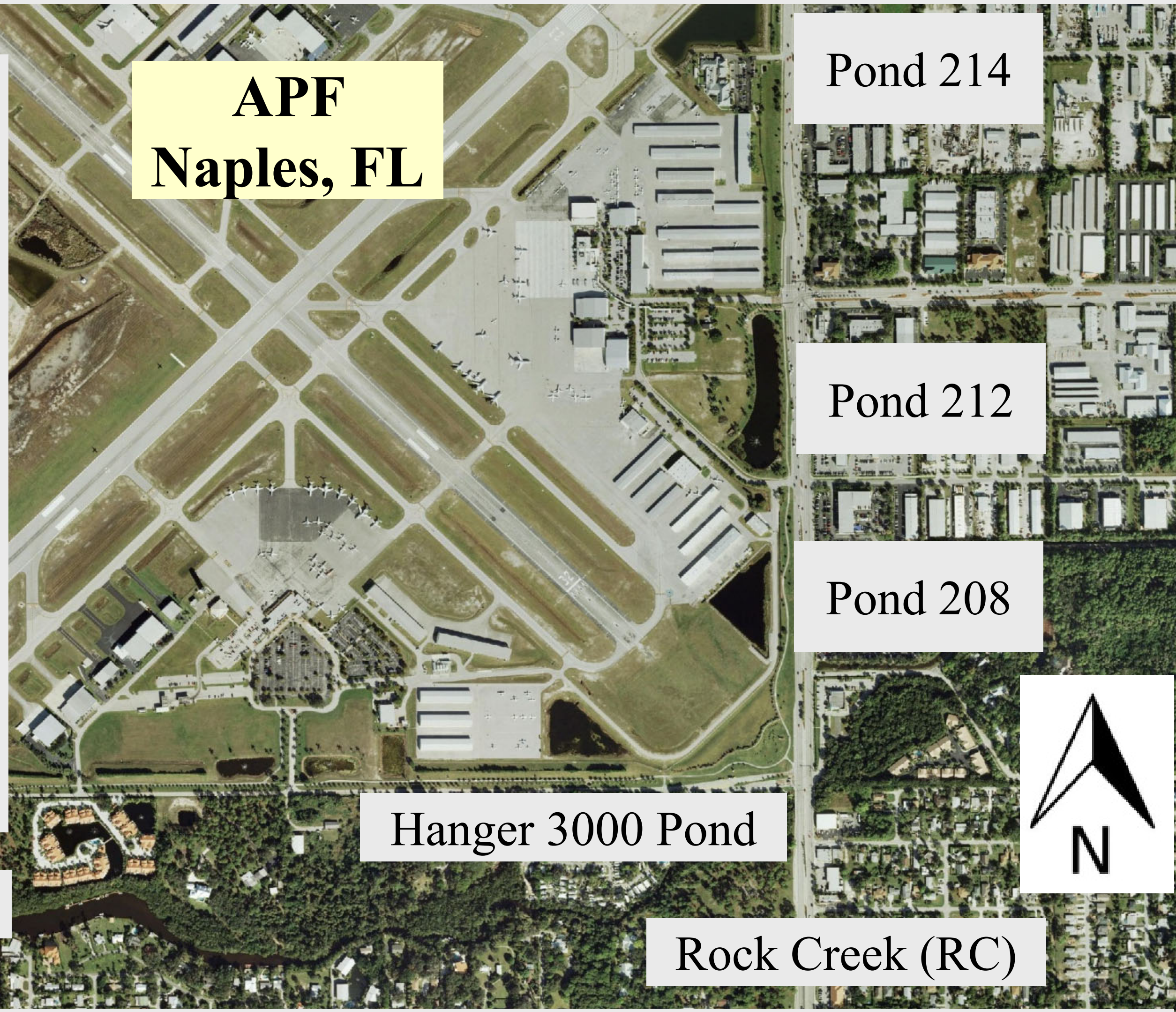
Optimizing Stormwater Pond Load Reduction and Economics: “The Times They Are A-Changin”



<u>Part I</u>:
The basics physics, chemistry, and monitoring as the foundation of a validated CFD-ML, *computational fluid dynamics-machine learning* tool

<u>Part II</u>:
Validation of CFD as a model of stormwater “pond” (clarifier) retrofit geometrics (hydrodynamics) and therefore, treatment benefits; and CFD coupling with machine learning (AI) for pond design/retrofit optimization

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Acknowledgments for validation case study (APF)

The pond analysis/design/retrofit is the result of the efforts, time, intellects, vision of collaborators, stakeholders, local/state/federal agencies: (22 engineers, 5 chemists, 3 geologists, 5 environmental scientists, many graduate students) as well as their support, guidance and faith in innovation from 2007-2018, including:

- CDM-Smith, Harry Downing
- City of Naples, FL
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- ESA, Julie Sullivan, Doug DiCarlo
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- FDEP, Borja Crane-Amores, Richard Musgrove, Eric Livingston
- FDOT Aviation Office, Abdul Hatim, Aaron Smith, Andy Keith
- Naples Airport Authority: Kerry Keith
- SJRWMD: Cammie Dewey
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- University of Florida: Dr. Haochen (Randolph) Li, Dr. David Spelman, Steven Wilson
- Universita di Parma: All of my Italian graduate students and visiting scholars who contributed

Framework of what is proposed ?

1. A CFD-ML simulation modeling tool (DeepXtorm) for stakeholders (regulators, engineers/scientists, infrastructure owner/operators, managers). DeepXtorm <u>optimizes stormwater treatment pond geometrics (intra-pond and/or external geometrics) to achieve load reduction goals</u> ***focused on chemicals of interest***, e.g. (in FL) TN, TP, dissolved/particulate N, P and particulate matter (PM) indices such as suspended solids (TSS) or SSC.

2. DeepXtorm's engine is powered by CFD simulations (> 100,000) based on existing pond geometrics and ML algorithms (e.g. ANN) w/computational results residing on UF's HiPerGator HiPerGator is the 3rd most powerful academic HPC worldwide.

3. DeepXtorm can be utilized either as a (I) research-based tool (as illustrated herein at APF) or (II) developed, licensed and deployed as a web-based app. If, as a user-friendly web-based app. (case II), educational/training workshops will be held to implement and maintain/upgrade DeepXtorm.

What are environmental/ecological and stakeholder benefits?

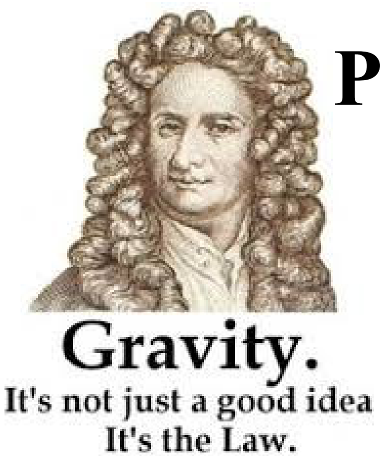
1. Stormwater ponds (most are impaired based in part on residence time, RT guidance) are the most prevalent unit operation/process (UOP) in the USA. With increasingly rigorous load reduction goals (e.g., 2024 FL *Clean Waterways Act)*, ***DeepXtorm is the only tool*** providing significant pond cost reduction ***while*** achieving load reduction goals of TN, TP, PM…

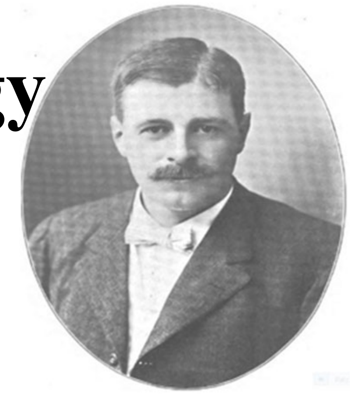
2. A stakeholder can deploy DeepXtorm in three modes for a chemical or PM:
   (1) analysis of existing pond geometrics/hydrodynamics for load goals,
   (2) design to optimize pond geometrics/hydrodynamics for load goals,
   (3) retrofit design (intra-pond geometrics {e.g. baffles}/hydrodynamics and/or pond area/volume) to meet load goals for an impaired pond.

3. DeepXtorm inputs are existing/proposed pond geometric (intra-pond or external shape/area/volume), hydrology/hydraulics loadings, nutrients (or any chemical database), partitioning (nominally dissolved vs. PM-bound) and particle size distribution (PSD) of PM (PSD databases published).

4. Future DeepXtorm modes are: BMPs, green infrastructure, other chemicals.

Pond (Basin) Design/Analysis Chronology




A. Hazen

98 (AD)
Roman engineering report: Roman settling basin receiving influent aqueduct flows
(Roman Water Commissioner)

1643-1727
Newton's Law of Gravitational Settling
(Newton, *Principia*, 1687)

1904
"On Sedimentation" Transactions of ASCE
(Allen Hazen)

1916
American Sewage Practice, First Flush Concept, Overflow Rate
(Metcalf & Eddy)

1970s
SWMM Introduced
(UF)

1980s through 1990s … current
First Flush Reincarnated as Water Quality Volume (WQV) Regulations across USA (and FL)

1983 - 1985
Assessment of Stormwater Management Programs (14-day RT)
(CDM)

1990 – 2023
Evaluation of Current Stormwater Design Criteria in Florida (Residence Time, RT guidance) (Harper)

2008-2023 …
APF basin, BMP tools w/CFD, Physical Models and ML tools (2020)
(Univ. of Florida, UF)

Time

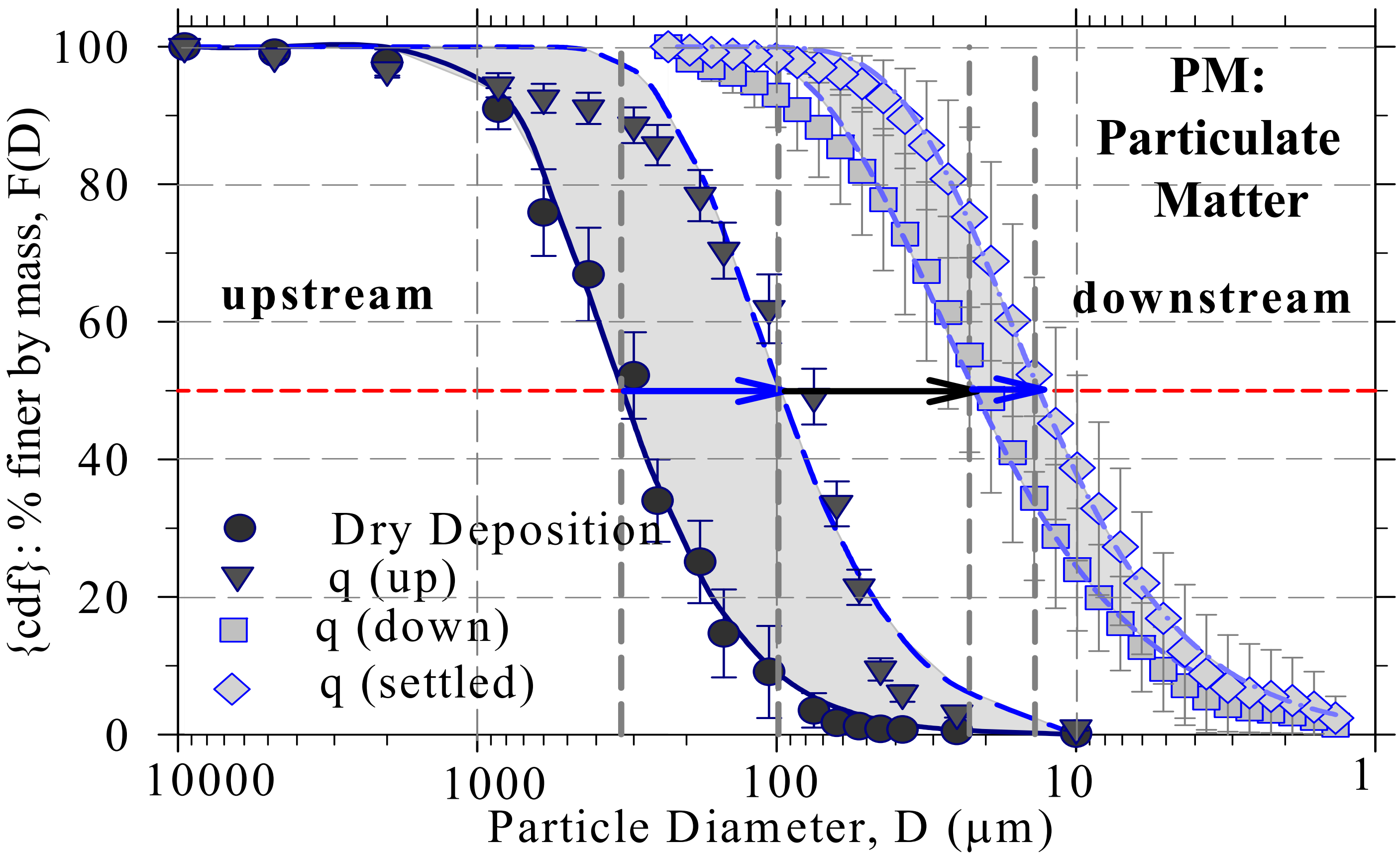
☆ -- Basis of UF Basin CFD Design for Florida (FL)

Physics and Chemistry of Particulate Matter (PM) and Chemical Load Challenges Generated from Stormwater

Particulate Matter (PM): Anthropogenic and Biogenic

- **PM is the predominate sink/source of chemical partitioning**
- **Management of PM = Control of chemical (nutrients, metals, EDC, PFAS...) load and concentration as well as load credits**
- Myths regarding PM is a function of how we sample and analyze
  - *samplers are designed for steady wastewater flows and organic PM*
  - *analysis based on sub-aliquot methods (TSS) without particle size data*
- Particle size distributions (PSD), particle number density PND:
  - *Required for modeling PM, solute and microbiological fate*
  - *Required for load inventories of PM and nutrients, maintenance*
- *While not an emerging contaminant, PM is the high surface area substrate for partitioning/transport of emerging contaminants !*

Transport modifies PM: From pavement PM deposition to catch basin through conveyance to "BMP" influent and effluent PM



PSD gamma model

$$f(D) = \frac{(D/\beta)^{\gamma-1} e^{(-D/\beta)}}{\beta \cdot \Gamma(\gamma)}$$

$$F(D) = \Gamma_D(\gamma)/\Gamma(\gamma)$$

$$\Gamma(\gamma) = \int_0^{\infty} x^{\gamma-1} e^{(-x)} dx$$

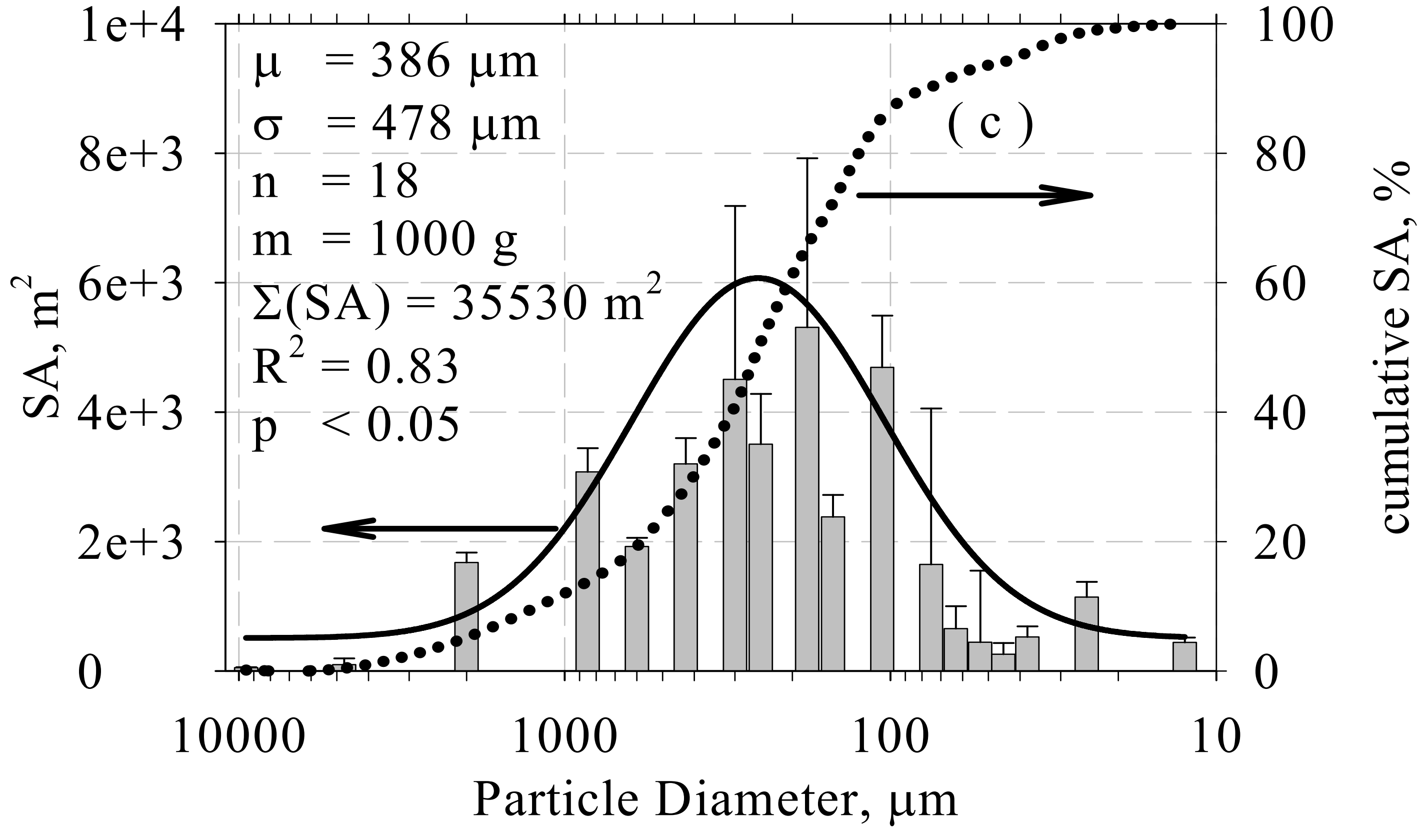
$$\Gamma_D(\gamma) = \int_0^{D} x^{\gamma-1} e^{(-x)} dx$$

BMP: Clarifier with 1 hr. of quiescent settling

Location	(γ, β)
DD	(2.06, 187.7)
q (up)	(1.90, 61.9)
q (down)	(1.23, 23.6)
q (settled)	(1.51, 11.1)

PSD of PM	DD Pavement ***Deposition***	q (up) CB or inlet ***Runoff***	q (down) BMP influent ***Runoff***	q (settled) BMP effluent ***Runoff***
D_{50m}	331 μm	99 μm	23 μm	14 μm

Chemical loads are correlated to PM surface area (SA)

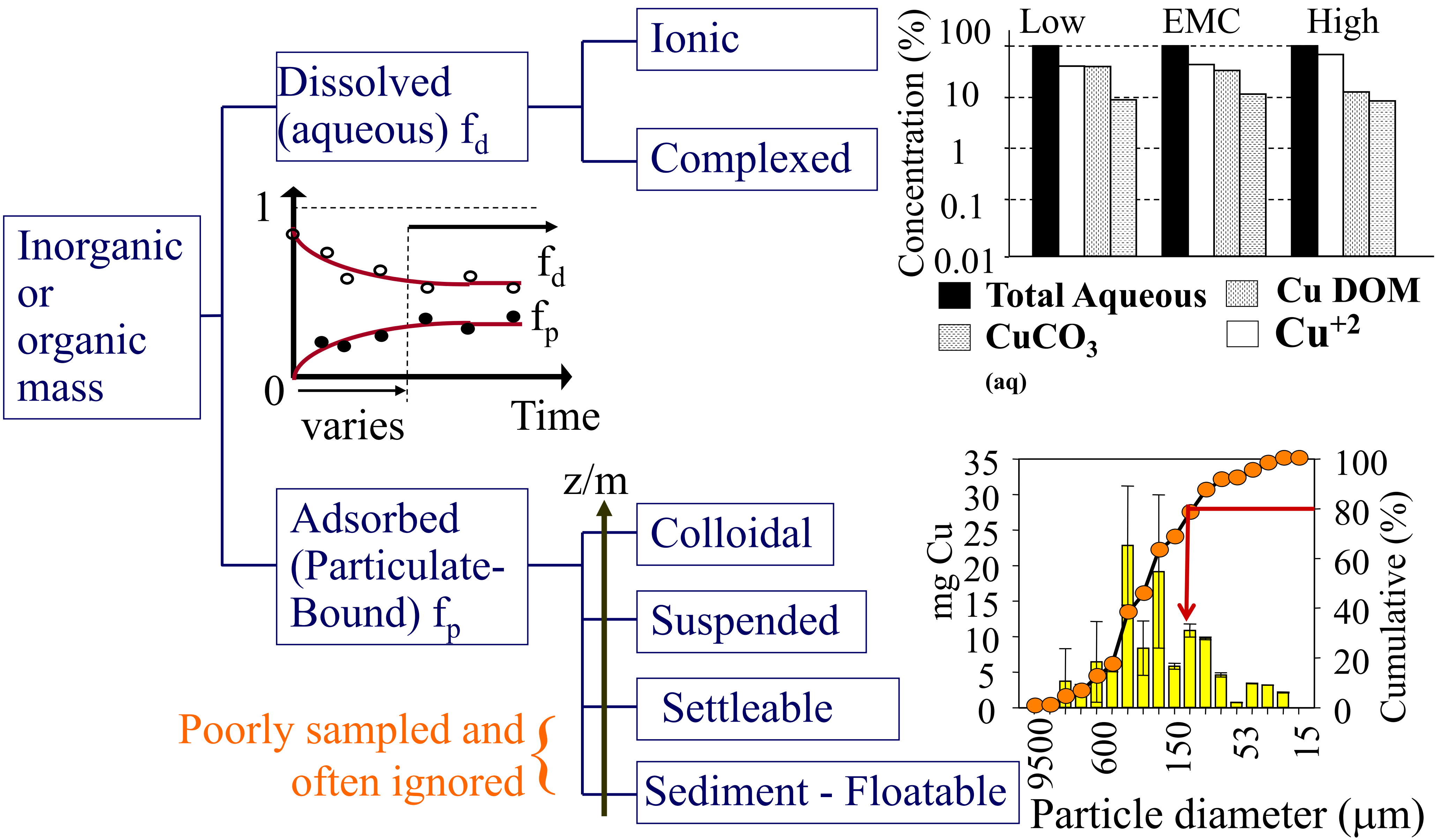


- Result represents the integration of PSD (mass) and specific surface area (SSA) to yield a resulting distribution of SA.
- PM-associated chemical mass (metals, nutrients) correlates to SA of PM not SSA.

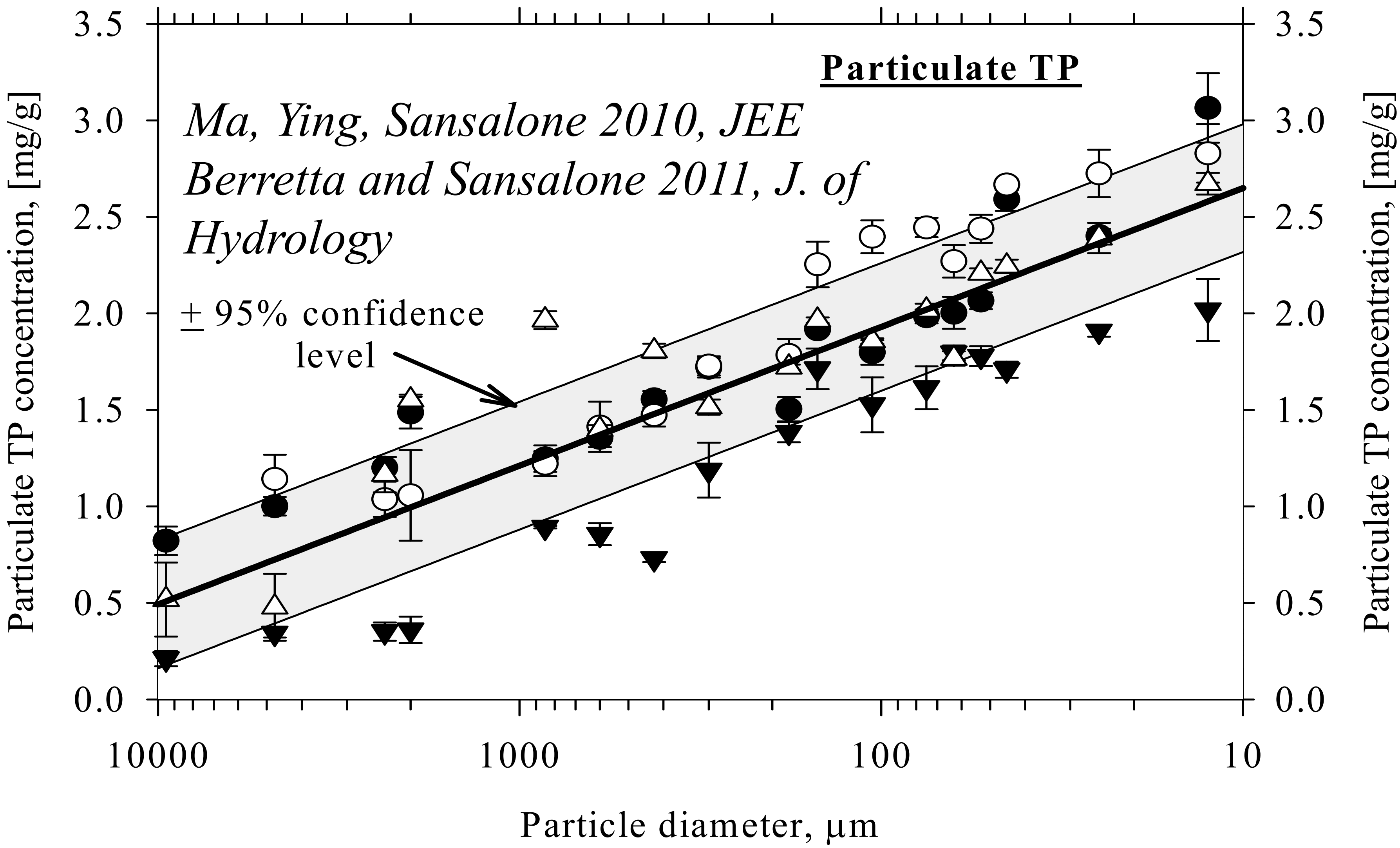
<u>Log normal distribution function of SA for PM:</u>

$$SA = SA_0 + r \cdot e^{\left[-0.5 \cdot \left(\frac{\ln(d) - \ln(d_0)}{t}\right)^2\right]} = 1187 + 12895 \cdot e^{\left[-0.5 \cdot \left(\frac{\ln(d) - \ln(255)}{0.39}\right)^2\right]}$$

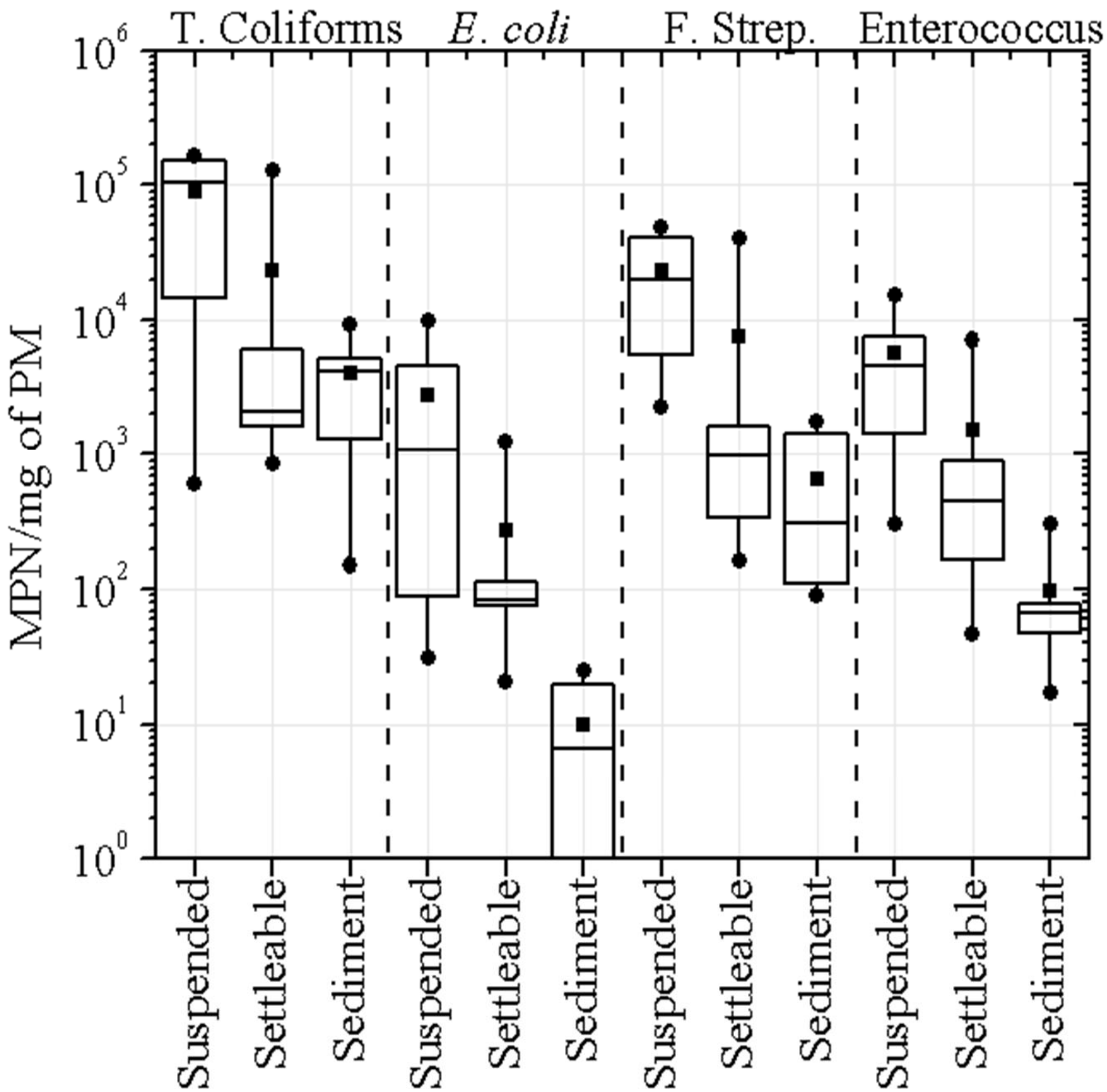
Partitioning and distribution of mass (example – Cu)



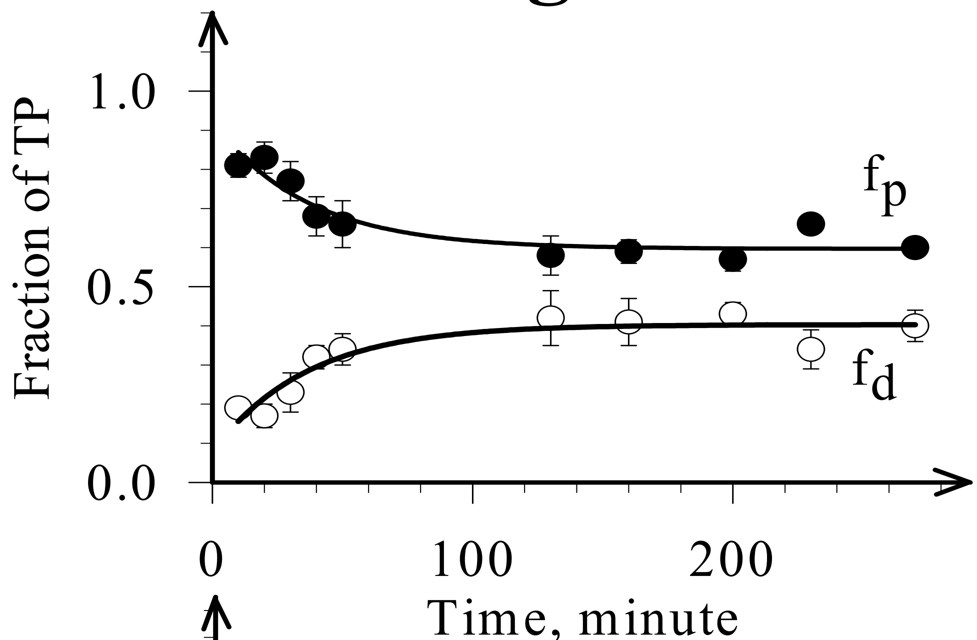
Relationship between granulometry and particulate TP based on FL rainfall-runoff event datasets

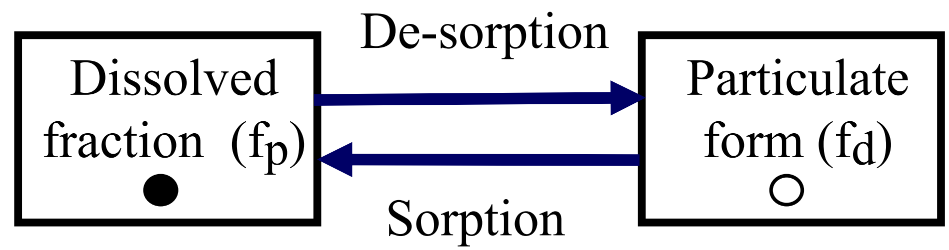


PM-associated pathogens in GNV runoff (Dickenson & Sansalone 2012)

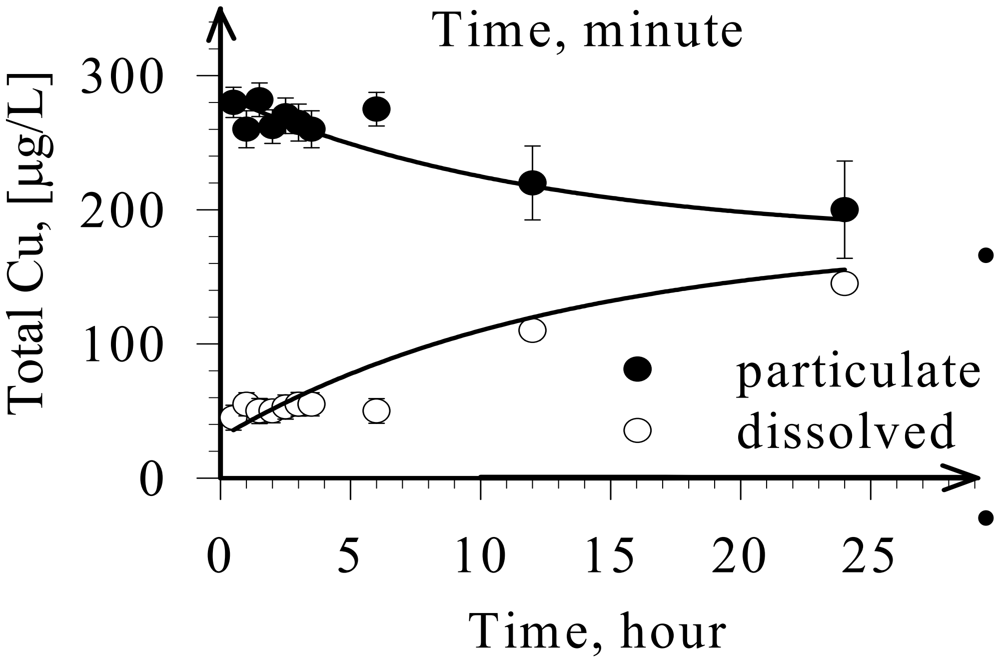


Partitioning kinetics and sample holding time





- Equilibrium f_p (TP) : 0.6
- Equilibrium f_d (TP) : 0.4
- Equilibrium Cu_d: 200 µg/L
- Equilibrium Cu_p: 150 µg/L

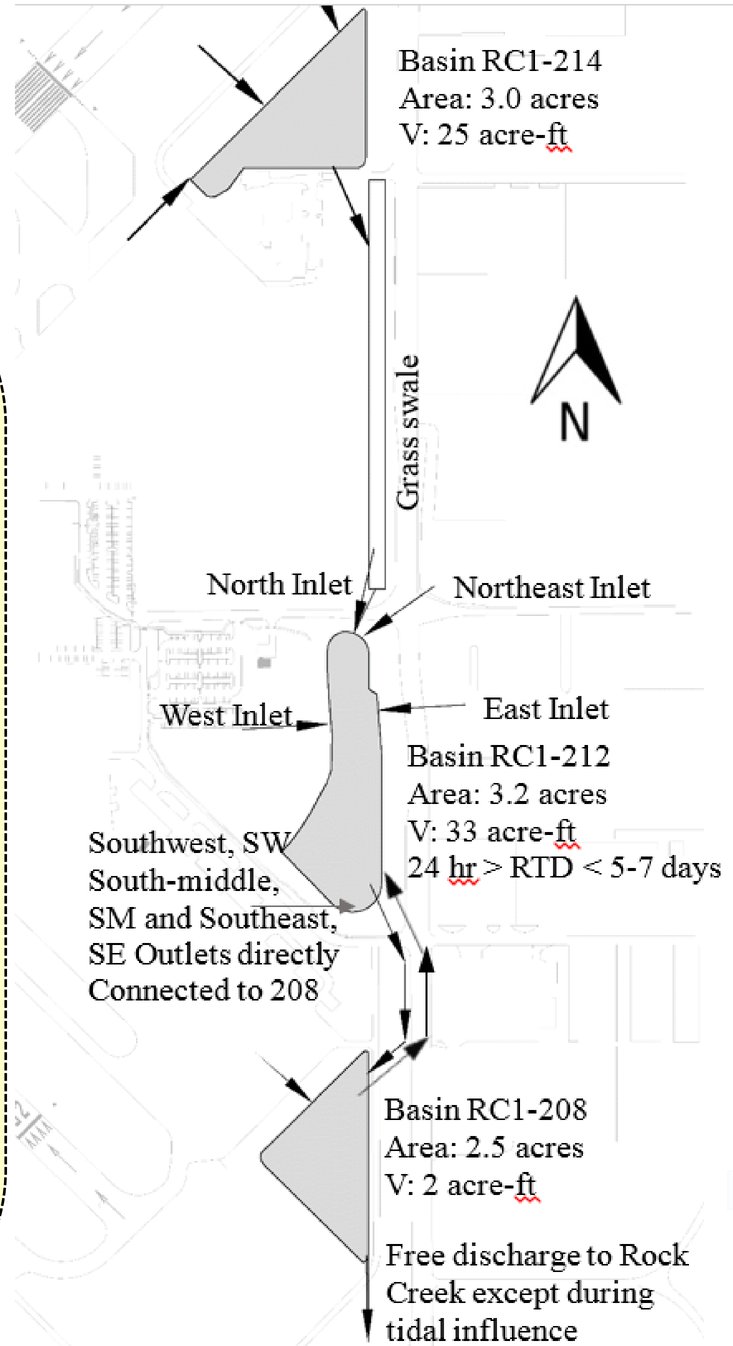


- Sample holding time is critical for accurate representation of partitioning, speciation and treatment effectiveness
- Water chemistry at a UOP is different than what the lab receives 24 hr. later

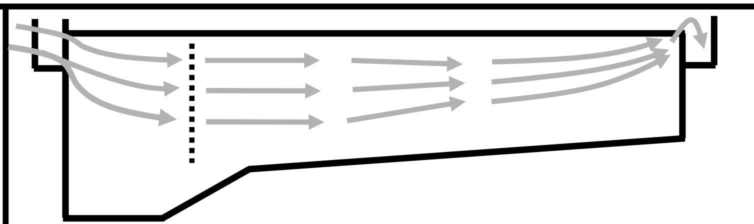
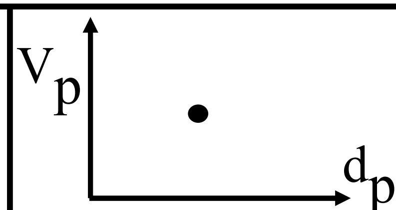
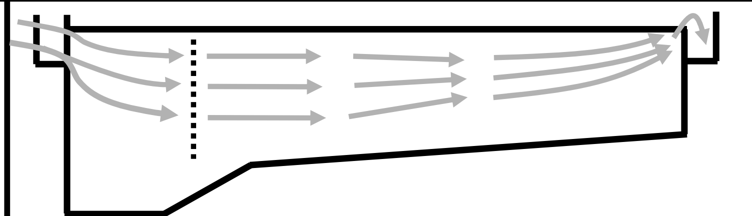
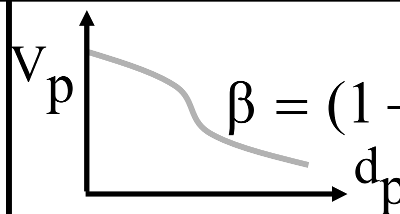
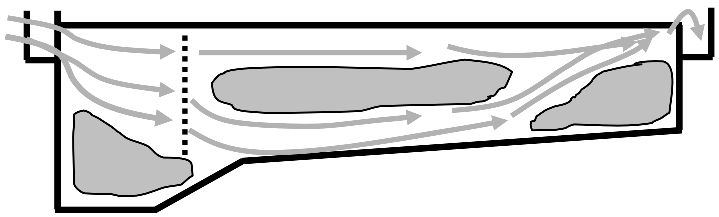
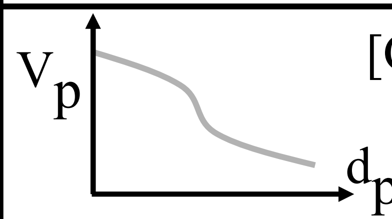
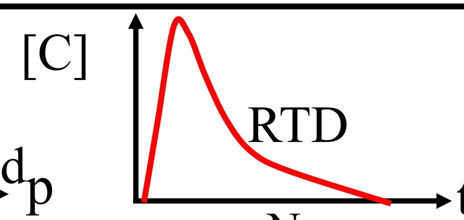
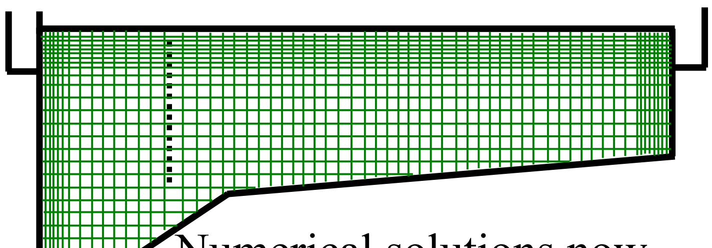
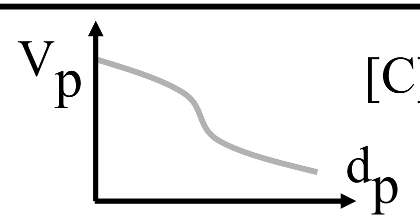
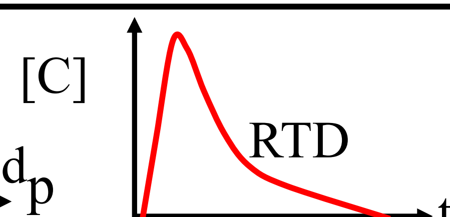

APF Pond 212
(before retrofit
using only CFD,
before ML and
HiPerGator)
circa 2010

Process Flow Diagram for APF Eastern N-S Drainage System

1. Focus of modeling/design/monitoring: Basin 212; although 208, is hydraulically, basin 212-extended
2. Very small hydraulic gradient between Basin 212 and 208; flow direction between 208 and 212 is driven by wind, gradient and tides. The system control is 208.
3. Basin 212 ***continuously*** conveys flows **from** the offsite commercial Northeast (NE) MS4 system
4. Basin 212 ***was and is*** a small on-line conveyance basin w/ groundwater and NE baseflow interactions
5. Basin 212 surface/watershed area ≈ 2% << 10-15%
6. Basin 212 geometrically oversized for inflows, PSDs
7. Constraints: *Environmental* (loads and hydrologic control), *Stakeholder* (basin is an aesthetic amenity), *Safety* (avian and wildlife interactions with planes)



Tools for Multiphase Treatment: Standard to Innovative

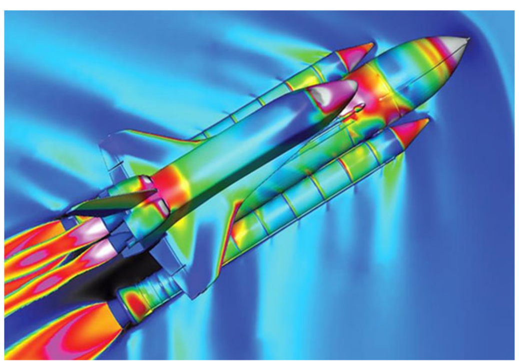
Ideal Overflow Rate w/o PSD - *most common*		 $V_c = \frac{Q_e}{A_s}$ or RT
Ideal Overflow Rate w/ PSD - *rare* (Case II)		 $\beta = (1 - X_c) + \int_0^{X_c} \frac{V_p}{V_c}\, dx$
Non-Ideal Semi-Empirical Models w/ PSD - *infrequent in USA, common in Europe*	 $N = \frac{t_{50}}{t_{50} - t_p}$	 $\beta = 1 - \left[1 + \frac{V_p A}{NQ}\right]^{-N}$
Multi-Phase CFD Models - *state of the art, more applied in practice, 2005* (Case IV)	 Numerical solutions now dominate analytical solutions	 $\beta = \int_{CV} (Q, \rho, \Gamma, \varphi)\, dx\, dy\, dz\, dt$

What is computational fluid dynamics (CFD)?

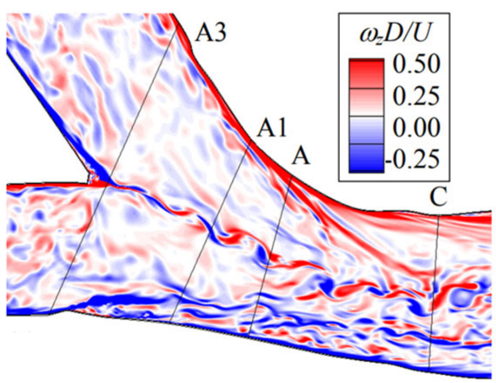
In physics, Navier–Stokes (N-S) equations is a system of partial differential equation (PDEs) that describes the fluid motions and substance transport; Newton's 2nd law numerically applied to fluids.

$$\frac{\partial}{\partial t}(\rho\,\mathbf{u}) + \nabla\cdot(\rho\,\mathbf{u}\otimes\mathbf{u}) = -\nabla p + \nabla\cdot\boldsymbol{\tau} + \rho\,\mathbf{g}$$

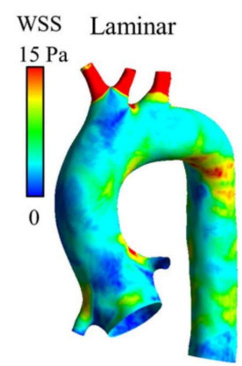
N-S equation typically does not have analytical solution. CFD is a branch of science that takes advantage of high-performance computing (HPC) and uses numerical method to solve N-S equation and simulate flow and substance transport. CFD is widely applied in a range of field.



NASA (2019)



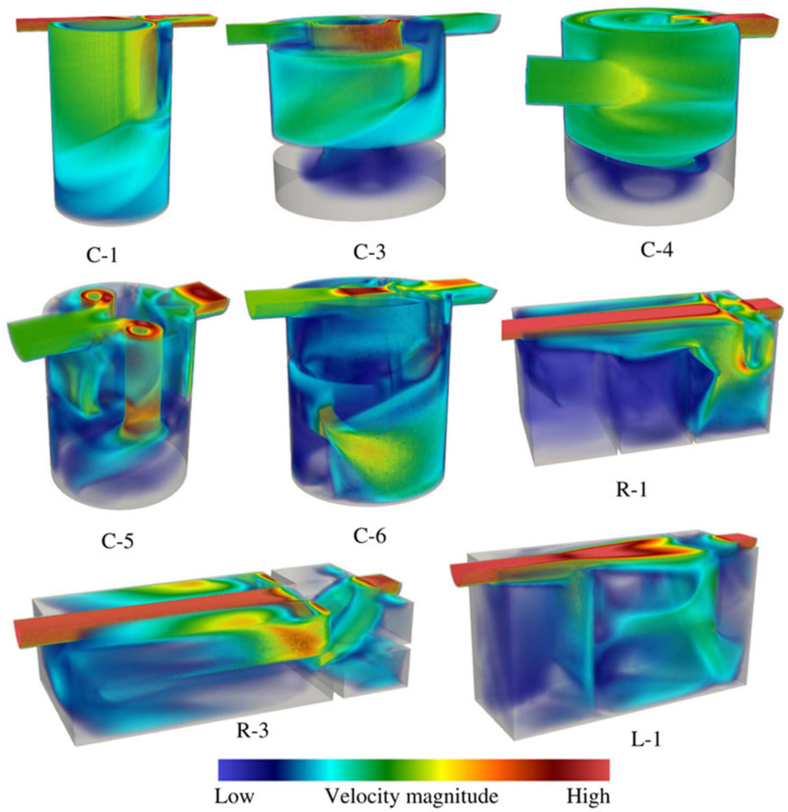
Rodi (2010)



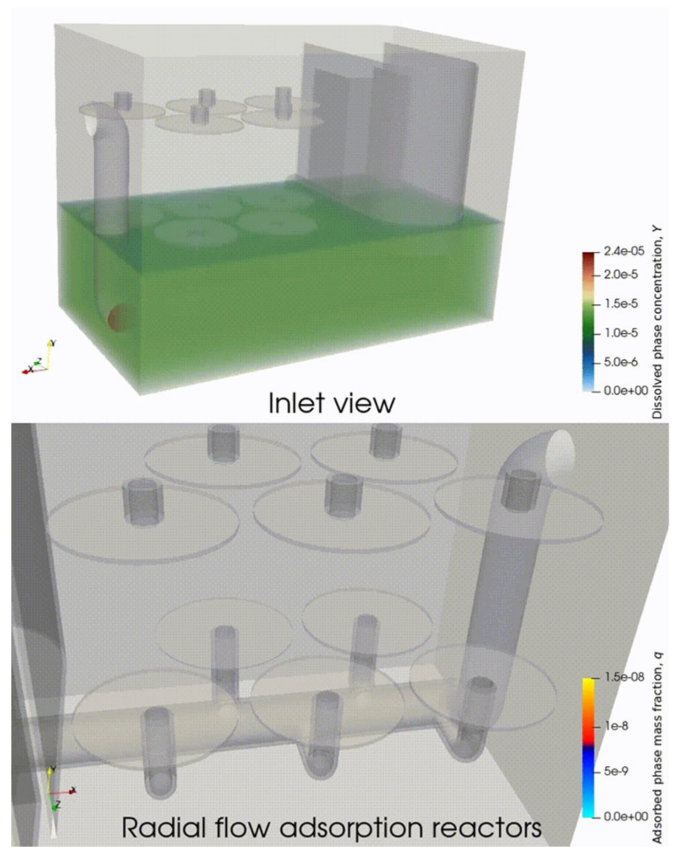
Miyazaki et al. (2017)

Li & Sansalone (2020)

Application of CFD in storm or wastewater treatment



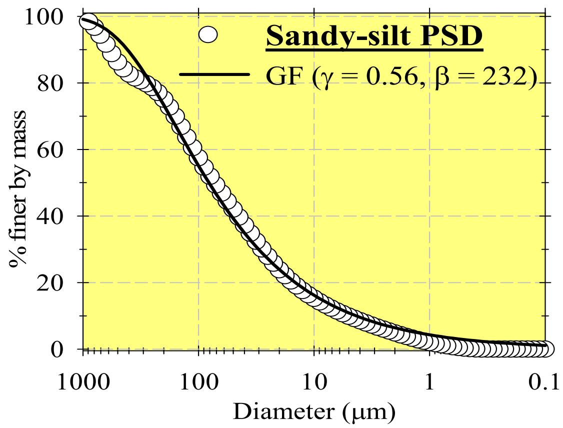
PM separation in commercial clarification systems
(Li and Sansalone, 2020)

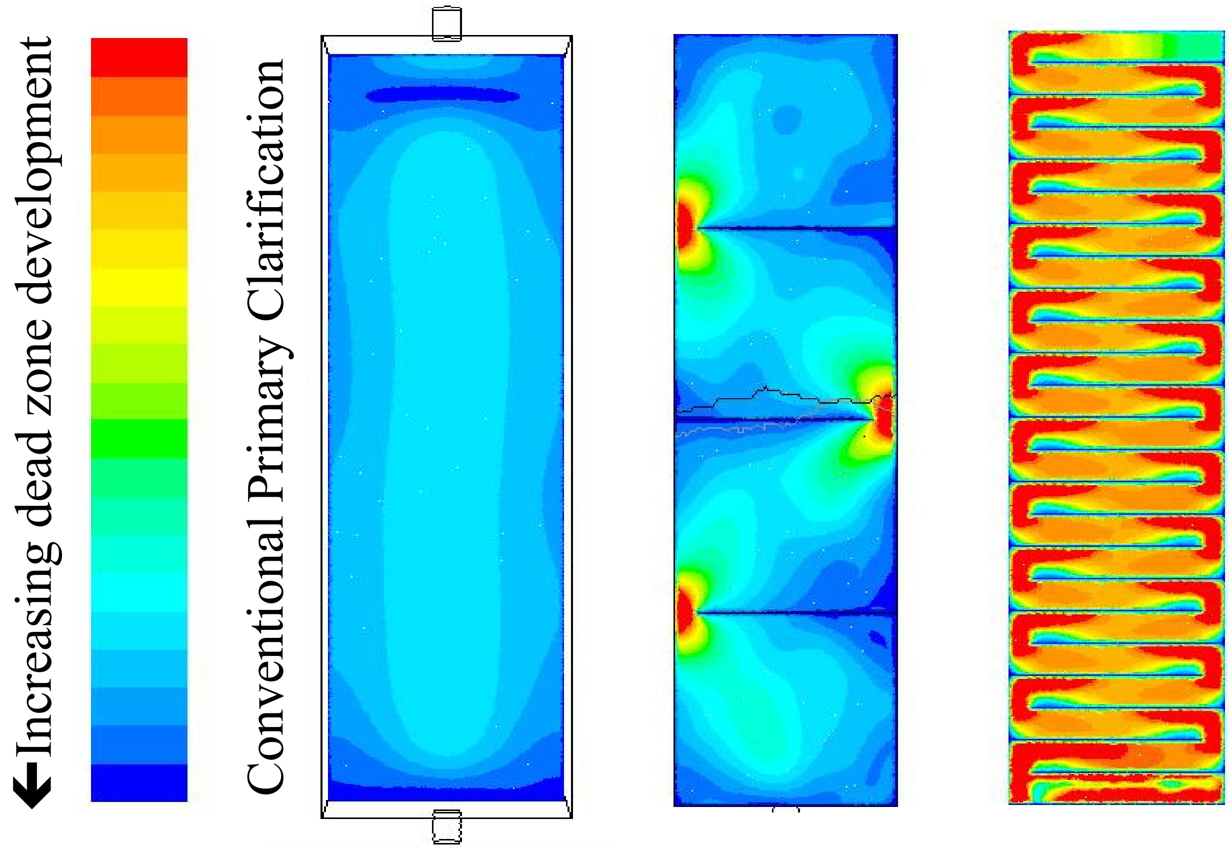


TDP removal dynamics in full-scale adsorptive reactor subject to unsteady flow
(Li and Sansalone, 2021)

Can treatment be improved through retrofit designs with computation fluid dynamics (CFD), circa 2008?

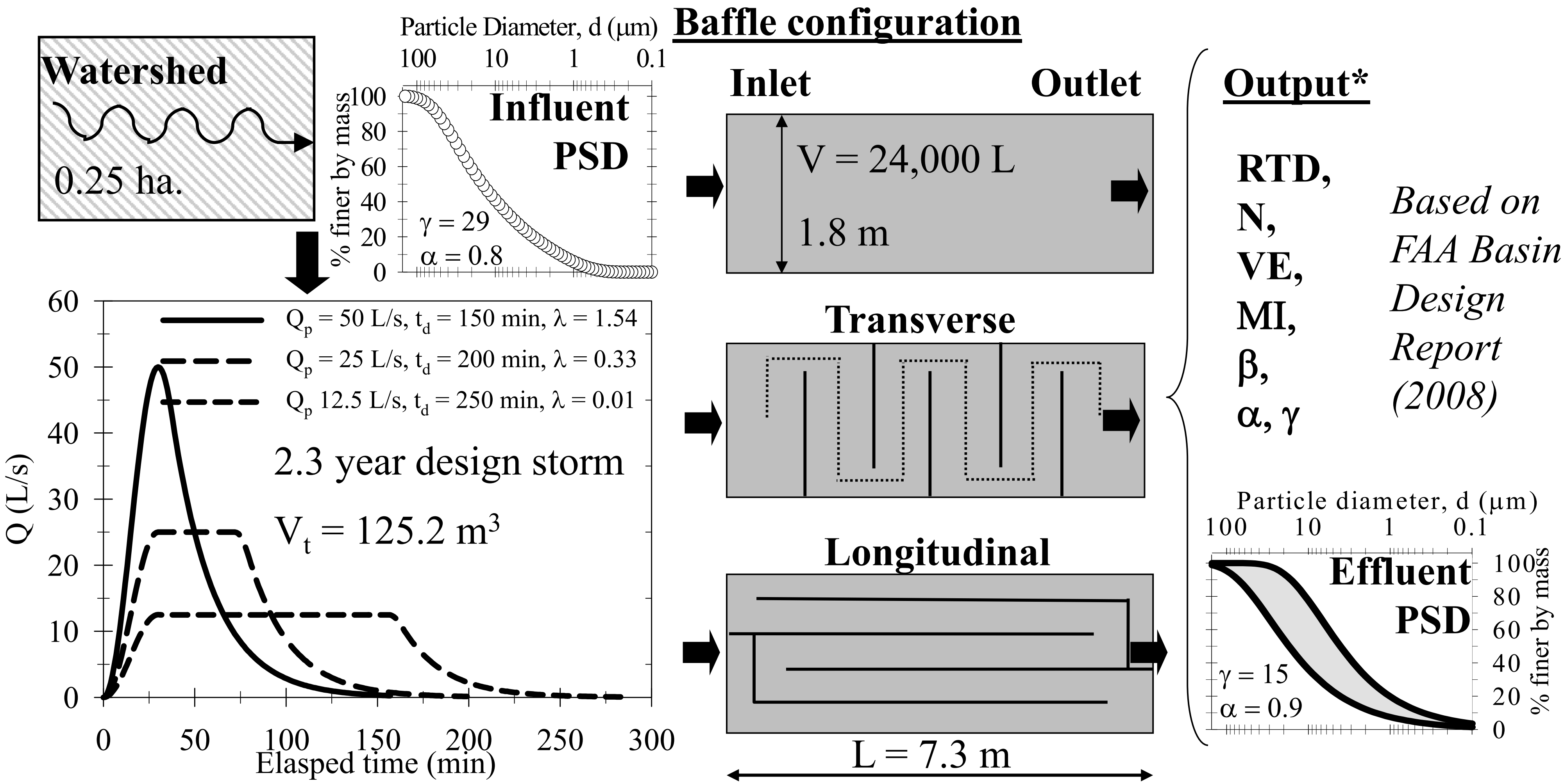
Physically-validated Model





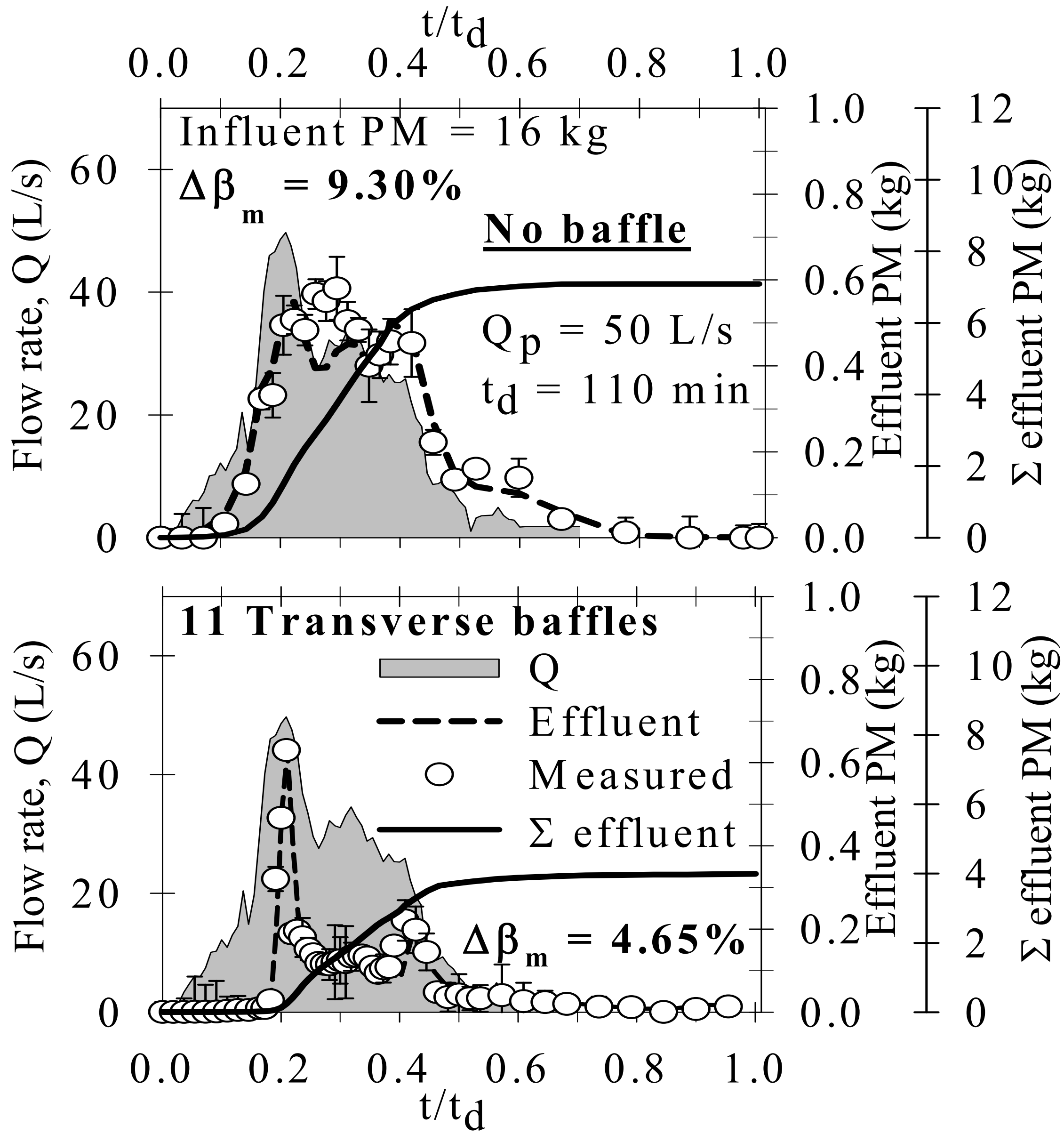
Number of Baffles	0	3	17
Δ PM (%) (β = 0.56 , γ = 232.6)	45 to 60	60 to 70	> 80%
Volumetric Efficiency (%)	5 to 10	20 to 30	60 to 85

Clarifier behavior as function of unsteadiness/baffles (2008 @ UF)



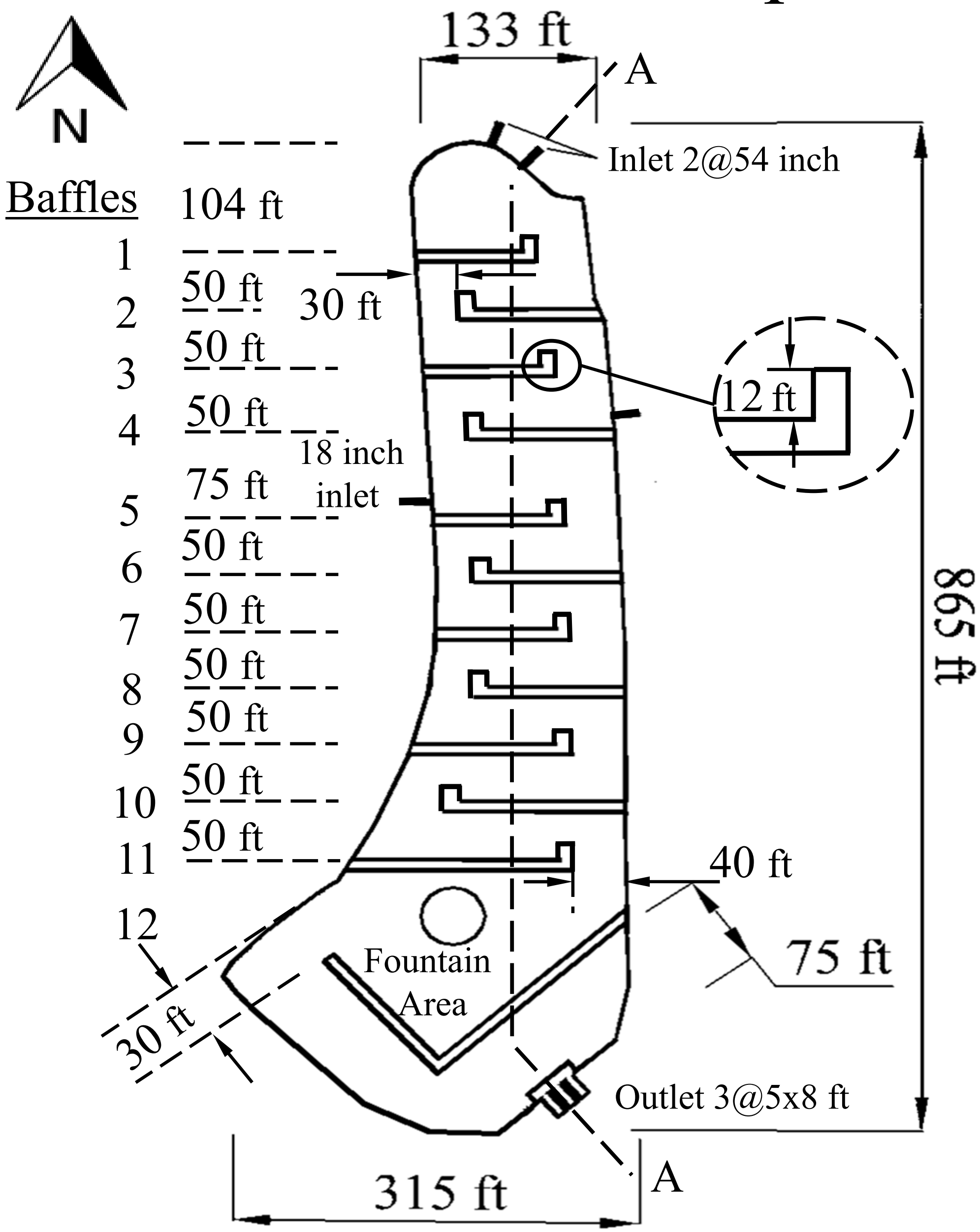
* VE: volumetric efficiency, RTD: residence time distribution, N: tanks -in series value, MI: Morrill dispersion index, V: clarifier volume, L_e/L: clarifier flow path tortuosity, β: PM removal efficiency, α and γ: gamma distribution parameters

Physical model validation of a CFD model for PM



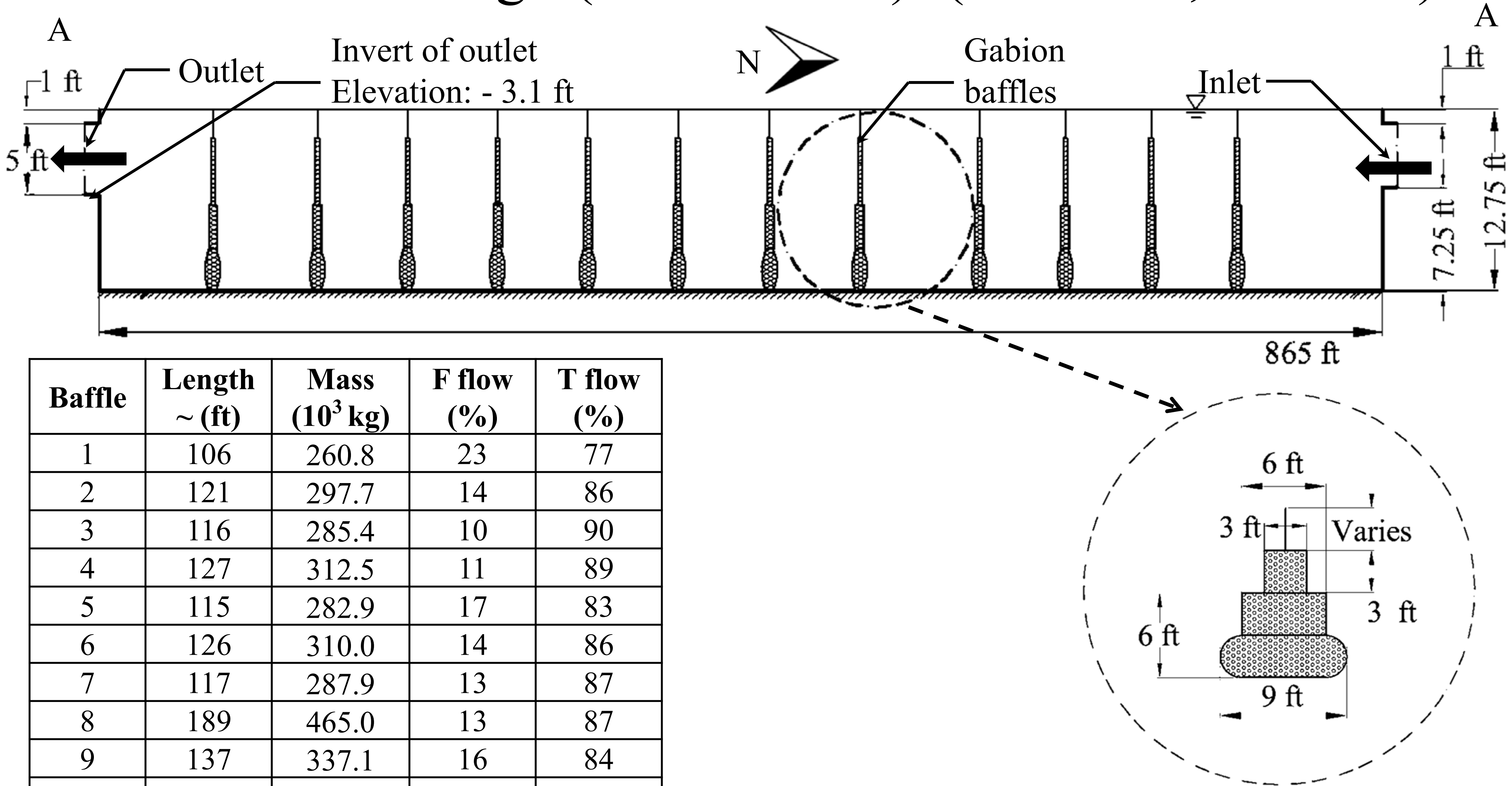
1. The PM separation efficiency is 56% for no baffle configuration
2. The PM separation efficiency is 75% for configuration with 11 baffles
3. These results show the beneficial effect of baffling on PM separation efficiency
4. The $\Delta\beta_m$ represents the absolute percentage of error between measured and modeled PM separation efficiency

Pond 212 retrofit: 12 permeable gabion baffles (pre-ML)



- Basin surface area: 3.2 acres
- Storage capacity: up to maximum of 40.0 acre-ft (12.75 ft)
  - 7.3% reduction in volume by adding baffles
  - Assuming 30% gabion porosity
- Range of water depth: 9 ~ 12 ft
- Water surface elevation: varies seasonally
- Linear feet of baffles: 1713
- Unit long gabion baffle mass: 8200 kg/m (5400 pounds/ft)
- Elevation based on NAVD88
- Gabions baskets of carbonated recycled concrete (CRC) aggregate (high SA) instead of sheet pile walls

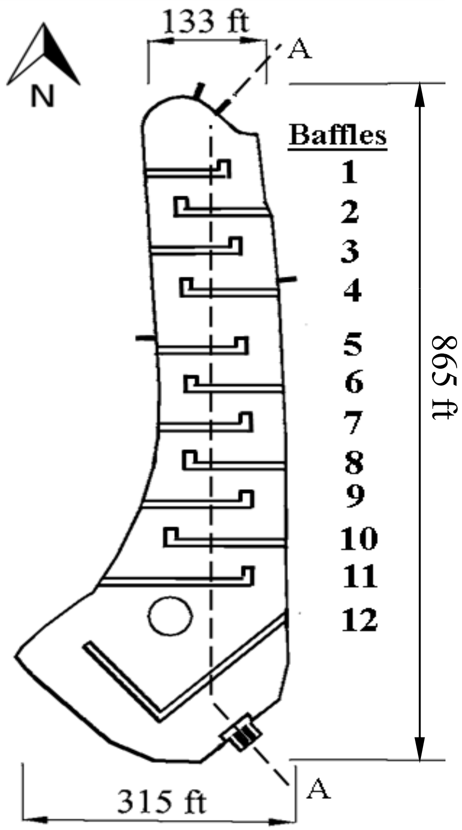
Basin 212 redesign (section A-A): (L 1:1250; H 1:125)



Baffle	Length ~ (ft)	Mass (10^3 kg)	F flow (%)	T flow (%)
1	106	260.8	23	77
2	121	297.7	14	86
3	116	285.4	10	90
4	127	312.5	11	89
5	115	282.9	17	83
6	126	310.0	14	86
7	117	287.9	13	87
8	189	465.0	13	87
9	137	337.1	16	84
10	152	374.0	14	86
11	184	452.7	20	80
12	319	784.9	21	79

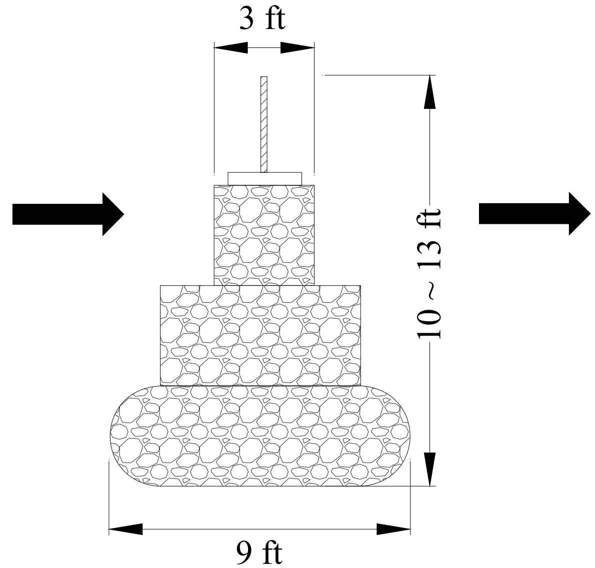
Filtration flow (F): through gabions
Tortuous flow (T): between gabions

Gabion Baffle of Carbonated Recycled Concrete (CRC)



Baffles at basin scale:

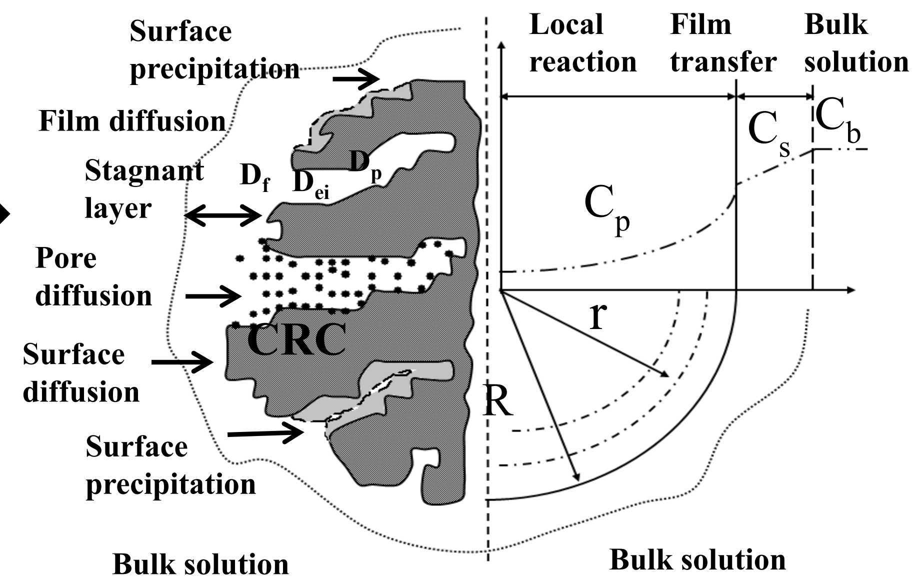
1. Volumetric utilization
2. Tortuosity increased
3. Plug flow increased
4. RTD improved



Baffles at gabion scale:

1. Hydraulically conductive
2. Tortuous effective porosity
3. Particulate matter filtration
4. Horizontal trickling filter

Wu and Sansalone, JEE, 2013 a,b,c

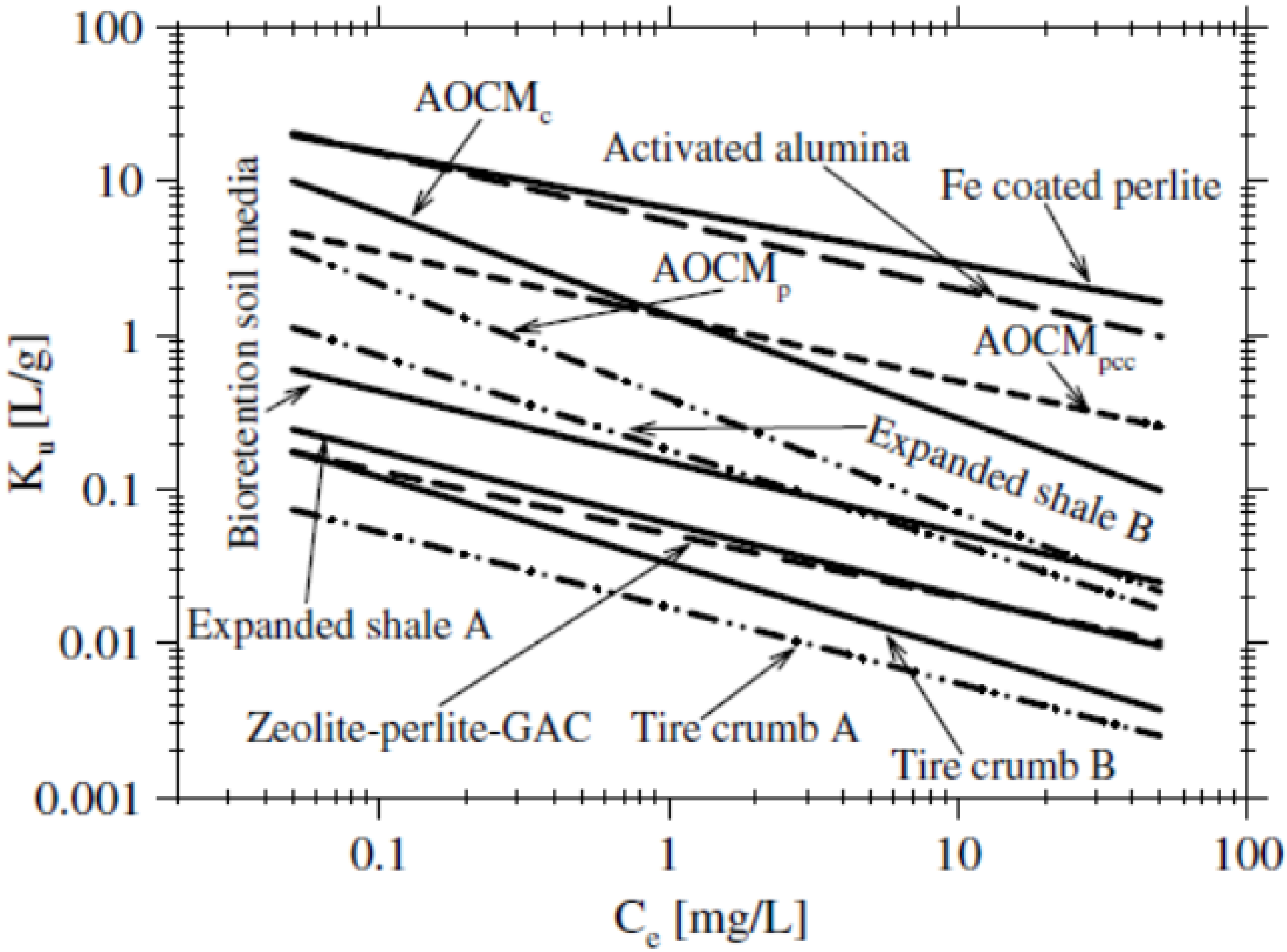


Baffles at CRC media scale:

1. Higher surface area, pH substrate
2. C-S-H, $Ca(OH)_2$, CSA substrate
3. Adsorption, chemical precipitation
4. Mass transfer of P to CRC:
   a. Equilibria
   b. Kinetics
   c. Breakthrough

Common media phosphorus adsorption capacity for polishing off-peak flows as a continuous time series

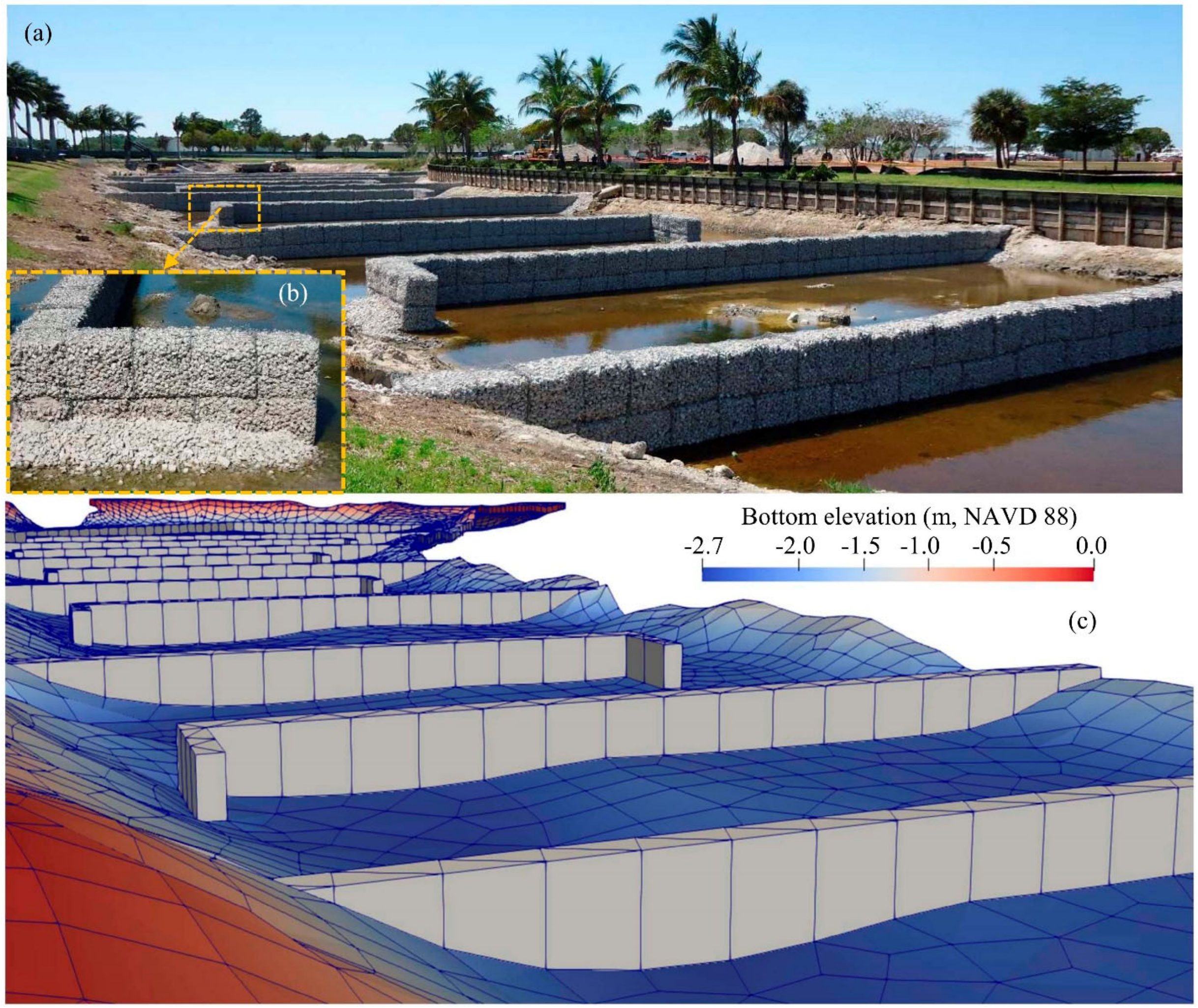
(Wu and Sansalone, 2011, J. Envir. Eng.)



APF pond 212 retrofit construction

Permeable Baffles and Numerical Bathymetry of Pond 212

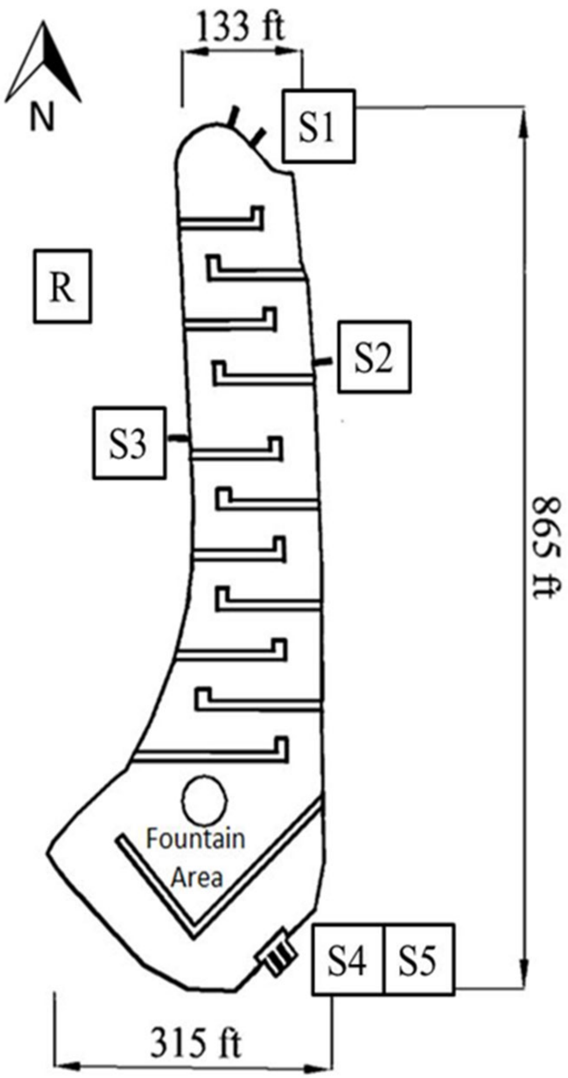
(numerical grid coarsened significantly for visual clarity only)




Basin 212 Retrofit
$RT_{50} \approx 5$ days $\ll$ 14 to 21 days)

Monitoring/Sampling/Analysis: Benchmarking

Monitoring locations and equipment for basin 212



Location	Size (h x w)	Type
East Inlet	15” x 36”	Elliptical
West Inlet	18” x 36”	Elliptical
Northeast Inlet	43” x 68”	Elliptical
North Inlet	43” x 68”	Elliptical
Southwest Outlet	5' x 8'	Box Culvert
South-Middle Outlet	5' x 8'	Box Culvert
Southeast Outlet	5' x 8'	Box Culvert

Location	Data Logger	Rain Gauge		
R	CR200x	CS700		
		Pressure Transducer	**Sampler**	**Velocimeter**
E In (S2)	CR1000	CS451-7.25psig	PVS5120D	SonTek-IQ Series Pipe
W In (S3)	CR1000	CS451-7.25psig	PVS5120D	SonTek-IQ Series Pipe
NE In (S1)	CR1000	CS451-7.25psig	PVS5120D	SonTek-IQ Series Plus
N In (S1)	CR1000	CS451-7.25psig	PVS5120D	SonTek-IQ Series Plus
SW Out (S4)	CR1000	CS451-7.25psig	PVS5120D	SonTek-IQ Series Plus
SM Out (S4)	CR1000	CS451-7.25psig	PVS5120D	SonTek-IQ Series Plus
SE Out (S5)	CR1000	CS451-7.25psig	PVS5120D	SonTek-IQ Series Plus

Stormwater Ponds in Florida for Load Reduction (Pond 212 results {2014-15 monitoring} vs. FL database)

History of use

1. Stormwater ponds have been the de-facto standard BMP in Florida for last 30+ years,
2. Used for water chemistry, PM load and hydrologic/hydraulic control,
3. ***Traditionally requires land area usage upwards of 10-15% of developed area,***
4. Load reduction of FL ponds without excluding impaired pond data*

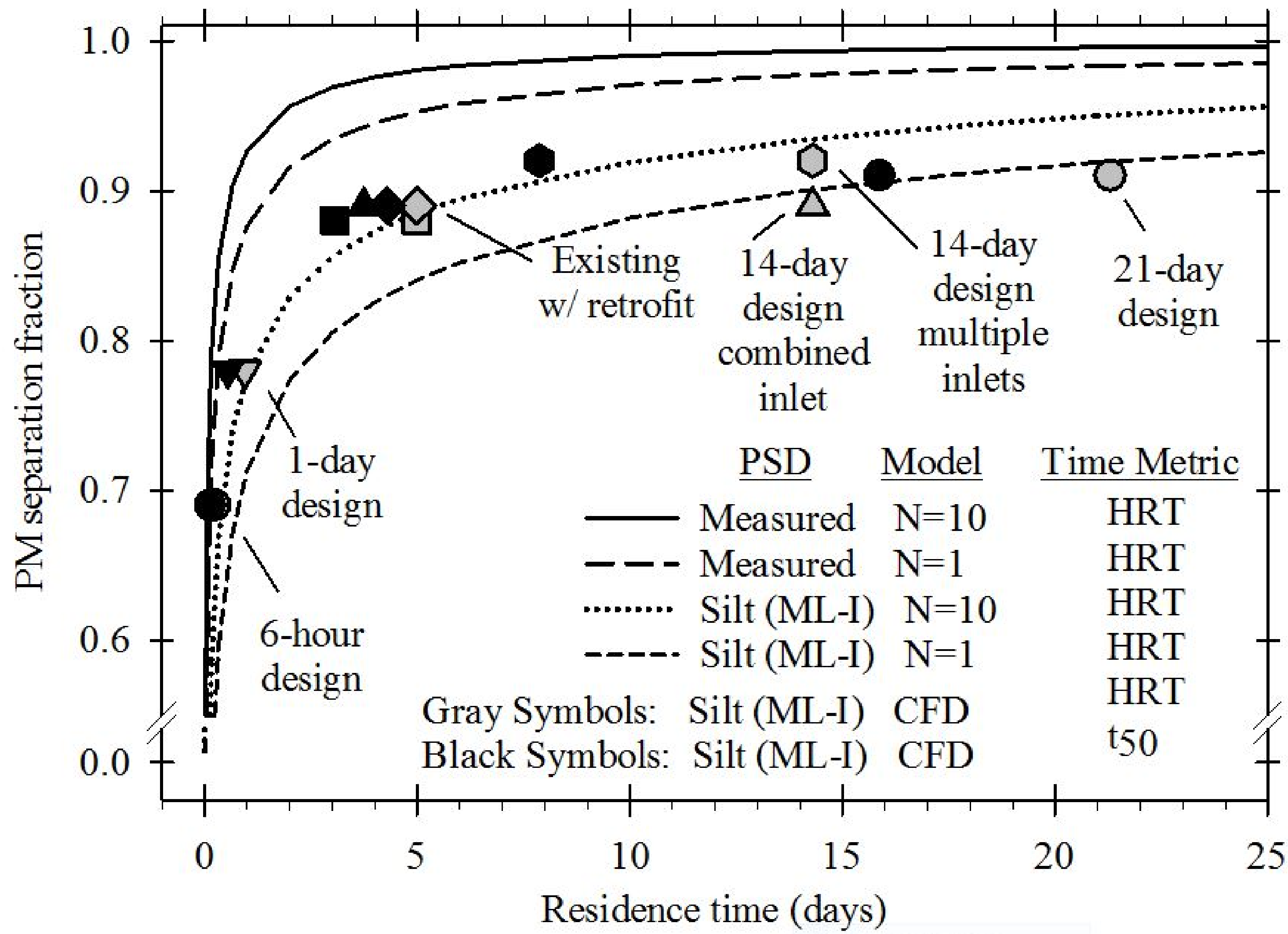
Cost

1. 5-100x lower: due to land area reqr., lost opportunity costs if pond area is expanded
2. There is a significant need to minimize cost and maximize environmental benefit given the 10,000+ stormwater ponds in FL

Constituent	**Load Reduction**	
	Pond 212 w/retrofit	**FL BMP Database***
TP	**78%**	**49%**
TN	**44%**	**22%**
PM (as TSS)	**88%**	**45%**
Zn (total)	Not measured	40%
Pb (total)	Not measured	58%
Cu (total)	Not measured	24%

Pond 212 w/ retrofit results exceeded FL BMP database tabular load reductions at < 2% of watershed drainage area

PM Separation vs. Pond 212 Residence Time (RT)



Comparison of Clarification Basin Designs

(Integrate these costs for clarification basins across Florida !)

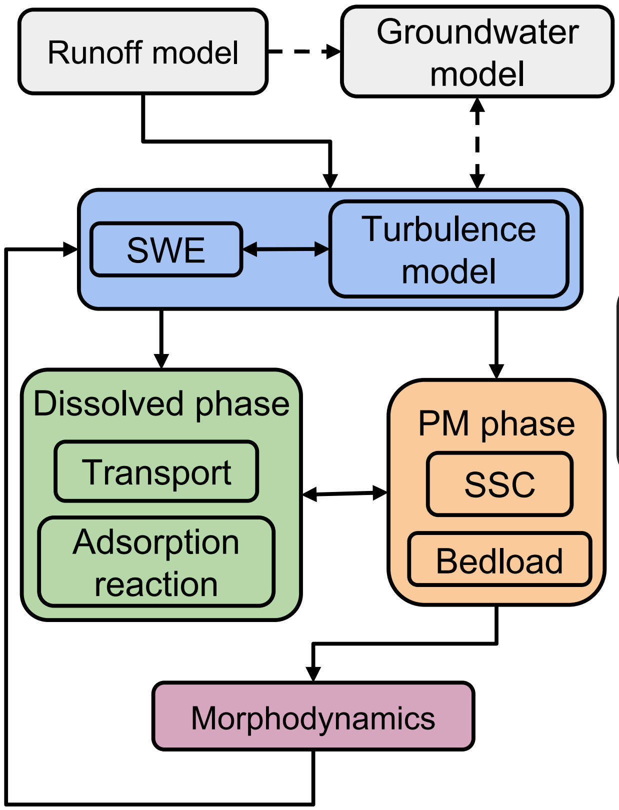
Design	**As Built**	**21 day RT**	**"ERP"***
Permanent pool volume (acre-ft)	23	78	157
Hydraulic residence time (day)*	6	21	43
Land requirement (acre)	3	9	16
Basin construction cost	$500,000	$1,150,000	$2,120,000
Internal basin retrofit cost	$325,000	$0	$0
Land present value	$2,200,000	$6,400,000	$11,600,000
Total basin cost	**$3,025,000**	**$7,550,000**	**$13,720,000**

*Wet season average

As built required the use of CFD and
to determine the effect of baffling
Engineering cost: **Higher** ↑

Traditional design
(WQV regulations)
Engineering cost = **Lower** ↓

Modeling framework for clarification infrastructure



basinFoam architecture
(Li and Sansalone 2020, 2021)

$$\frac{\partial h}{\partial t} + \nabla \cdot (h\mathbf{u}) = 0$$

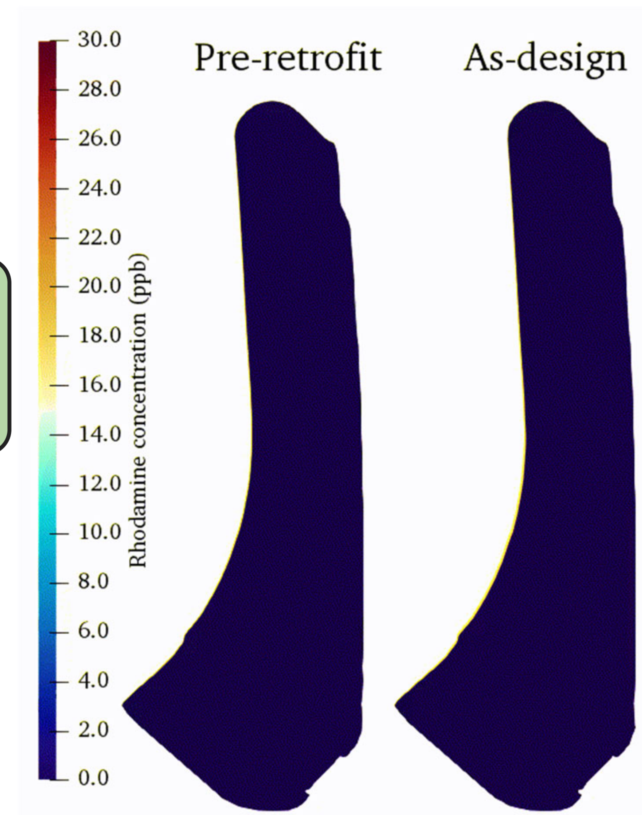
$$\frac{\partial h\mathbf{u}}{\partial t} + \nabla \cdot (h\mathbf{u}\mathbf{u}) = -|\mathbf{g}|\, h \nabla (h + h_0) + \nabla \cdot [h(\nu + \nu_t)\nabla \mathbf{u}] - \frac{\tau_b}{\rho} + \frac{\tau_w}{\rho} + \mathbf{s}$$

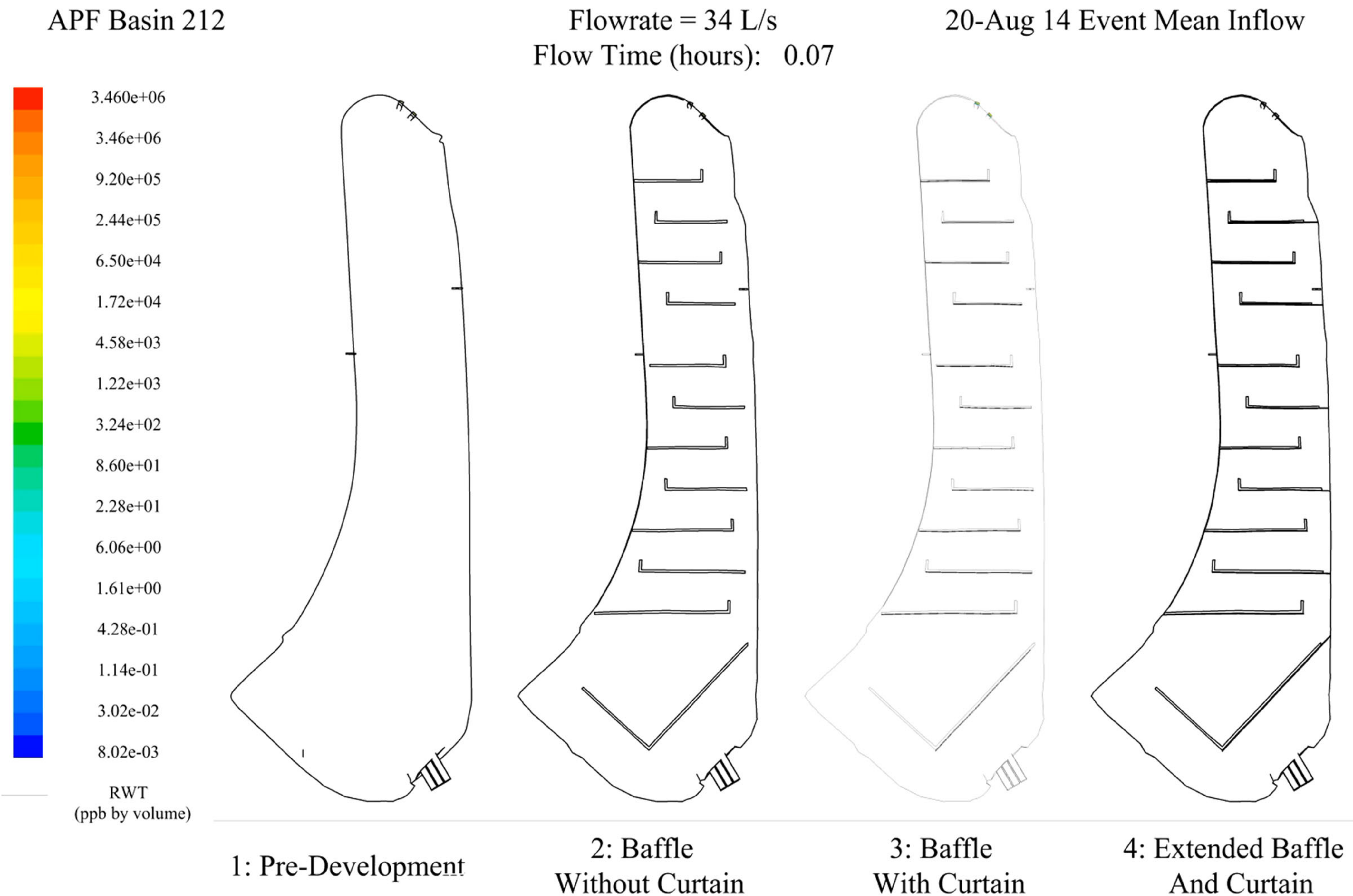
$$\frac{\partial hY_i}{\partial t} + \nabla \cdot (h\mathbf{u}Y_i) = \nabla \cdot [h(D + D_t)\nabla Y_i] - \omega_i$$

$$\omega_i = k_{fi} \prod_k [Z]_k^{v_{ki}^{*}} - k_{ri} \prod_k [Z]_k^{v_{ki}^{**}}$$

$$\frac{\partial hC_j}{\partial t} + \nabla \cdot (h\mathbf{u}C_j) = \nabla \cdot [h(D + D_t)\nabla C_j] - D_j + E_j + \theta_j$$

$$(1 - \phi)\frac{\partial h_0}{\partial t} + \nabla \cdot \mathbf{q}_b = \sum_j (D_j - E_j)$$




APF Basin 212
Flowrate = 34 L/s
Flow Time (hours): 0.07
20-Aug 14 Event Mean Inflow
3.460e+06
3.46e+06
9.20e+05
2.44e+05
6.50e+04
1.72e+04
4.58e+03
1.22e+03
3.24e+02
8.60e+01
2.28e+01
6.06e+00
1.61e+00
4.28e-01
1.14e-01
3.02e-02
8.02e-03
RWT
(ppb by volume)
1: Pre-Development
2: Baffle Without Curtain
3: Baffle With Curtain
4: Extended Baffle And Curtain

Coupling CFD w/ML (DeepXtorm) via HiPerGator

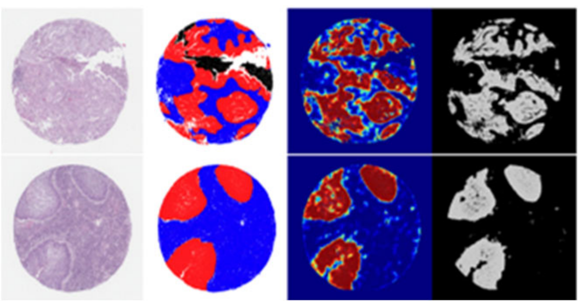
The Pond 212 intra-basin retrofit design with baffles and no geometric expansion (circa 2010), given the APF constraints, was based on individual CFD runs and individual baffle designs before implementation of UF's HiPerGator and ML algorithms. DeepXtorm optimizes pond performance through iterating the number/geometrics of baffles and/or pond geometrics shape/area/volume (if unconstrained).

HiPerGator and ML algorithms have made a profound advance in optimizing cost/benefit of pond design (intra-basin or shape/volume geometrics), and in particular retrofits which are more challenging.

If a current retrofit design of pond 212 is carried out the cost/benefit can be further improved with < 12 baffles of optimized geometrics without a parallel or regular baffle spacing.

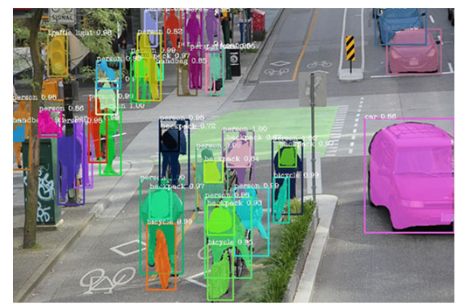
What is machine learning (ML)?

As a part of artificial intelligence (AI), ML is a scientific field that develops algorithms to discover and "learn" the underlying patterns and correlations automatically from the data. ML is widely applied in a range field from medicine, autonomous vehicle, to computer vision.



Burlutskiy et al. (2018)

UFTI-RTS-FDOT (2020)

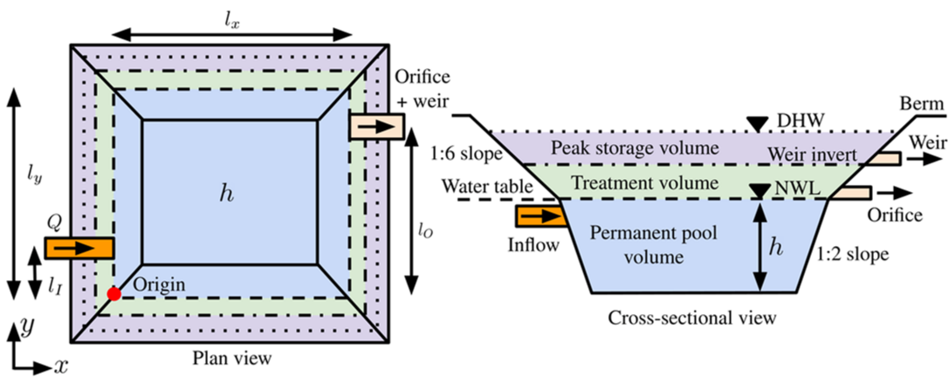


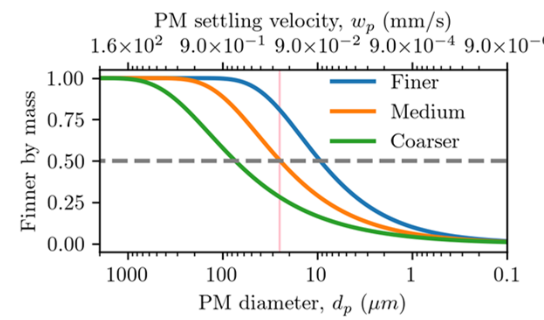
Google (2021)

Two *critical* benefits of ML for stormwater infrastructure design:

- ML can create *robust* surrogate model for CFD simulation. Once ML is developed and validated, pond performance analysis can be computed in *milliseconds*. Therefore a web-based app works.
- ML can be used to automatically *design* and *optimize* cost-effective stormwater system, for ponds this is the intra-pond baffle geometrics and/or pond shape/geometrics in new design or where external pond shape/geometrics are not economically or physically constrained for retrofits.

DeepXtorm forecasts basin performance for any geometry/loading

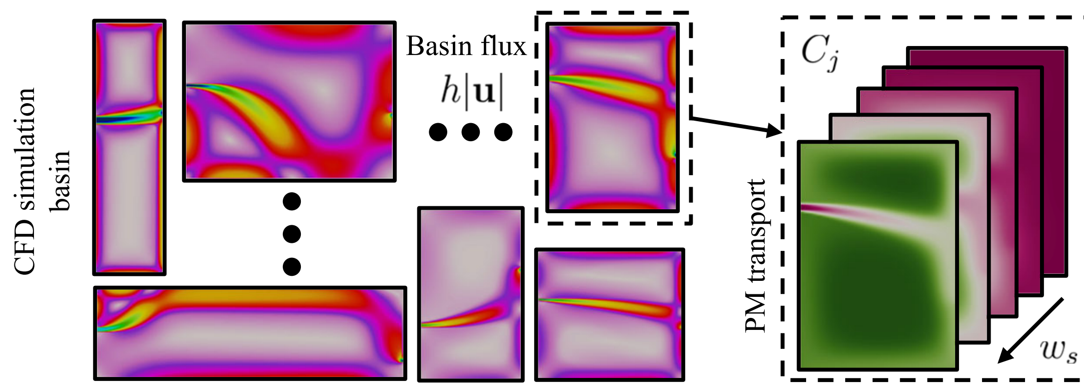




basinFoam (Li & Sansalone, 2020, 2010)

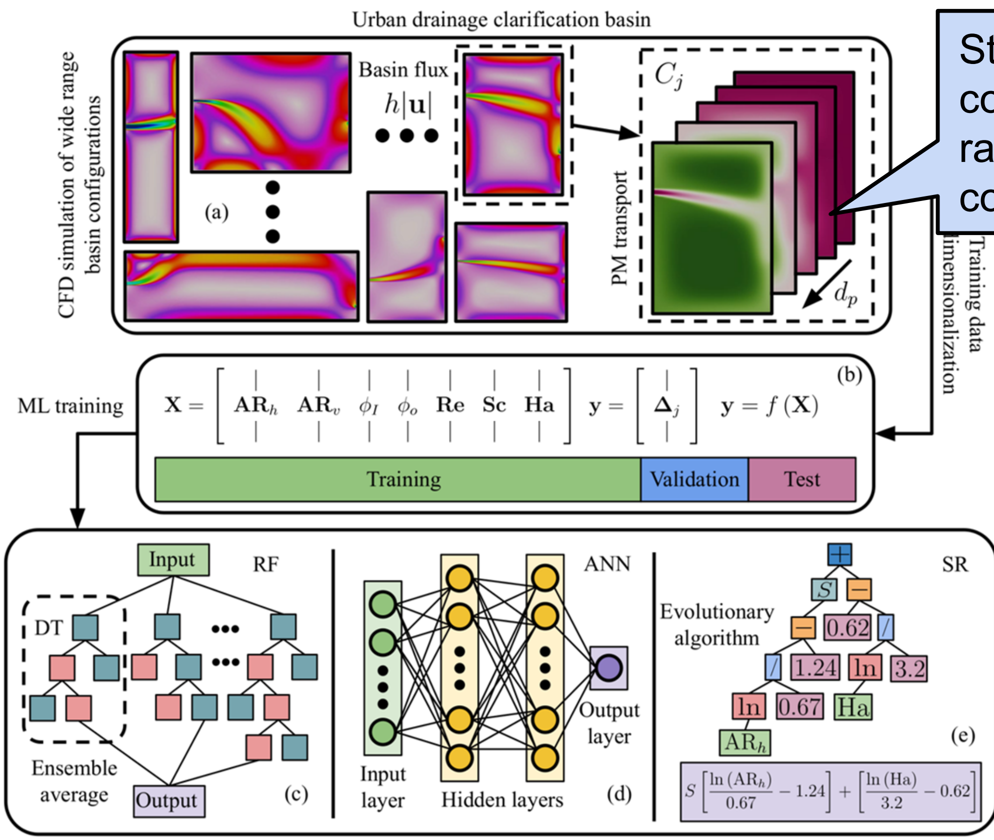
HiPerGator AI

3rd most powerful HPC in higher education *worldwide*

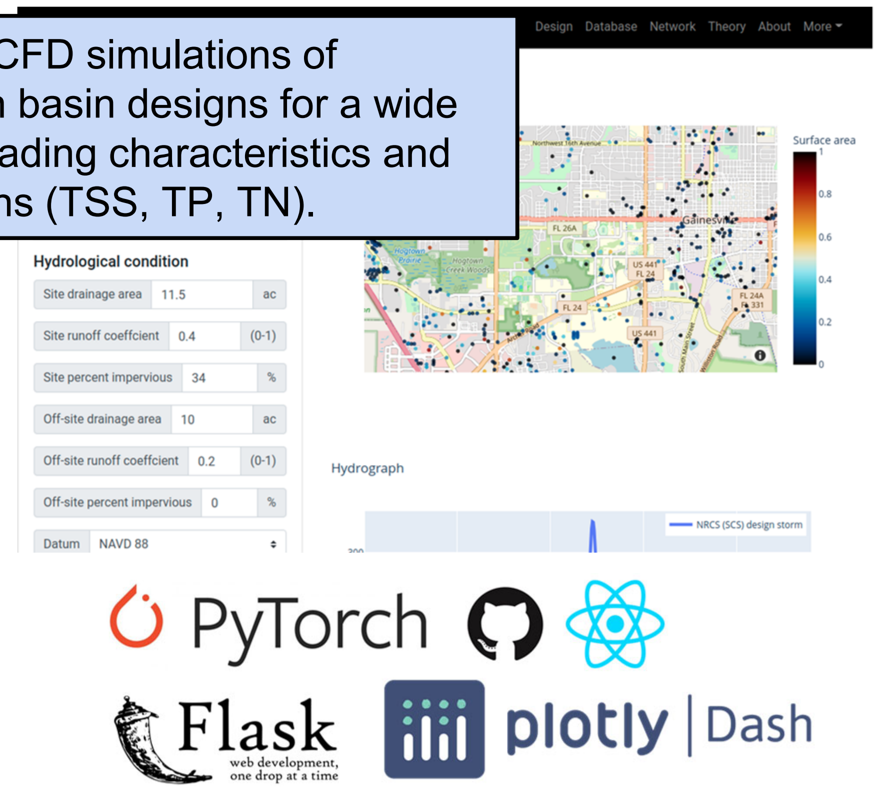


100,000+ simulations of common basin designs over a wide range of loading conditions

CFD-ML augmented pond design tool: **DeepXtorm**



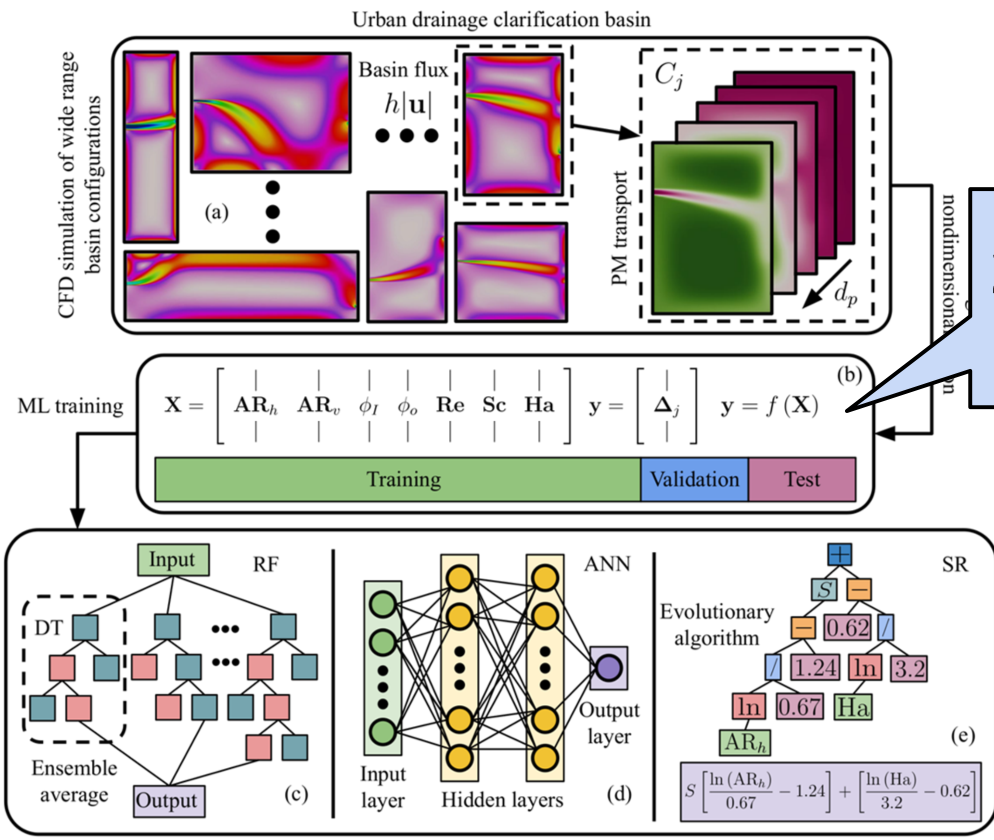
Step1: CFD simulations of common basin designs for a wide range loading characteristics and conditions (TSS, TP, TN).



Robust and *smart* analysis engine of **DeepXtorm** based on CFD and AI (ML)

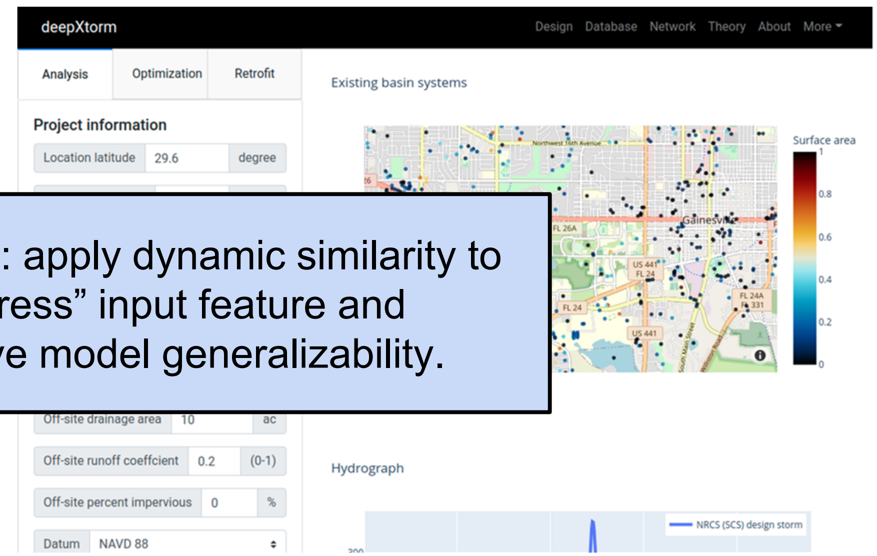
User-friendly web app interface of **DeepXtorm** based on modern web development frameworks

CFD-AI augmented basin design tool: **deepXtorm**



[Robust]() and [smart]() analysis engine of **deepXtorm** based on CFD and AI

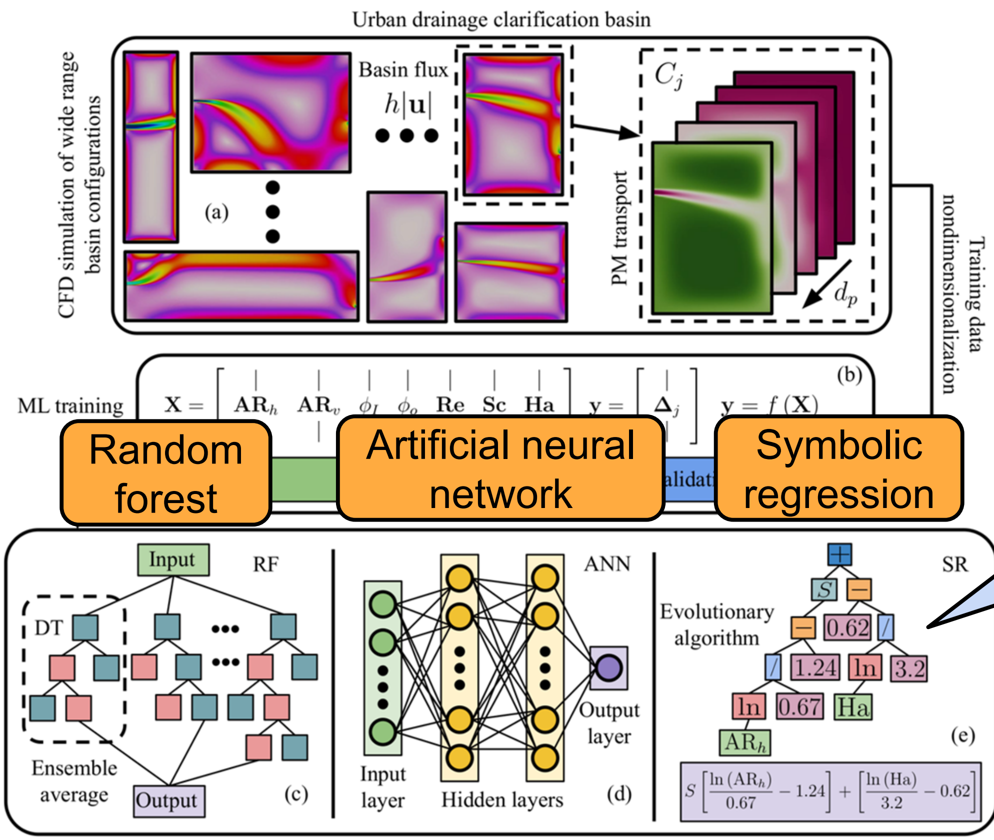
Step 2: apply dynamic similarity to "compress" input feature and improve model generalizability.



PyTorch · GitHub · React · Flask (web development, one drop at a time) · plotly | Dash

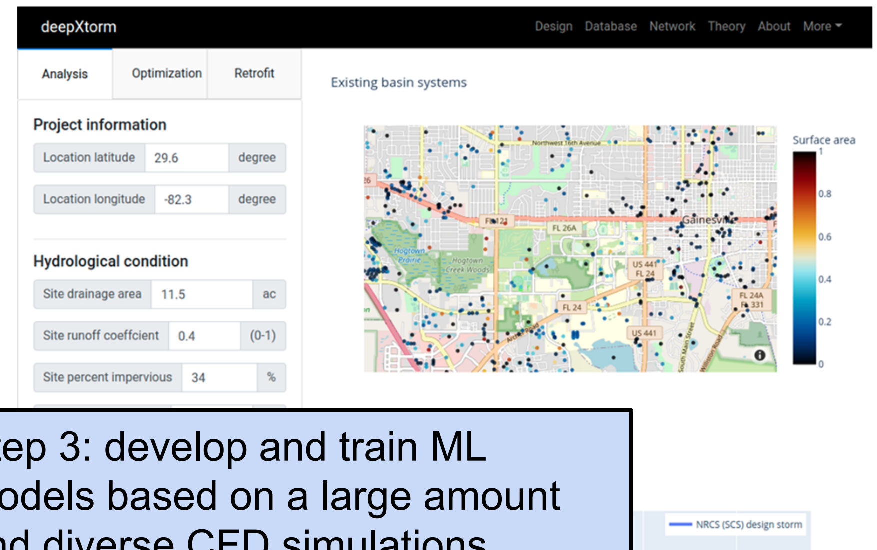
[User-friendly]() web app interface of **deepXtorm** based on modern web development frameworks

CFD-AI augmented basin design tool: **DeepXtorm**



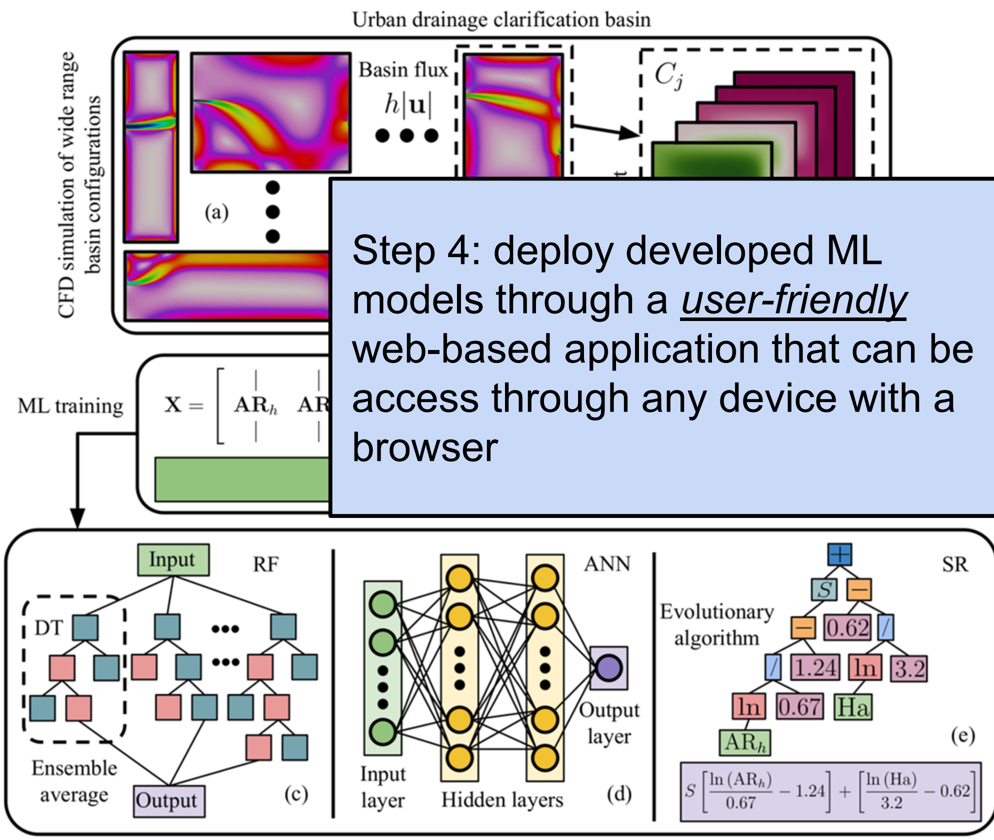
[*Robust*]() and [*smart*]() analysis engine of **deepXtorm** based on CFD and AI

Step 3: develop and train ML models based on a large amount and diverse CFD simulations (100,000+).

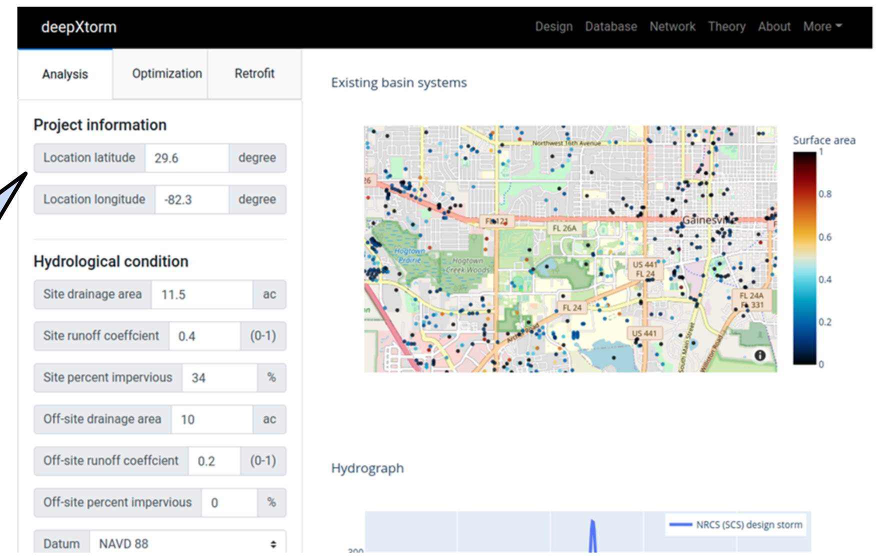


User-friendly web app interface of **deepXtorm** based on modern web development frameworks

CFD-AI augmented basin design tool: **DeepXtorm**



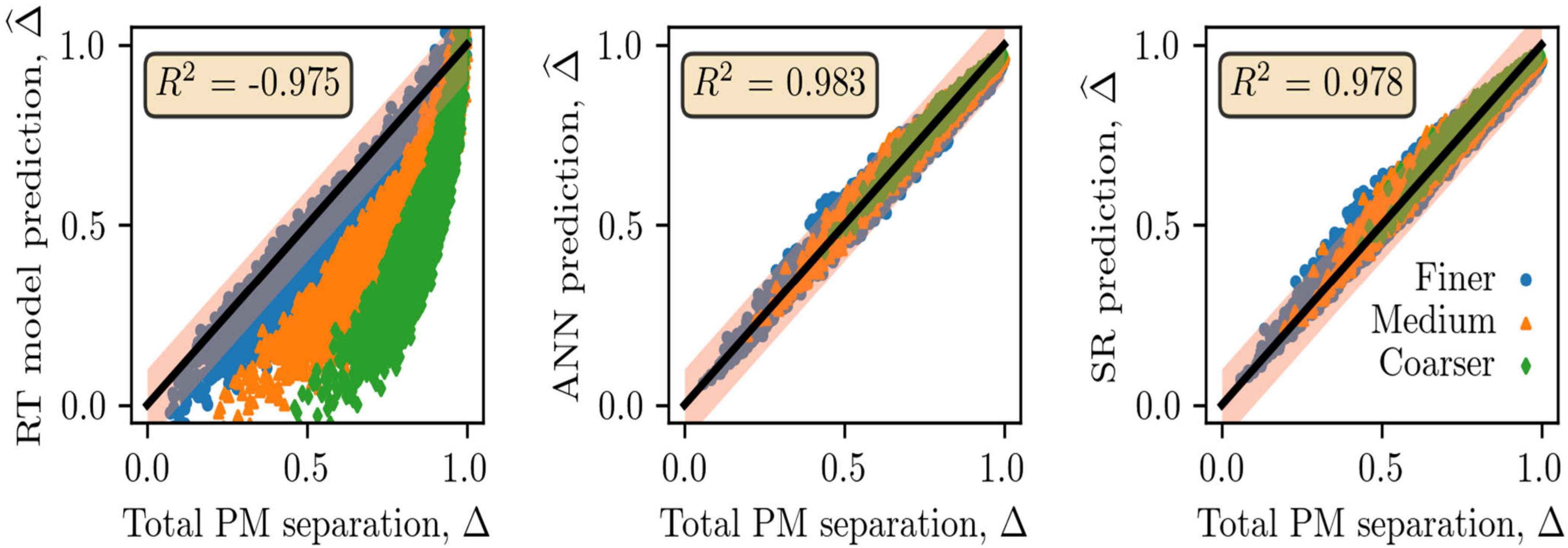
Step 4: deploy developed ML models through a *user-friendly* web-based application that can be access through any device with a browser



Robust and *smart* analysis engine of **deepXtorm** based on CFD and AI

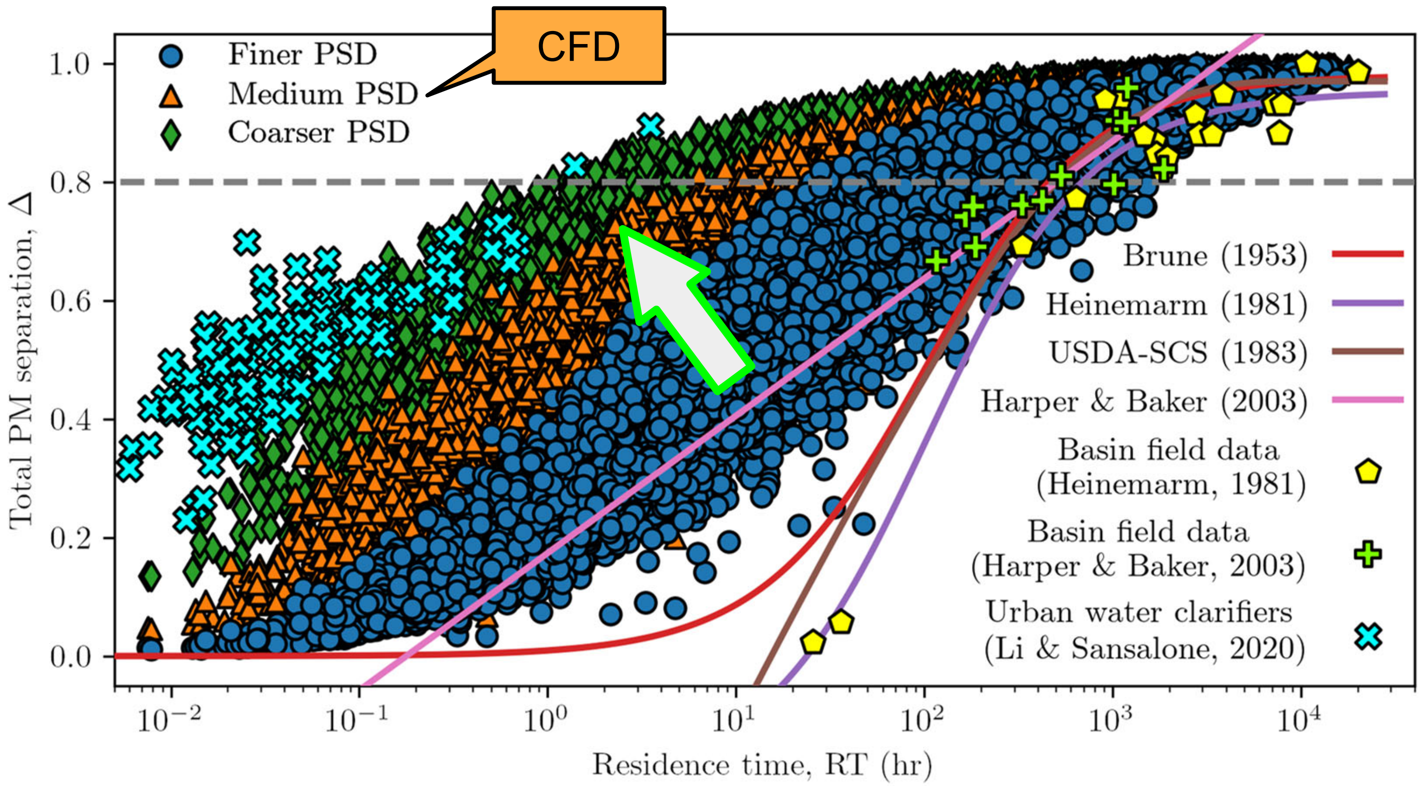
User-friendly web app interface of **deepXtorm** based on modern web development frameworks

A machine learning, ML model as a surrogate for CFD (therefore a stakeholder does not need to run CFD !)



We can debate the choice of a ML algorithm, here ANN and SR regression are shown. What is clear is that residence time, RT does not correlate to pond performance. As we progress with coupling CFD and ML we are moving to physics informed neural networks (PINNs).

The fatal attraction of residence time (RT) for pond performance



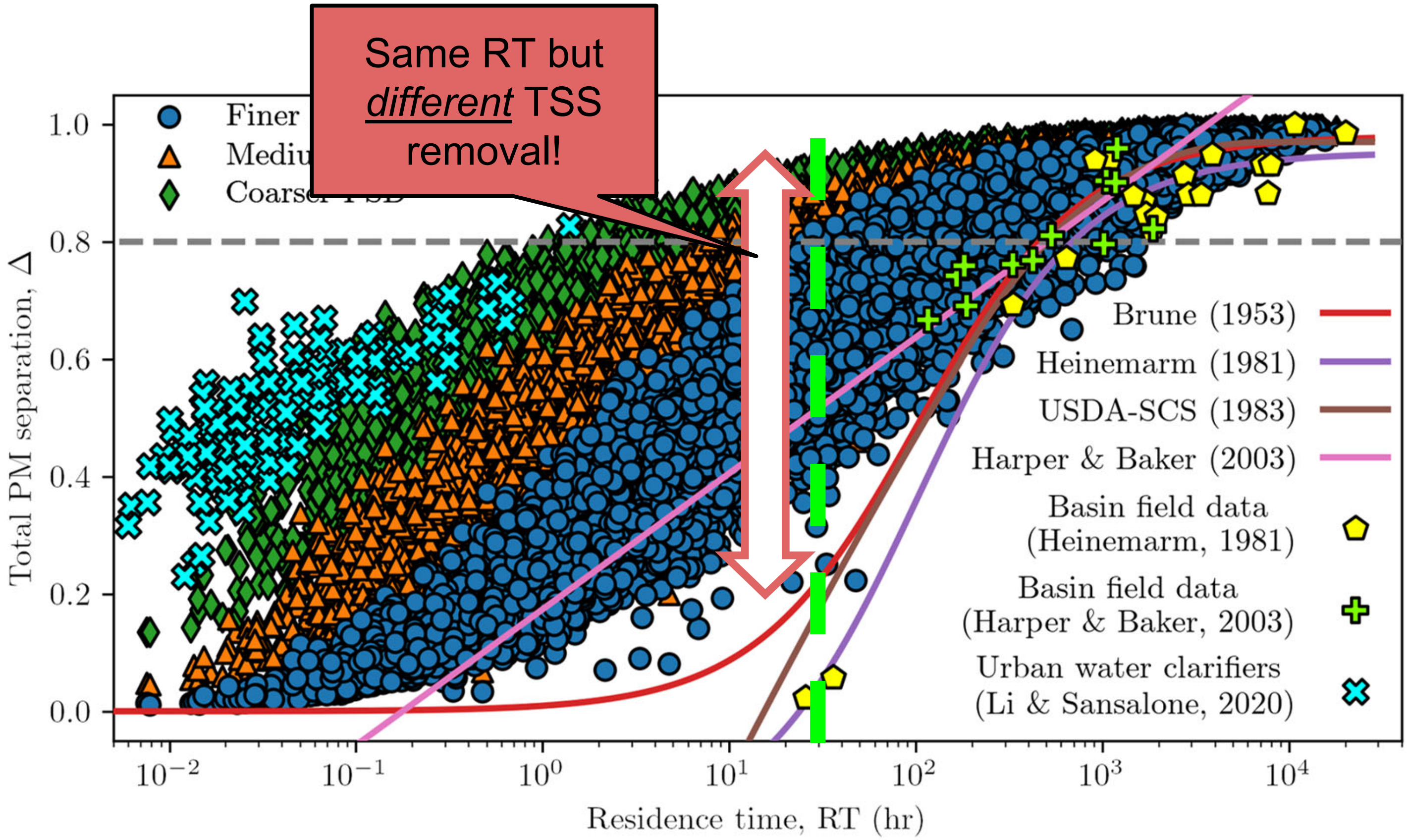
If you have limited samples, you have limited confidence!

In contrast to existing models, the geometry, PSD, and nutrient partitioning are explicit parameters in CFD!

160,000 CFD simulations for diverse geometry and loadings are illustrated !

- *Substantial influence* of PSD on basin performance and thereby basin design
- Residence time (RT) is *not robust and is not singular* to index basin performance
- Empirical method is *limited* by number of samples, *not representative* to generalize pond performance

Critical influence of particle size distribution (PSD)



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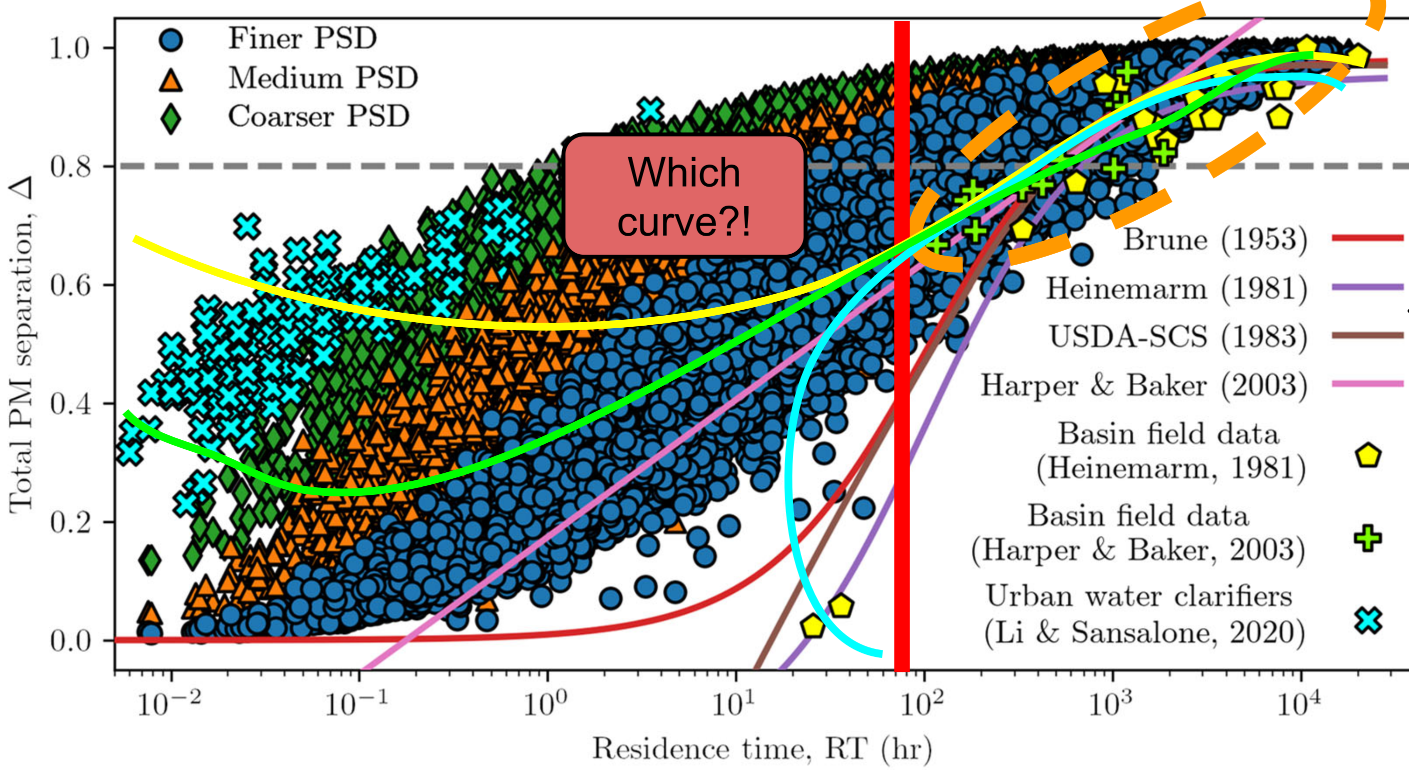
In contrast to existing models, the geometry, PSD, and nutrient partitioning are explicit parameters in CFD!

100,000+ CFD simulations for diverse geometry and loadings are illustrated !

- *Substantial influence* of PSD on basin performance and thereby basin design
- Residence time (RT) is *not robust and is not singular* to index basin performance
- Empirical method is *limited* by number of samples, *not representative* to generalize basin performance

Extrapolation of limited RT datasets



If you have limited samples, you have limited confidence!

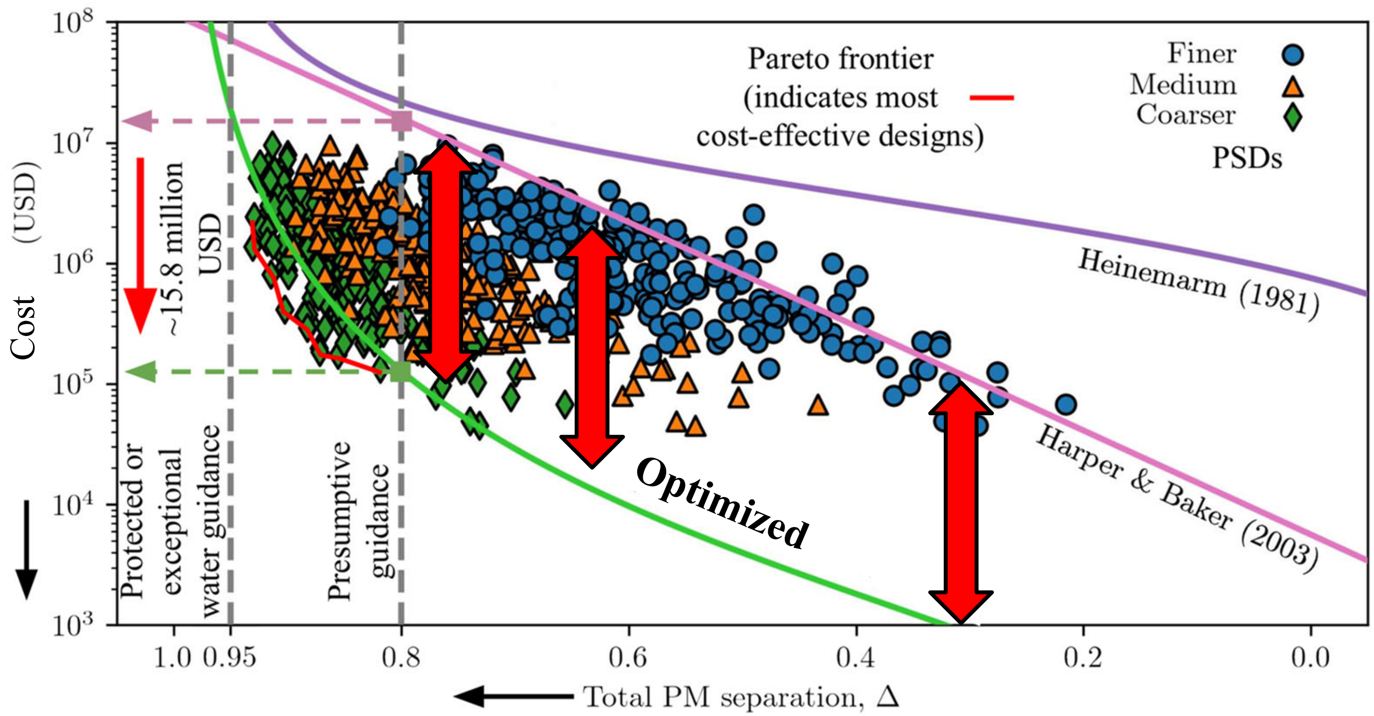
Existing methods

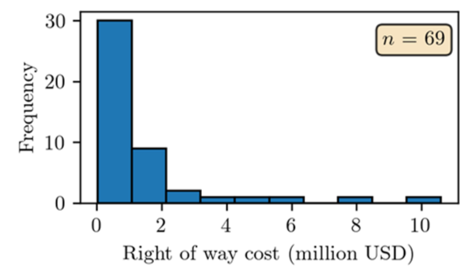
In contrast to existing models, the geometry, PSD, and nutrient partitioning are explicit parameters in CFD!

100,000+ CFD simulations for diverse geometry and loadings are illustrated !

- *Substantial influence* of PSD on basin performance and thereby basin design
- Residence time (RT) is *not robust and is not singular* to index basin performance
- Empirical method is *limited* by number of samples, *not representative* to generalize basin performance

Example: cost-effective 3.5 ac. basin **retrofit** design w/UF DeepXtorm model (benchmarked w/Florida data for PM as TSS, and TN/TP)





Basin of 3.5 ac.: benchmarking determined through 12 month in-situ monitoring

Bigger ponds do not equate to better treatment and smarter design !!

- *Exponential* scaling in land/construction cost, hence diminishing returns for basin cost-benefit
- Existing design guidance is not cost-effective, yielding nearly *100x* more costly basin design
- *Urgent need* for robust, scientifically-based, easy-to-use modern basin management tool!

Attributes of DeepXtorm compared to residence time indices

1. Physical scaling is required for empirical indices such as RT, by definition, since RT is empirical (not a fundamental model such as Newton's 2nd Law). Physical scaling is irrelevant for DeepXtorm which implements CFD analyses. The Navier-Stokes equations of CFD apply for large-scale fluid flows and also small-scale systems (see CFD slide). To infer that physical scaling is required for DeepXtorm is equivalent to stating that Newton's 2nd law is only applicable to a large pond and not to a small pond, or vice versa.

2. Nevertheless, the CFD engine (basinFoam) of DeepXtorm has been validated at a range of scales from (a) full-scale pond 212 tracer (rhodamine) with monitoring data collection by UF and peer-reviewed publications, (b) monitored prototype clarifier at UF as shown herein and (c) a bench-scale clarifier at UF illustrated in the reference peer-review publication list.

3. The Li and Sansalone (2020) publication and the Extrapolation of Limited RT Datasets slide clearly demonstrate that RT is fundamentally flawed based on 150 datasets from physically monitored systems. Furthermore, slide 41 with ML analyses also illustrates the flawed RT outcome. Slide 32 and 46 illustrate the unsustainable costs of RT for a single pond.

4. Li and Sansalone (2022 a,b,c) are in the top scientific journal in our field and address differences between DeepXtorm and Harper's RT method and economic consequences.

Science related to FL ponds, clarification, adsorptive-filtration media topics in this presentation

Li, H., Spelman, D., and Sansalone, J. (2024). Unit Operation and Process Modeling with Physics-Informed Machine Learning, *ASCE J. of Environmental Engineering*, 150 (4), 04024002

Baffled clarification basin hydrodynamics and elution in a continuous time domain. *Journal of Environmental Engineering*, *595*, 125958. https://doi.org/10.1016/j.jhydrol.2021.125958 (Basin 212, APF)

Li, H., and Sansalone, J. (2022a) Implementing machine learning to optimize the cost-benefit of urban water clarifier geometrics, *Water Research*, 118685

Li, H., and Sansalone, J. (2022b). A CFD-augmented ML alternative to residence time for clarification basin scaling, *Water Research*, 209, 117965 (Basin 212, APF)

Li, H., and Sansalone, J. (2022c). Interrogating common clarification models for unit operation systems with dynamic similitude, *Water Research*, 215, 118265 (Basin 212, APF)

Li, H., and Sansalone, J. (2022). InterAdsFoam: An Open-Source CFD Model for Granular Media–Adsorption Systems with DynamicReaction Zones Subject to Uncontrolled Urban Water Fluxes, *Journal of Environmental Engineering*, 148 (9), 04022049

Li, H. and Sansalone, J. (2021). Benchmarking Reynolds-Averaged Navier-Stokes Turbulence Models for Water Clarification Systems, *Journal of Environmental Engineering*, 147 (9), 04021031, **Publication received ASCE's 2023 Rudolph Hering Medal**

Li, H., Spelman, D., and Sansalone, J. (2021). Baffled clarification basin hydrodynamics and elution in a continuous time domain. *Journal of Hydrology*, *595*, 125958. https://doi.org/10.1016/j.jhydrol.2021.125958 (Basin 212, APF)

Li, H., and Sansalone, J. (2021). CFD with evolutionary optimization for stormwater basin retrofits. *Journal of Environmental Engineering*, *147*(7), 04021017. https://doi.org/10.1061/(ASCE)EE.1943-7870.0001881

Li, H., and Sansalone, J. (2020). CFD as a complementary tool to benchmark physical testing of PM separation by unit operations. *Journal of Environmental Engineering*, *146*(11), 04020122. https://doi.org/10.1061/(ASCE)EE.1943-7870.0001803

Wu T. and Sansalone J, (2013c). The Role of Aqueous Matrices and Media Substrates on Overall Mass Transfer Kinetics of Phosphorus to Filter Media, *Journal of Environmental Engineering,* 139 (1), 1-10, 2013., **FDEP funded research testing adsorptive media**

Wu T. and Sansalone J, (2013b). Phosphorus Equilibrium II: Comparing Filter Media, Models and Leaching, *Journal of Environmental Engineering,* 139, November, 1325-1335., **FDEP funded research testing adsorptive media**

Framework of what is proposed ?

1. A CFD-ML simulation modeling tool (DeepXtorm) for stakeholders (regulators, engineers/scientists, infrastructure owner/operators, managers). DeepXtorm <u>optimizes stormwater treatment pond geometrics (intra-pond and/or external geometrics) to achieve load reduction goals</u> ***focused on chemicals of interest***, e.g. (in FL) TN, TP, dissolved/particulate N, P and particulate matter (PM) indices such as suspended solids (TSS) or SSC.

2. DeepXtorm's engine is powered by CFD simulations (> 100,000) based on existing pond geometrics and ML algorithms (e.g. ANN) w/computational results residing on UF's HiPerGator HiPerGator is the 3rd most powerful academic HPC worldwide.

3. DeepXtorm can be utilized either as a (I) research-based tool (as illustrated herein at APF) or (II) developed, licensed and deployed as a web-based app. If, as a user-friendly web-based app. (case II), educational/training workshops will be held to implement and maintain/upgrade DeepXtorm.

What are environmental/ecological and stakeholder benefits?

1. Stormwater ponds (most are impaired based in part on residence time, RT guidance) are the most prevalent unit operation/process (UOP) in the USA. With increasingly rigorous load reduction goals (e.g., proposed FL *Clean Waterways Act)*, ***DeepXtorm is the only tool*** providing significant pond cost reduction ***while*** achieving load reduction goals of TN, TP, PM…

2. A stakeholder can deploy DeepXtorm in three modes for a chemical or PM:
   (1) analysis of existing pond geometrics/hydrodynamics for load goals,
   (2) design to optimize pond geometrics/hydrodynamics for load goals,
   (3) retrofit design (intra-pond geometrics {e.g. baffles}/hydrodynamics and/or pond area/volume) to meet load goals for an impaired pond.

3. DeepXtorm inputs are existing/proposed pond geometric (intra-pond or external shape/area/volume), hydrology/hydraulics loadings, nutrients (or any chemical database), partitioning (nominally dissolved vs. PM-bound) and particle size distribution (PSD) of PM (PSD databases published).

4. Future DeepXtorm modes are: BMPs, green infrastructure, other chemicals.