Microbial water quality: climatic drivers

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Outline

1. Microbial contamination of water and public health
2. Climatic drivers of the human exposure to pathogens
   – hydrology and beyond
3. Microbial water quality modeling and climatic scenarios
4. Risk assessment paradigm
5. Improvements in forecasts as a two-way street

How serious is the problem?

Exposure to fecally contaminated water is at the origin of 4 % of all deaths and 6 % of the total disease burden occurring worldwide (Pruss et al., 2002)

Drinking water

In the United States, almost 1 million illnesses and 1000 deaths occur each year as a result of microbial contamination of **drinking** water (Warrington 2001).

Between 2000 and 2007 in 14 European countries, there were 354 outbreaks of waterborne diseases related to **drinking** water, resulting in over 47,617 illnesses (WHO 2009).

Recreation waters

Approximately 246,400 river and stream miles (out of 560,000 assessed miles) in the United States contained unacceptably high levels of fecal indicator bacteria (USEPA 2004).

In Europe, more than half of the 127,000 surface water bodies are reported to be in less than good ecological status or potential, and in need of mitigation and/or restoration measures

Beaches

Indicator organisms – thermotolerant coliforms or *E. coli*. Threshold levels are established from epidemiological studies.

Indirect contact – irrigation

Roughly **<u>1 in 6 Americans</u>** (~50 millions) experience foodborne illness each year

Estimated annual loss of **<u>$ 0.5-33.0 billion</u>**

<u>Nearly half</u> of reported foodborne illnesses from 1998-2008 were attributed to vegetables and fruits contamination

Irrigation water and manure are main culprits

Unreported or underreported

Waterborne disease outbreaks that occur as gastroenteritis is notoriously under-reported.

Illnesses contracted by single individuals (i.e., non-outbreaks) are also typically unreported.

Virus diseases are not reported.

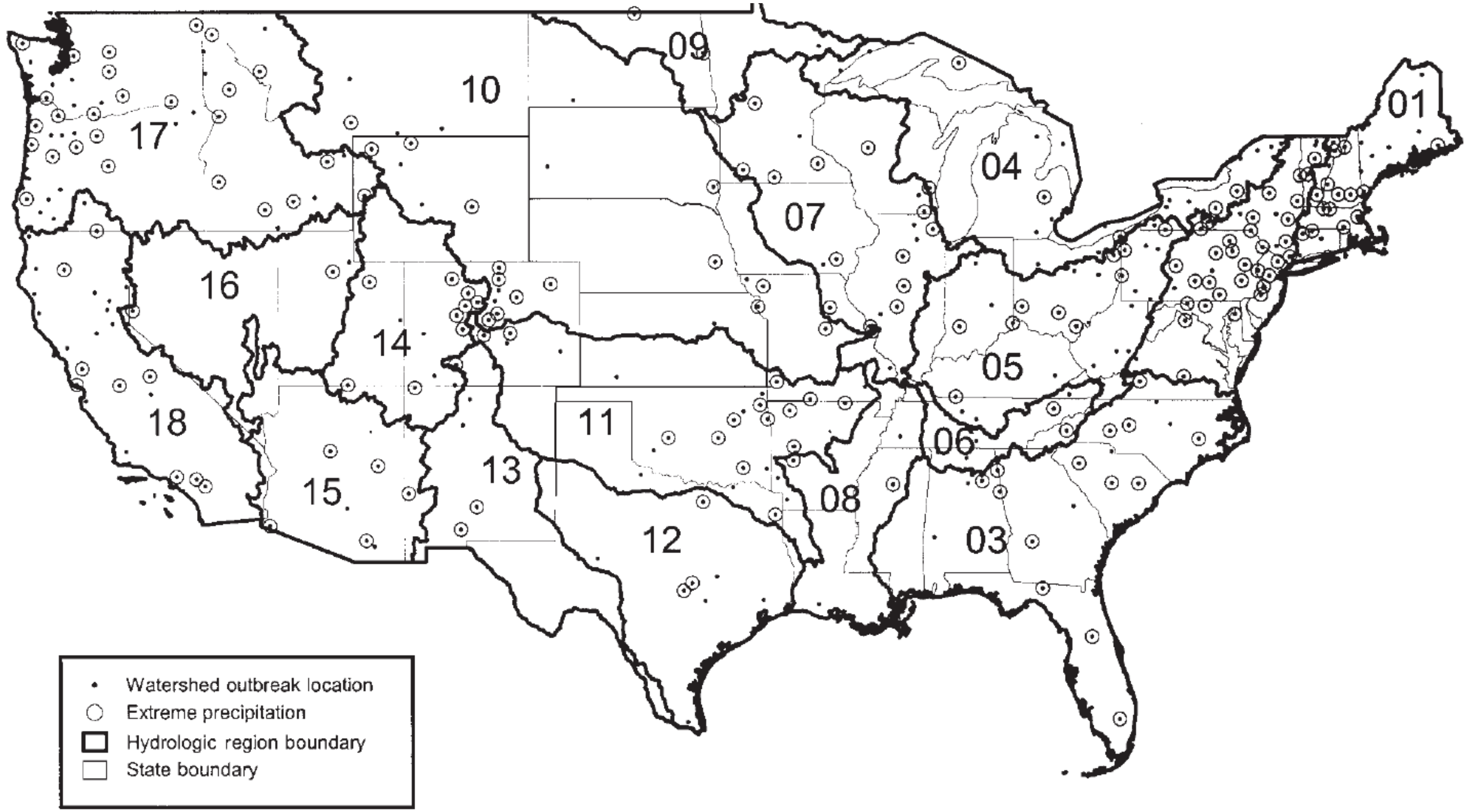
Other pathways

Shellfish, aquaculture, processing waters, roof water, ….

Other pathogens

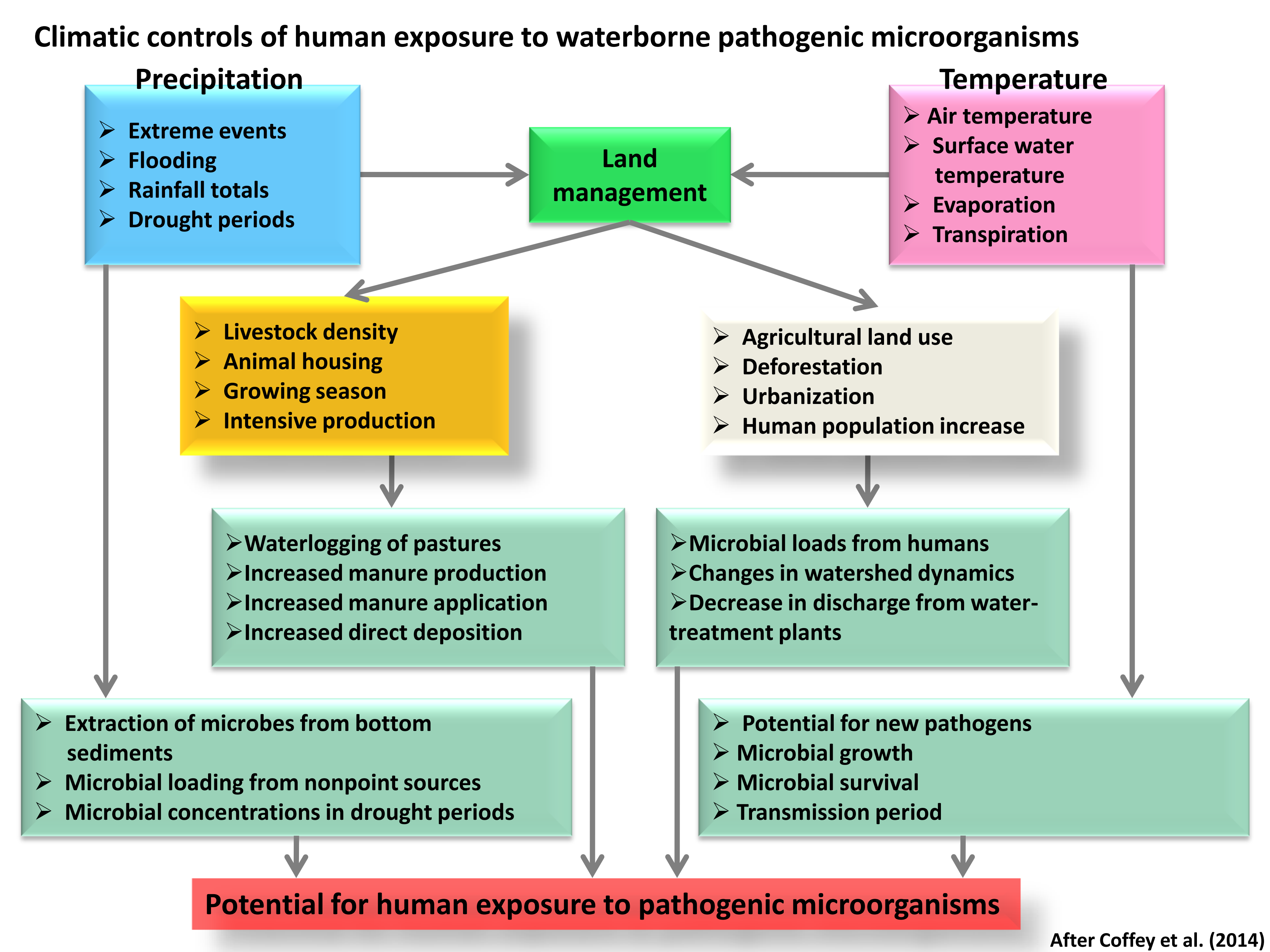
Protozoa, worms, ….

The Association Between Extreme Precipitation and Drinking Water-borne Disease Outbreaks in the United States, 1948–1994



Percentage of outbreaks	Percentile of the extreme event
51	> 90 (p=0.002)
68	>80 (p=0.001)

Curriero et al. 2001


Climatic controls of human exposure to waterborne pathogenic microorganisms
Precipitation
Extreme events
Flooding
Rainfall totals
Drought periods
Land management
Temperature
Air temperature
Surface water temperature
Evaporation
Transpiration
Livestock density
Animal housing
Growing season
Intensive production
Agricultural land use
Deforestation
Urbanization
Human population increase
Waterlogging of pastures
Increased manure production
Increased manure application
Increased direct deposition
Microbial loads from humans
Changes in watershed dynamics
Decrease in discharge from water-treatment plants
Extraction of microbes from bottom sediments
Microbial loading from nonpoint sources
Microbial concentrations in drought periods
Potential for new pathogens
Microbial growth
Microbial survival
Transmission period
Potential for human exposure to pathogenic microorganisms
After Coffey et al. (2014)

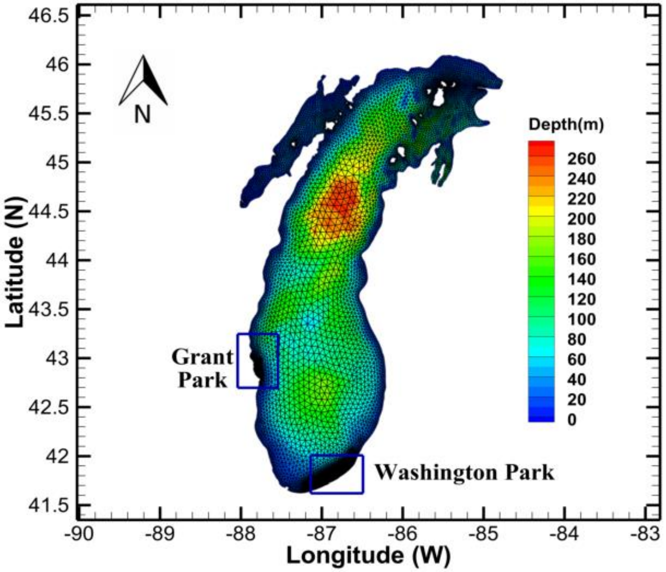
Two examples of microbial load projections

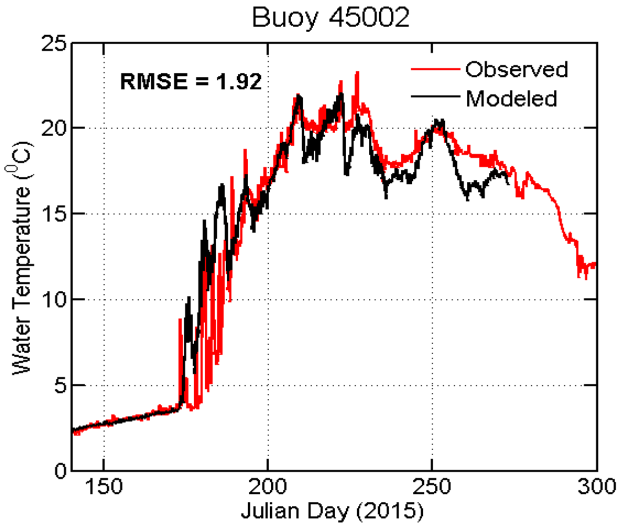
Watershed	Water quality model	Scenarios	Annual change	Seasonal changes	Source
Pigg River, VA , USA	HSPF	Climate Number: 7 Emission Storyline B2 GCM: CMIP3 Downscaled: CARA	Low flow year: +49%	Winter: +41 Spring: -33 Summer: +10 Fall: +212	Coffey et al., 2015
			Average flow year: +4%	Winter: +22 Spring: -26% Summer: -22% Fall: +106%	
			High flow year: +21%	Winter: +81% Spring: -17% Summer: -14% Fall: 50%	
Upper Pearl River, MS, USA	SWAT	Climate Numbet 1 Emission Storyline A1B GCM: CMIP3 Downscaled: LARS-WG	175%	Winter/Spring: Decreases Summer/Fall: Increases	Jayakody et al., 2015

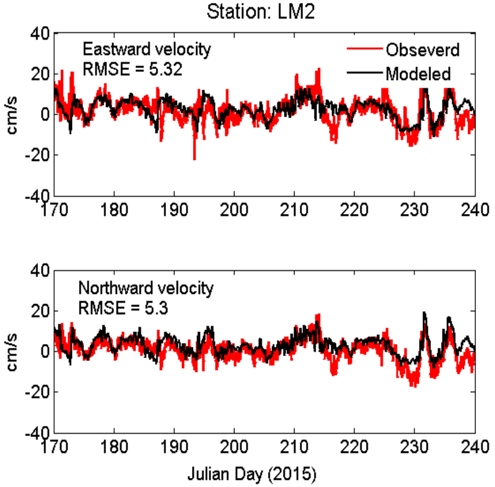
Extreme events are the most consequential

- Work should consider the full "envelope" of uncertainty in climate projections
- Statistical downscaling of climate controls is of paramount importance
- Variability strongly affects conclusions on compliancy to microbial water quality standards

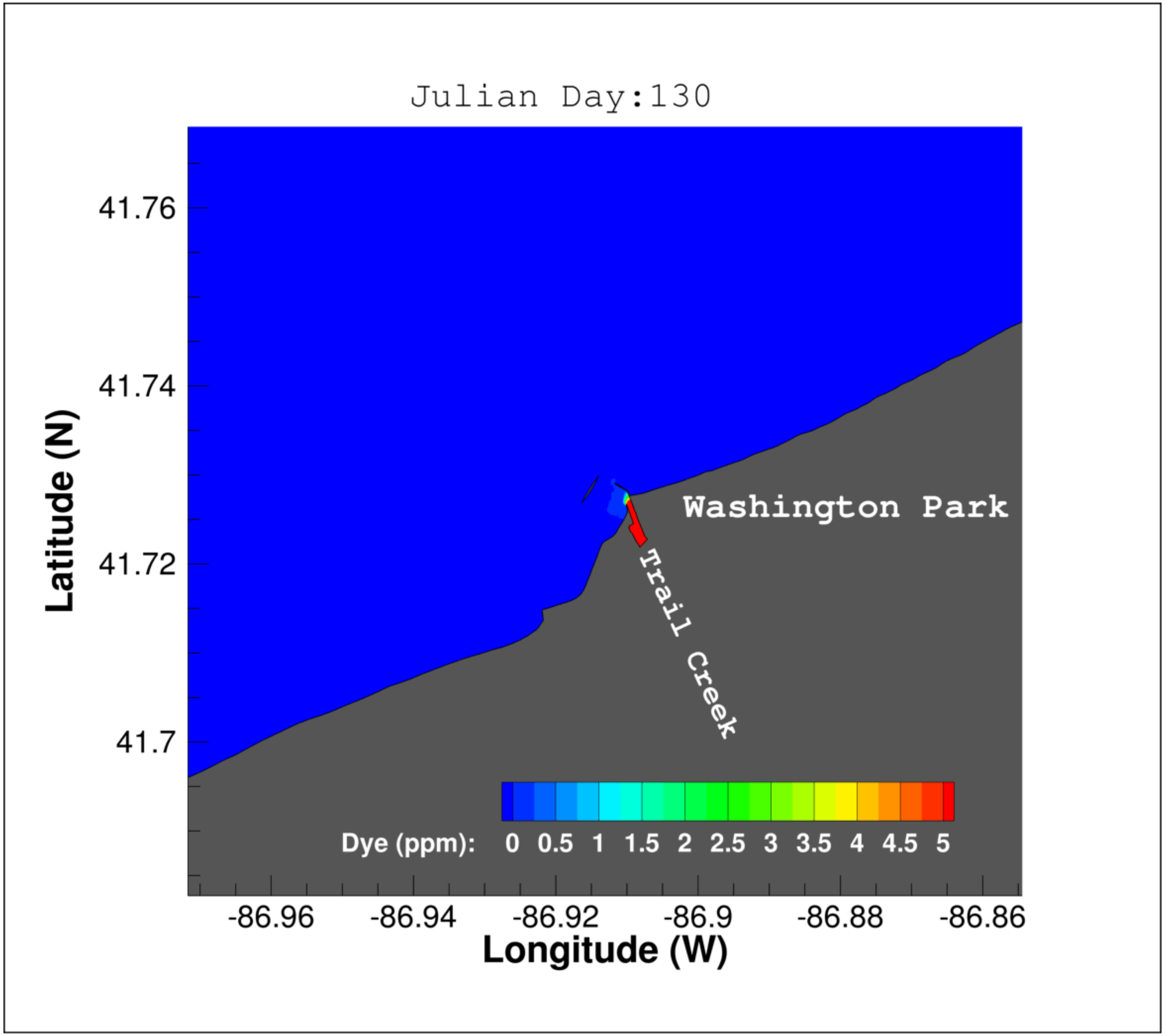
Example of freshwater beach compliancy issues







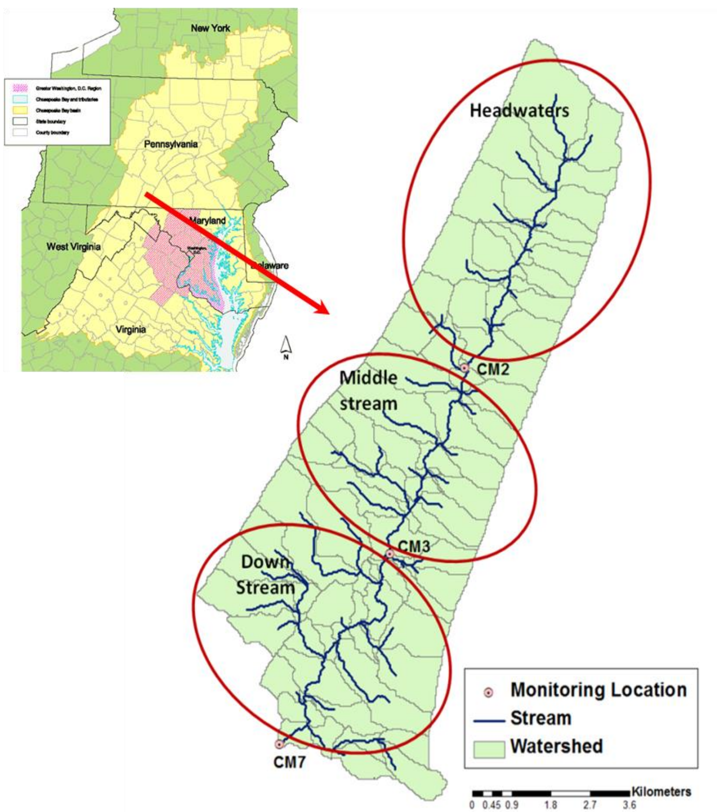
Vertically-integrated dye concentration at Trail Creek near Washington Park Beach simulated with FVCOM model



Interannual variability and irrigation water quality

Current regulations allow for 2 to 4 years to collect 20 samples to characterize microbial water quality of the irrigation water source. How <u>representative</u> is this characterization?

Cove Mountain watershed, southern PA



USDA ARS model SWAT

Monitoring data 2006-2008

After calibration, the model showed the ability to correctly predicted compliance with produce rule

Produce rule metrics: *E. coli*
geometric mean 135 CFU/100 mL
STV 410 CFU/100 mL

90 year of actual weather data

Results of simulations were sampled 5 times a year for 4 consecutive years
Same landuse

Eunmi Hong et al., 2017

Geometric mean (GM) and statistical threshold values (STV) of *E. coli* concentrations in 20 random samples for 4 consecutive years

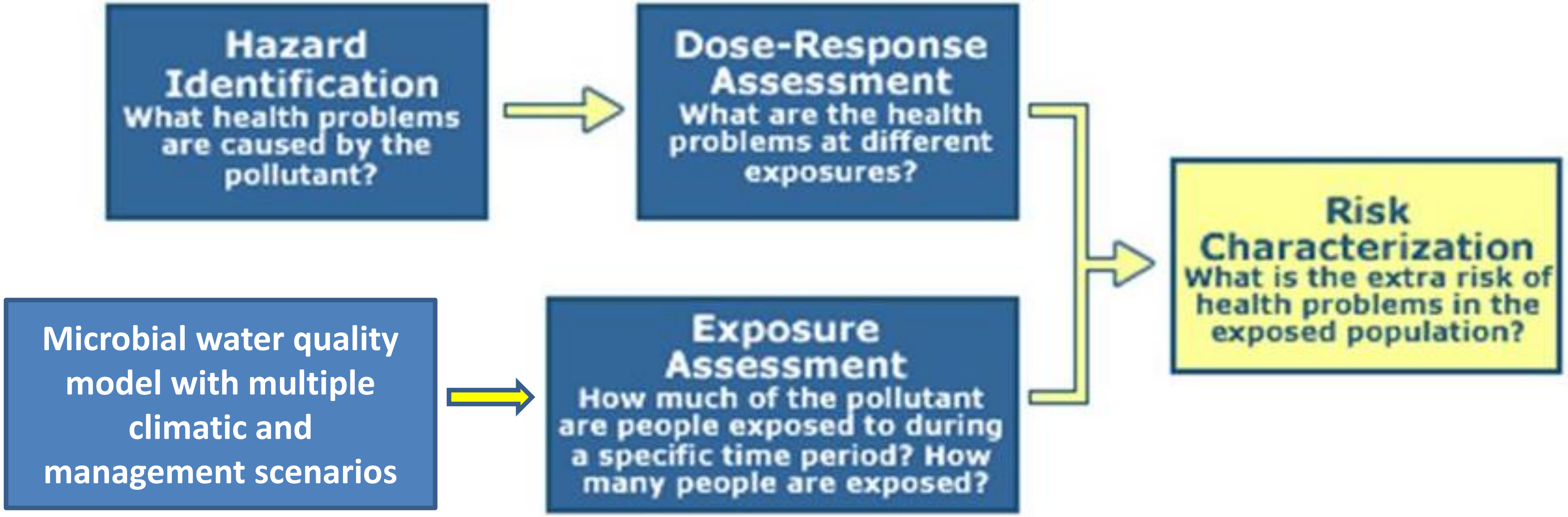
Locations and Months	GM (CFU/100 ml) avg	GM std	GM min	GM max	STV (CFU/100 ml) avg	STV std	STV min	STV max
Produce rule thresholds	126				410			
CM3								
Apr	155	22	84	229	223	29	129	690
May	164	36	82	466	409	319	121	2706
Jun	156	46	44	534	783	541	86	3913
Jul	108	33	22	354	599	452	56	3725
Aug	90	33	14	360	608	470	28	3475
Sep	83	32	16	397	580	477	35	3818
Growing season	122	36	24	425	513	409	64	3309
CM7								
Apr	202	34	98	320	312	48	135	526
May	201	40	101	564	437	235	145	1959
Jun	180	51	51	515	695	402	95	2833
Jul	121	38	26	366	519	320	62	2692
Aug	99	33	26	357	508	342	45	2595
Sep	91	33	22	343	512	373	52	2950
Growing season	142	41	33	429	490	294	81	2623

How does the interannual variability affect the representativeness?

- The regulatory threshold was exceeded from 16 % to 70% during the four-year sampling campaign.
- The variations in microbial concentrations and water quality metrics were affected by location, wetness of the hydrological years, and seasonality.
- Long-term assessment of microbial water quality may be quite different from the evaluation based on short-term observations.
- The results of this work demonstrate the value of using modeling to design and evaluate monitoring protocols to assess the microbial quality of water used to irrigate produce.

Eunmi Hong et al., 2017

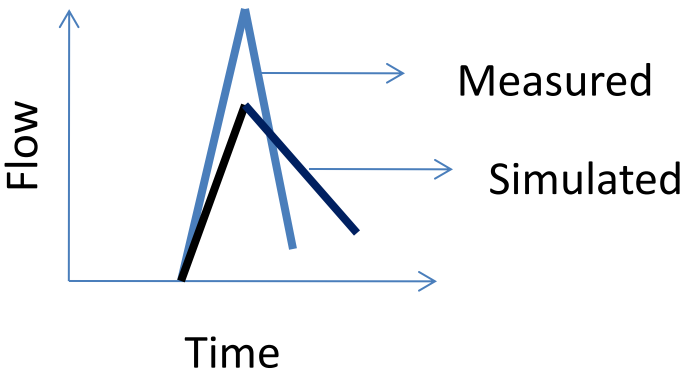
Risk assessment and microbial water quality modeling



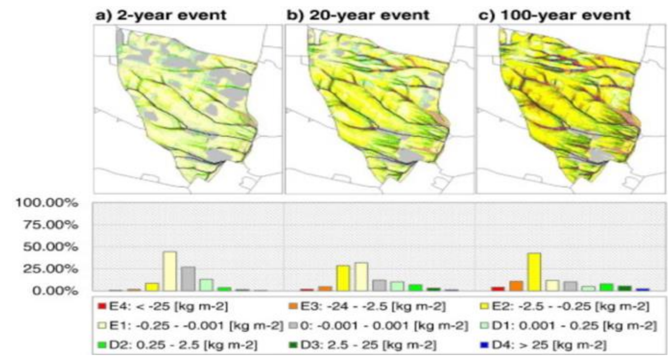
Future improvements in microbial fate and transport modeling

1. Spatial heterogeneity and subgrid variability

Accuracy of hydrological simulations with the daily time step is the lowest for extreme events (i.e., underestimated flows).



Runoff transport simulations are most uncertain during extreme events (connectivity).



Release from point sources is most uncertain during extreme events (overflows).

Future improvements in microbial fate and transport modeling

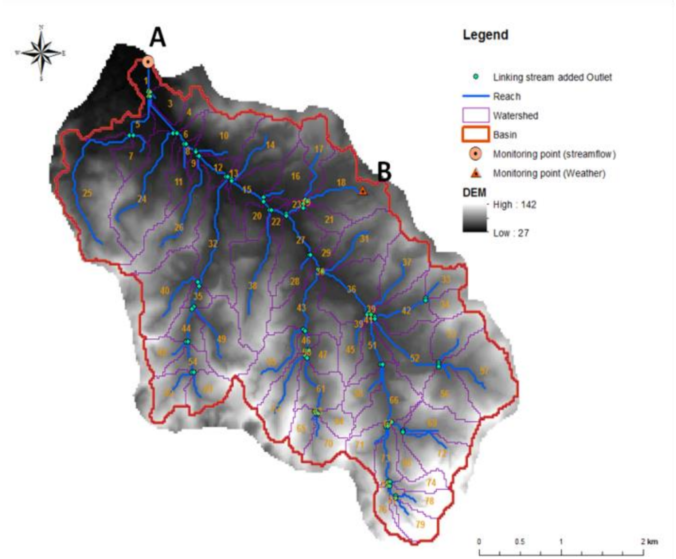
2. Microorganisms and nutrients

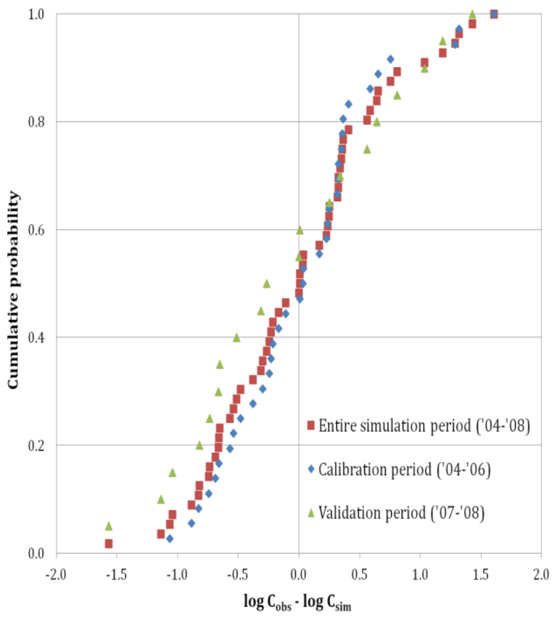
Currently simulated independently.

Need flexibility in simulating management practices

Soil and Water Assessment Tool (SWAT) -> Agricultural Policy Extender (APEX)

Toenepi watershed, New Zealand, with Richard Muirhead





Yongeun Park et al. (2016) microbial subroutine for APEX
Eunmi Hong et al. (2017) application to the Toenepi watershed

Future improvements in microbial fate and transport modeling

3. Microorganisms and algae

Currently simulated independently.

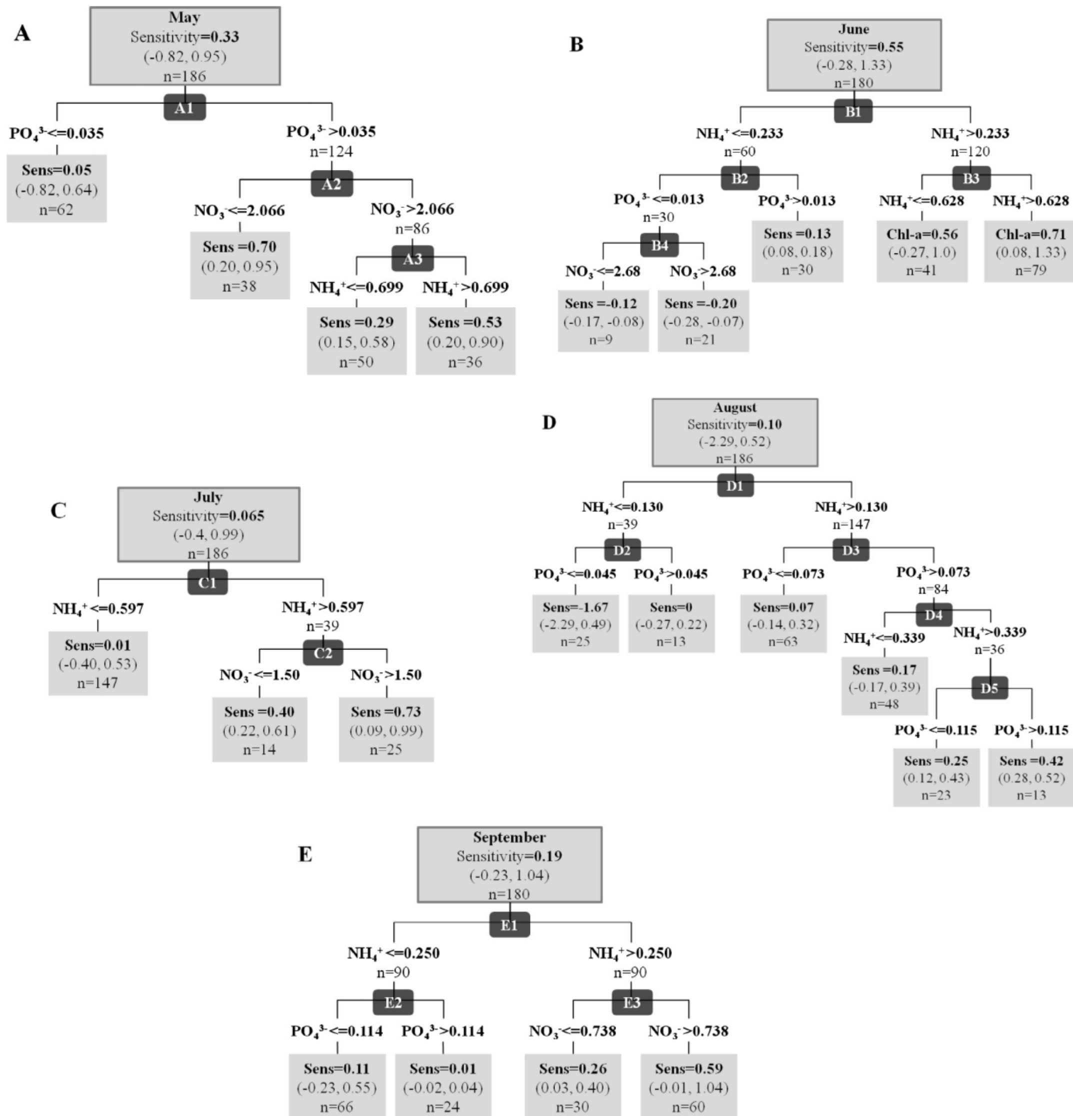
Microorganisms do not have a spectral signature. Algae do.

Survival of indicator organisms seems to be controlled by algae populations

Use of remote sensing data – monitoring, assimilation, forecast, management of exposure to pathogens

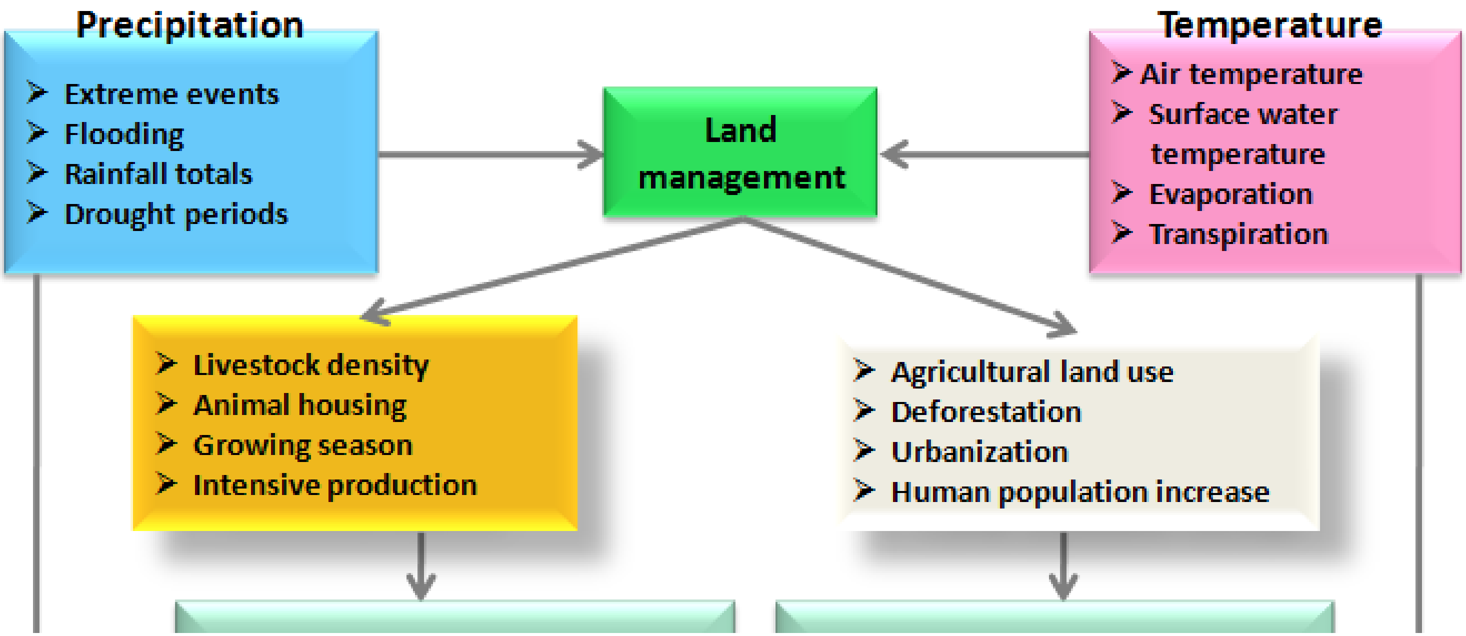
Responses of algae to climatic controls?
Bloom initiation, development, and termination,
as well as the exact nature of the toxins associated with them

Regression trees used to estimate the sensitivity of Chl-a to temperature



Yongeun Park et al. (2016) machine-learning based modeling in combination with the process model CE-QUAL-W2

Better inputs and better models are needed



Thank you for your attention!

Credits for the imagery

http://slideplayer.com/slide/5158998/

http://climate-energy-college.org/bioenergy-maize-and-soil-erosion%E2%80%94risk-assessment-and-erosion-control-concepts

http://www.stuff.co.nz/environment/84672789/these-are-christchurchs-most-polluted-streams

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https://en.wikipedia.org/wiki/Algal_bloom

http://russianriverkeeper.org/about-the-russian-river/river-issues/russian-river-low-flow-e-i-r/