A satellite-monitoring research agenda for urban stormwater infrastructure: capabilities, gaps, and a community-benchmark proposal

Saurav Kumar, Ph.D., P.E.*

2026-06-09

Abstract

Urban stormwater best management practices (BMPs) are a core component of urban-resilience portfolios worldwide. Per-asset performance monitoring, however, is both limited and difficult to enumerate at the global scale. We argue that publicly available satellite Earth observation has reached the capability point at which the resulting accountability gap can be closed at portfolio scale, and that the binding constraint on this transition is now community benchmark data rather than satellite data. We identify three operational capabilities available now. First, Human-in-the-loop segmentation efficiently yields survey-grade asset footprints. Second, the BMP type, historically the most difficult to discriminate, is recoverable from learned multi-physical embeddings. Third, per-asset spectral departures beyond seasonality and regional weather are detectable. All three capabilities share the same underlying gap: a lack of community benchmark data that limits

---

*School of Sustainable Engineering and the Built Environment, Arizona State University, Tempe, AZ 85287, USA. Email: sk2@asu.edu; Web: https://waterdmd.info

operationalization. This is the single research-agenda priority capable of converting present-day satellite capability into deployable accountability for a major class of urban environmental infrastructure that today operates with little per-asset verification.

The accountability gap

Urban stormwater best management practices (BMPs) are the engineered mechanisms through which urbanized watersheds meet nutrient, sediment, and metals loading targets under regulatory frameworks such as the US Total Maximum Daily Load (TMDL) program[1]. Driven by TMDL and similar programs globally, retention ponds, detention basins, bioswales, and constructed wetlands are deployed at scale across jurisdictions and embedded in private development under post-construction stormwater permits. These assets are subject to progressive aging, sediment and debris accumulation, and a corresponding loss of treatment capacity over their service life[2–4]. Excess nitrogen and phosphorus alone are estimated to drain billions of US dollars per year from the US economy through depressed property values, lost recreation, and elevated drinking-water treatment costs[5,6]. Despite the financial costs, asset performance monitoring remains rare and fragmented[7,8].

The monitoring gap is structural in origin. Flow-weighted composite sampling at a single BMP station needs flow measurements, chemical testing, and sample collections, all of which are expensive to operate[9]. The most comprehensive public repository we could identify for urban stormwater, the International Stormwater BMP Database (IBMPDB)[10], contains sustained inflow/outflow monitoring for fewer than 800 sites, and we are not aware of any aggregated count of BMPs under sustained monitoring at a national or global scale. Nation-scale enumeration is similarly partial. The US EPA's Municipal Separate Storm Sewer System (MS4) Phase II permit, a Clean Water Act programme regulating stormwater discharges from small MS4 operators, covers more than

6,800 entities, each typically managing hundreds to thousands of post-construction BMPs, with operations-and-maintenance, rather than design, failure dominating performance loss in those settings where it has been studied[11,12]. Regulatory compliance, in the absence of sustained monitoring, relies on static, type-averaged removal efficiencies drawn from the literature, with no account taken of site-specific hydrology, maintenance history, or ecological transitions[13,14].

The accountability gap is widening. Cities across South and Southeast Asia are deploying stormwater infrastructure at unprecedented rates under sponge-city programs[15], and analogous national urban-resilience missions (such as Indonesia's National Urban Flood Resilience Project and India's Atal Mission for Rejuvenation and Urban Transformation (AMRUT) 2.0) are extending to sub-Saharan Africa and Latin America through multilateral climate-adaptation finance from the World Bank and Green Climate Fund[16,17]. These programs embed measurement, reporting, and verification (MRV) requirements that track project-level outcomes; meeting MRV at the per-asset resolution where performance loss occurs is currently infeasible by in-situ means at scale. In many recipient cities, structured BMP monitoring is sparse, and asset inventories are unevenly covered. The verification gap appears widest in precisely those settings where the deployment rate is highest.

This Perspective advances three claims. **First**, satellite Earth observation has reached a point where portfolio-scale BMP accountability is technically feasible, as we demonstrate in a 36-site empirical pilot. **Second**, each capability is accompanied by a caveat that does *not* identify a missing satellite, sensor, or algorithm, but rather points to a single underlying gap. The field lacks a community benchmark dataset comparable to those provided by CAMELS[18] and Caravan[19] for catchment hydrology. **Third**, the construction of such a benchmark, undertaken in partnership with the municipal programs and multilateral funders that already manage these assets, is the single research-agenda priority capable of converting capability into both regulatory deployment and scientific tractability. Given the investment in these stormwater assets and the global stakes around their performance, the incentive is high for the field to close this gap; this is a high-value, near-term opportunity, and the resulting accountability would benefit both regulators and scientists.

Where the satellite stack stands today

Satellite Earth observation (EO) has closed analogous accountability gaps in agriculture[20,21], forestry[22,23], global surface-water extent[24], and inland water quality[25]. These successes share characteristics, namely large spatial extent and distinctive phenology, that stormwater BMPs lack. Individual BMP footprints are small, often <2 ha, are spectrally similar to adjacent greenspace, and have no shared management calendar. The remote-sensing community has accordingly given them comparatively little attention, despite their dominant role in engineered nonpoint nutrient removal in developed watersheds.

Several elements of the satellite and climate-reanalysis stack have nonetheless matured over the past decade: free 10-m optical imagery (Sentinel-2) at sub-weekly revisit, cloud-penetrating C-band synthetic-aperture radar (SAR; Sentinel-1), ERA5-Land global climate reanalysis[26], PRISM 4-km gridded climate over the conterminous United States[27], and sub-meter commercial imagery (PlanetScope, SkySat, Airbus) at task-on-demand cadence. To this stack has recently been added AlphaEarth Foundations, a 64-dimensional per-pixel learned embedding that distills Sentinel-2, Sentinel-1 SAR, Landsat, and ERA5-Land observations into a globally consistent multi-physical representation[28]. The resulting stack is freely available, global, and operational.

The fundamental difficulty of the BMP target itself, by contrast, has not changed. The asset is small relative to the satellite footprint, surrounded by spectrally similar land cover, and its primary function—removal of dissolved pollutants from water—is rarely visible in optical reflectance. Closing the accountability gap, therefore, requires what we term *operational decomposition*: separating the questions a satellite can plausibly answer with today's sensors (where the asset is, what type it is, whether its state has changed) from those it cannot (the instantaneous concentration of its outflow). Each of those operations interacts differently with the choice of feature substrate—spectral indices, raw spectral bands, or learned embeddings—and the substrate that is appropriate for one operation may be wrong for another. We treat the resulting substrate–operation matrix as an organizing principle for satellite-based BMP monitoring.

We illustrate this organizing principle with a 36-site empirical pilot across 12 US states, comprising 25 retention ponds, 7 wetland basins, and 4 detention basins observed during 2018–2024 (Methods and Supplementary Tables S1–S3). The pilot is intended as a capability test rather than a deployment. Given the limited sample size and the class imbalance across BMP types, the numerical results that follow should be read as existence proofs of operational tractability rather than as generalization estimates of deployable accuracy. Within that interpretive frame, three capabilities emerge in sequence, each accompanied by a caveat that identifies the binding constraint preventing its full operational realization.

Capability 1: Inventory is deployable today

We delineated all 36 BMP sites in 0.6-m National Agriculture Imagery Program (NAIP) four-band imagery using the Segment Anything Model (SAM, ViT-H backbone)[29] as implemented in `sam-geo`[30]. The workflow is human-in-the-loop at the labeling stage. SAM's automatic mask generator (ViT-H backbone, 12-point-per-side grid; Supplementary Methods) segments each NAIP tile into candidate objects without prompts, and an operator then selects the segment corresponding to the BMP and labels three to four adjacent reference objects (tree, grass, crop, impervious, open water); the labeled polygons are saved as GeoJSON. Multi-component sites yielded 75 polygons across the 36 sites, spanning approximately 500 m² to 8.26 ha (median 0.37 ha; Supplementary Figure S1). Labeling required, on average, less than 2 minutes per site. The polygons are released as GeoJSON and, to our knowledge, constitute the first publicly available footprint dataset for this number of monitored BMPs, since the IBMPDB contains only point coordinates, and municipal asset databases are non-uniform in coverage.

A two-minute-per-site labeling rate is sufficient to inventory thousands of post-construction BMPs over a period of days, rather than the months required by ground-based surveying. We used U.S. National Agriculture Imagery Program (NAIP) imagery[31]. NAIP coverage is restricted to the United States. Outside the United States, Planet Skysat and other commercial very-high-resolution archives[32] provide functionally equivalent inputs. The inventory capability is therefore operational at portfolio scale today.

Full automation, in which the BMP segment is identified among SAM's candidate masks without the operator's selection-and-labeling step, would require a labeled training set on the order of hundreds to thousands of BMPs in order to fine-tune the foundation model for what is a small-target, low-contrast detection task, and a training set of that scale does not yet exist in the public domain. The 36-polygon dataset released alongside this article constitutes an initial contribution toward such a corpus rather than a sufficient one.

Capability 2: Type is recoverable from the spectral-temporal substrate

BMP type determines hydrologic function and the expected biogeochemical pathway. Common BMP types include: Retention ponds (RP) that maintain a permanent pool with stable surface water; detention basins (DB) that drain dry between events and exhibit pronounced vegetation seasonality; and wetland basins (WB) that maintain a dynamic stage driven by both temperature and hydroperiod. The taxonomy contains numerous additional types, and we have selected these three as representative examples. Municipal asset databases lack standardized type-coding conventions, so any portfolio-scale monitor must first answer *"what kind is this?"* solely from imagery. Whether the spectral-temporal substrate carries enough information to do so has been an open question.

We evaluated three feature substrates in direct comparison on the 36-site pilot. Track A consists of six commonly used handcrafted indices (NDVI, NDWI, EVI, SAVI, NDMI, BSI) paired with 100-m annular-buffer residuals (BMP minus buffer, to remove regional context variance; Supplementary Methods), yielding 36 features per site. Track B comprises the BMP-side annual means of the 12 raw Sentinel-2 bands (12 features per site); separately, all 66 two-band normalized-difference indices were screened univariately as a control (Supplementary Methods). Track C employs AlphaEarth Foundations' annual 64-dim embeddings, mean-pooled per BMP polygon. For each substrate, three pairwise type discriminations were scored by area under the receiver-operating-characteristic curve (AUC) under leave-one-out logistic regression, with bootstrap confidence intervals and permutation-null mutual information.

The result is unambiguous in direction (Fig. 1; Table 1). The handcrafted spectral substrate (Track A) recovers the easier permanent-water-vs-vegetated-wetland pair but underperforms on the detention-basin pairs. The raw Sentinel-2 bands together with an exhaustive search over all 66 two-band normalized-difference indices (Track B) recover only the same easy pair, and only marginally: no single data-derived index survives correction for the 66-index search, and both detention-basin contrasts remain at chance. The difficulty, therefore, lies in discriminating between detention basins, which no linear treatment of the spectral bands can resolve. The learned multi-physical substrate (Track C) clears all three pairwise discriminations above chance, including the wetland-vs-detention pair that hinges on hydroperiod and surface-water dynamics. Post-hoc per-site correlations confirm that the AlphaEarth axes are physically grounded, with individual axes tracking vegetation greenness, water-vs-vegetation contrast, and bare-soil and moisture signatures (Supplementary Table S9). The 64-dimensional representation contains the physical signals that hand-crafted indices encode, along with Sentinel-1 SAR backscatter and ERA5-Land climate context, which are absent from optical-only indices.

The numerical AUCs at this *n* are not generalization estimates. The wetland-vs-detention discrimination is evaluated on 11 sites, and the retention-vs-detention discrimination on 29 sites, with a 25/7/4 imbalance overall. The pilot establishes that the *substrate carries the information*. To determine the field's achievable classifier accuracy in deployment, a substantially larger labeled sample is required. A *deployable* type classifier, as distinct from substrate-level recoverability, would require hundreds of labeled BMPs across the type taxonomy and climate–hydrology gradient. The IBMPDB's 820 BMPs lack standardized type labels and polygon footprints. Assembling a labeled training set is therefore a benchmarking task rather than a satellite-engineering one.

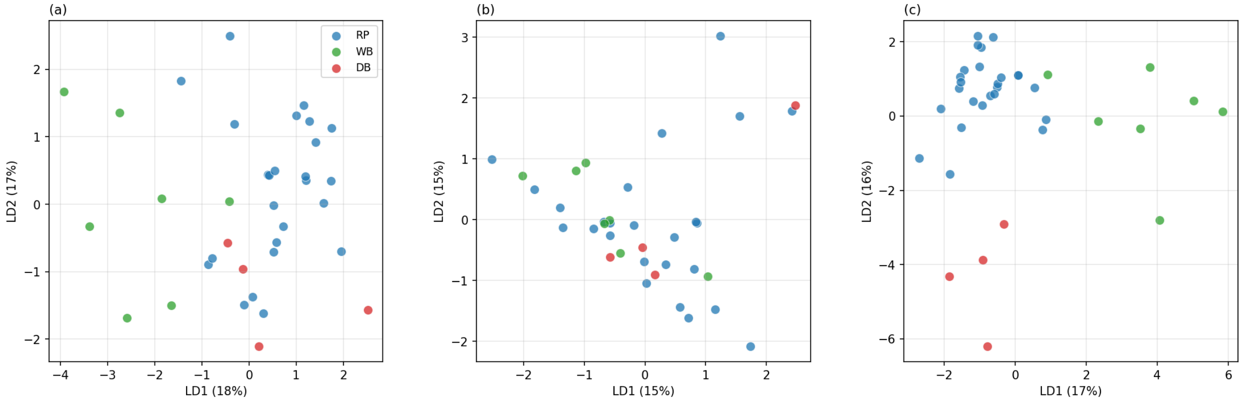

Figure 1: Fig. 1 | BMP type information is recoverable from learned multi-physical substrates. Linear discriminant analysis projects each per-site feature vector onto the two axes that maximize between-class versus within-class variance. (a) Hand-crafted indices (Track A); WB and DB are partially separate from RP but not from each other. (b) Raw S2 bands (Track B); little structure is evident. (c) AlphaEarth (Track C) shows visible three-way separation, with DBs concentrated in a distinct lower-left region, consistent with the Track C AUCs reported in Table 1. Per-site classification confidence on Track C ranges from 0.00 to 1.00, with 21 of 36 sites at confidence > 0.85 and three sites at confidence < 0.30 (Supplementary Table S4).

Table 1: Table 1 | Pairwise type-discrimination AUC (95% bootstrap CI) and mutual-information permutation p-value, per substrate.

Pair	Track A (hand-crafted indices)	Track B (S2 raw bands)	Track C (AlphaEarth, 64-d)
RP-vs-WB ($n = 32$)	**AUC 0.87 (0.70–1.00),** $p = 0.052$	AUC 0.65 (0.38–0.87), $p = 0.42$	AUC 0.79 (0.55–0.98), $p = 0.008$
WB-vs-DB ($n = 11$)	AUC 0.57 (0.18–0.90), $p = 0.54$	AUC 0.29 (0.00–0.67), $p = 0.33$	**AUC 1.00 (1.00–1.00),** $p = 0.004$
RP-vs-DB ($n = 29$)	AUC 0.36 (0.07–0.69), $p = 0.79$	AUC 0.04 (0.00–0.15), $p = 0.83$	**AUC 0.71 (0.33–0.96),** $p = 0.052$

Capability 3: Within-asset change is detectable beyond seasonality and weather

Change detection is the operational endpoint of portfolio-scale monitoring. Inventory establishes which assets exist; type identifies their intended hydrologic function; only change detection establishes whether that function is being maintained. The empirical difficulty is that the failure modes of interest, such as sediment accumulation, vegetation overgrowth or die-off, outlet clogging, and partial structural failure[3,33,34], produce spectral signatures that are small relative to the seasonal cycle and the regional weather variability common to every BMP regardless of condition, generating the false-positive load that has discouraged prior remote-sensing efforts at this asset class.

Distinguishing asset-specific signal from regional context is therefore the central methodological problem of this capability. We address it through a two-stage residualization that targets the two dominant sources of shared variance: (i) the recurring annual cycle and any long-term drift at the asset itself, and (ii) the asset's response to the regional climate context shared with surrounding land cover. Sequential removal of these components yields a per-asset, per-feature residual whose remaining variance cannot be attributed to season, drift, or shared weather, and on which the change-detection question can be posed.

Concretely, for each (site, role, feature) on the monthly tracks, a per-asset harmonic regression

$$y_t = a + bt + c\sin(2\pi t/12) + d\cos(2\pi t/12) + \varepsilon_t$$

is fit to the 2018–2024 series, and the residual ε_t is retained. The BMP-and-buffer paired differential of these residuals is then regressed against PRISM monthly precipitation and temperature anomaly z-scores at lags of 0, 1, and 3 months, and the second-stage residual η_t is retained as the BMP-specific spectral departure. The within-site temporal standard deviation $\tilde{\sigma}$ of η_t furnishes a per-asset, per-feature noise floor that adapts to portfolios spanning an order of magnitude in size, surrounding land cover, and local climate. Variance accounting for the two stages (Supplementary Table S8) confirms both contribute, with substrate-dependent asymmetry. The pipeline runs identically when ERA5 reanalysis is substituted for PRISM, the natural global generalization.

We aggregate the standardized residuals across substrate-internal features into a root-mean-square z-score

$$M_t = \sqrt{\mathrm{mean}_f\left[\left(\eta_{f,t}/\tilde{\sigma}_f\right)^2\right]}$$

and define an event as a maximal contiguous run of $M_t > 1.5$ persisting for ≥ 2 periods. Both the threshold and the persistence requirement are illustrative defaults at pilot scale and would be tuned to portfolio characteristics and operator risk tolerance in deployment. The squared-deviation aggregation yields interpretive consistency across substrates of different feature counts (6, 12, or 64).

Results across the 36-site pilot are summarized in Fig. 2 and Table 2, and they exhibit the diagnostic behavior of a sensitive but not yet specific monitor. The monthly substrates flag within-asset departures at 44–61% of sites, a portfolio-level rate too high to act upon without further triage; raising the threshold suppresses the small genuine signals that motivate the monitoring effort. We address triage through a second filter, *cross-substrate consistency*, defined as the same site being flagged by another substrate within ±6 months. The premise is that a real condition change should leave a coordinated fingerprint across feature representations, with the underlying physical mechanisms (water encroachment, vegetation stress, surface darkening, sediment plume settling) affecting different bands at temporally offset lags rather than simultaneously. In the present pilot, the resulting shortlist comprises four physical assets: Shop Creek Pond (RP, CO), Carver County Dry Detention Pond (DB, MN), Cottonwood Wetlands (WB, CO), and Natomas Basin 4 (RP, CA), with event signatures detailed in Supplementary Table S6. Because Tracks A and B both derive from Sentinel-2 reflectance, this filter is a cross-substrate *consistency* check rather than independent confirmation.

The annual AlphaEarth substrate (Track C), which dominated the type-discrimination problem, flags only one event across 2017–2024 and contributes zero cross-substrate-consistent events when paired with the monthly tracks. The binding constraint is temporal cadence, not substrate quality: the annual representation cannot resolve the monthly variability that within-asset change detection requires. This is an artifact of AlphaEarth's annual release rather than a limitation of learned multi-physical representations; foundation models such as Clay[35] and Prithvi[36,37] operate at finer cadence and could in principle support both operations from a single representation. The broader point for benchmark design holds nonetheless. No single representation is simultaneously optimal across the inventory, type, and change-detection operations at the cadences each requires, and the appropriate substrate must therefore be selected per operation rather than chosen once for the portfolio. A community benchmark must accommodate the full range of cadences and feature dimensionalities in the satellite stack, rather than tuning to whichever representation happens to dominate a single benchmark task. Complete event listings for all three substrates are provided in Supplementary Tables S5–S6.

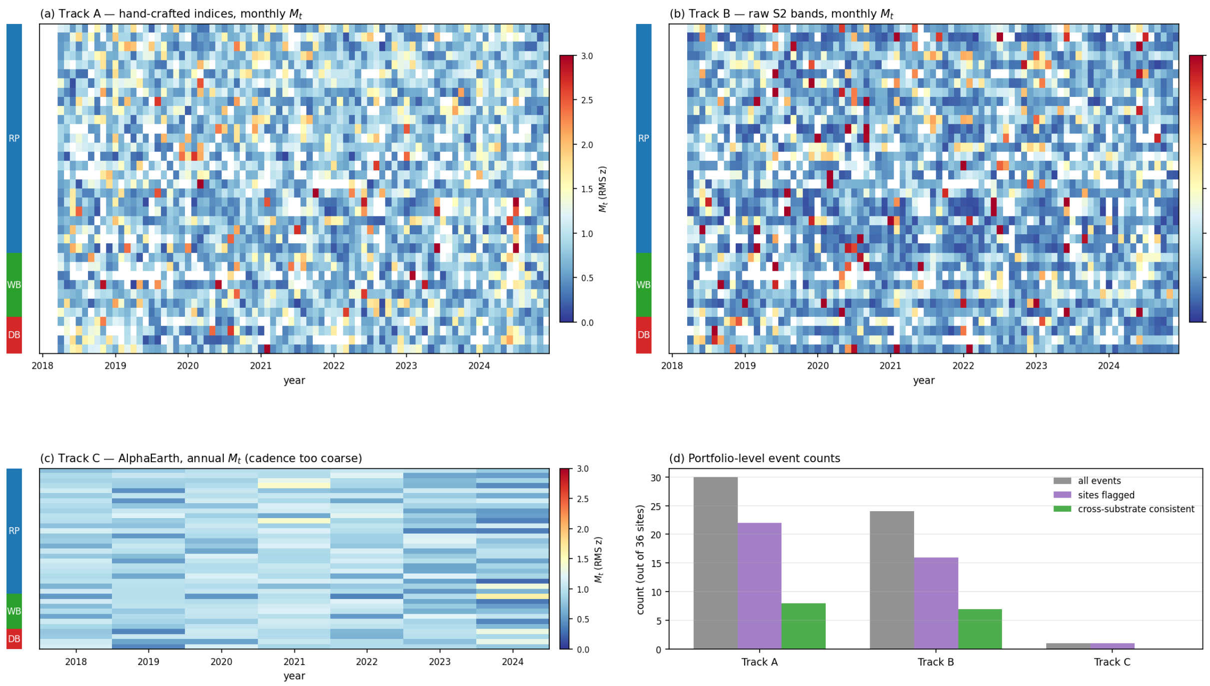

Figure 2: Fig. 2 | Within-asset departures are detectable from monthly spectral substrates after two-stage residualization. (a, b) Per-site monthly departure magnitude M_t (RMS z-score across substrate-internal features) for Track A (hand-crafted indices) and Track B (raw S2 bands), 2018–2024; rows are sites grouped by type (RP/WB/DB), and columns are months. Red cells exceed the $M_t > 1.5$ event threshold. (c) Track C (annual AlphaEarth) over the same site set, illustrating that the annual cadence is too coarse to surface within-asset events. (d) Portfolio-level event counts per substrate, including total events, sites flagged, and cross-substrate-consistent events (a site flagged by another substrate within ±6 months). The substrate that performs best on type discrimination (Track C) is the substrate least suited to change detection at the relevant timescale, and temporal cadence is the dimension along which this trade-off is most evident.

Table 2: Table 2 | Per-substrate change-detection portfolio summary. Cross-substrate consistency is defined as another substrate flagging the same site within ±6 months (or within the same year for Track C). Five IBMPDB BMPIDs corresponding to four physical assets carry consistent events; Shop Creek Pond is one physical asset monitored across two non-overlapping IBMPDB epochs.

Substrate	Cadence	Events	Sites flagged (% of 36)	Cross-substrate consistent events
Track A (hand-crafted indices)	monthly	30	22 (61%)	8

Substrate	Cadence	Events	Sites flagged (% of 36)	Cross-substrate consistent events
Track B (S2 raw bands)	monthly	24	16 (44%)	7
Track C (AlphaEarth, 64-d)	annual	1	1 (3%)	0

A flagged event is not an identified cause. Sediment accumulation, vegetation overgrowth, outlet clogging, scheduled mowing, planned retrofit, and climate stress can all produce residualized departures of similar magnitude and duration. Attribution requires *paired field-condition records* (inspections, maintenance logs, bathymetric and vegetation surveys) at scale and with explicit dating, which exist within individual operating jurisdictions but have not been aggregated into a community resource. In each of the three capabilities, satellite capability terminates where ground-paired data is required; the limiting factor is the community's data infrastructure, not the satellite stack.

At Cottonwood Wetlands, the only pilot site with continuous water-quality monitoring overlapping the satellite era (391 outflow records across five analytes, 2018–2022, aggregated to monthly medians), monthly outflow nitrogen and phosphorus correlate strongly with raw spectral state but collapse to $|r| \leq 0.221$ after harmonic deseasonalization (Supplementary Fig. S2). The case bounds what single-site spectral monitoring can deliver against ground truth: seasonal coupling is recoverable, within-season concentration is not[38]. A single coupling at a single site cannot substitute for the population-level relationships a community benchmark would reveal.

The binding constraint and a community-benchmark response

Each of the three preceding capability assessments terminates at the same boundary. Inventory automation requires labeled BMP polygons at scale; type classification requires more labeled BMPs distributed across the climate–hydrology gradient; and change attribution requires paired field-condition records with explicit dating. None of these requirements represents a satellite-side limitation, and each of them represents a community-data limitation.

Catchment hydrology faced an analogous bottleneck a decade ago. CAMELS[18] and its global extension Caravan[19] assembled standardized large-sample bundles of catchment attributes paired with hydrometeorological time series. The community-benchmark format unlocked a body of work that fragmented per-study datasets could not previously support. Among the contributions that followed are large-sample LSTM rainfall-runoff models that outperformed conceptual process-based hydrology[39], prediction in ungauged basins, hydrologic-similarity classification, and large-sample diagnosis of those regimes in which conceptual models systematically fail. The cost of CAMELS was assembly rather than collection, since most of the constituent records already existed, scattered across agencies and formats, and the scientific dividend has continued to compound with growth. The same pattern repeated in inland water-quality remote sensing with AquaSat[40], which paired in-situ samples with co-located satellite reflectance and unlocked a body of EO-based water-quality work that per-study datasets had not supported.

The scientific dividend of an analogous benchmark for urban stormwater would be of the same character. Whether the type-averaged removal efficiencies that anchor TMDL regulation are empirically defensible at the population scale is today untestable; with paired type, climate, age, design, and performance records across hundreds to thousands of BMPs, that question becomes tractable with direct regulatory consequence. Within-type variance decomposition (the climate, maintenance, design, and site-idiosyncratic share of asset performance) is similarly out of reach without large-sample data. Failure-mode attribution mapping spectral departures to physical mechanisms requires paired, dated condition records that do not exist at scale; without them, a portfolio screen cannot serve as a diagnostic instrument. Method development across the operational decomposition is data-bottlenecked rather than algorithm-bottlenecked. Cross-study replication, today essentially impossible because every BMP study employs its own protocol and pipeline, would become routine once a standardized per-asset record exists. The benchmark would therefore carry dual value: regulatory accountability for asset operators and funders, and scientific accountability for the field's own claims about what BMPs do, under what conditions, and for how long.

Urban stormwater BMPs occupy the same position that the catchment-hydrology community occupied before CAMELS. Records exist (IBMPDB monitoring data; municipal MS4 asset inventories with maintenance histories; state department-of-transportation (DOT) BMP databases; private-development as-builts; multilateral-funder MRV reporting), but they are fragmented, non-standardized, and not paired with the satellite-derived attribute layers that data-driven monitoring requires.

A CAMELS-for-stormwater benchmark would assemble, per asset, the following five layers.

1. **Delineated polygon footprints** (the limiting input for satellite-derived attribute extraction; producible today by SAM in two minutes per site).
2. **Multi-sensor time series** (Sentinel-2 indices and bands; Sentinel-1 SAR; PlanetScope, where available; AlphaEarth annual embeddings) extracted identically over the BMP footprint and a standardized reference buffer.
3. **Type and design attributes** (drainage area, treatment volume, outlet configuration), comprising the static metadata that the IBMPDB already partially carries, in standardized form.

4. **Gridded climate context** (PRISM in the United States; ERA5-Land globally) at the lags the residualization pipeline requires.
5. **Field-condition records with dates** (inspections, bathymetry, vegetation surveys, maintenance interventions, retrofits, water-quality grab samples, and continuous monitoring where available).

Layer 5 is the most institutionally distributed of the five. It is also the layer that converts spectral departures into causal claims, and therefore the layer that converts the capability statement "satellites can monitor BMPs" into deployable accountability. The institutional substrate for layer 5 may already exist in distributed form. In the US, Municipal MS4 programs are required to maintain inspection records; state DOTs operate hundreds to thousands of BMPs each under documented maintenance schedules; and multilateral climate-adaptation finance (GCF, World Bank) is increasingly conditioning disbursement on standardized MRV reporting. The inputs to a community benchmark, therefore, already exist in jurisdiction-specific archives. What does not yet exist is the assembly, harmonization, and curation effort that would render those archives collectively usable.

Global stakes and a deployment pathway

The benchmark gap is most acute in settings with the highest deployment rates. China's sponge-city program covers more than 30 pilot cities[15]; India's AMRUT 2.0 mission funds urban stormwater and water-resilience infrastructure across more than 500 cities[41]; World Bank urban-resilience portfolios are deploying multi-billion-dollar pipelines under MRV requirements that in-situ monitoring cannot meet at scale[42]; and the Green Climate Fund's nature-based-solutions windows carry similar verification mandates. The satellites are in orbit, the climate reanalyses are running, and the analytical framework demonstrated here is constructed from globally available inputs. The next methodological step is replication of the residualization pipeline on global climate reanalyses (substituting ERA5-Land for PRISM) in order to confirm transferability outside the conterminous United States. Without a benchmark, the framework remains a capability rather than an accountability instrument.

Kigali (Rwanda) illustrates a near-term deployment pathway. The city has 37 inventoried urban wetlands[43], World Bank-financed stormwater infrastructure[44], ESA satellite-monitoring support[45], and newly engineered retention features whose construction signatures are well-suited to the residualized anomaly pipeline. A Kigali-scale pilot would be small enough for first-principles MRV instrumentation, large enough to populate a benchmark layer, and sufficiently high-leverage to anchor a multilateral-funder verification standard. We highlight Kigali as illustrative rather than exclusive, since analogous opportunities exist across South and Southeast Asian, sub-Saharan African, and Latin American cities currently entering large-scale stormwater deployment cycles.

A research agenda

We propose three concrete actions, ordered by increasing scope.

1. **Standardize the per-asset record format.** A delineated polygon, a multi-sensor extraction recipe, a climate residualization protocol, and an event/inspection schema should be published openly so that independent groups can produce comparable records. The 36-site dataset and code released with this Perspective offer a starting format.
2. **Aggregate existing records into a v0 benchmark.** The IBMPDB, municipal MS4 inventories, state DOT BMP databases, and multilateral-funder MRV reports already contain layers 3–5 in fragmented form. Federation under a common schema, following the model that Caravan established by federating CAMELS, CAMELS-AUS, CAMELS-BR, CAMELS-CL, and CAMELS-GB, can produce a v0 community resource at hundreds to low thousands of sites within an achievable timeframe.

3. **Pair the benchmark with deployment partnerships.** A CAMELS-for-stormwater benchmark without operational uptake will remain academic. Co-development with one or two MS4 programs, one state DOT, and one multilateral climate-finance window would tie benchmark expansion to concrete verification needs and create the institutional pull required to sustain data flow over time.

A major class of urban environmental infrastructure should not operate without per-asset verification, and the technical instruments required to address that condition (satellites, climate reanalyses, learned global representations, and foundation-model segmentation) are now available in operational form. What remains absent is the community-data substrate that would convert those instruments into deployable monitoring and convert present-day spectral observations into testable answers to population-scale scientific questions about how BMPs perform, age, and fail under realistic operating conditions. We have argued that the assembly of such a substrate is a tractable and time-bounded task, and that the response of the research and operating communities over the coming decade will determine whether urban stormwater accountability follows the trajectory that catchment hydrology established with CAMELS in the 2010s, or instead remains a structural blind spot through the urban-resilience deployment wave of the 2020s and 2030s.

Methods

Thirty-six BMP sites were selected from the IBMPDB across 12 US states and three types (25 RP, 7 WB, 4 DB), each with documented type, verifiable coordinates, a multi-year monitoring record, and a footprint of at least 0.05 ha. Footprints were delineated in 0.6-m NAIP imagery using SAM[30], and a 100-m annular buffer served as the per-asset reference. Three feature substrates were extracted at the BMP and buffer for 2018–2024, namely (A) six hand-crafted indices computed from monthly Sentinel-2 L2A composites, (B) the 12 Sentinel-2 bands

(BMP-side annual means), with all 66 two-band normalized-difference indices screened separately as a univariate control, and (C) annual AlphaEarth Foundations 64-dim embeddings (`GOOGLE/SATELLITE_EMBEDDING/V1/ANNUAL`;[28]). Each monthly Sentinel-2 composite is the per-band median of L2A scenes with scene-level cloud cover below 20 percent, without a per-pixel cloud mask, so per-site temporal completeness varies with regional cloud climatology, ranging from 47 to 84 of the 84 possible months across the pilot. The per-asset harmonic deseasonalization requires at least eight valid monthly observations per series, a threshold satisfied at every site. Type-discrimination AUCs were computed by leave-one-out logistic regression with shrinkage and 1,000-sample bootstrap confidence intervals (conditional on the leave-one-out scores, quantifying ranking stability rather than model-refit uncertainty; Supplementary Methods), and mutual-information significance was assessed against a 500-permutation null. Within-asset change detection used per-asset harmonic deseasonalization combined with PRISM climate residualization at lags of 0, 1, and 3 months, aggregated to a per-substrate departure magnitude M_t (the RMS z-score across features) with an $M_t > 1.5$ threshold and a $\geq$ 2-period persistence requirement. All polygons, time series, residualized signals, code, and figure-generation scripts are released in the accompanying repository. Full methods, including AlphaEarth axis interpretability, residualization variance accounting, and the Cottonwood water-quality coupling analysis, are provided in the Supplement.

AI use declaration. Large language model assistants [Claude Opus 4 (Anthropic) and ChatGPT (OpenAI; GPT-5)] were used during manuscript preparation for prose editing, structural revision, and code development under author supervision. All scientific claims, analytical choices, citations, and final wording were verified by the authors.

Data availability

The derived data supporting this study — the extracted multi-sensor time series, the residualized per-asset signals, the 36 BMP polygon and reference-buffer labels, and the separability and change-detection outputs — are available in the project repository at https://github.com/skp703/bmp-eo-monitoring, released as a seed contribution toward a CAMELS-for-stormwater community benchmark (derived data tables and polygon labels under CC-BY-4.0). The raw inputs are not redistributed but are publicly available from their original sources — Sentinel-2, NAIP, AlphaEarth Foundations, and PRISM via Google Earth Engine; PlanetScope via Planet Labs; and the International Stormwater BMP Database via bmpdatabase.org — and the repository provides scripts to acquire each.

Code availability

All analysis code is available in the project repository at https://gith

1. Council, N. R. *Assessing the TMDL Approach to Water Quality Management*. (National Academies Press, 2001).

2. Al-Rubaei, A. M., Engström, M., Viklander, M. & Blecken, G.-T. Long-term hydraulic and treatment performance of a 19-year old constructed stormwater wetland—Finally maturated or in need of maintenance? *Ecological Engineering* **95**, 73–82 (2016).

3. Liu, Y. *et al.* Modeling framework for representing long-term effectiveness of best management practices in addressing hydrology and water quality problems: Framework development and demonstration using a Bayesian method. *Journal of Hydrology* **560**, 530–545 (2018).

4. Liu, Y. *et al.* A review on effectiveness of best management practices in improving hydrology and water quality: Needs and opportunities. *Science of The Total Environment* **601–602**, 580–593 (2017).

5. Dodds, W. K. *et al.* Eutrophication of U.S. Freshwaters: Analysis of Potential Economic Damages. *Environ. Sci. Technol.* **43**, 12–19 (2009).

6. Wurtsbaugh, W. A., Paerl, H. W. & Dodds, W. K. Nutrients, eutrophication and harmful algal blooms along the freshwater to marine continuum. *WIREs Water* **6**, e1373 (2019).

7. Dolowitz, D., Keeley, M. & Medearis, D. Stormwater management: can we learn from others? *Policy Studies* **33**, 501–521 (2012).

8. Dhakal, K. P. & Chevalier, L. R. Urban Stormwater Governance: The Need for a Paradigm Shift. *Environmental Management* **57**, 1112–1124 (2016).

9. Barrett, M. E. Performance, Cost, and Maintenance Requirements of Austin Sand Filters. *J. Water Resour. Plann. Manage.* **129**, 234–242 (2003).

10. Clary, J., Jones, J., Leisenring, M., Hobson, P. & Strecker, E. *International Stormwater BMP Database: 2016 Summary Statistics*. https://bmpdatabase.org (2017).

11. Drake, J. & Guo, Y. Maintenance of Wet Stormwater Ponds in Ontario. *Canadian Water Resources Journal* **33**, 351–368 (2008).

12. Lenhart, H. A. & Hunt, W. F. Evaluating Four Storm-Water Performance Metrics with a North Carolina Coastal Plain Storm-Water Wetland. *J. Environ. Eng.* **137**, 155–162 (2011).

13. Strecker, E. W., Quigley, M. M., Urbonas, B. R., Jones, J. E. & Clary, J. K. Determining Urban Storm Water BMP Effectiveness. *J. Water Resour. Plann. Manage.* **127**, 144–149 (2001).

14. Kumar, S. *et al.* Rethinking TMDLs: Perspective Based on Community Survey. *J. Environ. Eng.* **151**, 04025034 (2025).

15. Chikhi, F., Li, C., Ji, Q. & Zhou, X. Review of Sponge City implementation in China: performance and policy. *Water Science & Technology* wst2023312 (2023) doi:10.2166/wst.2023.312.

16. World Bank. Indonesia — National Urban Flood Resilience Project (P173671). https://projects.worldbank.org/en/projects-operations/project-detail/P173671 (2023).

17. Green Climate Fund. SAP Technical Guidelines: Water security. https://www.greenclimate.fund/document/sap-technical-guidelines-water-security (2023).

18. Addor, N., Newman, A. J., Mizukami, N. & Clark, M. P. The CAMELS data set: catchment attributes and meteorology for large-sample studies. *Hydrol. Earth Syst. Sci.* **21**, 5293–5313 (2017).

19. Kratzert, F. *et al.* Caravan - A global community dataset for large-sample hydrology. *Sci Data* **10**, 61 (2023).

20. Weiss, M., Jacob, F. & Duveiller, G. Remote sensing for agricultural applications: A meta-review. *Remote Sensing of Environment* **236**, 111402 (2020).

21. Wu, B. *et al.* Challenges and opportunities in remote sensing-based crop monitoring: a review. *National Science Review* **10**, nwac290 (2023).

22. Hansen, M. C. *et al.* High-Resolution Global Maps of 21st-Century Forest Cover Change. *Science* **342**, 850–853 (2013).

23. Pickens, A. H. *et al.* Rapid monitoring of global land change. *Nat Commun* **16**, 8948 (2025).

24. Pekel, J.-F., Cottam, A., Gorelick, N. & Belward, A. S. High-resolution mapping of global surface water and its long-term changes. *Nature* **540**, 418–422 (2016).

25. Feng, L. *et al.* Harmful algal blooms in inland waters. *Nat Rev Earth Environ* **5**, 631–644 (2024).

26. Muñoz-Sabater, J. *et al.* ERA5-Land: a state-of-the-art global reanalysis dataset for land applications. *Earth Syst. Sci. Data* **13**, 4349–4383 (2021).

27. Daly, C. *et al.* Physiographically sensitive mapping of climatological temperature and precipitation across the conterminous United States. *Intl Journal of Climatology* **28**, 2031–2064 (2008).

28. Brown, C. F. *et al.* AlphaEarth Foundations: An embedding field model for accurate and efficient global mapping from sparse label data. Preprint at https://doi.org/10.48550/arXiv.2507.22291 (2025).

29. Kirillov, A. *et al.* Segment Anything. Preprint at https://doi.org/10.48550/arXiv.2304.02643 (2023).

30. Wu, Q. & Osco, L. P. samgeo: A Python package for segmenting geospatial datawith the Segment Anything Model (SAM). *JOSS* **8**, 5663 (2023).

31. U.S. Department of Agriculture - Farm Service Agency - Aerial Photography Field Office. National Agriculture Imagery Program (NAIP). https://www.usgs.gov/centers/eros/science/usgs-eros-archive-aerial-photography-national-agriculture-imagery-program-naip (2023).

32. Maxar Technologies. WorldView-3 Satellite. https://earth.esa.int/eogateway/missions/worldview-3 (2023).

33. Flynn, K. M., Linkous, B. W. & Buechter, M. T. Operation and Maintenance Assessment for Structural Stormwater BMPs. in *World Environmental and Water Resources Congress 2012* 3662–3673 (American Society of Civil Engineers, Albuquerque, New Mexico, United States, 2012). doi:10.1061/9780784412312.368.

34. Rieck, L. *et al.* Phase II MS4 challenges: moving toward effective stormwater management for small municipalities. *Urban Ecosyst* **25**, 657–672 (2022).

35. Clay Foundation. Clay Foundation Model (v1.5). Clay Foundation (2025).

36. Jakubik, J. *et al.* Foundation Models for Generalist Geospatial Artificial Intelligence. Preprint at https://doi.org/10.48550/arXiv.2310.18660 (2023).

37. Szwarcman, D. *et al.* Prithvi-EO-2.0: A Versatile Multi-Temporal Foundation Model for Earth Observation Applications. Preprint at https://doi.org/10.48550/arXiv.2412.02732 (2026).

38. Reddy, K. R. & DeLaune, R. D. *Biogeochemistry of Wetlands.* (CRC Press, 2008). doi:10.1201/9780203491454.

39. Kratzert, F., Klotz, D., Brenner, C., Schulz, K. & Herrnegger, M. Rainfall–runoff modelling using Long Short-Term Memory (LSTM) networks. *Hydrol. Earth Syst. Sci.* **22**, 6005–6022 (2018).

40. Ross, M. R. V. *et al.* AquaSat: A Data Set to Enable Remote Sensing of Water Quality for Inland Waters. *Water Resources Research* **55**, 10012–10025 (2019).

41. Ministry of Housing and Urban Affairs (Government of India). *AMRUT 2.0 Operational Guidelines*. https://amrut.mohua.gov.in/uploads/AMRUT_2.0_Operational_Guidelines.pdf (2021).

42. World Bank. City Resilience Program (CRP). https://www.worldbank.org/en/topic/disasterriskmanagement/brief/city-resilience-program (2023).

43. Rwanda Environment Management Authority & Rwanda Water Board. *Urban Wetlands of Kigali*. https://waterportal.rwb.rw/sites/default/files/2019-04/Urban%20wetlands%20of%20Kigali.pdf (2019).

44. World Bank. *Second Rwanda Urban Development Project (RUDP II) - Project Appraisal Document*. https://documents1.worldbank.org/curated/en/861071604372550162/pdf/Rwanda-Second-Urban-Development-Project.pdf (2020).

45. European Space Agency. Urban Wetlands: EO-based tools to support wetland restoration in Rwanda. https://gda.esa.int/story/urban-wetlands-eo-based-tools-to-support-wetland-restoration-in-rwanda/ (2023).