

The risk assessment of microplastics using the Bayesian network relative risk model-San Francisco Bay

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In collaboration with Diana Lin
San Francisco Estuary Institute



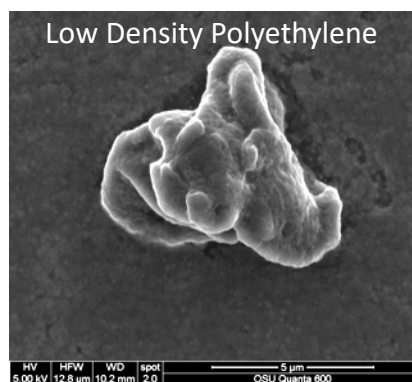
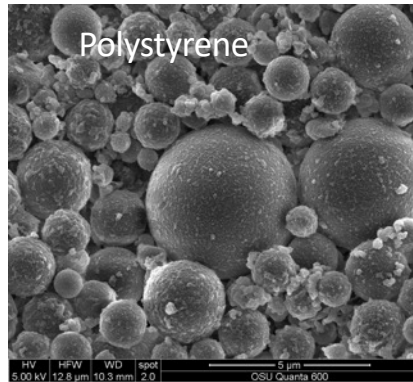
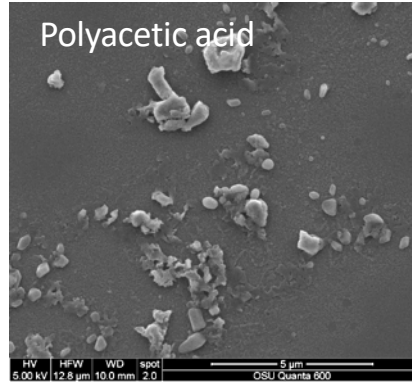
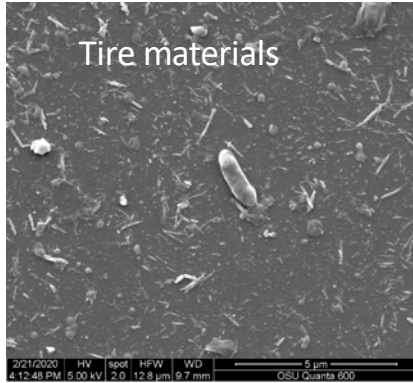
Pacific Northwest
Consortium on Plastics

Outline for the talk

1. Microplastics as an interesting and ubiquitous stressor
2. Modern risk assessment using Bayesian networks
3. San Francisco Bay example
4. Application to the Chesapeake Bay

Microplastics as an interesting and ubiquitous stressor

SEM-Jared Stine, OSU



5 μm

E. coli 1-2 μm

- A variety of compositions
- A variety of sizes
- Many different shapes and sizes
- Can be found in mixtures in the environment with other plastic materials, chemicals and biologicals

Modern risk assessment using Bayesian networks

Special series in the January issue of Integrated Environmental Assessment and Management-10 papers.

Integrated Environmental Assessment and Management — Volume 00, Number 00—pp. 1–16

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Special Series

The Origin, Development, Application, Lessons Learned, and Future Regarding the Bayesian Network Relative Risk Model for Ecological Risk Assessment

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Bellingham, Washington, USA*

The basic methods of the Bayesian network relative risk model have been demonstrated in a variety of cases

Adaptive management

Integrated Environmental Assessment and Management — Volume 13, Number 1—pp. 115–126
Received: 22 February 2016 | Revised: 5 April 2016 | Accepted: 27 May 2016

Health & Ecological Risk Assessment

A General Risk-Based Adaptive Management Scheme Incorporating the Bayesian Network Relative Risk Model with the South River, Virginia, as Case Study

Wayne G Landis,^{*†} April J Markiewicz,[‡] Kim K Ayre,[‡] Annie F Johns,[‡] Meagan J Harris,[‡] Jonah M Stinson,[‡] and Heather M Summers[‡]

[†]Institute of Environmental Toxicology, Huxley College of the Environment, Western Washington University, Bellingham, Washington, USA

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Environmental Management

Using Bayesian Networks to Predict Risk to Estuary Water Quality and Patterns of Benthic Environmental DNA in Queensland

Scarlett E Graham,^{†‡} Anthony A Chariton,[§] and Wayne G Landis^{*†}

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Australian estuaries

Testing management alternatives

100

Integrated Environmental Assessment and Management — Volume 13, Number 1—pp. 100–114
Received: 1 December 2015 | Accepted: 28 January 2016

Health & Ecological Risk Assessment

Using the Bayesian Network Relative Risk Model Risk Assessment Process to Evaluate Management Alternatives for the South River and Upper Shenandoah River, Virginia

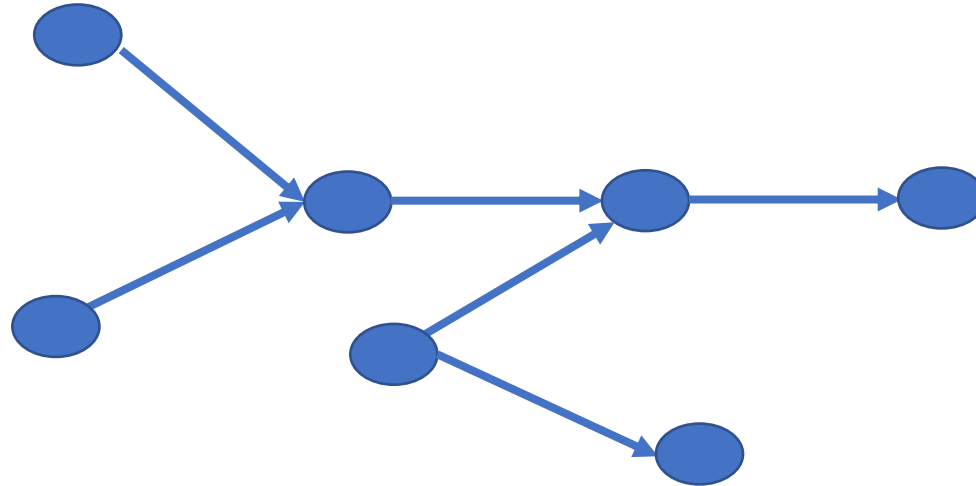
Annie F Johns,[‡] Scarlett E Graham,^{†‡} Meagan J Harris,[‡] April J Markiewicz,[‡] Jonah M Stinson,[‡] and Wayne G Landis^{*†‡}

[‡]Environmental Science, Western Washington University, Bellingham, Washington, USA

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Modern risk assessment using Bayesian networks

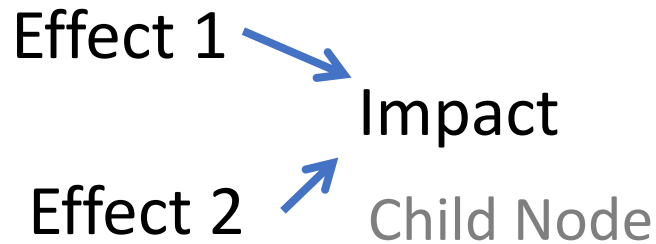
Directed Acyclic graph-left
to right-some draw them
vertical.



Bayesian networks (BN) are directed acyclic graphs

Bayesian Networks (BNs)-even shorter introduction-

Parent Nodes



The result in the child node is determined by a conditional probability table (CPT).

Bayesian Networks (BNs)-short introduction

Bayesian networks are Directed Acyclic Graphs (DAGs) that represent relationships between variables.

Source — Stressor — Habitat — Effect → Impact

In other words cause-effect pathways also known as conceptual models.

Pesticides and water quality

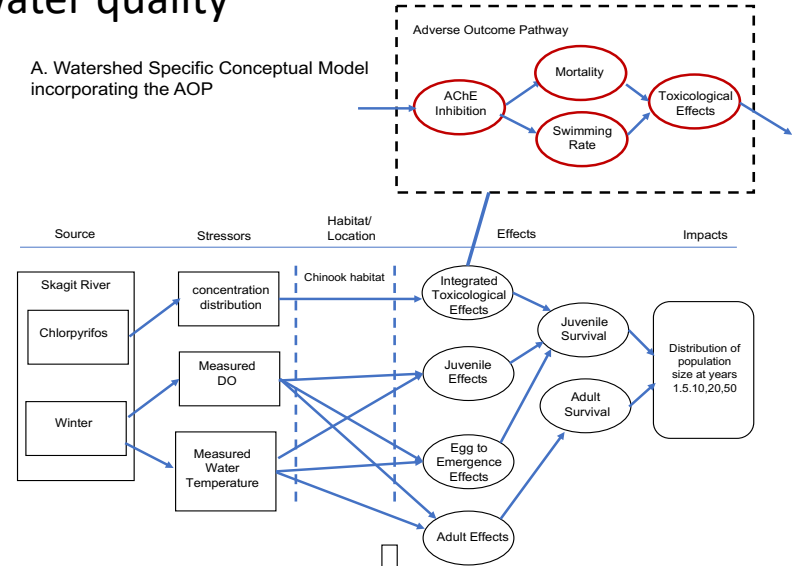
It does get more involved-an example from Landis et al 2020.

Pesticides and water quality with Chinook salmon as an endpoint.

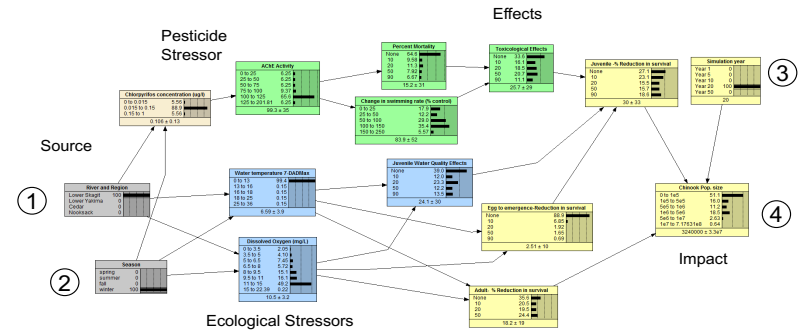
Conceptual model of cause and effect

The BN that describe and quantifies the predictions

A. Watershed Specific Conceptual Model incorporating the AOP

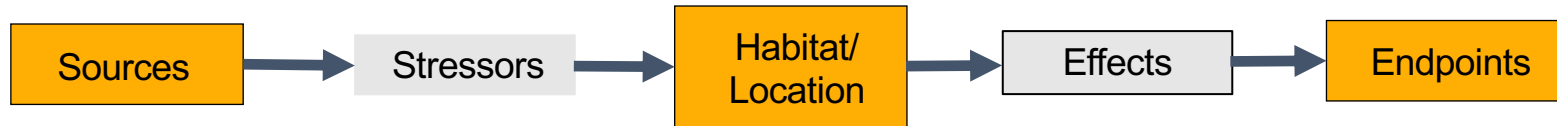


B. Bayesian network set for Skagit, winter, 20 year simulation



This is the backbone of the risk assessment approach (Sharpe and Landis-San Francisco Bay)

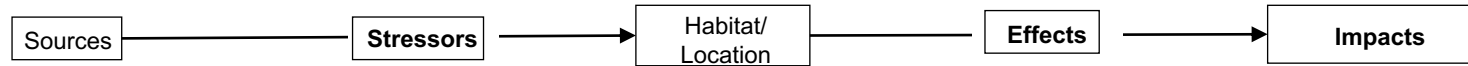
This is a diagram of the basic risk assessment approach, the boxes are nodes, and the arrows are the cause-effect interactions. The functions describe how the probability distributions for each node interact and result in an estimate of risk to valued ecological services (impacts).



History and details reviewed in Landis (2021)

The generic marine conceptual model

Straw-man Conceptual Model for Microplastics-Marine/Estuarine



Land use types

Agriculture
Residential
Commercial
Industrial

Transportation

Effluents

Wastewater and Industrial treatment

Waste Disposal dumping- historical or current

Shipboard dumping

Commercial
Military
Recreational

Long-range transport

Tsunami events
Atmospheric transport
Transportation
Large rivers

Plastics

Defining and classifying multiple types and size ranges

Physical interactions, interference,

Plasticizers and other materials composing the plastic

Absorbed materials from use as containers

Tire Particles from Roads and Stormwater

Absorbed or Adsorbed environmental pollutants

Metals
PCBs, PDBEs, PFOSs, Dioxins and furans, EDCs
Pharmaceuticals
Antibiotics

Invasive species

Bacteria-virus
Protists
Fungi
Emergent Diseases
Spores/resistant forms

Marine gyres
North Atlantic Gyre
North Pacific Gyre

Estuaries
Puget Sound
Chesapeake Bay
San Francisco Bay
Newport

Coastal Ocean
Gulf of Mexico
English Channel
Salish Sea
Pacific Coast
Black Sea

Urbanized Embayments
Boston Harbor
Portland
Tokyo Bay
Antwerp
Pearl Harbor
San Diego

Habitat Effects

Loss of production

Fish/Mammals/Birds

Direct effects - egg, larval, adult mortality
Indirect effects - behavioral, sensory, neurotoxicity, immunosuppression, disease, change in age structure, species abundance and diversity, trophic structure and function

Community Structure

invertebrate community structure, change in phytoplankton biomass, change in trophic transfer of nutrients/energy

Bioconcentration/ Biomagnification

Tissue contamination
Trophic transfer:

Ecological Services including but not limited to:

Water quality, quantity, fishability, swimability

Species

Key invertebrate, fish, reptiles, mammals and birds

Fisheries

Key species
Suitability for human consumption

Recreational uses

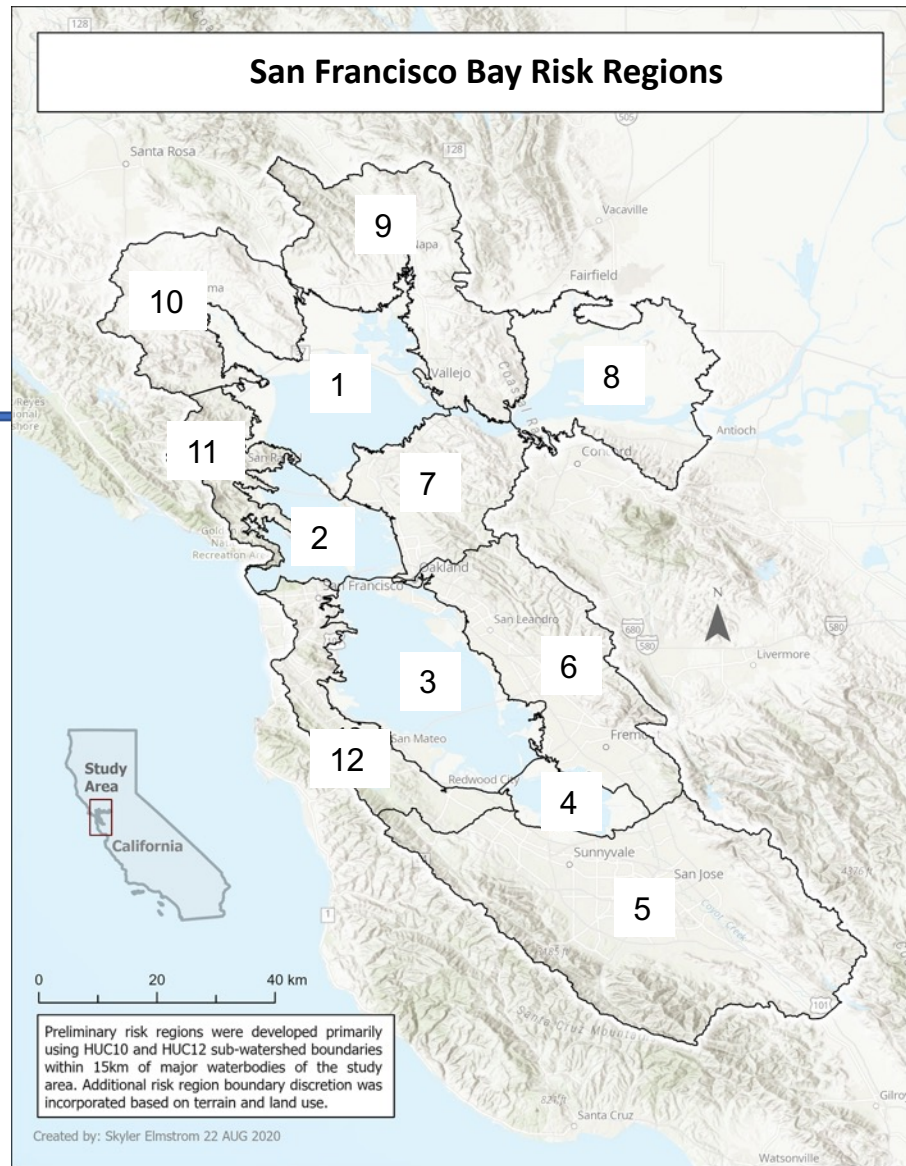
Fisheries
Hunting
Boating

Park Activities
Swimming
Picnicking
Boating, canoeing
Sunbathing

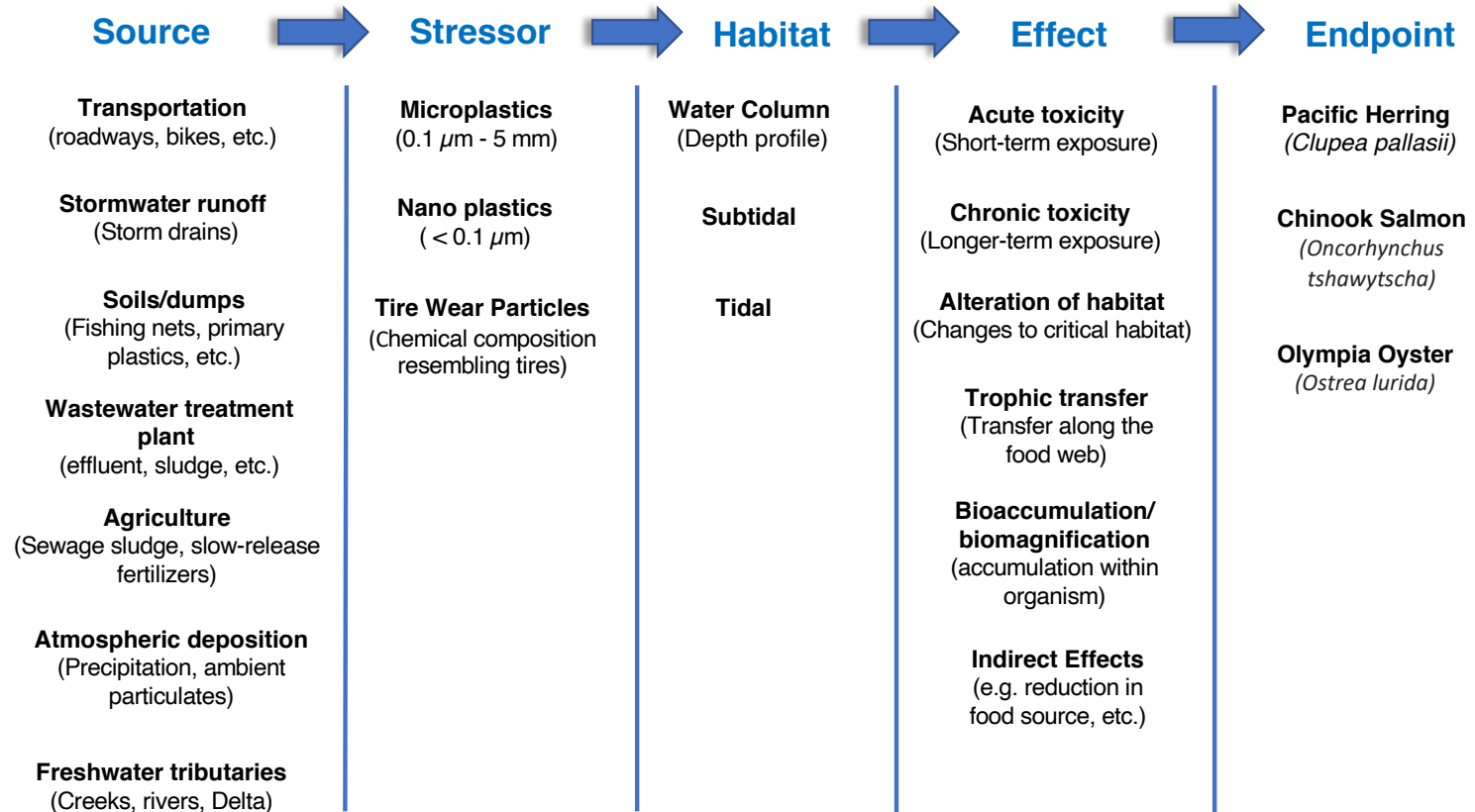
ESA Listed Species

San Francisco Bay Microplastic risk assessment teaming with SFEI

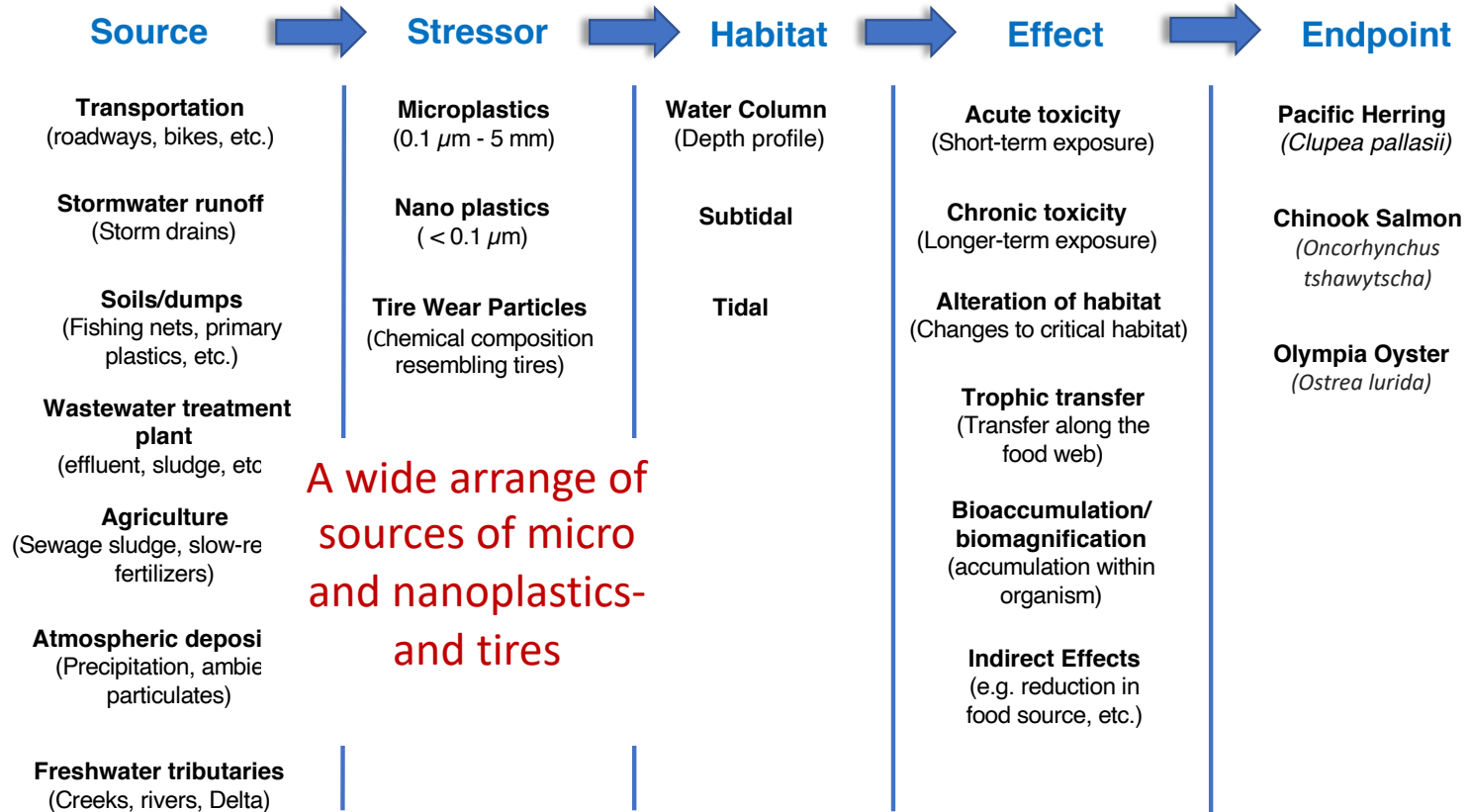
A case study is very useful. Ours is the San Francisco Bay. It is broken into 12 risk regions based on land use, drainages, and characteristics of the marine system.



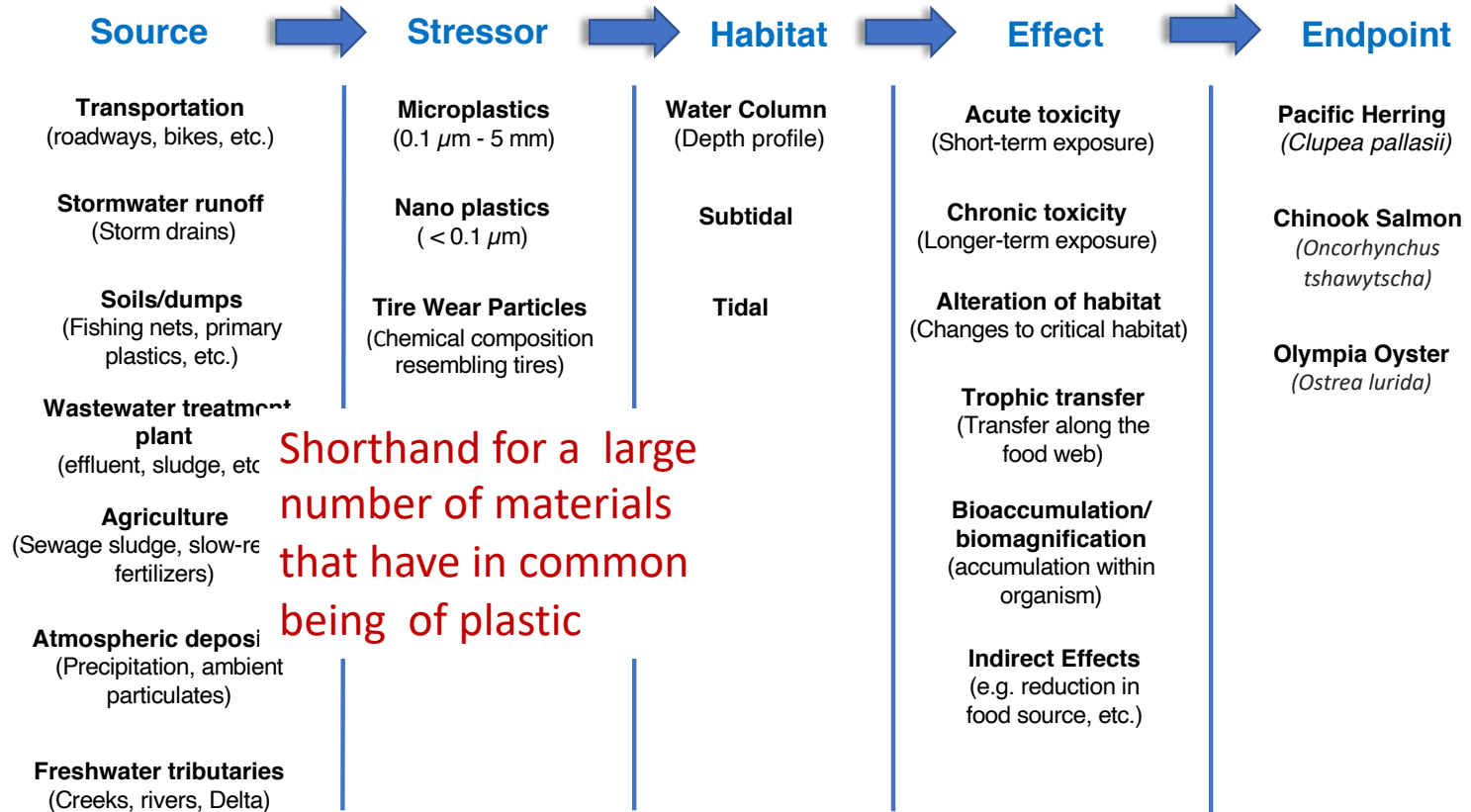
Site-specific San Francisco Bay Microplastic Risk Assessment structure.



Site-specific San Francisco Bay Microplastic Risk Assessment

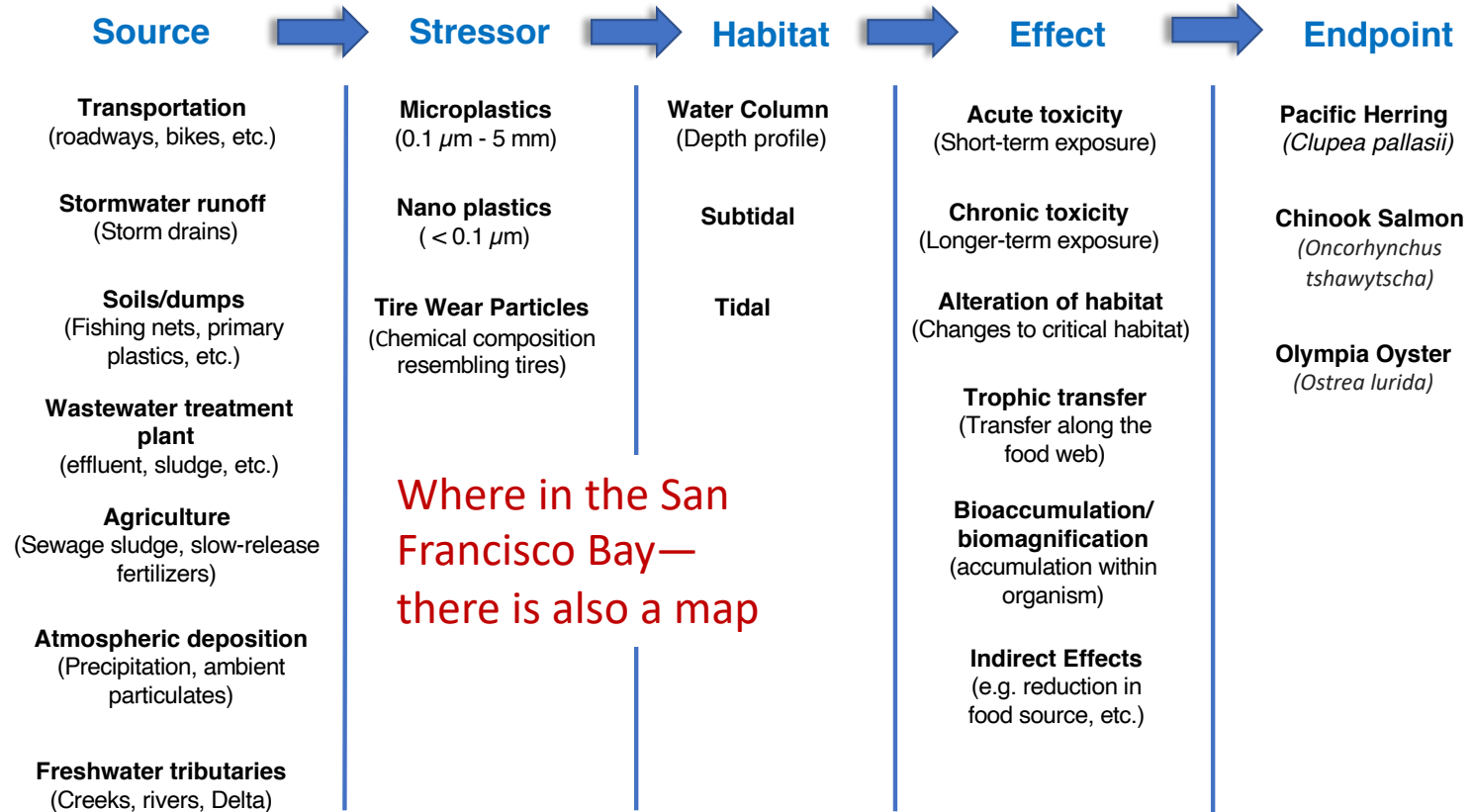


Site-specific San Francisco Bay Microplastic Risk Assessment



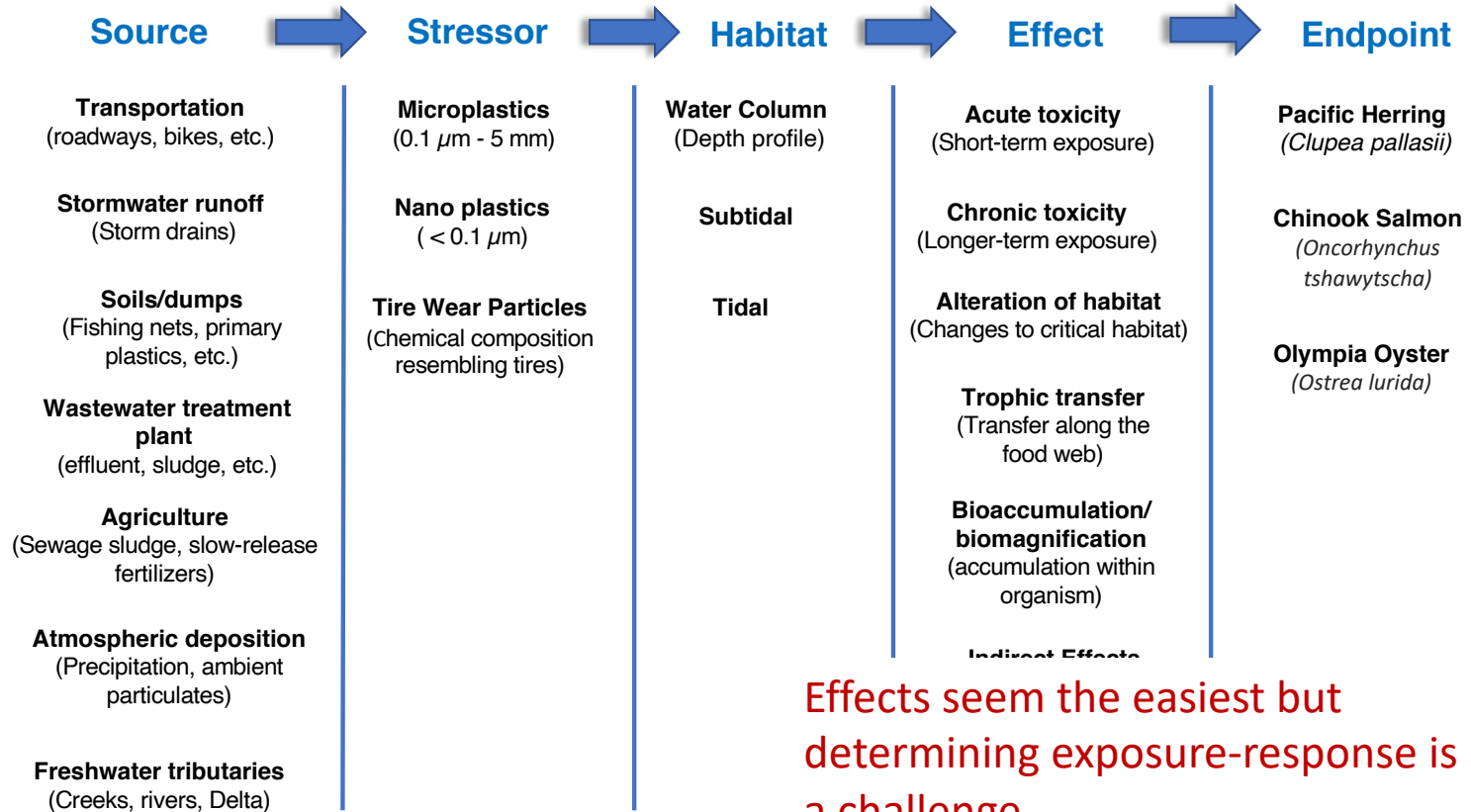
Site-specific San Francisco Bay Microplastic Risk Assessment-E.

Sharpe presentation with discussion on Thursday.



Site-specific San Francisco Bay Microplastic Risk Assessment-E.

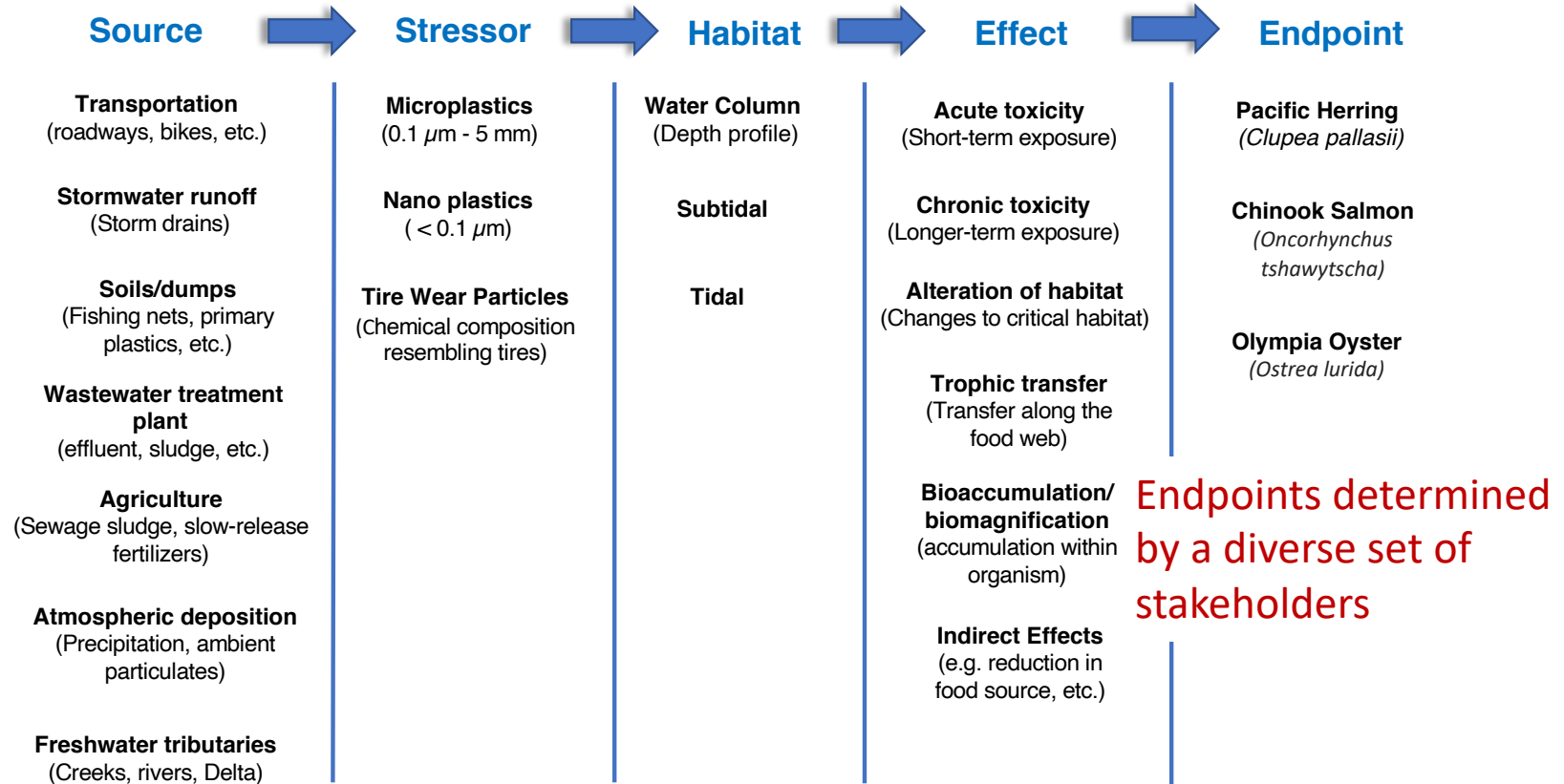
Sharpe presentation with discussion on Thursday.



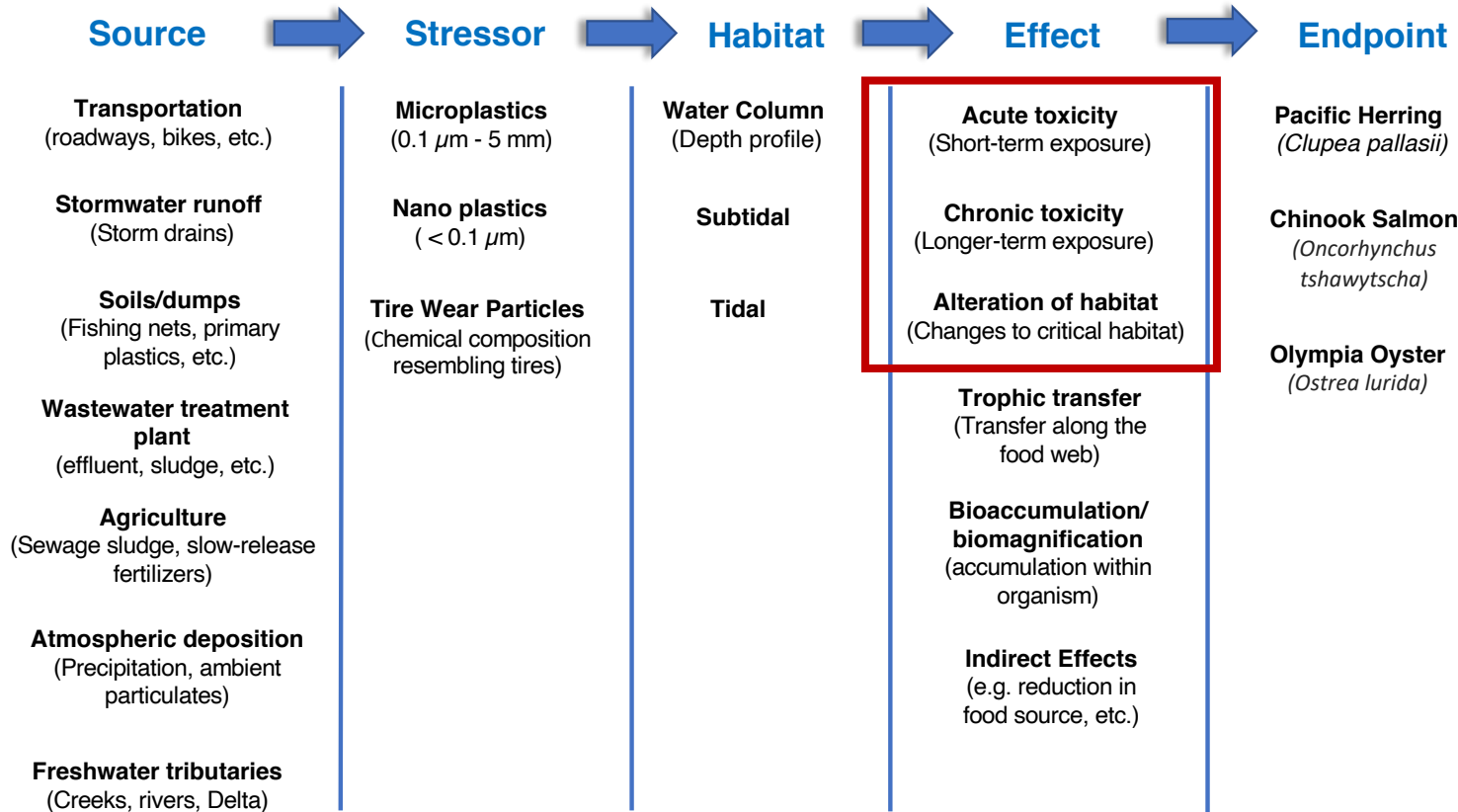
Effects seem the easiest but determining exposure-response is a challenge.

Site-specific San Francisco Bay Microplastic Risk Assessment-E.

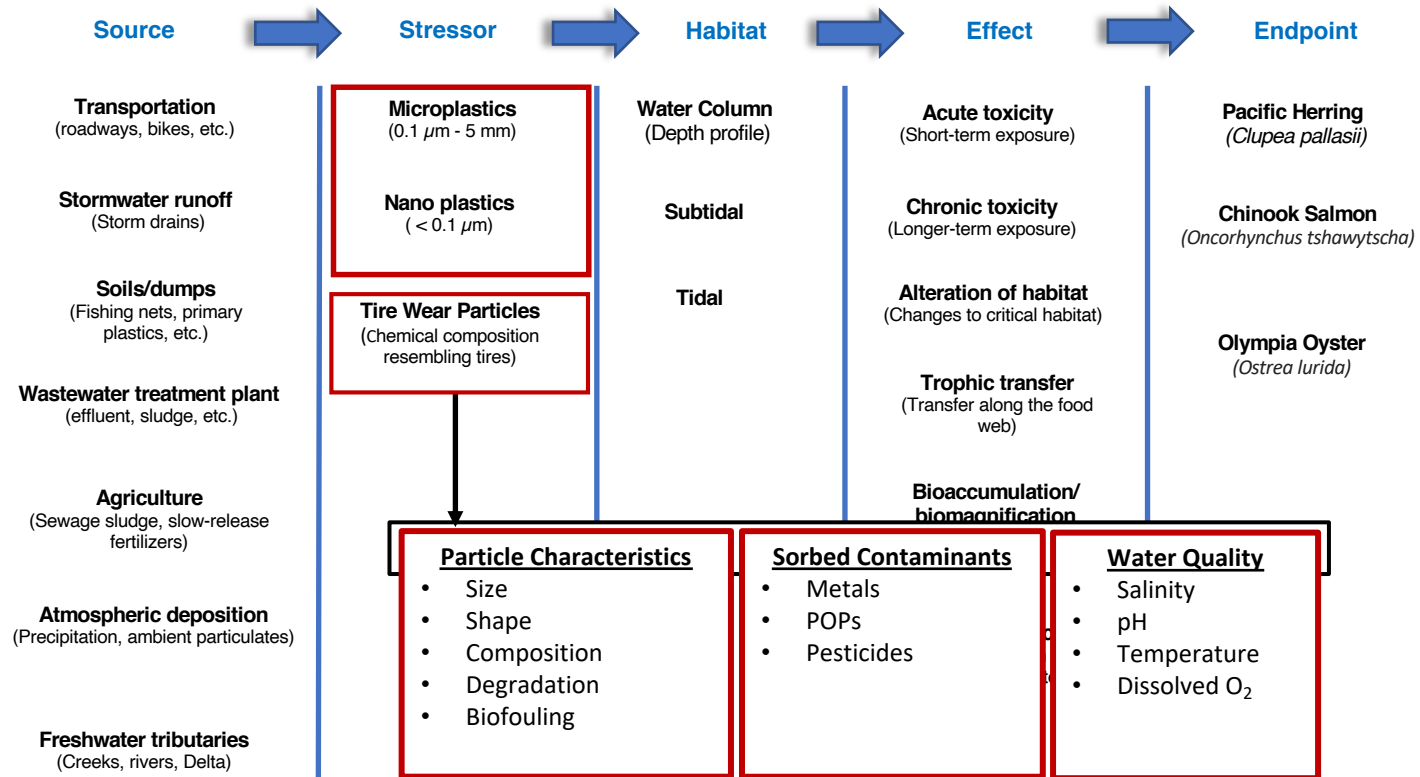
Sharpe presentation with discussion on Thursday.



Focus is on the description of the stressor portion of the conceptual model and some implication for estimating effects.



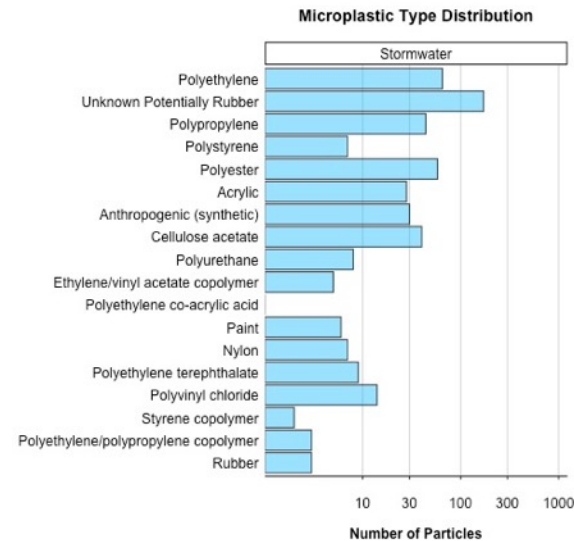
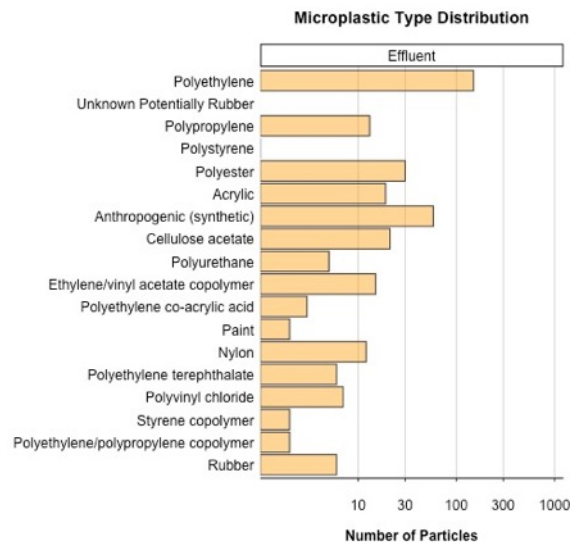
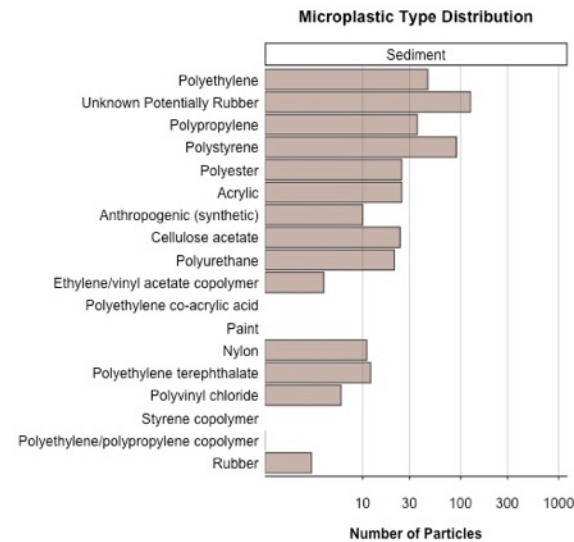
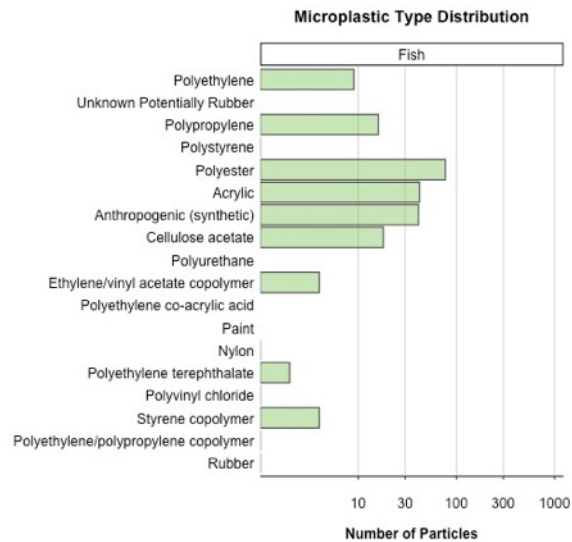
Stressor Characteristics-we are now treating Tire Wear Particles as a distinct category.



Microplastic distribution in San Francisco Bay

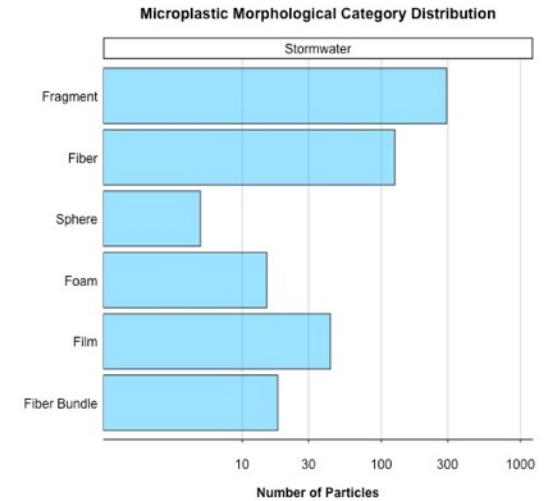
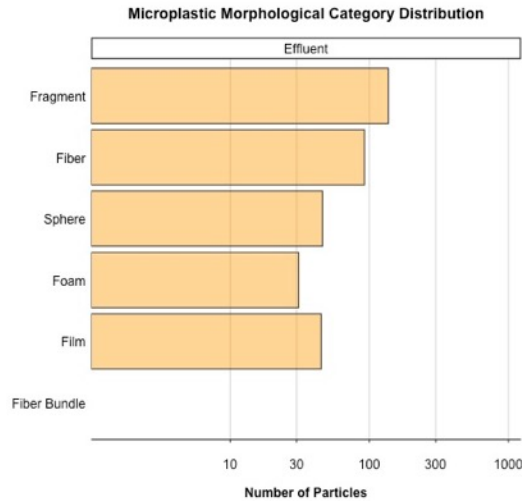
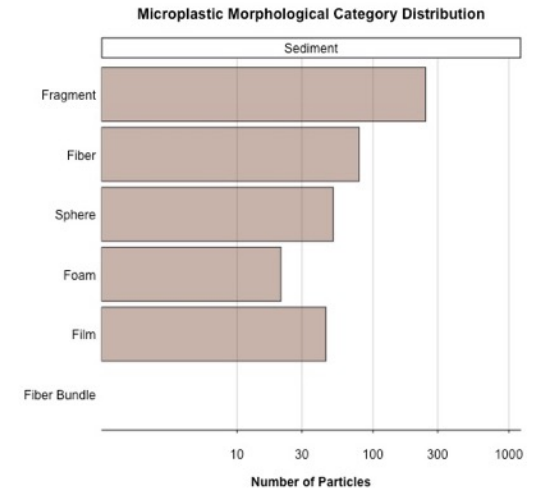
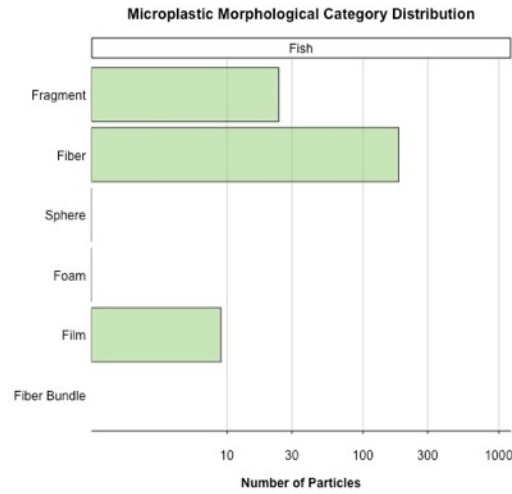
Type of microplastic

SEFI data-Diana Lin
 Dataset compilation –
 Skyler Elmstrom
 Plots-Emma Sharpe



Microplastic distribution in San Francisco Bay Morphology

SEFI data-Diana Lin
Dataset compilation –
Skyler Elmstrom
Plots-Emma Sharpe



Other contaminants exist and may interact as a component or in concert.

Table 1. The dataset used to develop this table was sourced from the California Department of Pesticide Regulation Surface Water Database (SURF). The dataset contains pesticide water concentrations from a culmination of different databases and monitoring studies during 2019.

Contaminant Name	Concentration Measurement Count ¹	Max Concentration ² (ppb)	Exceedances ³
Diazinon	5699	331	FA, FC, IA, IC
Chlorpyrifos	4105	9.4	FA, FC, IA, IC
Malathion	1013	46	FA, FC, IA, IC
Azinphos-methyl	151	6.53	FA, FC, IA, IC
Dimethoate	968	16.4	IC
Dichlorvos	171	4.88	IA, IC
Methidathion	347	15.1	FA, FC, IA, IC
Naled	59	8.24	FC, IA, IC
Phorate	133	3.5	FA, FC, IA, IC
Imidacloprid	1094	165	IA, IC
Bifenthrin	1360	5.63	FA, FC, IA, IC
Cyfluthrin	545	3.4	FA, FC, IA, IC
Esfenvalerate	275	3.48	FA, FC, IA, IC
lambda-Cyhalothrin	403	1.61	FA, FC, IA, IC
Permethrin	723	180.9	FA, FC, IA, IC
Deltamethrin	208	62.3	FA, FC, IA, IC
Cypermethrin	249	2.37	FA, FC, IA, IC
Fipronil	772	2.11	IA, IC
Fipronil Sulfide	74	0.26	IA

¹ This includes all the concentration measurements recorded over zero. This does not take into account the level of quantification or the method detection level and is meant to serve only as a preliminary relative concentration count.

² The maximum recorded concentration for each pesticide.

³ Using the EPA's aquatic life benchmarks for pesticides, if the max concentration was above any of the benchmarks it is notated as follows: IA = Invertebrate Acute, IC = Invertebrate Chronic, FA = Fish Acute, FC = Fish Chronic

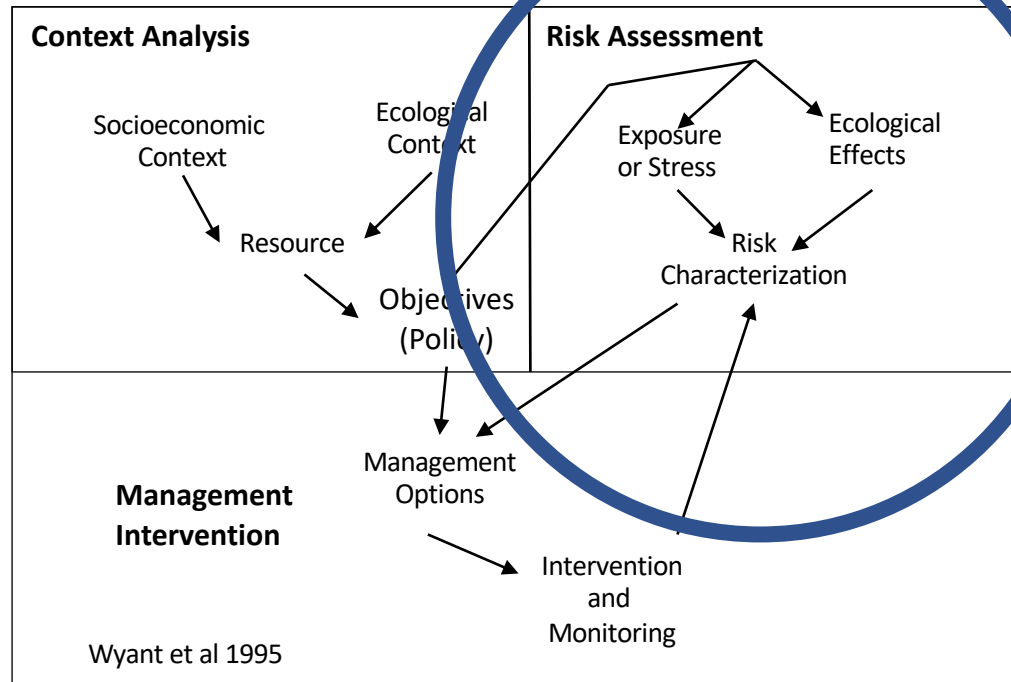
Microplastics, Chesapeake Bay and risk assessment

1. Build spatially explicit conceptual models
2. The risk assessment process will point out the critical variables and identify data needs
3. Risk assessment as part of an adaptive management decision making process.

The goal is to manage ecological structures

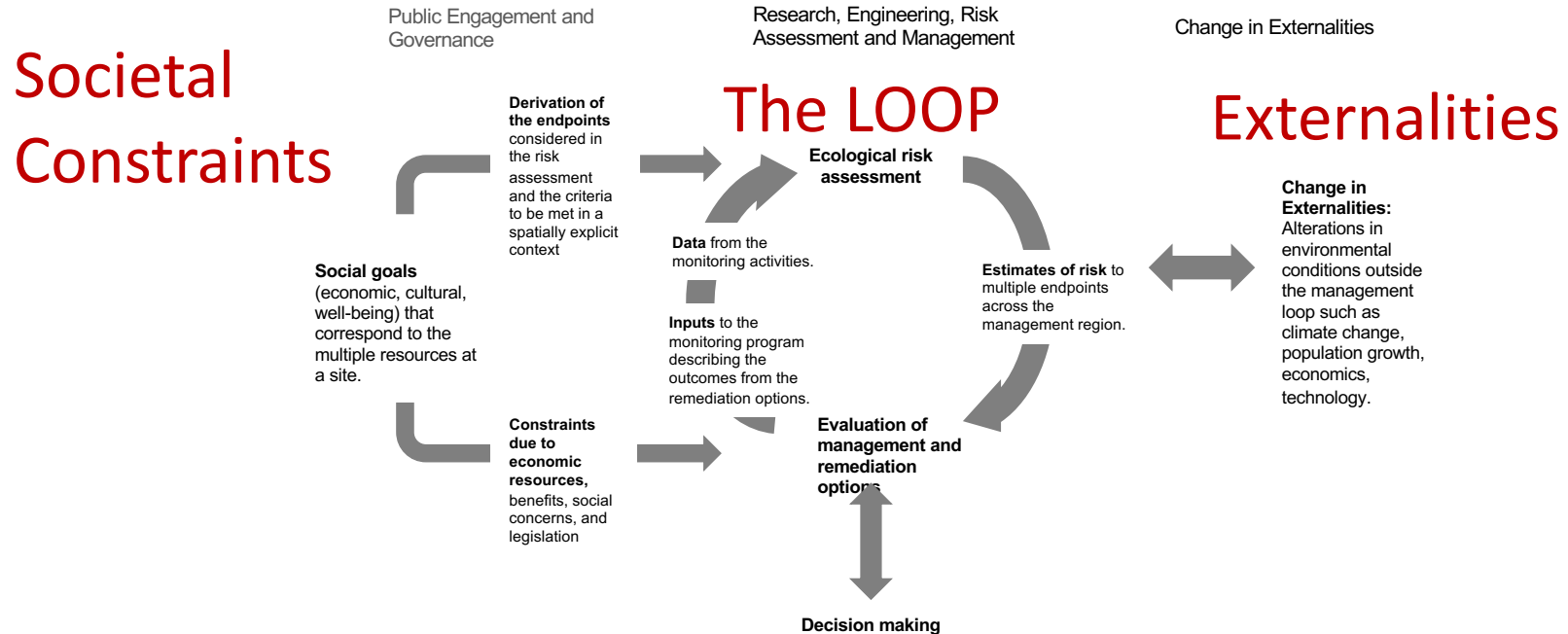
Wyant, Meganck, Ham
1995

Long-time ago but
understood that the
systems were non-
equilibrium and
dynamic.



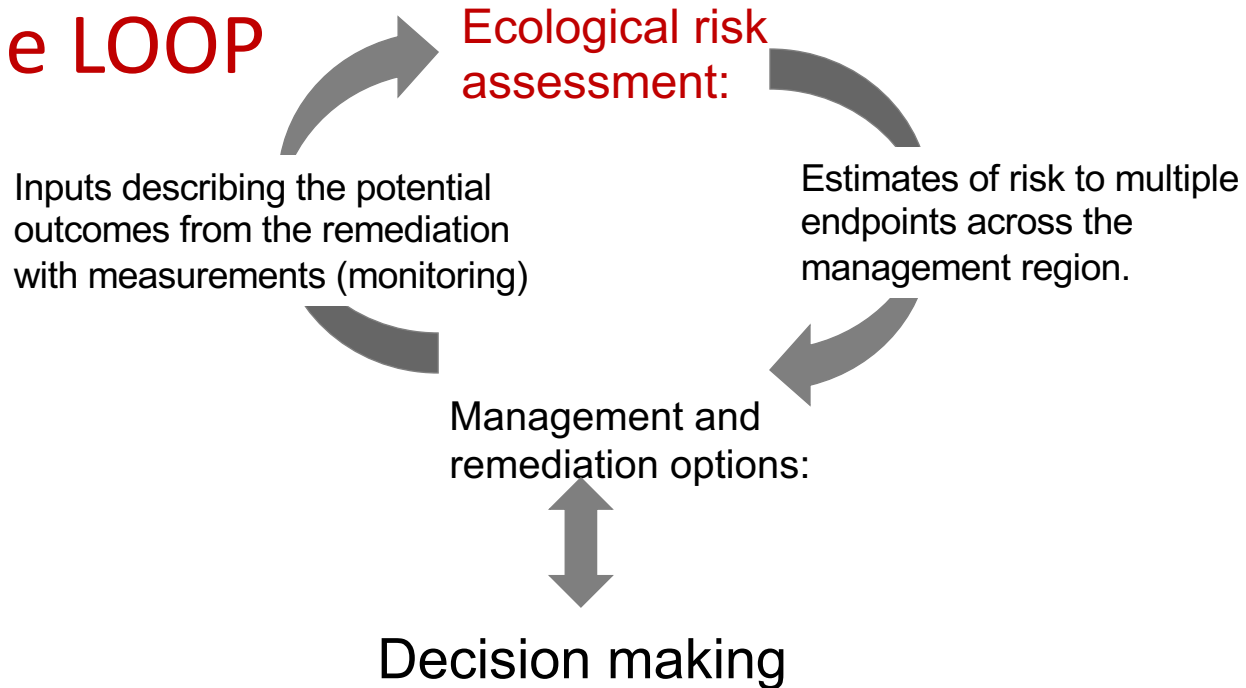
Adaptive Management and Risk Assessment

Landis WG, Markiewicz AJ, Ayre KK, Johns AF, Harris MJ, Stinson JM, Summers HM. 2017. A general risk-based adaptive management scheme incorporating the Bayesian network Relative Risk Model with the South River, Virginia, as case study. *Integr Environ Assess Manag.* 13:115-126



Adaptive Management and the applications of quantitative tools.

The LOOP



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Website: pnwmicroplastics.org

National Science Foundation Growing
Convergence Research Big Idea - Grants
#1935028 and #1935018

