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A 3D terrain-aware Framework for Rain Gauge Network Optimization

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Abstract

Rain-gauge network optimisation in complex terrain should consider more than station density or planar spacing. It should also assess whether the existing gauges adequately sample the elevation ranges and terrain settings that influence spatial rainfall variability. This study proposes a terrain-aware Composite Gap Coverage (COMP) strategy for augmenting an operational rain gauge network in the Wupper River catchment, western Germany. COMP translates residual terrain representativeness gaps into an interpretable station selection problem by combining Digital Elevation Model (DEM) derived elevation mismatch, horizontal spacing, and terrain complexity in a Composite Terrain Gap Score (CTGS). Candidate locations are selected through a greedy coverage procedure that prioritises areas where the current network remains structurally under-representative.

The framework is designed as a planning support tool rather than as a claim of unique optimal station placement. In the full domain application, COMP identified five terrain-aware priority zones that improved model-based interpolation uncertainty, spatial coverage, elevation distribution representativeness, and terrain weighted coverage relative to the 17 gauge baseline network. A weight sensitivity analysis showed that exact grid cell rankings depend on CTGS weights, so the recommendations are interpreted as planning level priority zones rather than fixed installation coordinates.

A core domain proxy validation was then performed using four additional gauges. These proxy gauges reproduced 96.1% of the ideal geometric variance reduction and produced moderate monthly prediction error reductions of about 7–8%. The results show that COMP provides a transparent and interpretable way to identify terrain related monitoring gaps in operational rain gauge networks.

1. Introduction

1.1 Precipitation monitoring in complex terrain

Precipitation exhibits strong spatial variability, particularly in complex terrain where elevation gradients, valleys, ridges and slope conditions can lead to systematic differences in rainfall distribution (Roe, 2005). Empirical studies in mountainous catchments have also shown that substantial rainfall differences can occur over relatively short spatial distances (Buytaert et al., 2006). As a result, a rain gauge network in such regions should not only provide sufficient spatial coverage, but also represent the main terrain conditions that influence local precipitation patterns. This is especially important for operational hydrological networks, where gauges may be concentrated in accessible valley floors or near water management infrastructure rather than placed primarily to ensure terrain representativeness (Frei and Schär, 1998).

Rain gauges provide direct and temporally detailed observations at the ground and remain an essential source of precipitation information for hydrological modelling, flood forecasting, and water resources management (Mishra and Coulibaly, 2009, Chacon-Hurtado et al., 2017). They are also important for the calibration and validation of radar and satellite based precipitation products (Wu et al., 2020). However, each gauge represents rainfall only at a specific location. A network must therefore contain a sufficient number of appropriately distributed stations to represent the precipitation field between measurement locations. This requirement is especially difficult to satisfy in mountainous or hilly regions, where strong local gradients may not be captured by a sparse network. Even automatic gauges with fine temporal resolution cannot adequately describe spatial rainfall variability when the network configuration does not sample the relevant terrain and precipitation regimes (Xu et al., 2015).

General network density recommendations provide an initial reference for monitoring design (Rodda, 2011), but station density alone does not guarantee adequate spatial representation. Two networks with the same number of gauges may differ substantially in their ability to capture precipitation variability because their stations occupy different horizontal locations, elevation ranges, and terrain settings. Existing stations are also frequently concentrated in accessible areas, settlements, valleys, or locations that are convenient for installation and maintenance. As a result, some types of the terrain may be repeatedly sampled, while uplands, steep slopes, or spatially isolated areas remain underrepresented. Such configurations can introduce representativeness gaps even when the nominal station density appears sufficient.

The adequacy of a monitoring network also depends on the spatial and temporal scale of the intended application. Network configurations that are suitable for annual or catchment average precipitation may not be sufficient for monthly variability, local rainfall fields, or short duration events. Previous research has shown that the priority and required number of stations can change with temporal aggregation and spatial resolution (Suri and Azad, 2024, Wei et al., 2014). More generally, hydrometric network design must be related to the process being monitored and to the intended use of the observations rather than being defined by a universally applicable station density (Mishra and Coulibaly, 2009, Chacon-Hurtado et al., 2017).

These considerations make precipitation monitoring in complex terrain a problem of spatial representativeness rather than merely one of gauge quantity. An effective network should not only reduce large horizontal gaps but should also sample the terrain conditions associated with spatial rainfall variability. Evaluating an existing network therefore requires identifying which parts of the study area are poorly represented in geographical and topographical terms, and determining where additional gauges could provide complementary information. This motivates network augmentation methods that explicitly consider terrain related coverage gaps alongside conventional measures of spatial interpolation uncertainty.

1.2 Rain gauge network design and optimization

Rain gauge network design aims to determine a station configuration that provides sufficient and representative precipitation information while limiting installation, operation, and maintenance costs. Existing studies commonly distinguish among three design scenarios: network reduction, in which redundant gauges are removed; network augmentation, in which new gauges are added to improve an existing network; and network relocation, in which poorly positioned gauges are transferred to more informative locations (Chacon-Hurtado et al., 2017, de Oliveira Simoyama et al., 2023). The present study addresses the augmentation problem, because the objective is to identify additional locations that complement an already operational monitoring network.

A wide range of methods has been developed for rain gauge network design. Entropy-based approaches evaluate the information content and redundancy of rainfall observations, and have been used to prioritise candidate gauges under different spatial and temporal aggregation scales (Wei et al., 2014, Su and You, 2014). Xu et al. further showed that entropy-based multi-criteria resampling can be linked to hydrological model performance, highlighting that network design objectives depend on the intended downstream application (Xu et al., 2015). Recent hybrid entropy formulations also combine information-transfer measures with metaheuristic search to optimise gauge density and location (Eslamian et al., 2025). Spatial-correlation approaches have likewise been used to evaluate existing networks and identify improved station configurations from inter-station rainfall relationships (Nazaripour and Mansouri Daneshvar, 2017).

Kriging-based approaches define network quality through interpolation uncertainty, with kriging variance or kriging error used to identify locations where additional gauges are expected to reduce estimation uncertainty (Cheng et al., 2008, Pardo-Igúzquiza, 1998, Adhikary et al., 2015). More recently, (Henriksen et al., 2024) demonstrated that this idea can be scaled to large networks by replacing repeated kriging calculations with a computationally efficient kriging emulator. Other studies have extended the design problem by including satellite precipitation information (Huang et al., 2020) or multi-criteria decision analysis in complex terrain (Volkmann et al., 2010). For example, Shepherd and Taylor used geoinformation system (GIS)-based multi-criteria analysis to support the siting of an urban rain gauge network, showing that practical placement constraints can be integrated into the optimisation workflow (Shepherd et al., 2004).

For the present study, the central concern is terrain representativeness. In hilly and mountainous catchments, orographic processes can create persistent precipitation differences over short distances (Roe, 2005). An operational network may therefore be dense enough for routine monitoring but still undersample particular elevation bands, ridges, steep slopes, or spatially isolated terrain zones, even though such topographic attributes are related to precipitation patterns (Basist et al., 1994). A method that only optimises information content or interpolation uncertainty does not necessarily diagnose these terrain-related representation gaps, especially when the existing gauges are concentrated in accessible valley and mid-elevation areas. This motivates a terrain-aware augmentation strategy that explicitly identifies where the existing network is structurally underrepresentative and selects additional locations that reduce these remaining terrain-related gaps.

1.3 Research gap and study contributions

The research gap addressed in this paper is therefore not the absence of rain gauge network optimisation methods in general, but the need for an interpretable terrain-aware augmentation procedure for existing operational networks in complex terrain. The focus is on identifying where the current network under represents important terrain conditions and on testing whether the resulting priority zones are supported by independent observations.

This study makes three main contributions. First, it introduces a terrain-aware Composite Gap Coverage (COMP) strategy that combines horizontal distance, elevation under representation, and local terrain complexity to identify residual monitoring gaps in an existing rain gauge network. Within this strategy, the Composite Terrain Gap Score (CTGS) is used to describe cell level terrain gaps, while the COMP selection procedure uses greedy residual gap coverage to select candidate locations for network augmentation.

Second, COMP is applied to the full Wupper River catchment domain to propose five candidate gauge locations for network augmentation. This full domain application is used to describe how the recommended augmentation changes model-based interpolation uncertainty, spatial coverage, elevation distribution representativeness, and terrain weighted coverage relative to the to the existing baseline network. The purpose of this step is diagnostic and planning oriented: it shows where COMP identifies terrain-aware priority zones, rather than establishing a universal optimum over all possible network design objectives.

Third, the recommended locations are independently evaluated within a core observation domain using nearby proxy gauges that were not used in the original network design procedure. Kriging variance reduction is used to assess the geometric benefit of the augmented configurations, while leave-one-proxy-out regression kriging errors are used to evaluate observation based performance. This two level assessment separates full domain terrain gap diagnosis from core domain predictive validation.

2. Study area and data

The study area is located in the Wupper River catchment in the Bergisches Land region of North Rhine Westphalia, western Germany, approximately between $51.0°$ and $51.4°$N, and between $6.9°$ and $7.7°$E. The terrain is characterised by a pronounced west–east elevation gradient, ranging from low-lying river valleys in the west to higher upland areas in the east. Deeply incised valleys, steep hillslopes and elevated ridges create strong local topographic variability, which can influence both the spatial distribution of precipitation and the representativeness of point based rain gauge observations.

The study uses precipitation observations from the operational rain-gauge network maintained by Wupperverband, the regional water authority responsible for hydrological monitoring

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in the Wupper River catchment. These observations provide the baseline network for the terrain-aware augmentation experiments presented in this study.

Topographic information was derived from the Shuttle Radar Topography Mission (SRTM) DEM. For the network design analysis, the DEM was clipped to the study area and represented on a 50×50 regular analysis grid, corresponding to an effective grid spacing of approximately $1.5\mathrm{km}$. Elevation values from this grid were used to characterise the terrain range of the catchment and to derive the terrain based indicators used in the proposed station selection procedure, including elevation mismatch, spatial coverage gaps and local slope.

The precipitation dataset used for the full-domain planning experiment contains 17 data-eligible rain gauges with daily precipitation records for the 2024–2025 analysis period. The network was developed primarily for operational hydrological monitoring and water resources management. Consequently, several stations are located along river valleys or near reservoirs and dam facilities. Many gauges are situated in accessible valley floors and mid elevation terrain, whereas elevated ridges, steep slopes and parts of the upper elevation range are less well represented. The resulting network configuration is therefore well aligned with its original operational purposes but is not necessarily balanced with respect to the full range of terrain conditions relevant to spatial precipitation variability.

3. Methodology

The overall methodological framework is shown in Figure 1. The proposed Composite Gap Coverage (COMP) strategy is a terrain-aware rain gauge network augmentation algorithm. COMP is not a single composite score; rather, it consists of five linked steps: derivation of terrain based gap indicators, calculation of a Composite Terrain Gap Score (CTGS) for each DEM cell, candidate filtering, distance decay gap coverage, and greedy forward station selection.

Within this framework, CTGS is the cell level terrain-aware gap score. It identifies where the existing gauge network is insufficient in terms of elevation representation, horizontal coverage, and local terrain complexity. COMP then uses CTGS as the input to a residual gap coverage procedure to select a spatially distributed set of new stations. In other words, CTGS identifies where the network is weak, whereas COMP determines which additional stations should be selected to cover the remaining gaps most effectively.

Rainfall observations are processed in a parallel modelling component using regression kriging with elevation as the deterministic trend. The interpolated rainfall field is not used to calculate CTGS or to select COMP candidates. Instead, the regression kriging model is used to characterise spatial rainfall variability and to support the subsequent assessment of the augmented network. The network configurations generated by COMP are finally evaluated using diagnostic criteria that are separated from the CTGS-based selection objective itself.

The optimisation framework therefore separates gap diagnosis from station selection. The first step quantifies different aspects of monitoring deficiency across the study area, while the second step iteratively selects new stations to maximise the reduction of the remaining coverage gaps. This separation improves the transparency and interpretability of the overall optimisation process.

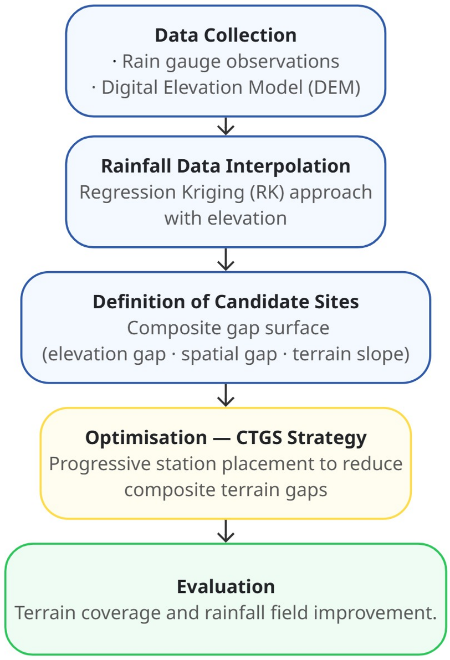

Figure 1. Workflow of the proposed three-dimensional terrain-aware framework for augmenting an existing rain-gauge network in complex terrain. The COMP strategy includes terrain-derived gap indicators, CTGS calculation, candidate filtering, distance-decay gap coverage, and greedy station selection.

3.1 Problem formulation

Let

$$\mathcal{S}_0 = \{\mathbf{s}_1, \dots, \mathbf{s}_n\} \tag{1}$$

denote the existing rain gauge network, where each station $\mathbf{s}_j$ has a horizontal position and an elevation $z(\mathbf{s}_j)$. The terrain of the planning domain Ω is represented by a DEM grid

$$\mathcal{D} = \{\mathbf{x}_1, \dots, \mathbf{x}_m\}, \tag{2}$$

where each grid cell $\mathbf{x}_i$ is associated with an elevation z_i and a local terrain slope value q_i.

The network augmentation problem is to select a set

$$\mathcal{A}_k = \{\mathbf{a}_1, \dots, \mathbf{a}_k\} \subseteq \mathcal{C}, \tag{3}$$

containing k new stations from a feasible candidate set $\mathcal{C}$. The existing network remains unchanged, and the augmented network is therefore

$$\mathcal{S}_k = \mathcal{S}_0 \cup \mathcal{A}_k. \tag{4}$$

The selected locations must satisfy a minimum distance constraint with respect to both the existing stations and the other newly selected stations:

$$d_H(\mathbf{a}, \mathbf{s}) \geq d_{\min}, \qquad \mathbf{a} \in \mathcal{A}_k,\ \mathbf{s} \in \mathcal{S}_0, \tag{5}$$

and

$$d_H(\mathbf{a}_r, \mathbf{a}_l) \geq d_{\min}, \qquad r \neq l, \tag{6}$$

where $d_H(\cdot, \cdot)$ denotes the Haversine distance. The objective is to select the k locations that minimise the terrain related monitoring gaps remaining within the candidate domain. The number

k may be determined by the available installation budget or by a predefined augmentation scenario.

The planning domain used for candidate generation is defined independently of the spatial domain used for subsequent interpolation validation. This distinction allows candidate stations to address network gaps near the boundary of the existing core network without requiring the validation domain to be extrapolated beyond the area supported by the baseline observations.

3.2 Terrain derived gap indicators

The use of DEM derived terrain indicators is motivated by the established statistical relationship between topographic attributes and precipitation patterns (Basist et al., 1994). Three complementary indicators are calculated for every DEM cell. They describe elevation representativeness, horizontal network coverage, and local terrain complexity.

3.2.1 Elevation gap The elevation gap of grid cell $\mathbf{x}_i$ is defined as the minimum absolute elevation difference between the cell and any existing rain gauge:

$$G_{\mathrm{e}}(\mathbf{x}_i) = \min_{\mathbf{s}_j \in \mathcal{S}_0} |z_i - z(\mathbf{s}_j)| \,. \tag{7}$$

A high value of G_{e} indicates that the terrain elevation at $\mathbf{x}_i$ is poorly represented by the existing station network. This indicator operates in elevation space and is therefore different from horizontal distance to the nearest station.

3.2.2 Spatial gap The spatial gap is calculated as the horizontal distance from a DEM cell to its nearest existing station:

$$G_{\mathrm{d}}(\mathbf{x}_i) = \min_{\mathbf{s}_j \in \mathcal{S}_0} d_H(\mathbf{x}_i, \mathbf{s}_j). \tag{8}$$

Large values identify spatially isolated parts of the planning domain where precipitation observations are weakly supported by nearby gauges.

3.2.3 Terrain complexity Local terrain complexity is represented by the magnitude of the DEM gradient:

$$G_{\mathrm{t}}(\mathbf{x}_i) = \|\nabla z_i\| = \sqrt{\left(\frac{\partial z}{\partial x}\right)_i^2 + \left(\frac{\partial z}{\partial y}\right)_i^2}. \tag{9}$$

The indicator gives higher priority to steep or rapidly changing terrain, where point measurements located only in neighbouring valleys or on smoother terrain may provide limited topographic representativeness.

Because the three indicators have different physical units, each indicator is transformed to the interval $[0, 1]$ by min–max normalisation:

$$G_r^*(\mathbf{x}_i) = \frac{G_r(\mathbf{x}_i) - \min_{\mathbf{x}\in\mathcal{D}} G_r(\mathbf{x})}{\max_{\mathbf{x}\in\mathcal{D}} G_r(\mathbf{x}) - \min_{\mathbf{x}\in\mathcal{D}} G_r(\mathbf{x})}, \qquad r \in \{\mathrm{e}, \mathrm{d}, \mathrm{t}\}. \tag{10}$$

The normalised indicators are combined into the CTGS:

$$G_{\mathrm{CTGS}}(\mathbf{x}_i) = w_{\mathrm{e}} G_{\mathrm{e}}^*(\mathbf{x}_i) + w_{\mathrm{d}} G_{\mathrm{d}}^*(\mathbf{x}_i) + w_{\mathrm{t}} G_{\mathrm{t}}^*(\mathbf{x}_i), \tag{11}$$

where G_{e}^*, G_{d}^*, and G_{t}^* denote the normalised elevation gap, spatial gap, and terrain complexity terms, respectively. The weights w_{e}, w_{d}, and w_{t} are non negative and sum to one. They control the relative importance assigned to elevation representativeness, planar spatial coverage, and terrain complexity in a given application.

High CTGS values indicate locations that are spatially isolated, poorly represented in elevation space, and situated in comparatively complex terrain, depending on the chosen weighting of the three components.

The CTGS defined high gap evaluation grid is defined as

$$\mathcal{E} = \left\{ \mathbf{x}_i \in \mathcal{D} \;\middle|\; \begin{array}{l} G_{\mathrm{CTGS}}(\mathbf{x}_i) \geq Q_\tau(G_{\mathrm{CTGS}}) \\ \text{or } z_i > \max\limits_{\mathbf{s}_j \in \mathcal{S}_0} z(\mathbf{s}_j) \end{array} \right\}. \tag{12}$$

where Q_τ denotes the τ-quantile of the CTGS values. The set $\mathcal{E}$ is not the feasible station set; it is the part of the terrain grid over which the residual terrain representativeness gap is evaluated.

The second condition explicitly retains terrain above the maximum elevation represented by the existing network, even where such cells do not pass the CTGS threshold. This rule is motivated by a common practical feature of rain gauge networks in complex terrain: station placement is often influenced by accessibility, maintenance requirements, population or traffic feasibility, and operational constraints, which can leave mountainous or ridge areas under represented (Wei et al., 2014, Wu et al., 2020). In the Wupper River catchment, the same issue appears as a clear lack of gauges in the upper elevation range. The elevation envelope condition therefore translates this general representativeness problem into a case specific candidate retention rule. In other applications, it can be replaced by a more general rule for retaining any underrepresented terrain class.

The feasible candidate set is obtained by removing cells that are too close to an existing station:

$$\mathcal{C} = \left\{ \mathbf{x}_i \in \mathcal{E} \;\middle|\; \min_{\mathbf{s}_j \in \mathcal{S}_0} d_H(\mathbf{x}_i, \mathbf{s}_j) \geq d_{\min} \right\}. \tag{13}$$

For the present implementation, the upper 30% of CTGS values are retained, corresponding to $\tau = 0.70$, and the minimum station separation is set to $d_{\min} = 3\,\mathrm{km}$.

3.3 Composite Gap Coverage objective

The previous subsection defines CTGS as a terrain-aware gap score for individual DEM cells. COMP uses this score in a residual gap coverage objective. A new station is assumed to improve monitoring representativeness primarily in its surrounding area, and this contribution decreases gradually with horizontal distance. The coverage provided by a station placed at candidate location $\mathbf{a}$ is represented by an exponential distance decay kernel:

$$K(\mathbf{x}_i, \mathbf{a}) = \exp\left(-\frac{d_H(\mathbf{x}_i, \mathbf{a})}{\sigma}\right), \tag{14}$$

where σ controls the spatial scale of the coverage effect. The parameter σ controls the spatial scale of the distance-decay coverage kernel. Larger values allow a selected station to reduce gap scores over a broader neighbourhood, whereas smaller values restrict the effect to more local areas. This parameter is an algorithmic coverage scale and should not be interpreted as a rainfall correlation range.

For a selected set of additional stations $\mathcal{A} \subseteq \mathcal{C}$, the residual gap at evaluation cell $\mathbf{x}_i$ is defined as

$$R(\mathbf{x}_i \mid \mathcal{A}) = \max\left\{0,\, G_{\mathrm{CTGS}}(\mathbf{x}_i) - \sum_{\mathbf{a}\in\mathcal{A}} K(\mathbf{x}_i, \mathbf{a})\right\}. \quad (15)$$

The lower bound of zero prevents the accumulated station coverage from producing negative residual gaps. The network level objective is the mean residual gap over the fixed high gap evaluation grid:

$$J(\mathcal{A}) = \frac{1}{|\mathcal{E}|}\sum_{\mathbf{x}_i\in\mathcal{E}} R(\mathbf{x}_i \mid \mathcal{A}). \quad (16)$$

The optimal augmentation set is therefore expressed as

$$\mathcal{A}_k^* = \arg\min_{\substack{\mathcal{A}\subseteq\mathcal{C}\\ |\mathcal{A}|=k}} J(\mathcal{A}), \quad (17)$$

subject to the minimum distance constraints defined above.

This formulation makes the distinction between gap identification and gap coverage explicit. CTGS determines where the existing network is terrain representationally insufficient, whereas the COMP coverage objective determines how much of the remaining CTGS defined gap would be addressed by a new station. COMP therefore favours a spatially distributed set of stations instead of repeatedly selecting neighbouring cells from the same high gap cluster.

3.4 Greedy station selection

An exhaustive evaluation of all possible k station combinations is computationally prohibitive when the candidate grid is large. Therefore, the augmentation set is constructed using greedy forward selection, a commonly used heuristic for rain gauge network design (de Oliveira Simoyama et al., 2023).

Let

$$\mathcal{A}^{(0)} = \varnothing \quad (18)$$

be the initial augmentation set, and let the initial residual gap be

$$R^{(0)}(\mathbf{x}_i) = G_{\mathrm{CTGS}}(\mathbf{x}_i). \quad (19)$$

At iteration t, each currently eligible candidate $\mathbf{a} \in \mathcal{C}_t$ is evaluated according to the residual objective that would result from adding that station:

$$J_t(\mathbf{a}) = \frac{1}{|\mathcal{E}|}\sum_{\mathbf{x}_i\in\mathcal{E}} \max\left\{0,\, R^{(t)}(\mathbf{x}_i) - K(\mathbf{x}_i, \mathbf{a})\right\}. \quad (20)$$

The next station is selected as

$$\mathbf{a}_{t+1}^* = \arg\min_{\mathbf{a}\in\mathcal{C}_t} J_t(\mathbf{a}). \quad (21)$$

Equivalently, the selected station maximises the marginal reduction in the residual CTGS defined gap:

$$\mathbf{a}_{t+1}^* = \arg\max_{\mathbf{a}\in\mathcal{C}_t} \Delta_t(\mathbf{a}), \quad (22)$$

where

$$\Delta_t(\mathbf{a}) = J\left(\mathcal{A}^{(t)}\right) - J\left(\mathcal{A}^{(t)} \cup \{\mathbf{a}\}\right). \quad (23)$$

After selecting $\mathbf{a}_{t+1}^*$, the residual gap is updated for all cells in the fixed evaluation grid:

$$R^{(t+1)}(\mathbf{x}_i) = \max\left\{0,\, R^{(t)}(\mathbf{x}_i) - K(\mathbf{x}_i, \mathbf{a}_{t+1}^*)\right\}. \quad (24)$$

The selected station and all candidate locations within $d_{\min}$ of it are removed from the feasible candidate pool:

$$\mathcal{C}_{t+1} = \left\{\mathbf{a} \in \mathcal{C}_t \setminus \{\mathbf{a}_{t+1}^*\} \mid d_H(\mathbf{a}, \mathbf{a}_{t+1}^*) \geq d_{\min}\right\}. \quad (25)$$

Finally, the augmentation set is updated as

$$\mathcal{A}^{(t+1)} = \mathcal{A}^{(t)} \cup \{\mathbf{a}_{t+1}^*\}. \quad (26)$$

The procedure is repeated until k stations have been selected. The ordering of the selected stations also provides an explicit installation priority: the first station produces the largest reduction in the initial CTGS defined network gap, whereas each subsequent station addresses the residual gaps not sufficiently covered by the stations selected earlier.

The kernel scale σ is an algorithmic coverage parameter and should not be interpreted as a rainfall correlation range or as the range parameter of the variogram used in the subsequent regression kriging evaluation.

4. Experimental evaluation

The experimental evaluation was designed to assess the proposed COMP strategy from two complementary perspectives. First, a full-domain application was used to examine which locations COMP recommends when the complete 17-gauge baseline network and the wider terrain domain are considered. This step provides a planning-oriented assessment of the terrain and spatial gaps that remain in the existing network. Because no independent observations are available at the recommended future locations, this analysis is supported by diagnostic evaluation metrics and sensitivity analyses of the CTGS weights and algorithmic parameters. Second, a core-domain validation was used to examine whether COMP recommended locations are supported by nearby independent proxy gauges. This second step therefore serves as an empirical validation exercise rather than a second parameter-sensitivity experiment.

The two analyses use different spatial domains because they answer different questions. The full-domain analysis uses the complete study area, the 17 data-eligible baseline gauges, and an augmentation budget of five stations. It is intended to show the main COMP recommendation under the broad network densification problem. The core-domain validation uses the convex hull of the 13 gauges located in the densest part of the existing network. Within this domain, COMP was recomputed to derive a four-gauge augmentation scenario that could be evaluated against nearby independent proxy gauges. This design makes the two experiments complementary rather than symmetric: the full-domain analysis evaluates prospective planning behaviour, whereas the core-domain analysis tests whether the same type of COMP recommendation is supported by independent observations.

4.1 Full domain planning experiment

The first analysis applies COMP to the full study domain. The initial network $\mathcal{S}_0$ consists of the 17 data eligible rain gauges. Candidate locations were defined on the DEM based candidate grid and were subject to the same minimum distance and domain constraints used in the COMP selection procedure. For the experiments in this paper, the three CTGS components were assigned equal weights, $w_\mathrm{e} = w_\mathrm{d} = w_\mathrm{t} = 1/3$. The algorithmic parameters were set to $\sigma = 8\,\mathrm{km}$, $d_{\min} = 3\,\mathrm{km}$, and $\tau = 0.70$. These values are used as a transparent reference configuration rather than as empirically tuned optimal hyperparameters. Five additional locations were then chosen sequentially by maximising the reduction of the remaining CTGS. After each selection, the new location was added to the current network before the next location was determined.

Figure 2 shows the full domain COMP candidate ranking and the five recommended gauge locations. The selected locations are not restricted to the densest part of the existing network. Instead, they cover both under monitored low elevation areas and the eastern uplands. The selected locations span a broad elevation range from 143 to 413 m, as listed in Table 1, and include one location above 400 m, where the original network had no gauge. This behaviour is consistent with the design of COMP: the algorithm does not only search for large horizontal gaps, but also accounts for elevation gaps and local terrain complexity.

Rank	Coordinates (°N, °E)	Elev. (m)
1	(51.2141, 7.4702)	413
2	(51.1441, 7.1534)	143
3	(51.2211, 7.3550)	382
4	(51.2632, 7.2686)	323
5	(51.1021, 7.0958)	156

Table 1. Recommended full-domain COMP gauge locations under a five-gauge augmentation budget. Coordinates are reported in decimal degrees, and elevations were extracted from the DEM.

The effect of the five site COMP augmentation was examined with respect to the main design concerns of this study. Relative to the 17 gauge baseline network, the augmented configuration reduced the mean regression kriging variance over the evaluation domain by 10.8%, indicating lower model-based interpolation uncertainty under the adopted variogram. The 90th percentile of the nearest gauge distance decreased by 22.9%, showing that the selected locations mainly improve poorly covered parts of the catchment rather than simply densifying already well monitored areas. The elevation distribution represented by the network also became closer to that of the study domain, with a 22.0% reduction in the elevation distribution discrepancy. In addition, the slope weighted nearest gauge distance decreased by 21.9%, suggesting that the augmentation improves coverage particularly in areas where spatial gaps coincide with more complex terrain. Overall, these changes show that the selected sites improve several dimensions of network representativeness. This supports the aim of reducing terrain-related monitoring gaps rather than merely increasing station density.

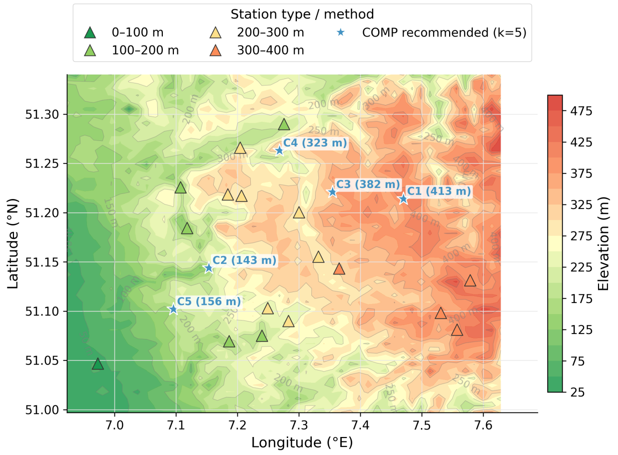

Figure 2. Full-domain COMP candidate ranking and recommended gauge locations under a five-gauge augmentation budget.

Sensitivity analyses were performed to examine whether these results depend on the chosen reference configuration. First, the CTGS component weights were perturbed by $\pm 20\%$. Second, the three algorithmic parameters σ, $d_{\min}$, and τ were also perturbed by $\pm 20\%$, resulting in 27 parameter scenarios including the reference setting. For the parameter sensitivity analysis, all scenarios were evaluated using the same four diagnostic metrics: mean regression kriging variance reduction, 90th percentile nearest gauge distance reduction, elevation distribution representativeness, and slope weighted distance reduction. The reference setting achieved the highest min–max normalised composite diagnostic score among the tested parameter scenarios and was not strictly dominated by any other scenario in a Pareto comparison. However, the exact identity of the top-ranked grid cells was sensitive to weight and algorithmic parameter perturbations. The selected top-five cells showed limited exact cell-level overlap in the three-parameter sensitivity analysis. Therefore, the result is interpreted at the level of planning priority zones rather than as a unique set of optimal installation coordinates.

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These values are used here to describe the geometric and terrain related effect of the COMP recommendation. They should not be interpreted as a general proof of optimality over all possible rain gauge network design objectives. Together with the weight and parameter sensitivity checks, these results suggest that the COMP output is best understood as a set of planning level priority zones rather than exact installation coordinates.

4.2 Core domain proxy validation

The core domain validation evaluates whether the COMP prioritised gaps remain practically meaningful in a controlled core domain setting. The analysis was restricted to the convex hull of the 13 gauges located in the densest part of the baseline network. Within this domain, the COMP objective was evaluated on the DEM grid and the four highest priority locations were treated as an ideal augmentation scenario. Because these ideal locations do not correspond to installed instruments, each site was paired with a nearby independent proxy gauge. The validation therefore combines two complementary tests: a geometry based regression kriging variance comparison and a strict leave-one-proxy-out regression kriging validation using observed precipitation.

Figure 3 shows the core domain validation setting. The four COMP locations are distributed within the main under represented part of the core domain and are paired with nearby proxy gauges. Two of the proxy gauges are close spatial substitutes for the corresponding COMP locations, whereas the remaining two pairs are less ideal because of boundary effects or larger elevation and distance offsets. Therefore, the proxy validation should be interpreted as a real world approximation of the ideal COMP augmentation, rather than as a test using gauges installed exactly at the recommended coordinates.

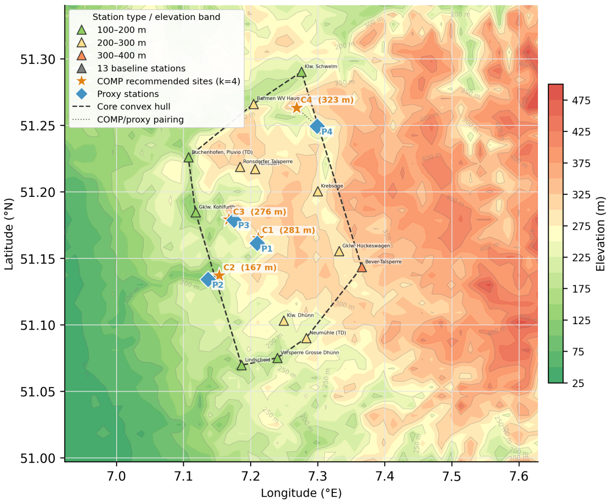

Figure 3. Core-domain validation setting. The four COMP-recommended locations are paired with nearby independent proxy gauges and evaluated within the convex hull of the 13 core baseline gauges.

The first validation step compares the reduction in hull mean regression kriging variance. Table 2 shows that adding the four ideal COMP locations reduced the mean kriging variance from 0.003540 to 0.003106, corresponding to a 12.27% reduction relative to the 13 gauge baseline. Replacing the ideal coordinates with the four actual proxy gauges reduced the mean kriging variance to 0.003123, corresponding to an 11.79% reduction.

Configuration	Gauges	Mean var.	Reduction
Core baseline network	13	0.003540	–
Ideal COMP locations	17	0.003106	12.27%
Matched proxy gauges	17	0.003123	11.79%

Table 2. Regression-kriging variance reduction relative to the 13-gauge core baseline network.

Thus, the proxy gauges recover 96.1% of the theoretical geometric benefit of the ideal COMP locations. This indicates that the COMP selected sites correspond to real geometric monitoring gaps in the core network.

The second validation step evaluates whether this geometric benefit also translates into improved prediction of independent observations. A strict leave-one-proxy-out design was used. For each target proxy gauge, the baseline model was trained using only the 13 core gauges, whereas the augmented model was trained using the same 13 core gauges plus the other three proxy gauges. The target proxy gauge was never used for training. Regression kriging was used, with elevation as the deterministic trend. The validation was performed at the monthly scale using monthly mean daily precipitation as the target variable; therefore, the error unit remains $\mathrm{mm\,day^{-1}}$. The results are summarised in Table 3.

Metric	Baseline	Augmented	Improvement
RMSE $(\mathrm{mm\,day^{-1}})$	0.3595	0.3330	7.4%
MAE $(\mathrm{mm\,day^{-1}})$	0.2461	0.2273	7.6%

Table 3. Monthly leave-one-proxy-out regression-kriging validation results. The target variable is monthly mean daily precipitation.

Across 48 station month validation samples, the augmented network reduced the root mean square error (RMSE) from 0.3595 to 0.3330 $\mathrm{mm\,day^{-1}}$, corresponding to a 7.4% improvement. The mean absolute error (MAE) decreased from 0.2461 to 0.2273 $\mathrm{mm\,day^{-1}}$, corresponding to a 7.6% improvement. The simultaneous reduction in RMSE and MAE suggests that the improvement is not driven only by a small number of extreme monthly cases.

Overall, the core domain validation supports the practical relevance of the COMP recommendations. The proxy gauges reproduce almost all of the ideal COMP geometric variance reduction under the adopted variogram and also provide a measurable reduction in monthly prediction error. At the same time, the empirical gain should be interpreted as moderate rather than dramatic, because the realised benefit depends on proxy quality, local geometry and cross network consistency. Therefore, the core domain validation supports the four COMP prioritised locations as meaningful monitoring gaps, but it should not be read as evidence that every proxy gauge improves every prediction target under all temporal aggregations.

5. Conclusion

This study presented a terrain-aware rain gauge network augmentation strategy for identifying locations where additional gauges can improve the representativeness of an existing monitoring network in complex terrain. The proposed COMP strategy treats network design as a residual gap coverage problem and combines elevation representation, spatial coverage, and terrain complexity. It is therefore particularly suited to small and medium scale catchments where operational gauges may be biased toward accessible valley and mid elevation locations.

In the Wupper River catchment, the full domain application shows that the five COMP recommended locations reduce regression kriging uncertainty, extreme nearest gauge distance, elevation distribution mismatch, and slope weighted distance relative to the 17 gauge baseline. Sensitivity analyses indicate that exact grid cell rankings are affected by both CTGS weights and algorithmic parameters. The reference setting $\sigma = 8\,\mathrm{km}$, $d_{\min} = 3\,\mathrm{km}$, and $\tau = 0.70$ was not Pareto dominated by the tested perturbation scenarios and provided the highest composite diagnostic score, but it is interpreted as a transparent and balanced reference configuration rather than as a uniquely optimal parameter choice. The COMP recommendations should therefore be read as planning level priority zones rather than fixed installation points.

The core domain validation with independent proxy gauges supports the practical relevance of the selected priority zones. The four proxy gauges recover approximately 96% of the theoretical kriging variance reduction of the ideal COMP coordinates, and monthly regression kriging cross validation shows moderate RMSE and MAE reductions of about 7–8%. These results suggest that terrain-aware gap coverage is a useful and interpretable planning support principle for rain gauge densification, while detailed field feasibility, longer precipitation records, wind exposure, radar or satellite products, and operational constraints should be incorporated in future extensions.

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