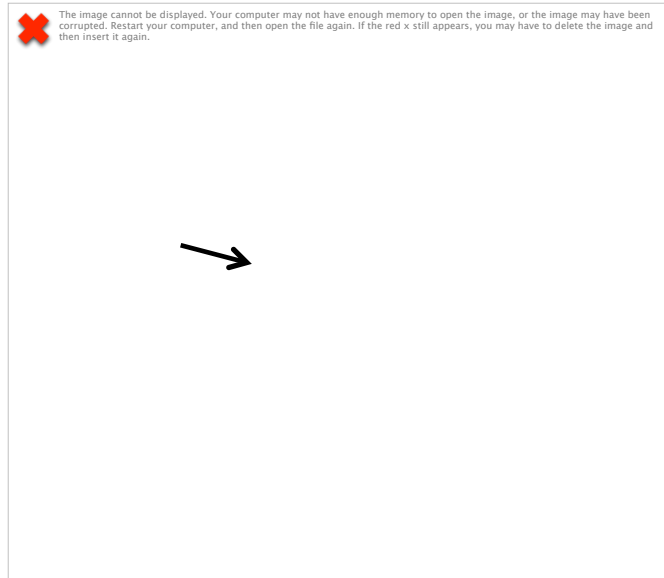
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- **CLIMATE CHANGE MODELS- ESPECIALLY CORRELATIVE MODELS- ASSUME STATIONARITY IN TIME (SPACE FOR TIME SUBSTITUTION)**

# Testing model stationarity with and without physiological mechanism



Model of mussel (*M. edulis*) distribution  
based on lethal temperatures

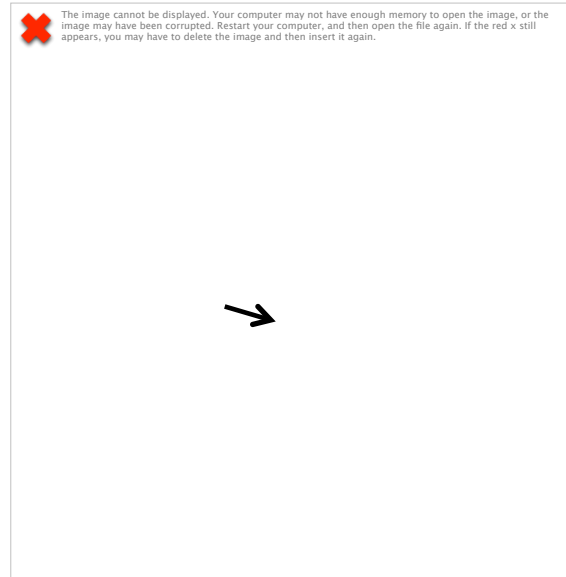
# Model that works for the US fails in Europe



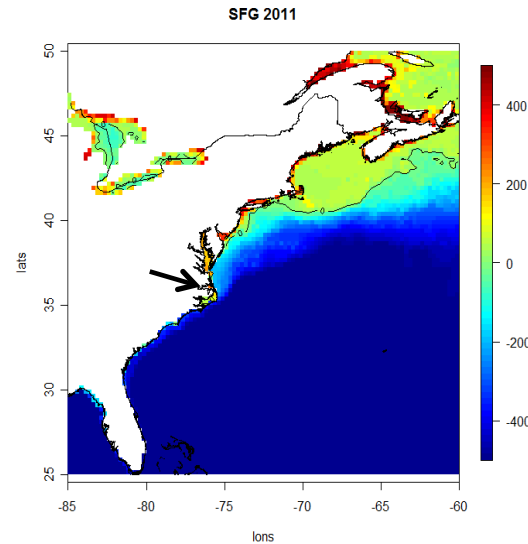
Model of mussel (*M. edulis*) distribution  
based on lethal temperatures

# Testing model stationarity with and without mechanism

## Lethal temperatures



## Energetics

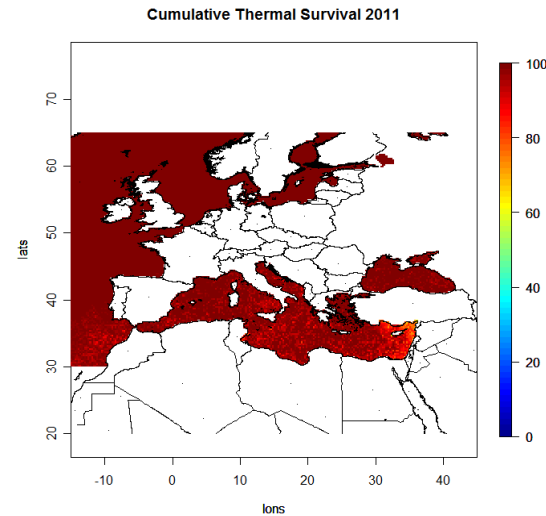


Two models of mussel (*M. edulis*) distribution- one with details and one without give similar results

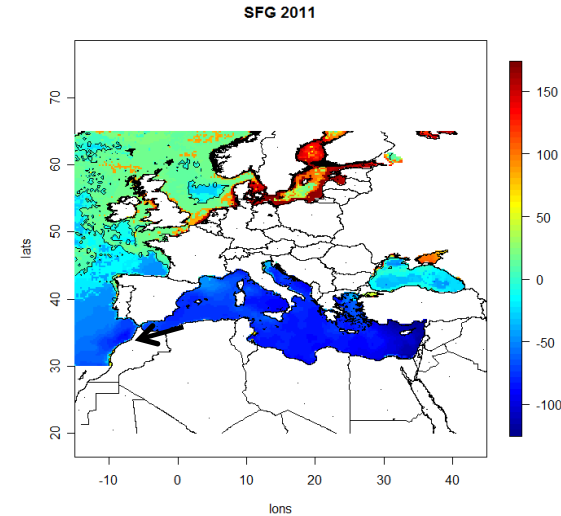
(Woodin, Hilbish, Helmuth, Jones and Wetthey 2013)

# Testing model stationarity with and without mechanism

Lethal temperatures



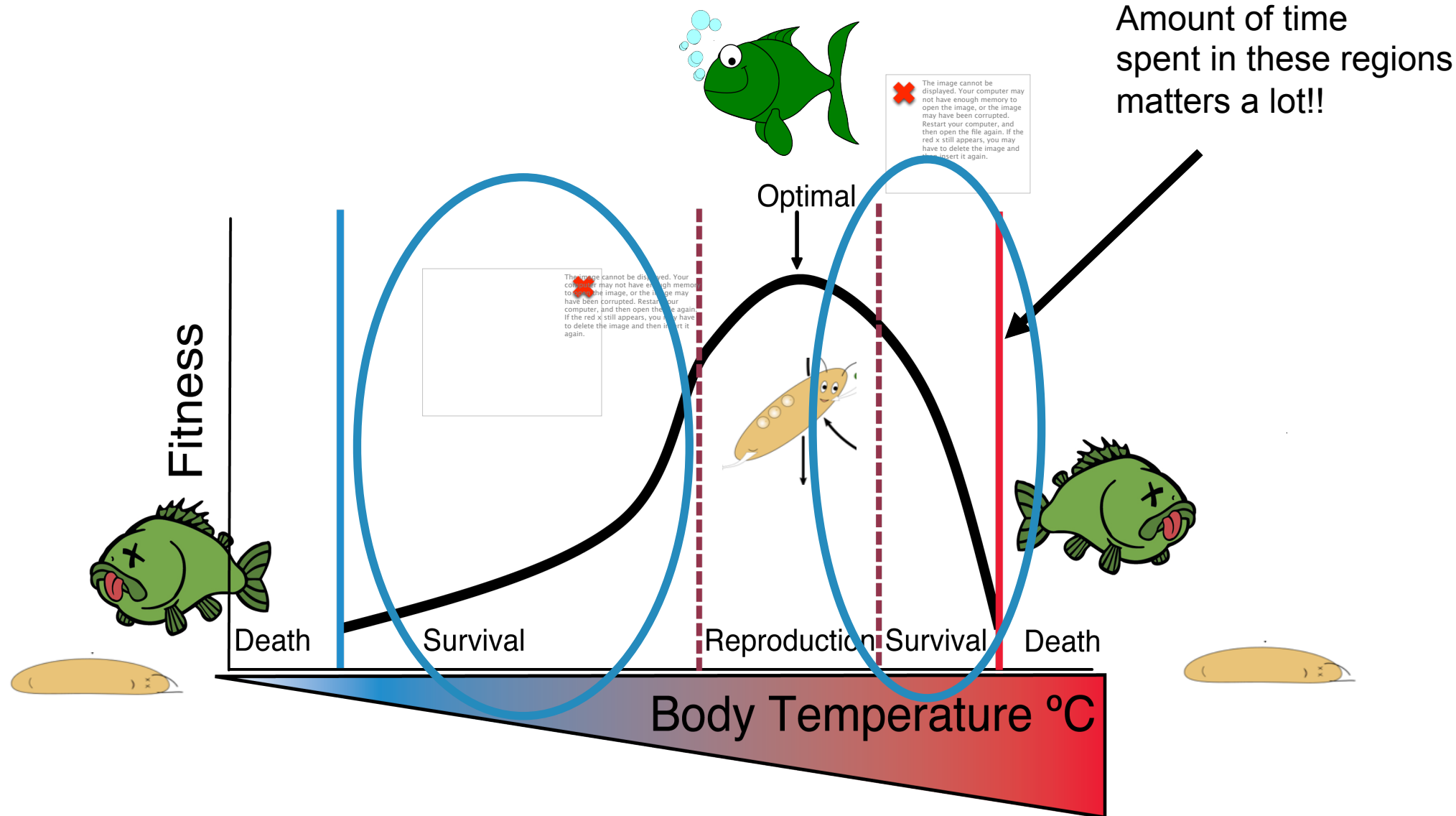
Energetics



Lethal model fails miserably when applied to Europe;  
Energetics model does well

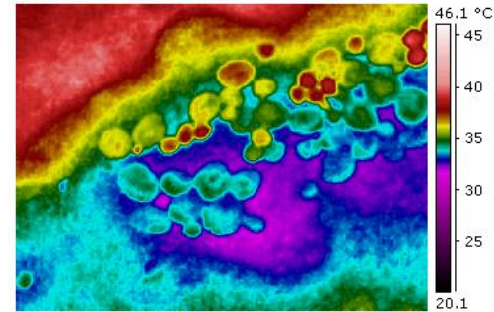
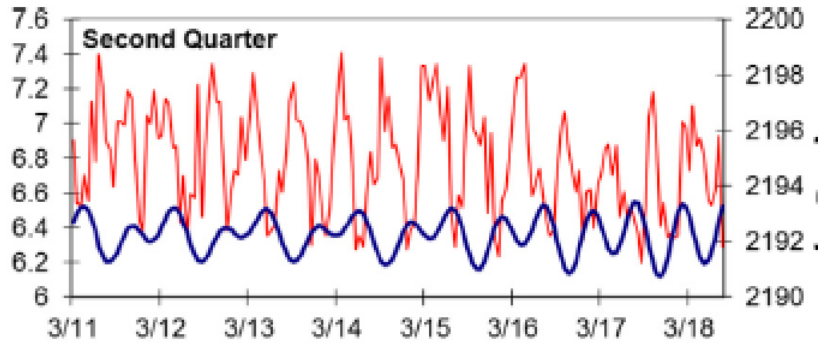


# PHYSIOLOGICAL PERFORMANCE CURVES

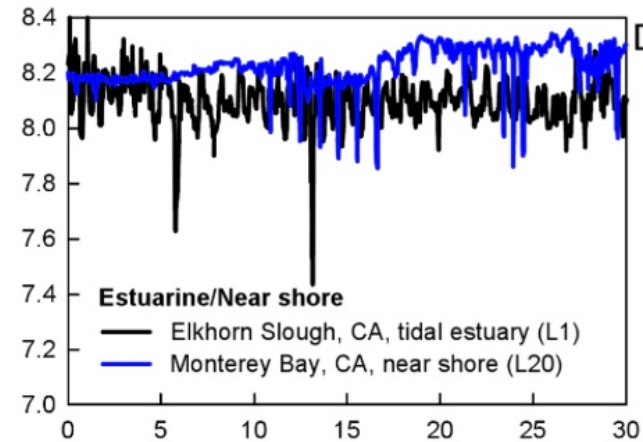
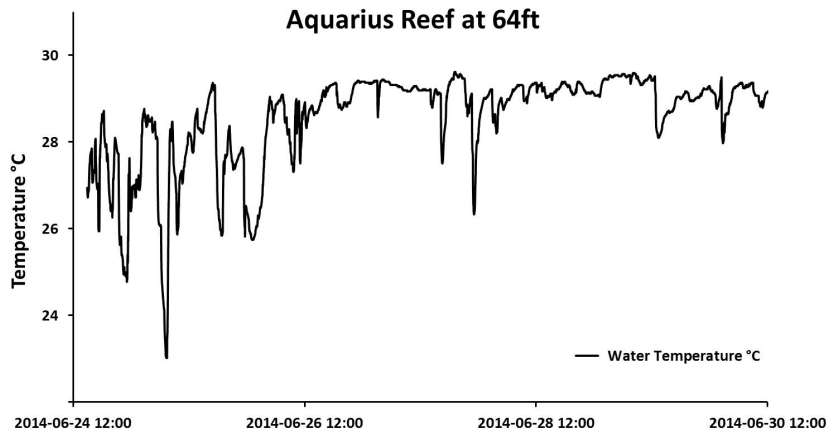


# THE REAL WORLD IS FREQUENTLY MESSY WITH HIGH SPATIAL AND TEMPORAL VARIABILITY

Lee et al. 2015: Hydrothermal Vents



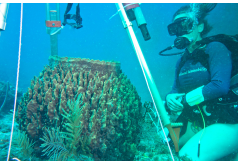
Terrestrial and intertidal (and even shallow subtidal) body temperature driven primarily by solar radiation (Helmuth 2002)



Large changes in nearshore pH over scales of hours (Hofmann et al. 2011)

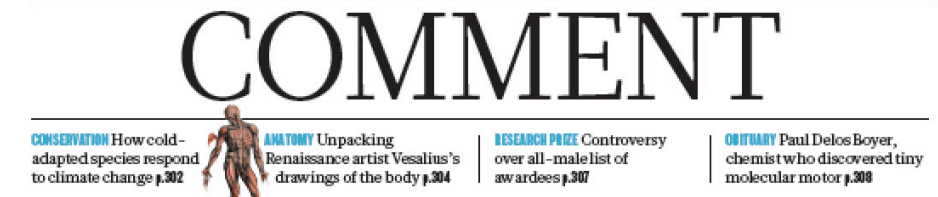
Internal waves, wind and upwelling lead to large and rapid changes in temperature and  $p\text{CO}_2$  on reefs and shallow coastal regions

The image cannot be displayed. Your computer may not have enough memory to open the image, or the image may have been corrupted. Restart your computer, and then open the file again. If the red x still appears, you may have to delete the image and then insert it again.



# THE MYTH OF A STABLE OCEAN

- TECHNOLOGICAL LIMITATIONS TO OUR ABILITY TO MEASURE THE ENVIRONMENT AT COARSE TEMPORAL AND SPATIAL RESOLUTION HAS BEEN CONFLATED WITH THE ASSUMPTION THAT THESE ARE THE ONLY SCALES THAT MATTER TO SPECIES DISTRIBUTIONS



Fish and other marine life are affected by ocean weather: drastic variations in temperature, pH, oxygen and salinity that are in turn influenced by climate change.

## Biologists ignore ocean weather at their peril

Bates et al. 2018 *Nature* Vol. 560

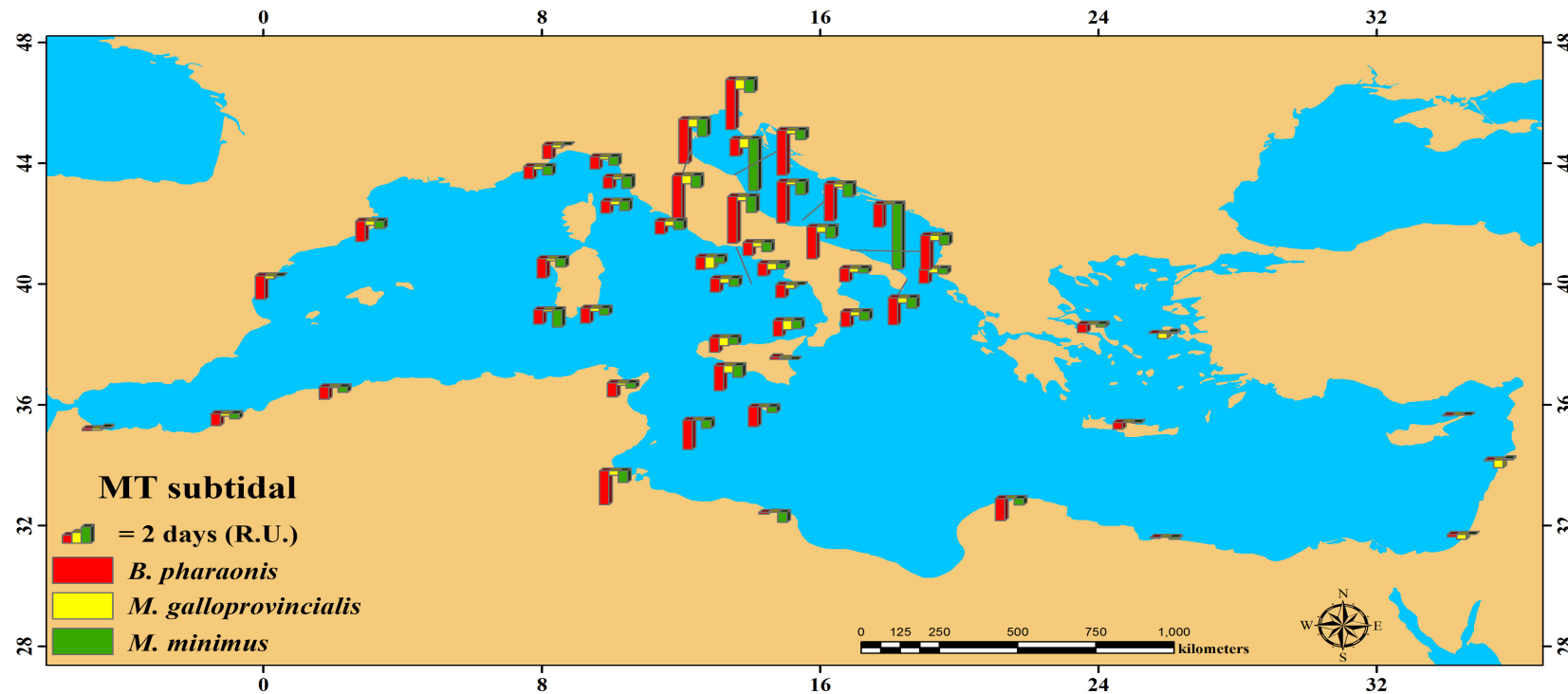






# FORECASTS OF MATURATION TIME USING DEB MODEL FOR THREE SPECIES OF MUSSELS IN THE MED.

Valeria Montalto

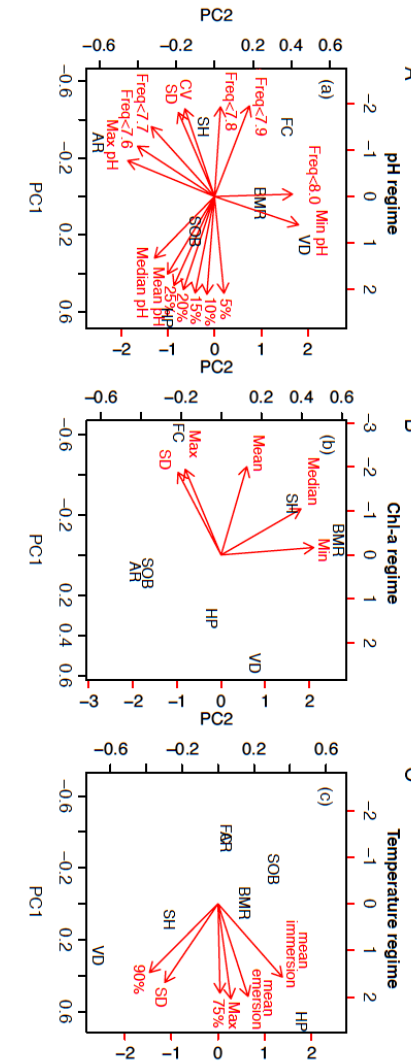


# SPATIO-TEMPORAL COINCIDENCE OF MULTIPLE DRIVERS

Patterns of mussel growth best explained by coincidence of low food, low pH and high intertidal temperatures



Kroeker et al., 2016 *Ecology Letters*



# DYNAMIC ENERGY BUDGET THEORY

- CAN PROVIDE QUANTITATIVE MEANS OF LOOKING AT CUMULATIVE ROLE OF FLUCTUATING ENVIRONMENT, AND ESPECIALLY THE INTERACTION OF FOOD AND STRESS
- BUT *ONLY* WHEN WE USE ENVIRONMENTAL DATA AT THE RIGHT SPATIAL AND TEMPORAL SCALES
- *CANNOT* USE ANNUAL MEANS OR CLIMATE AVERAGES TO FORECAST ANY KIND OF MEANINGFUL ECOLOGICAL EFFECTS UNLESS THE ENVIRONMENT TRULY IS STATIC IN TIME AND UNIFORM IN SPACE

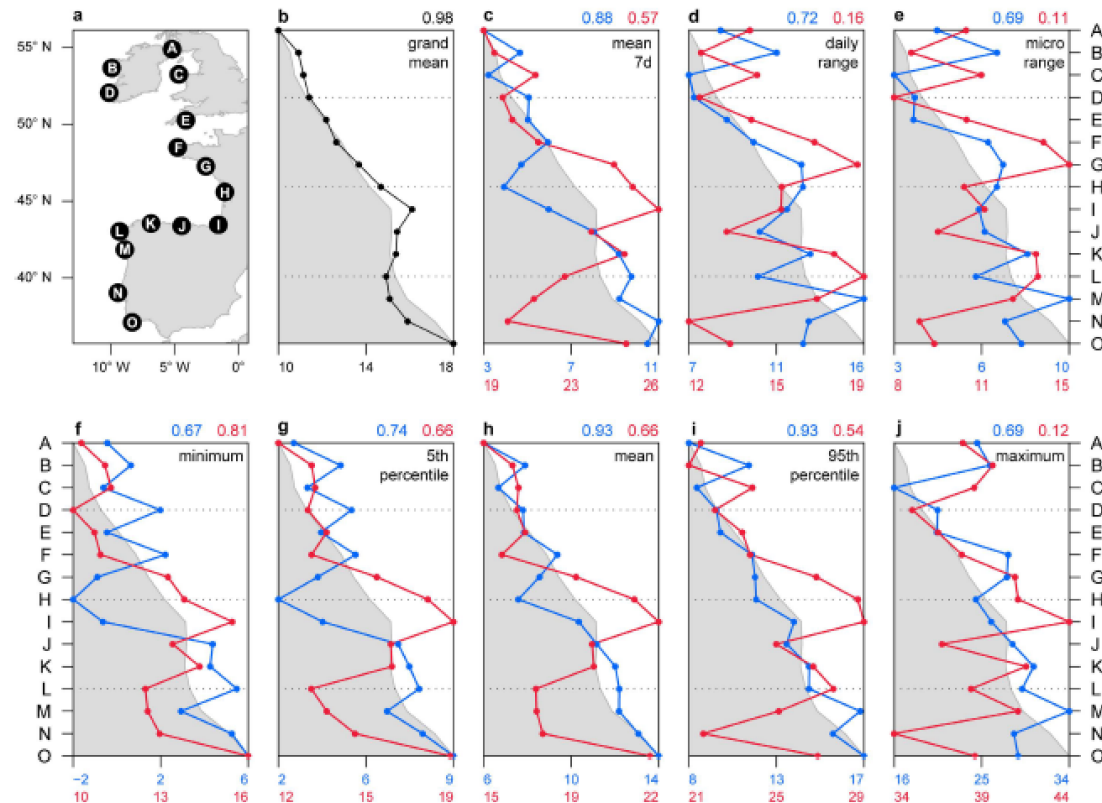




# WHAT DEB CAN TELL US ABOUT CLIMATE CHANGE IMPACTS

- MARINE SPATIAL PLANNING: IDENTIFYING HOT SPOTS, REFUGIA AND STEPPING STONES, AND THE POTENTIAL ROLE OF SMALL-SCALE SPATIAL HETEROGENEITY
- 

# WE NEED TO BE VERY CAREFUL OF WHICH “ENVIRONMENTAL SIGNALS” WE PAY ATTENTION TO OVER GEOGRAPHIC SCALES

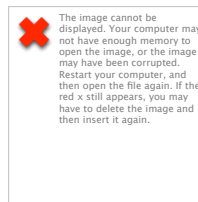


**Figure 1. Patterns of temperature metrics across the European Atlantic intertidal ecosystem. (a)** Locations surveyed. Geographic pattern of metrics: **(b)** grand mean, **(c)** 7 day mean, **(d)** daily range, **(e)** microhabitat range, **(f)** minimum, **(g)** 5<sup>th</sup> percentile, **(h)** mean, **(i)** 95<sup>th</sup> percentile, **(j)** maximum. Black line **(b)** is grand mean, calculated using all data from each shore. Red and blue lines **(c-j)** calculated using the warmest and coldest 30 days of each year (7 days for **(c)**), per shore. The shaded area is the pattern expected if each metric was perfectly correlated with latitude. Points in shaded area are “cooler than expected given latitude”, and points outside shaded area are “hotter than expected”. Correlation coefficients between each

# MEASURING THE ENVIRONMENT AT SCALES RELEVANT TO ORGANISMS WITH BIOMIMETIC SENSORS



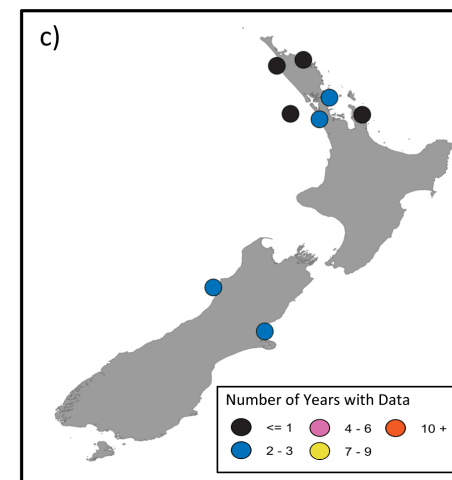
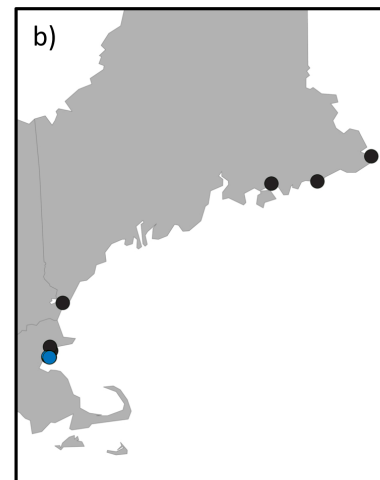
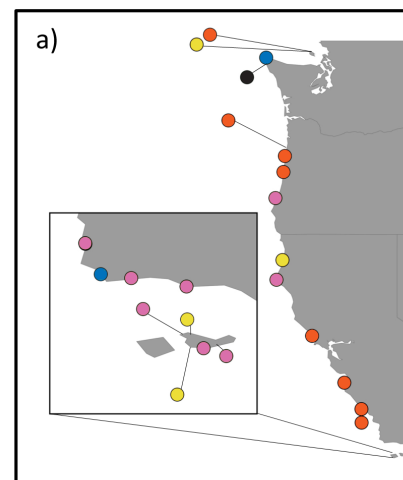
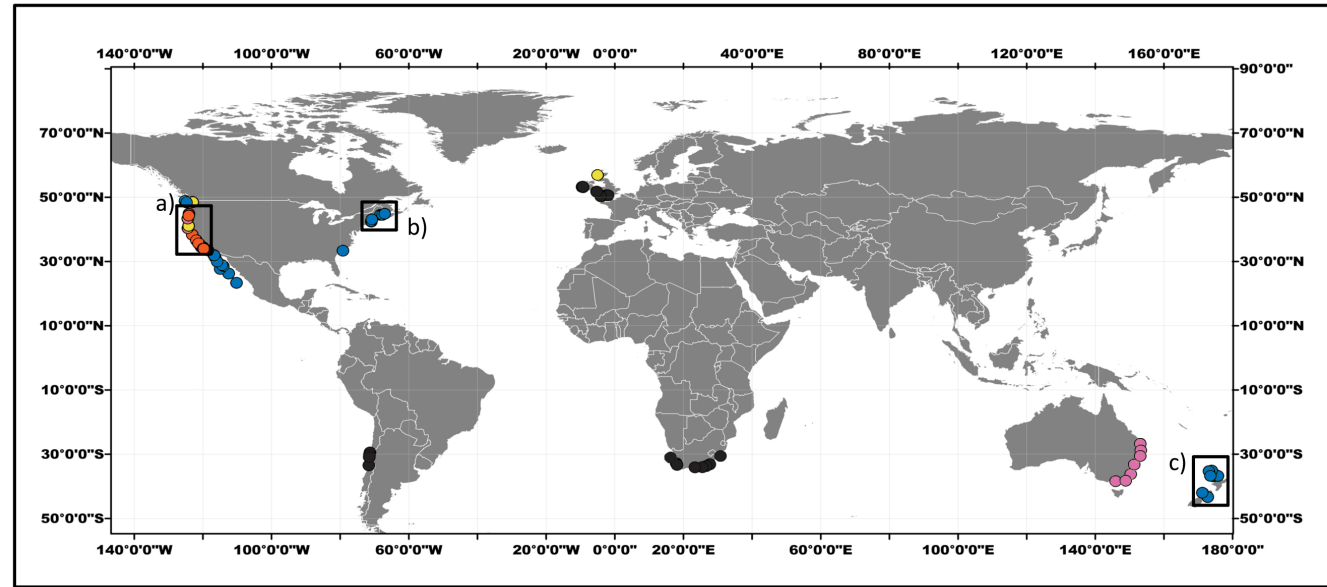
“Robomussel”



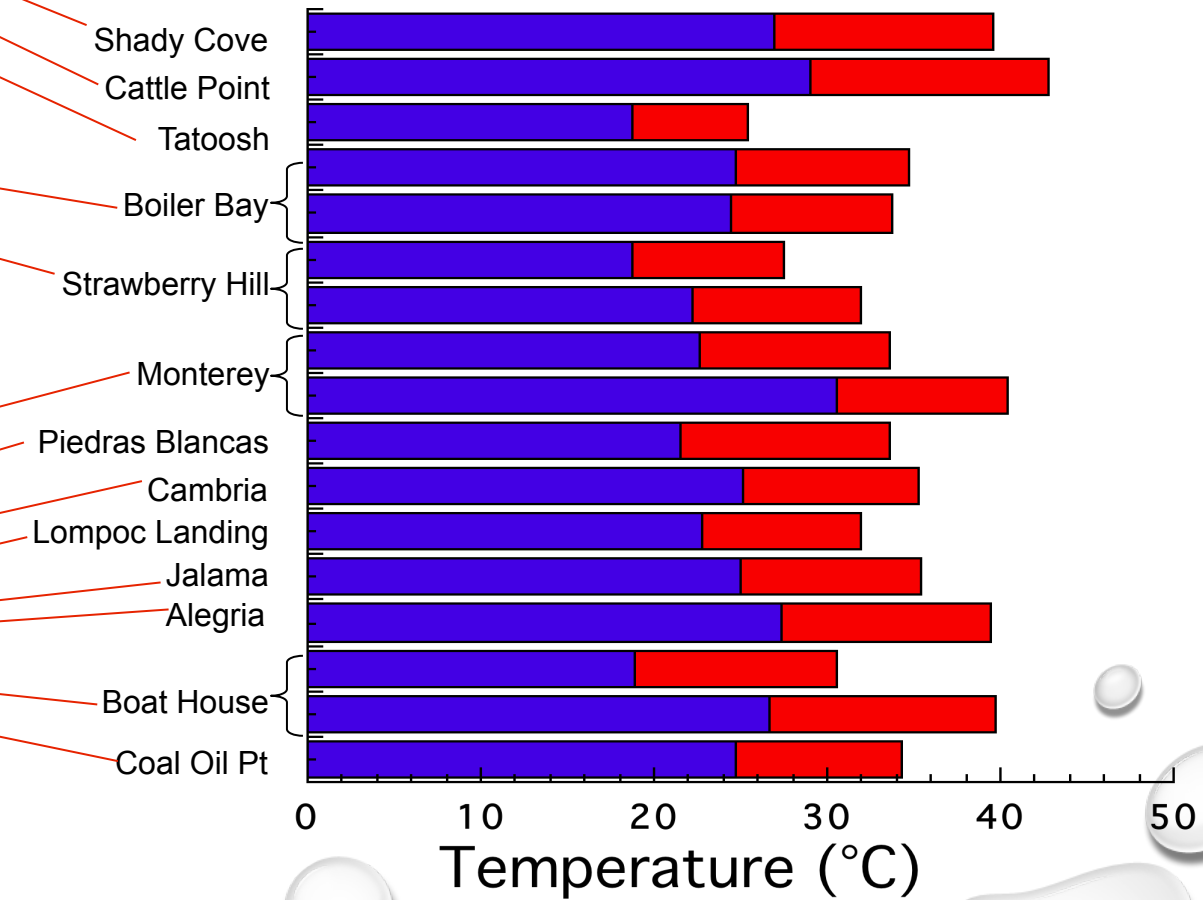
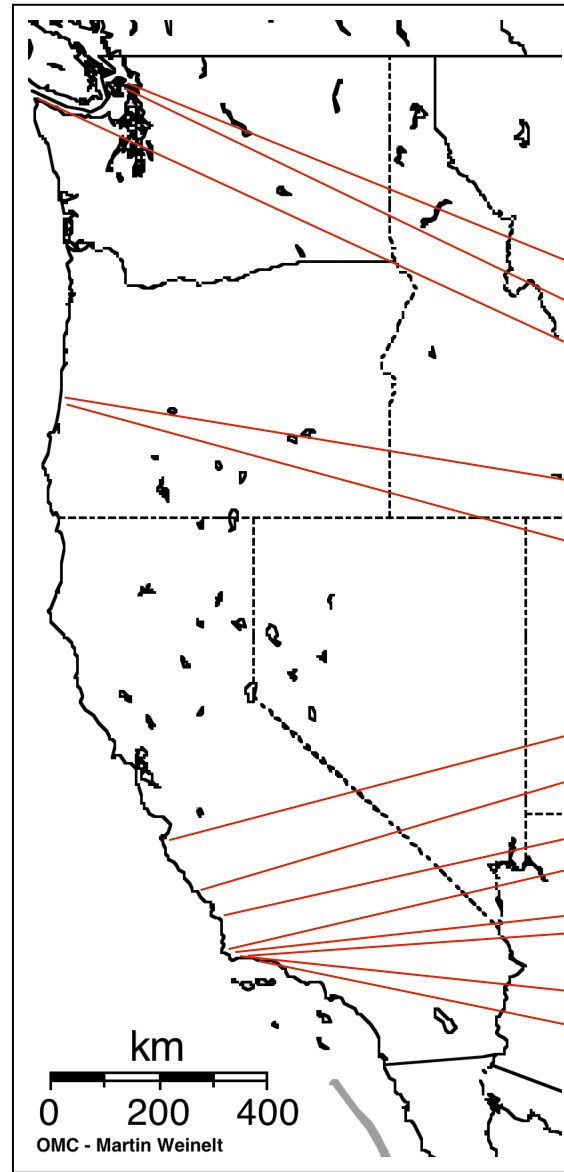
California mussel, *Mytilus californianus*

Unmatched loggers regularly create errors of  $>14^{\circ}\text{C}$ ;  
Thermally matched loggers incur errors of  $\sim 2^{\circ}\text{C}$

# 71 INTERTIDAL SITES WORLDWIDE, RECORDING CONTINUOUSLY

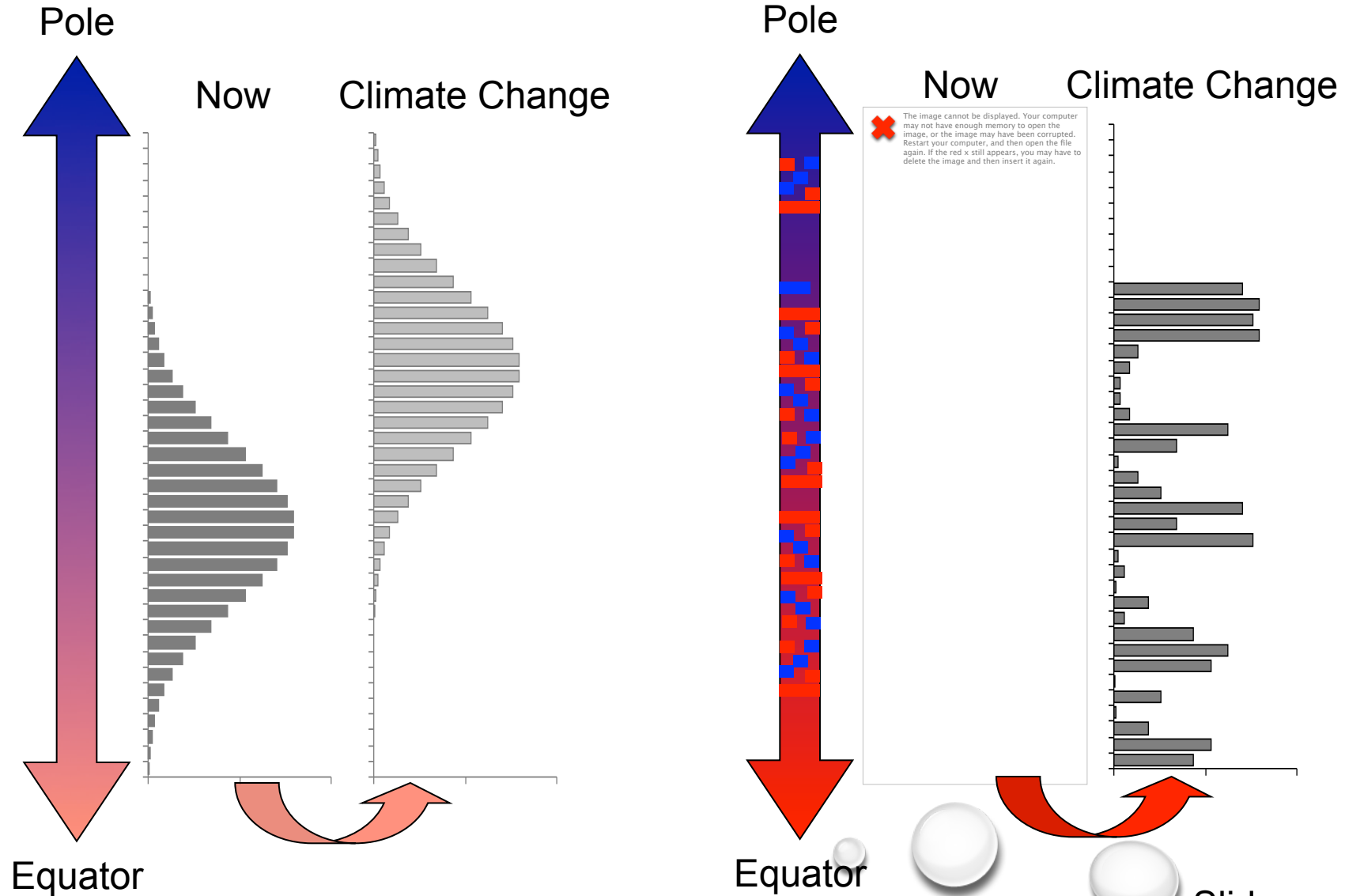


# THERMAL MOSAIC IN MUSSEL BODY TEMPERATURES



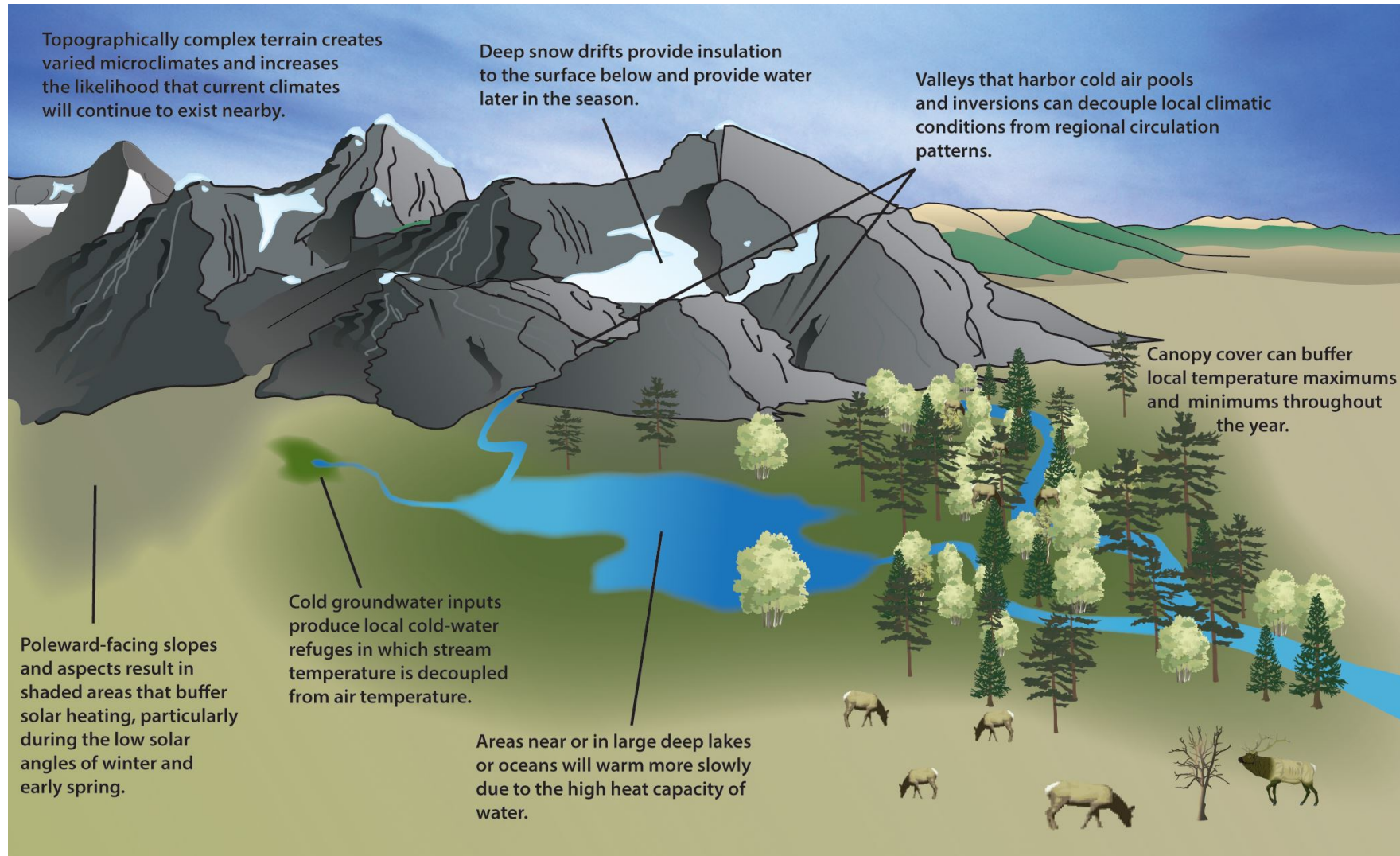
# CONCEPT OF A "THERMAL MOSAIC"

- Helmuth et al 2002, Gilman 2006, Finke et al. 2007, Torossian et al. 2016



Slide courtesy Sarah Gilman

# CLIMATE REFUGIA



Morelli et al. 2016 "Managing climate refugia for climate adaptation" PLOS ONE 12: e0169725

# CLIMATE REFUGIA IN CLIMATE ADAPTATION

- HABITATS THAT PERMIT SURVIVAL DURING EXTREME EVENTS, AND SUBSEQUENT RECOVERY
- ARE BEING DISCOVERED IN MULTIPLE ECOSYSTEMS
- MAY SERVE AS A MEANS OF ENHANCING RESILIENCE



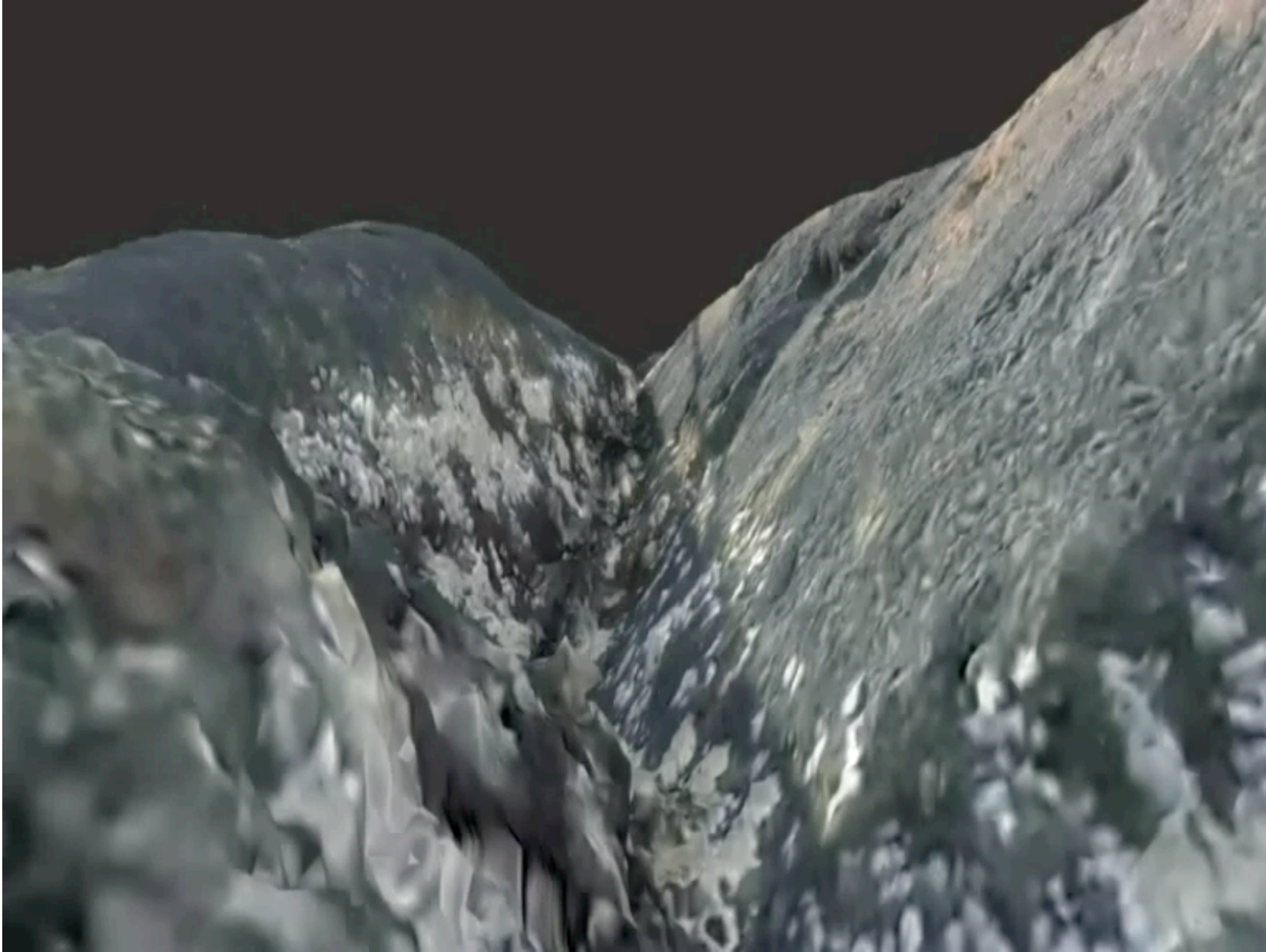
# DOES THE SCALE OF “RESCUE EFFECTS” CHANGE WITH BODY SIZE AND BEHAVIOR?

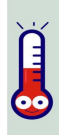
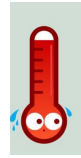
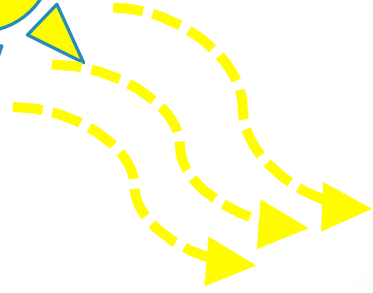
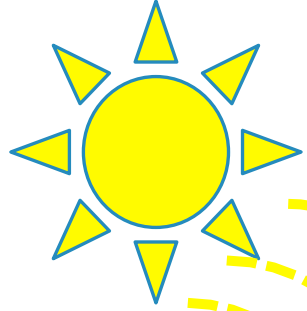


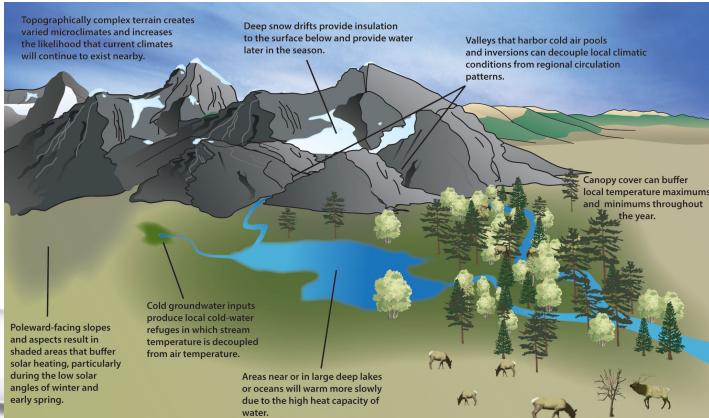
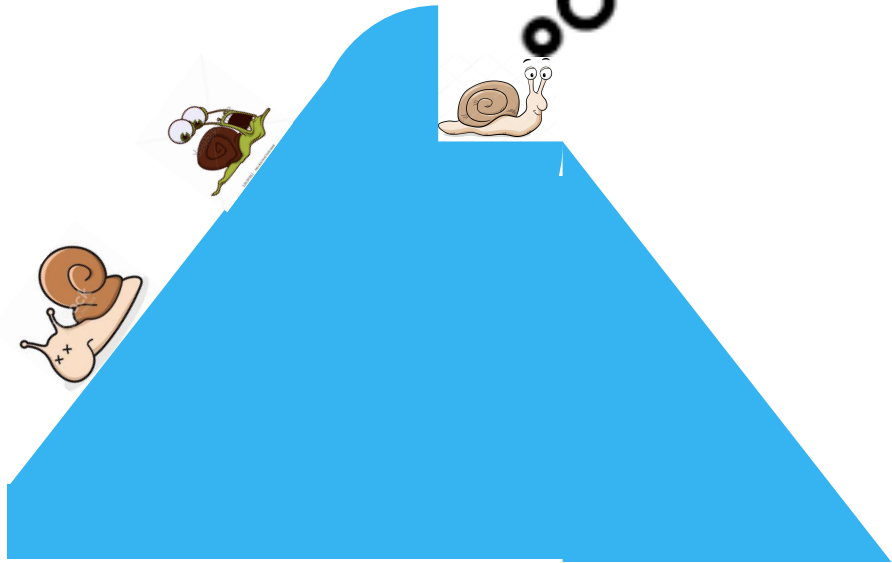
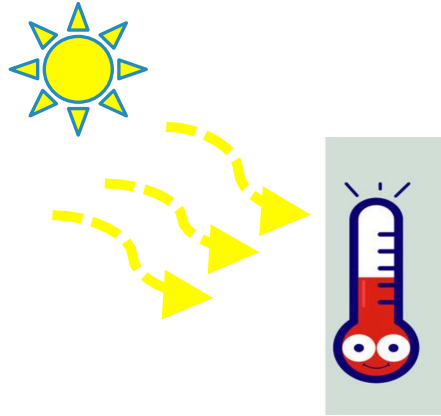
[http://bpic.588ku.com/back\\_pic/00/00/69/40/18cbd649961b9b92762ec31fac5c34e6.jpg!/fh/300/quality/90/unsharp/true/compress/true](http://bpic.588ku.com/back_pic/00/00/69/40/18cbd649961b9b92762ec31fac5c34e6.jpg!/fh/300/quality/90/unsharp/true/compress/true)

<https://www.worldwildlife.org/species/whale>

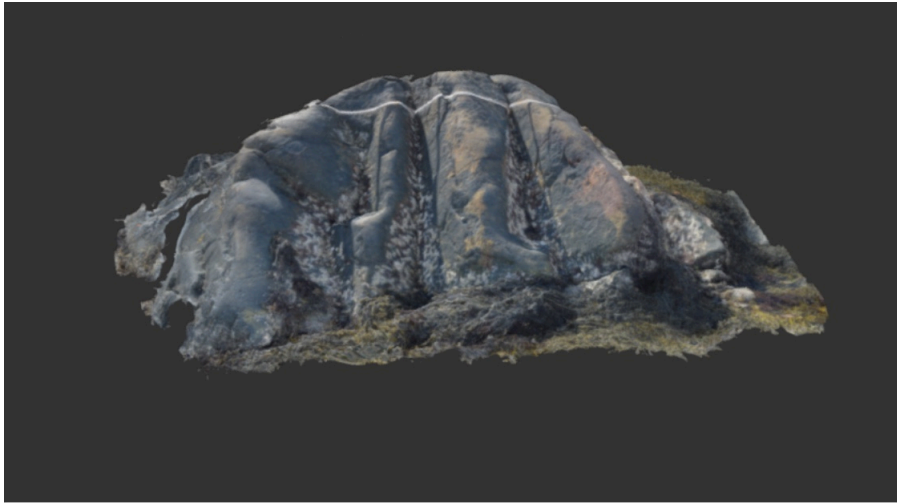
# A snail's eye view of the world







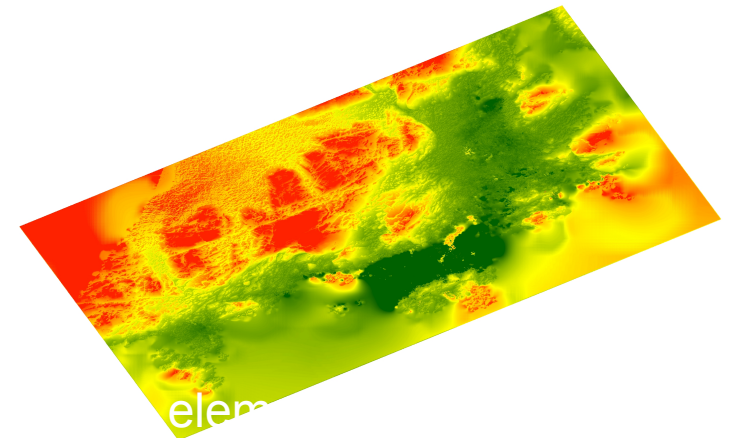
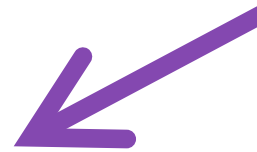
# MAPPING SMALL-SCALE THERMAL ENVIRONMENTS



3D modeling



Drone imagery

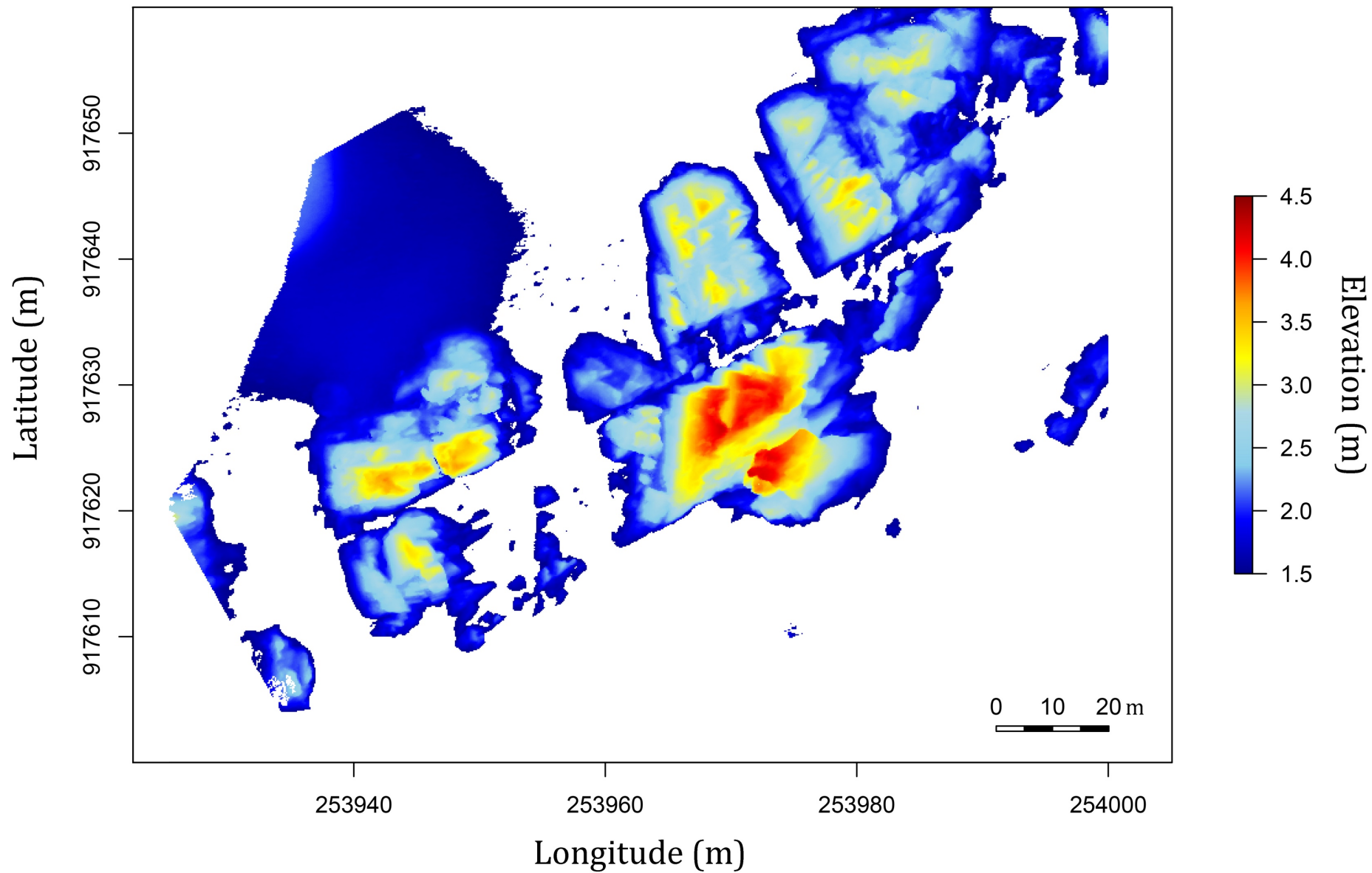


Heat budget models



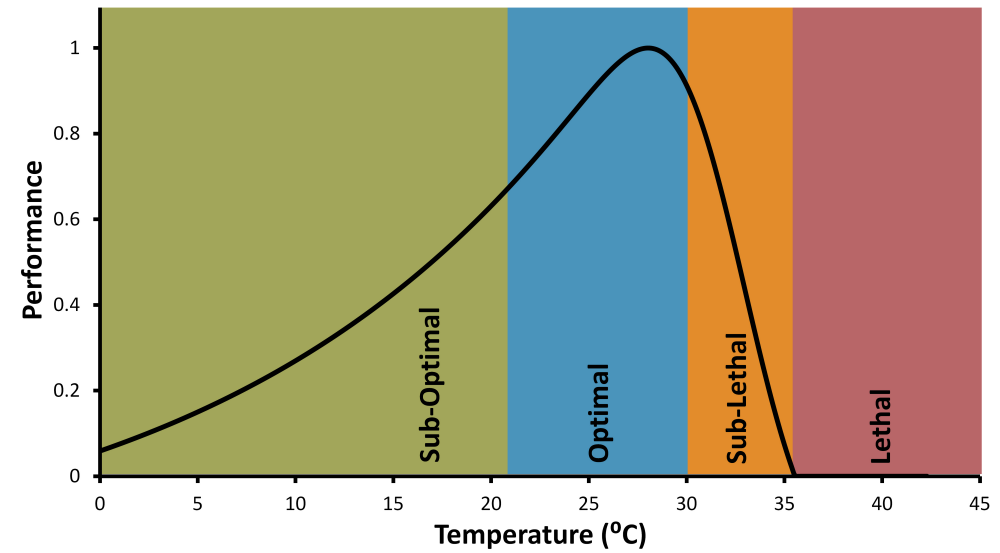
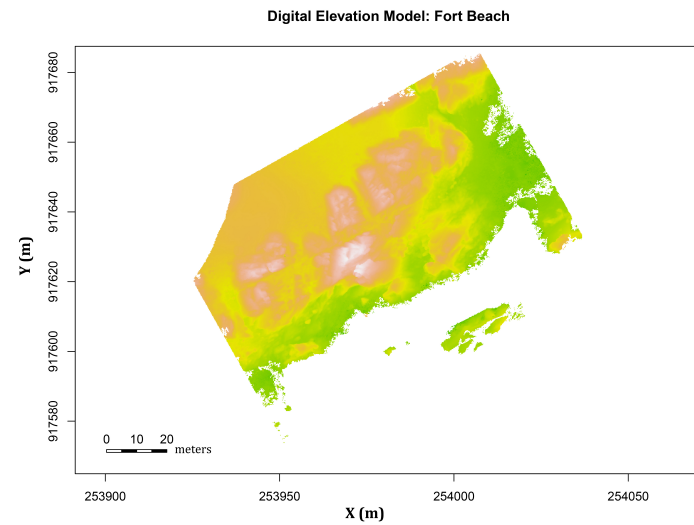
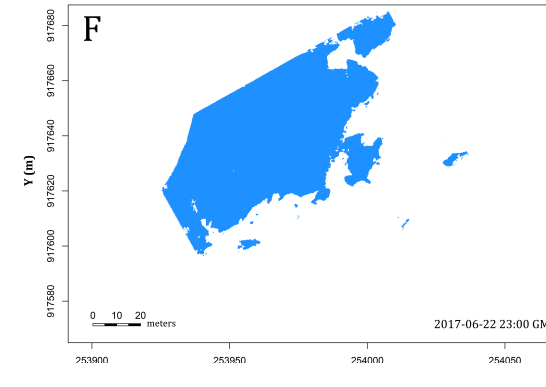
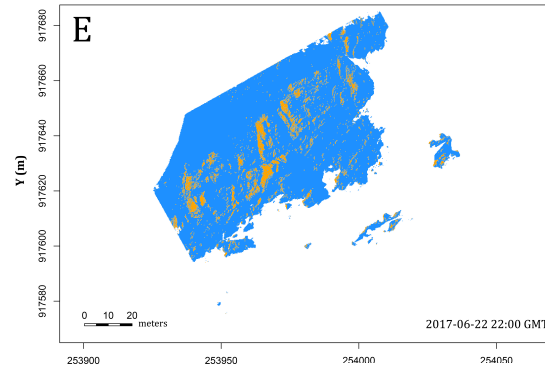
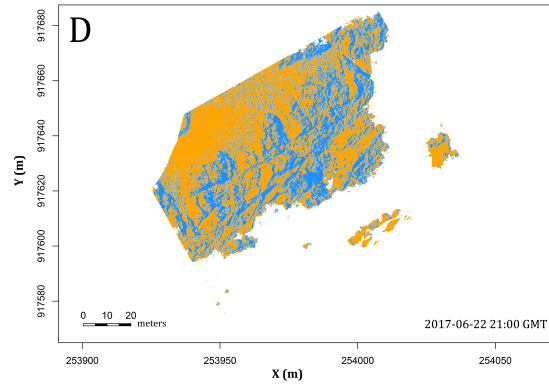
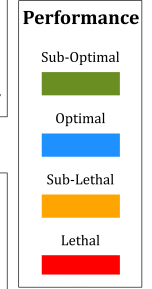
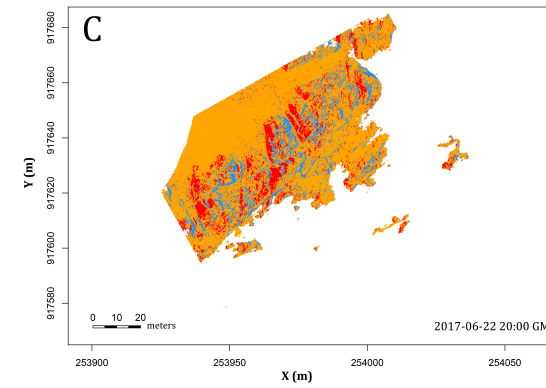
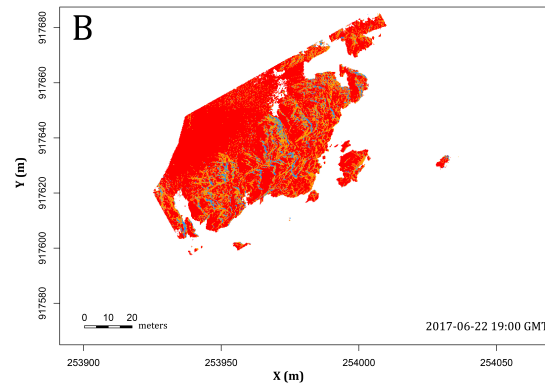
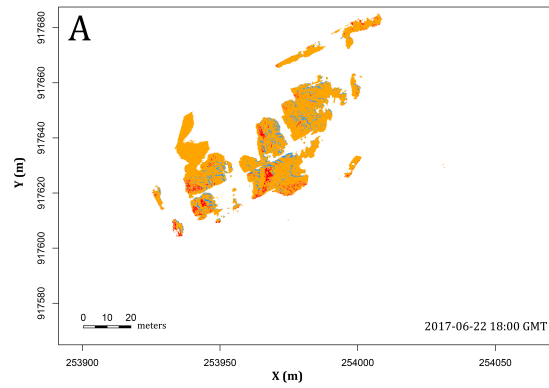


# Digital Elevation Model: Mid to High Intertidal



3 Million pixels for a ~100x 25m site





# PATTERNS OF WEIGHT GAIN IN MUSSELS

DEB parameters for *M edulis*  
from AMP:

2017-12-05 23:00:00 GMT

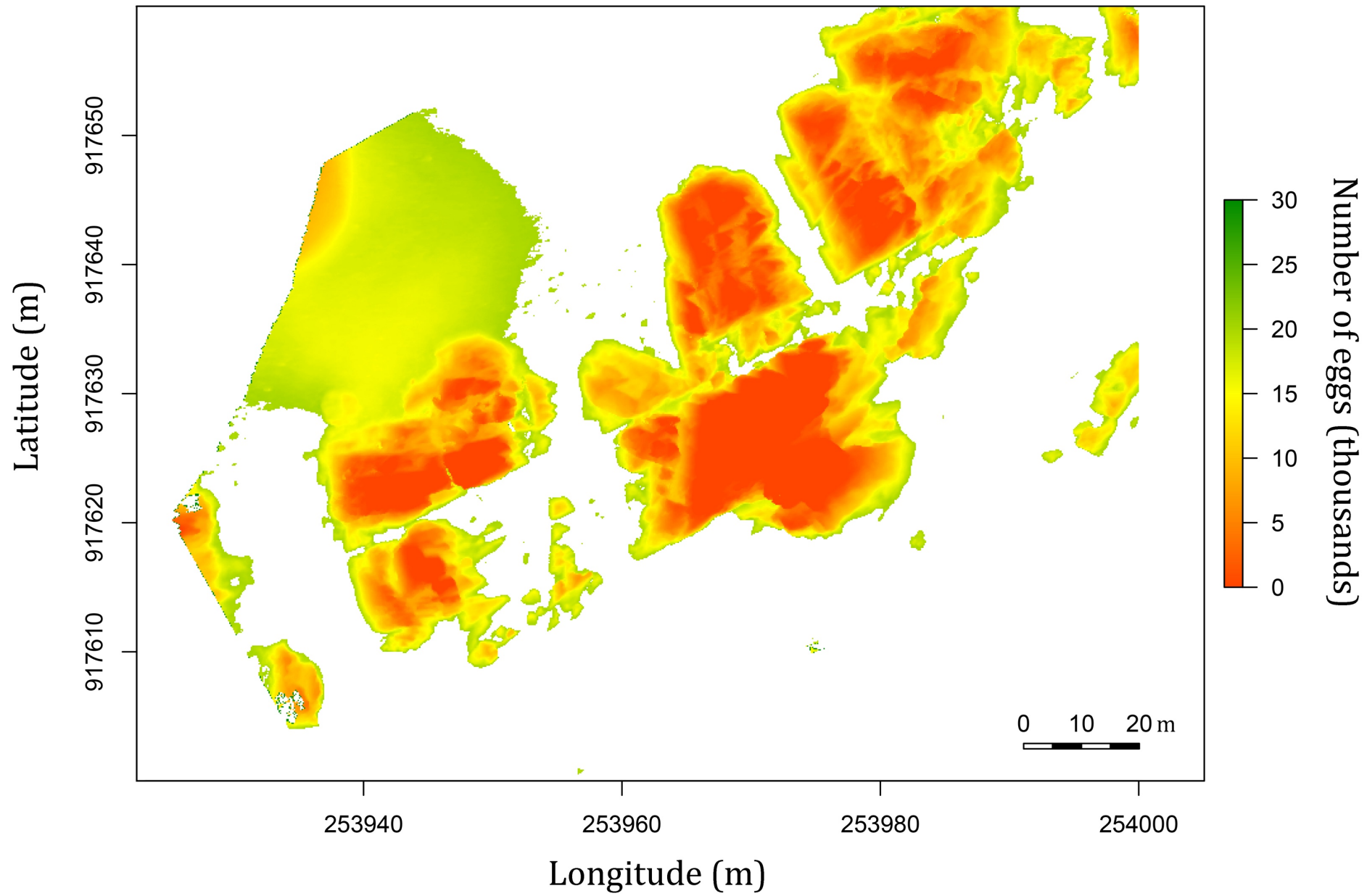
Saraiva and Kooijman. 2017. AmP  
*Mytilus edulis*, version 2017/11/1

Model code by C. Monaco

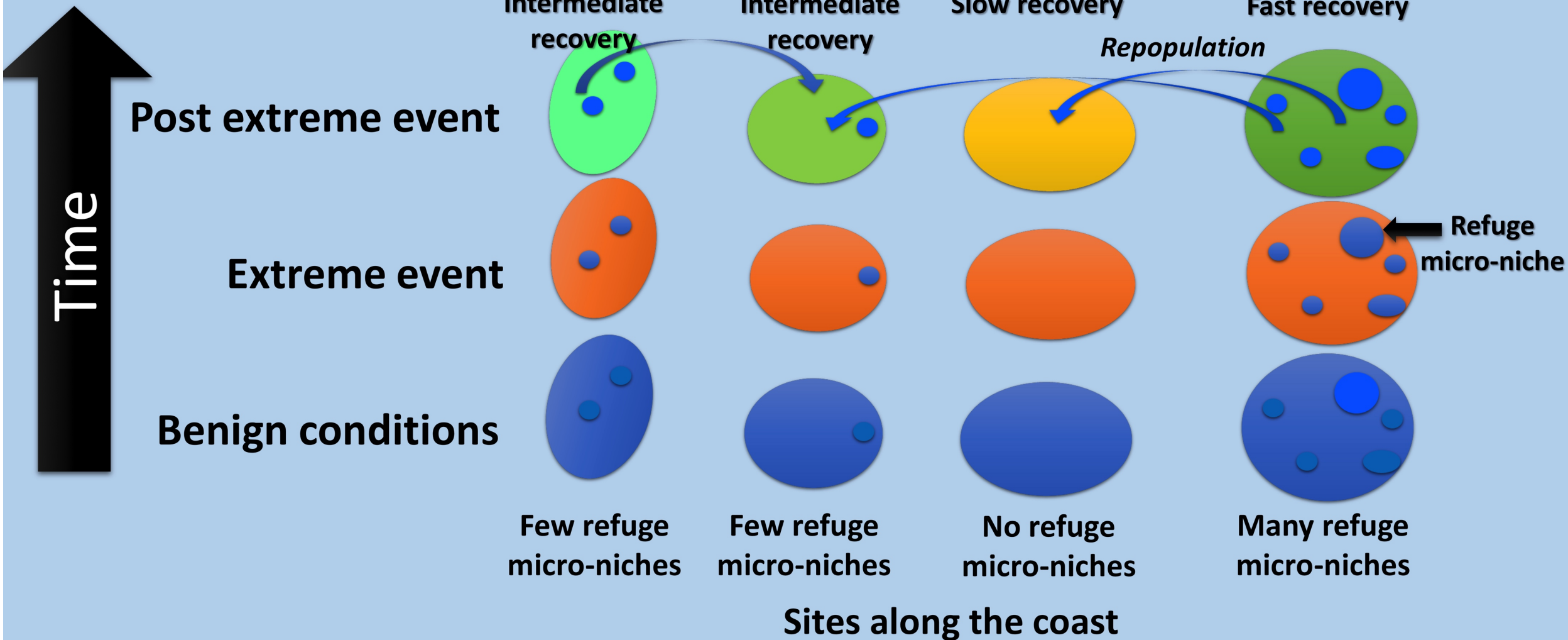
Constant food assumed (2  $\mu\text{g/l}$ )

Run time: ~5 days for one year of  
hourly data for each of 3  
million pixels





# Conceptual meta-community framework



# LARGE-SCALE PATTERN DRIVEN BY SMALL-SCALE PROCESSES?

- *SMALL-SCALE PROCESSES AT LEVEL OF MICROHABITATS MAY HAVE EMERGENT PROPERTIES AT GEOGRAPHIC SCALES, BY PROVIDING STEPPING STONES AND REFUGIA DURING EXTREME EVENTS*

# WHERE DOES THIS LEAVE US?

- IMPACTS MAY BE OCCURRING IN UNEXPECTED LOCATIONS, AND IF WE ONLY LOOK AT RANGE EDGES WE ARE LIKELY MISSING A LOT!

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- THE DETAILS OF MECHANISM MATTER AND PATTERNS OF VULNERABILITY MAY REFLECT EMERGENT PROPERTIES OF PROCESSES AT VERY SMALL AND TEMPORAL SCALES

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- IMPACTS MAY BE OCCURRING IN UNEXPECTED LOCATIONS, AND IF WE ONLY LOOK AT RANGE EDGES WE ARE LIKELY MISSING A LOT!
- THE DETAILS OF MECHANISM MATTER AND PATTERNS OF VULNERABILITY MAY REFLECT EMERGENT PROPERTIES OF PROCESSES AT VERY SMALL AND TEMPORAL SCALES
- DEB CAN PROVIDE A CRITICAL WAY OF EXPLORING THESE PROCESSES, BUT CAREFUL DEB/  
PHYSIOLOGICAL INFORMATION MUST BE MATCHED WITH EQUALLY CAREFUL ENVIRONMENTAL DATA (BE CAREFUL WITH AVERAGING!!)





# Thank you



For more information please visit [northeastern.edu/helmuthlab](http://northeastern.edu/helmuthlab)



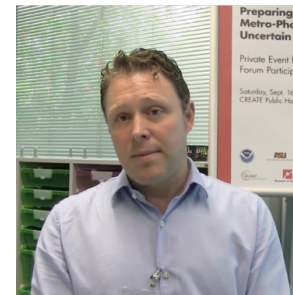
Francis  
Choi



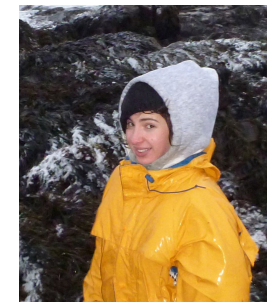
Ashley  
Cryan



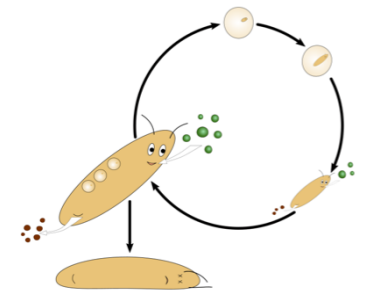
Aubrey  
Foulk



David  
Sittenfeld



Jess  
Torossian



[b.helmuth@northeastern.edu](mailto:b.helmuth@northeastern.edu)

@aquanaut1967



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