



FIELD GEOMETRY-AWARE OPTIMIZATION OF SENSOR NODES FOR SMART IRRIGATION AND SOIL MONITORING

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Abstract

Efficient sensor deployment in irregular field geometries, non-uniform terrain, and spatially heterogeneous agricultural environments remains a major challenge for wireless sensor networks used in smart irrigation and soil monitoring. This paper presents a Geography-Aware Hybrid Adaptive Swarm Optimization model to optimize sensor node placement by prioritizing geographical coverage rather than conventional network-centric coverage. The proposed framework integrates raster-based field modeling, slope-based zoning, heterogeneity-guided candidate sampling, and multi-objective optimization to balance coverage, energy consumption, sensor count, and redundancy. A hybrid optimization strategy combining particle swarm optimization, genetic operators, and adaptive parameter control is used to generate efficient deployment patterns. The results show that the proposed framework places more sensors in environmentally variable zones while reducing redundant deployment in uniform areas, thereby improving sensing efficiency and resource use. Compared with baseline approaches, the model achieves a practical trade-off between monitoring performance and operational cost. From an environmental science perspective, the framework supports sustainable agricultural monitoring by improving water-use efficiency, reducing energy demand, and enabling climate-smart resource management.

Keywords – precision agriculture; wireless sensor networks; sensor placement optimization; smart irrigation; geographical coverage

1.INTRODUCTION

Precision agriculture is developing at a remarkable pace and has, accordingly, dramatically changed the way farmers were used to do their business by introducing the concept of Internet of Things (IoT) and Wireless Sensor Networks (WSNs). These systems can in real-time track significant environmental conditions such as soil moisture, nutrient levels and microclimatic conditions and utilize the information to make sound irrigation and crop management decisions. More recent developments have shown that intelligent sensor implementation and optimization strategies can significantly improve the performance of monitoring and resource management in an agricultural setting [1]. Moreover, optimization-based and agent-based methods of sensor placement have been considered to enhance the

irrigation performance and scalability in size-scale crop fields [2]. Although this has happened, the application of WSNs in agriculture has become a big challenge, especially in fields with non-uniform geometries, non-homogenous geometries, and dynamic geometries. The existing deployment techniques of grid based, and clustering techniques have provided feasible platforms through which soil monitoring and irrigation schedule could be achieved [3], and localization and energy-wise techniques have also been used to maximize the efficiency in the system and water conservation [4], [5]. Evidence of practical uses of WSN-based irrigation systems also exists empirically that highlights the necessity to ensure the availability of good sensing and communication solutions that can enable sustainable agricultural practices [6], [7]. It has also been supported through

combination of IoT-based sensing systems that have been applied to the promise of precision irrigation systems to maximize resource allocation and enhance crop productivity [8] and more general research confirms that WSNs are an increasingly important component of smarter agricultural ecosystems [9]. More recently, the hybrid optimization and machine learning based approaches have been proposed to address the energy efficiency and resource allocation issues as well, which also indicates that the intelligent and adaptable deployment mechanisms are required [10].

However, one of its critical flaws is that most of the existing literature assumes simplified field conditions, such as regular geometric patterns, a homogeneous terrain, which is not reflective of real-world agricultural environments. In practice, there is a tendency of irregular shapes of agricultural fields, slopes, and heterogeneity of soil characteristics in space that have a direct impact on sensing requirements. The traditional method tends to present the network or connectivity as much as possible and pay little concern to the geographical and environmental differences of the area. This means that the strategies are likely to lead to inefficient configuration of sensor, redundancy in sensing homogeneous regions, and uncovering of areas of concern. This separation of theory and reality reveals one key issue: the lack of a framework of deployment that might consider both the geometry of the field and variability of the terrain, not to mention the energy-efficient sensing. To deal with this issue, the current work is devoted to the optimization of sensor node distribution in irregular fields of agriculture, when geographical coverage is taken into consideration as opposed to network-centric measures. The work will include the modeling of real-world field geometries based on spatial data as rasters, the identification of terrain induced heterogeneity based on slope analysis and a multi-objective optimization problem balancing coverage, energy usage, the number of sensors and redundancy. Although the research offers a detailed design of sensors deployment, it is essential to note that there are some limitations. The simulation analysis is performed in an artificial setting that is informed by geospatial data and real-time validation in field is not executed. Also, other environmental conditions like time-related changes in the soil conditions and weather dynamics are taken as implicit and not with real-time combinations. Even though these limitations exist, the suggested framework provides a strong and scalable

framework of intelligent sensor implementation in precision agriculture.

The importance of the study is that it is going to assist in closing the gap between theoretical optimization model and the actual agricultural requirements. The suggested solution will enable the sensing resources to be exploited more effectively, reduce unnecessary redundancy, and achieve better energy efficiency with the implementation of field geometry and spatial heterogeneity in the deployment scheme, and the event-based communication scheme. This has direct consequences of cost reduction in deployment, lifetime of the network as well as accuracy of irrigation decisions. Besides this, it is the goal of the framework to develop a common goal of climate-smart agriculture achieved by enhancing sustainable use of resources and adaptive monitoring practices. In that regard this research attempts to do so.:

- Develop a system of geometry sensitive modeling whose property can model irregular agricultural fields and spatially varying features in an accurate fashion depending on the terrain features.
- Create a heterogeneity-based sensor deployment model which can dynamically vary sensor density to spatial information distribution to offer effective geographical coverage; and
- Design and implement a multi-objective sensor placement optimization model along the lines of coverage, energy usage, the number of sensors and redundancy with a Geography-Aware Hybrid Adaptive Swarm Optimization (GA-HASO) algorithm.

When the centre of location of uniform sensing is relocated to an intelligent and variability-oriented location, a proposed framework will provide a plausible and scalable solution to make agricultural monitoring systems more effective and sustainable.

2.LITERATURE REVIEW

WSNs have emerged as one of the key enabling technologies in precision farming since they can be used to conduct constant field surveillance, optimize irrigation, and make resource allocation decisions based on data. The quality of deployment in WSN-based systems has a direct effect on the sensing reliability, communication efficiency, energy consumption and network lifetime. Recent research has thus shifted away the simple heuristic layouts to hybrid and metaheuristic deployment schemes. Hybrid metaheuristic methods have enhanced the node placement, network reliability and security and demonstrated that deployment of

sensors is not just a geometric arrangement problem but a more general system-level optimization problem [11]. Other comparative studies in Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) also suggest that the population-based algorithms can be applied in the optimization of conflicting objectives e.g. coverage, energy, and computational efficiency of the IoT enabled WSNs [12]. It is also verified in reviews of bio-inspired optimization techniques that they are appropriate in nonlinear, constrained, and high-dimensional problems of WSN deployment [13]. Nevertheless, most of the current deployment models are based on simplified assumptions which restrict their usage in real agricultural settings. Initial studies of using PSO-based sensors deployment usually assumed a homogeneous sensor field and uniform distribution of nodes [14]. These assumptions are convenient mathematically but poorly applicable in agricultural lands which tend to have disorganized boundaries, terrain changes, non-even soil cover and spatial heterogeneity. More recent research on smart agriculture has highlighted sensor localization and connectivity as key demands of sustainable agricultural monitoring [15]. However, the methods tend to have more focus on connectivity or localization accuracy but not on a realistic representation of field geometry and terrain-applied variability. Wireless sensor scheduling has also been optimized by evolutionary algorithms, demonstrating that dynamic operational behavior is significant to consider, as well as the position of nodes, which is static [16]. Additionally, research on sensing-model studies illustrates that the assumptions about sensing range, interaction with nodes, and the environment have a strong influence on coverage performance [17]. So, agricultural coverage cannot be used as an abstract geometrical measure; it must be a physical and spatial measure on the field of observation. Context-sensitive node location is also found to be relevant in agricultural sensing. In the real-case studies of soil water estimation, the site where the sensor is placed directly affects the quality of estimation and sensor deployment hence becomes a determinant of the quality of agronomic data [18]. Similarly, the WSN-based smart irrigation monitoring systems emphasize the need of decentralized, timely, and reliable field observation to support the management of water [19]. This activity is enhanced to a new level by the irrigation systems based on the IoT and machine-learning, which enables making predictions and controlling it automatically [20]. These research state that the positioning of sensors determines

both the effectiveness of the network as well as the effectiveness of making agricultural decisions based on the sensed information. At the same time, adaptive coverage control and energy management are becoming a subject of increased interest. Adaptive PSO and node-sleeping have been shown to be capable of trading sensing performance and energy saving in resource-constrained sensor networks [21].

The latest advances in the use of IoT in the agricultural sector further support the importance of smart and energy-conscious implementation systems. In-depth analyses indicate that IoT technologies are revolutionizing agriculture by employing real-time monitoring, automation, data analytics, and intelligent decision support [22]. Hybrid energy-conscious WSN models that integrate clustering, routing, PSO, fuzzy logic, and self-organising maps have been put forward to enhance the network lifetime and functional efficiency [23]. IoT irrigation systems that use machine-learning have also increased the use of agricultural sensing to crop recommendation, soil classification, and disease detection [24]. Moreover, the combination of IoT and artificial intelligence has been recognized as one of the key trends of site-specific agricultural management [25]. The significance of the smart farming setting power-conscious monitoring can also be further evidenced using hybrid energy and IoT-based irrigation systems [26].

Although these studies have gone a mile in optimization of WSN, IoT-based agriculture, energy-aware routing, and smart irrigation, there remains a large research gap. Most of the current strategies predominantly focus on connectivity, routing, energy management, automation, and general IoT intelligence, yet irregular field geometry and spatial heterogeneity are given little attention. In practice, in real-life farming, the sensor density should be a function of the terrain characteristics and the heterogeneity of the soils and not necessarily a uniform deployment scheme or a strictly network-based scheme. Therefore, the multi-objective optimization model that considers coverage, redundancy, energy consumption, and the number of sensors is required, which is geography sensitive. The current study fills this gap by proposing a Geography-Aware Hybrid Adaptive Swarm Optimization model in the localization of sensor nodes in smart irrigation and in soil surveillance.

3. METHODOLOGY

3.1 Research Design and Geospatial Modeling

The paper adopts a computational-experimental design to optimize the deployment of sensor nodes in irregular agricultural environments by integrating geospatial analysis with metaheuristic optimization. The agricultural field is modeled as a continuous spatial domain,

$$\Omega \subset \mathbb{R}^2 \quad (1)$$

on the raster geospatial information that includes elevation and terrain data. The field boundaries are determined by masking, and clipping processes creating irregularly shaped polygons, which are very close approximations of non-uniform agricultural fields. Each spatial location,

$$\mathbf{x} = (x, y) \in \Omega, \quad (2)$$

is assigned terrain characteristics. In particular, the slope $S(\mathbf{x})$ is computed from elevation gradients and used as a proxy for spatial heterogeneity.

3.2 Spatial Heterogeneity and Sampling Strategy

To avoid inefficient uniform deployment, the field is partitioned into K zones:

$$\Omega = \bigcup_{k=1}^K \Omega_k \quad (3)$$

we also utilized data about tomato irrigation [27] and terrain slope change [28] utilizing space coordinates. Population space is the space of all possible sensor locations in Ω , and a smaller sample space is obtained by sampling variability. In particular, the significance of each zone is determined as:

$$W_k = \text{Var}(S(x)), x \in \Omega_k \quad (4)$$

and the size of the candidate points sampled within each zone is proportional to W_k . This guarantees that areas that are more terrain varied are better represented by the sensor, whereas homogeneous ones are underrepresented. The sampling strategy integrates population definition and data reduction in the methodology, so that the spatial information is not lost, and the optimization can be efficiently done.

3.3 Coverage, Redundancy, and Energy Modeling

The geographical coverage is determined with respect to the sensing radius R . A point $\mathbf{x} \in \Omega$ is considered covered if its distance to at least one deployed sensor node is less than or equal to R :

$$\min_j d(\mathbf{x}, \mathbf{x}_j) \leq R. \quad (5)$$

The overall geographical coverage is then expressed as

$$C_{\text{geo}}(X_i) = \frac{1}{|\Omega|} \int_{\Omega} \mathbb{I} \left(\min_j d(\mathbf{x}, \mathbf{x}_j) \leq R \right) d\mathbf{x} \quad (6)$$

where $\mathbb{I}(\cdot)$ is the indicator function, which equals 1 when the condition inside it is satisfied and 0 otherwise.

To prevent excessive clustering of sensors, a redundancy penalty is introduced as,

$$R_d(X_i) = \sum_{p \neq q} \mathbb{I}(d(\mathbf{x}_p, \mathbf{x}_q) < d_{\min}) \quad (7)$$

where d_{\min} is the minimum allowable separation distance between two sensor nodes.

Energy consumption is modeled by considering both sensing and communication costs:

$$E(X_i) = N_{\text{sense}} e_s + N_{\text{tx}} e_t, \quad (8)$$

where N_{sense} denotes the number of sensing operations, e_s is the energy consumed per sensing operation, N_{tx} represents the number of event-triggered transmissions, and e_t is the energy consumed per transmission. This formulation reflects an event-based IoT paradigm, in which data transmission is performed only when critical environmental conditions are detected.

3.4 Multi-Objective Optimization Formulation

The sensor placement problem is formulated as a multi-objective optimization task:

$$F(X_i) = w_1 C_{\text{geo}}(X_i) - w_2 E(X_i) - w_3 N_s(X_i) - w_4 R_d(X_i) \quad (9)$$

where C_{geo} , E , N_s , and R_d represent geographical coverage, energy consumption, number of sensors, and redundancy penalty, respectively. The optimization is based on spatial and operational constraints:

$$x_j \in \Omega, d(x_p, x_q) \geq d_{\min}, N_s \leq N_{\max}, C_{\text{geo}} \geq C_{\min} \quad (10)$$

3.5 GA-HASO Optimization Framework

The suggested Geography-Aware Hybrid Adaptive Swarm Optimization (GA-HASO) algorithm comes out as a combination of the particle swarm optimization and genetic operators. The candidate solutions are subsets of sensor locations all of which are sampled by sampling the sampled population.

The PSO-based update is defined as:

$$V_i^{t+1} = \omega_t V_i^t + c_{1,t} r_1 (P_i^t - X_i^t) + c_{2,t} r_2 (G^t - X_i^t) \quad (11)$$

$$\hat{X}_i^{t+1} = X_i^t + V_i^{t+1} \quad (12)$$

To enhance diversity, a genetic refinement stage is applied:

$$\begin{aligned} \tilde{X}_i^{t+1} &= \text{Crossover}(\hat{X}_i^{t+1}, P_j^t), X_i^{t+1} = \\ &\text{Mutation}(\tilde{X}_i^{t+1}) \end{aligned} \quad (13)$$

Adaptivity is introduced through time-varying parameters:

$$\omega_t = \omega_{max} - \frac{t}{T}(\omega_{max} - \omega_{min}), c_{1,t} = c_{1,max} - \frac{t}{T}(c_{1,max} - c_{1,min}), c_{2,t} = c_{2,min} + \frac{t}{T}(c_{2,max} - c_{2,min}) \quad (14)$$

This process progressively changes the search behavior or exploration to exploitation enhancing the stability of convergence.

3.6 Event-Driven Sensing and Analytical Evaluation

Sensor nodes operate under an event-driven communication model, where data transmission occurs only when environmental thresholds are violated:

$$M(x) < M_{th} \text{ or } N(x) < N_{th} \quad (15)$$

This will go a long way in reducing overheads in communication and energy wastage. The optimized deployment is compared to the standard deployment techniques, including random, grid-based, clustering-based and standard PSO. Performance metrics, such as coverage efficiency, energy usage, sensor utilization, and convergence behavior will be used to make certain that the proposed framework is fully assessed.

4. RESULTS AND ANALYSIS

4.1 Spatial Heterogeneity and Zoning Analysis

The usefulness of the suggested framework starts with the fact that it is capable of properly addressing the spatial heterogeneity of the irregular agricultural plots. According to the diagram in Figure 1 (Geography-Based Zoning), the research area is divided into several zones characterized by the slope of the terrain and space features. The clustering shows that there are different regions of different density and distribution which means that there is a lot of heterogeneity in the field.

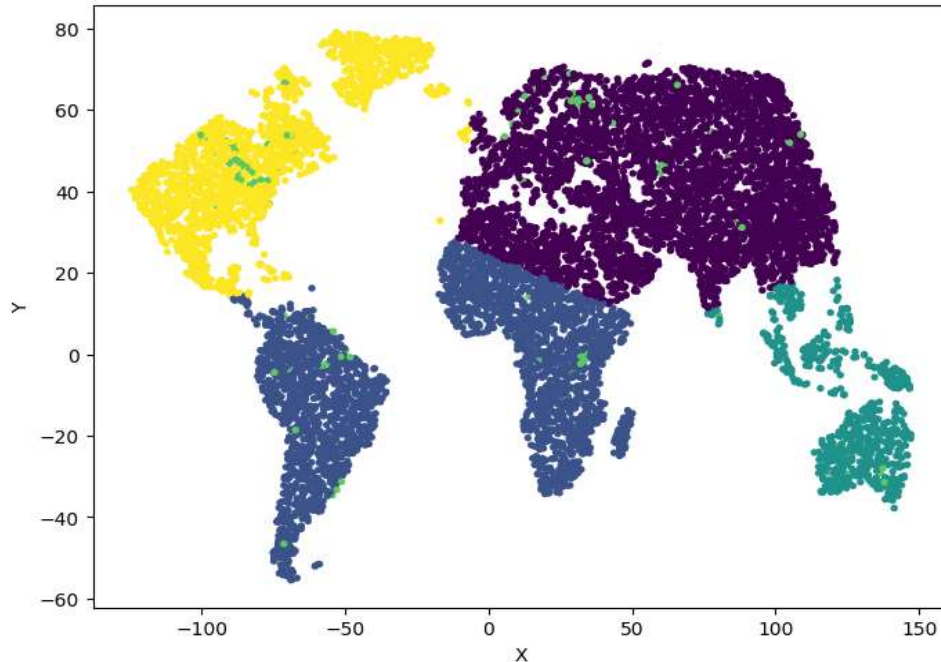


Figure 1. Geography-Based Zoning

Interestingly, the density clusters are observed to be higher in places where there is a high variability of slope with more homogenous distributions in a relatively homogenous area. This validates the first hypothesis, that agricultural fields are non-uniform

and require adaptive sensing solutions. The zoning mechanism is an alternative to the conventional grid-based methods; it may be applied to conduct data-based segmentation, which is the basis of successful sensor deployment.

It has a direct impact on the following procedures, especially, on the selection of candidates and their optimization due to the zoning structure. With greater emphasis on regions that are more variable, the framework guarantees that critical areas get sufficient sensing coverage without any unnecessary redundant deployment in homogeneous areas.

4.2 Candidate Sensor Distribution

The sampling plan is good since it is shown in Figure 2 (Candidate Sensor Points). The sampling mechanism of heterogeneity is observed in the distribution of candidate points. Areas that have been highlighted as highly variable in Figure 1 are densely populated with candidate points and uniform areas are densely populated with a few points.

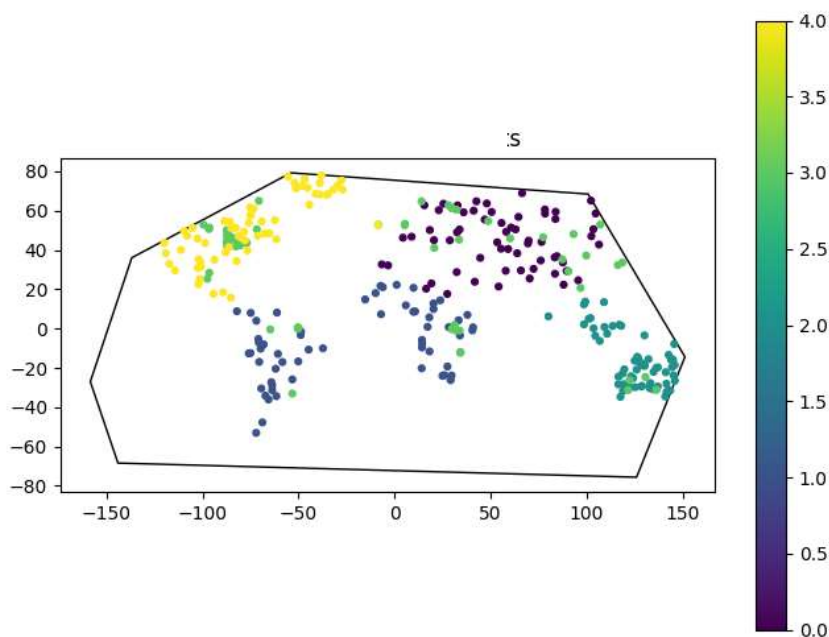


Figure 2. Candidate Sensor Points

This non-uniform sampling is significant to reduce the computational complexity but ensure required spatial details. The strategy is not targeted at all areas, but at those that are more informational. The result is that optimization process is conducted over a smaller yet representative search space, with efficiency being attained without compromising accuracy.

This step also combines the definition of the population and sampling into the optimization process. It ensures that there is no arbitrary

creation of a pool of candidates but that it is geographically inclined towards the field.

4.3 Optimized Sensor Deployment

Figure 3 (GA-HASO Sensor Placement) shows the final sensor position that is obtained with the proposed GA-HASO algorithm. The resulting structure is clearly not similar to the traditional homogeneous or grid based locating plans because it exhibits adaptive spatial distribution depending on the geographical features.

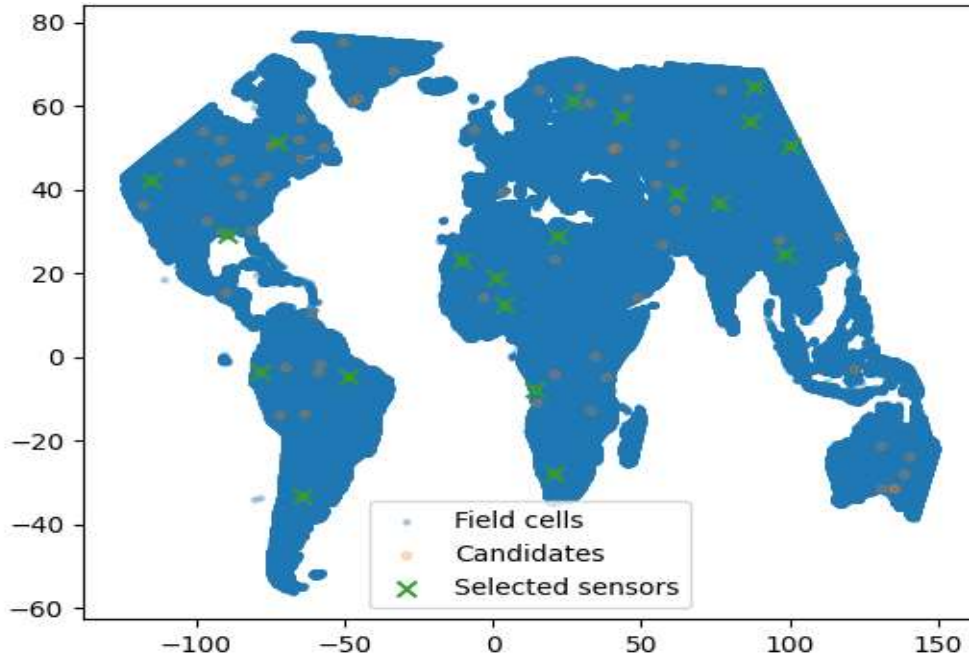


Figure 3. GA-HASO Sensor Placement

Sensor nodes (green crosses) are evenly spaced, with greater concentration in regions with more spatial variability, and fewer sensors in homogeneous regions, attesting to effective geometry-conscious and heterogeneity-directed deployment. The optimized deployment eliminates the under-coverage of the crucial areas and does not over-deploy the sensors, and the fact that there is no clustering also means that the redundancy penalty is operating correctly, and there is sufficient inter-sensor separation. Moreover, the distribution is indicative of a balanced exploration exploitation process, which

leads to a well dispersed but focused deployment pattern. Practically, it will result in a smaller number of sensors, lower cost of deployment and more efficient monitoring. In general, the findings confirm the hypothesis that GA-HASO framework can be used efficiently, scalable and terrain-consciously to deploy sensors to smart irrigation and soil monitoring applications.

4.4 Coverage Performance Evaluation

The comparative coverage performance across different methods is illustrated in Figure 4 (Coverage Comparison Across Methods).

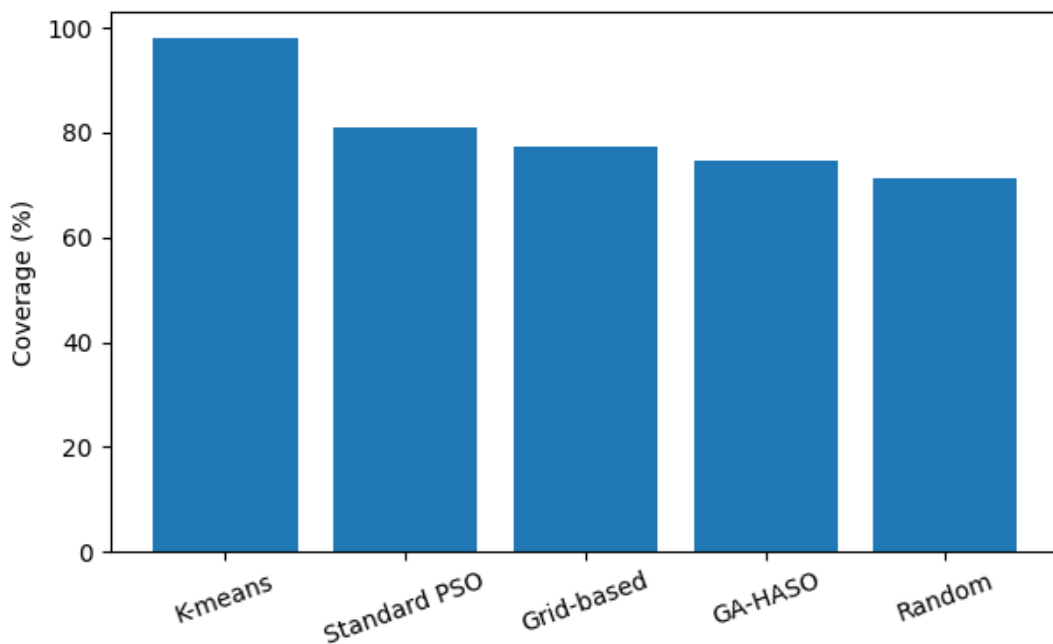


Figure 4. Coverage Comparison Across Methods

To produce the coverage comparison graph, all sensor deployment methods were applied to the same irregular agricultural field, and the resulting sensor-node configurations were evaluated using the geographical coverage measure in Equation (5). For each method, the distance between every valid raster cell of the field domain Ω and its nearest sensor node was computed. A raster cell was considered covered when this minimum distance

was less than or equal to the sensing radius R . The total number of covered cells was then divided by the total number of valid field cells and expressed as a percentage. Thus, the bar height in Figure 4 represents the percentage of agricultural area covered by each deployment method. The corresponding numerical coverage values are summarized in Table 1.

Table 1: Coverage Performance Across Methods

Method	Coverage (%)
K-means	~98
Standard PSO	~81
Grid-based	~77
GA-HASO	~74
Random	~71

As shown in Table 1, K-means appears to provide the highest coverage at first sight. However, this result should be interpreted with caution because the K-means algorithm can produce dense sensor clustering, which improves nominal coverage but may increase redundancy and deployment cost. Conversely, GA-HASO achieves competitive coverage while maintaining a more efficient and structured deployment pattern.

Conversely, GA-HASO has a higher competitive coverage (~74) and is much more efficient. In comparison with grid based and random techniques, GA-HASO offers:

- More structured deployment
- Reduced redundancy
- Balanced coverage

The overall argument that comes out in this case is that the optimum coverage is not the best one. The proposed method emphasizes on efficient coverage

where the acceptable coverage is achieved with the minimum resources used.

4.5 Comparative Efficiency Analysis

Table 2 was done by using all the bases and optimized deployment strategies on a unity agricultural field Ω . The coverage value of every resultant sensor configuration was calculated using the sensing-radius condition established in Equation (4) and the geographical coverage formulation equation in Equation (5). Raster implementation involved testing each valid field cell against its nearest sensor node; the Raster implementation was to count the number of them covered. The percentage of coverage reported was calculated as the proportion of covered cells to the total number of viable cells in the field. Thus, a graph/table is created based on the coverage equation when each method has created its respective sensor placement.

Table 2: Baseline vs Optimized Performance

Method	Coverage (%)
Random Baseline	~76
Zone-Centroid Baseline	~28
Optimized (GA-HASO)	~75

The optimized approach has similar coverage as the random baseline with several unique benefits,

such as structured deployment, less randomness, and better interpretability. In contrast to all-

stochastic methods, the GA-HASO model yields uniform and spatially sensible sensor configurations, so the decision to deploy sensors is informed by the underlying field properties instead of randomness. This indicates that GA-HASO is more dependable and practically applicable in comparison to random baseline because it is a systematic and reproducible solution.

4.6 Interpretation of Optimization Behavior

Although not depicted as such, the optimization procedure has a gradual convergence to it, and one can attribute this fact to the fact that the GA-HASO algorithm is hybrid. The PSO element will assist in searching the space worldwide to ensure that the potential optimal areas are well explored. In the meantime, the genetic operators add diversity into the population, and it avoids stagnation and increases the variability of solutions. The adaptive mechanism also maintains the balance between exploration and exploitation by adaptively modifying algorithm parameters with each iteration. The overall combination of these factors allows avoiding the risk of premature convergence and finding the near-optimal solutions within a limited number of iterations.

4.7 Trade-offs inherent in sensor deployment

The findings indicate several significant trade-offs in the implementation of sensors in smart agriculture. First, coverage versus sensor count is an apparent trade-off where more coverage a person wants, the more sensors it can add, yet again this would lead to increase in cost of deployment and redundancy. Second, coverage versus energy consumption will be a trade-off between the dense sensor deployments with increased communication overheads and with optimal deployments that reduce the frequency of transmissions and contributes to the energy efficiency. Third, the trade-off between efficiency and redundancy must be a key consideration; whereas the algorithm such as K-means would potentially optimise the coverage, it often leads to an enormous redundancy, and the proposed GA-HASO model offers a more reasonable trade-off. On the whole, the proposed method effectively deals with these trade-offs by its formulation of multi-objective optimization to ensure efficient, cost-effective and energy-conscious placement of sensors.

4.8 Implications for Smart Agriculture

The results show a tremendous practical implication of the proposed methodology in the field of precision agriculture. It allows the cost to

be saved since it will need less sensors and, at the same time, it will not impair the quality of monitoring, which decreases costs of deployment and maintenance (even more). It is also more energy efficient since it is event driven communication, thereby decreasing the number of unnecessary data transmissions and increasing the length of the network.

Moreover, the method can be significantly scaled and applied in bigger and more complex agrolocations that are of varying topographies. In addition, it fosters good decision making because the sensors will be in the optimum location resulting in more accurate and representative data that will be used to inform the irrigation management. Overall, geospatial intelligence and adaptive optimization can be a potent and scalable solution to effective and sustainable agricultural monitoring infrastructures.

5. DISCUSSION

This paper demonstrates that sensor placement based on spatial heterogeneity offers a more useful remedy to agricultural surveillance than does homogenous or merely geometric placement policies. The zoning results indicate that the field of study is endowed with obvious terrain differences, which have direct impact to sensing demand variation among the sites. The most effective deployment scheme supports the notion that the suggested GA-HASO framework distributes a larger number of sensors in areas of high variability and fewer sensors in comparatively homogeneous areas which are not a necessity. This observation allows to confirm the main hypothesis of the research: the efficiency of deployment in the case of smart irrigation and soil monitoring is not related to the uniformity of the spatial distribution, but rather to the capacity to match the intensity of sensing with the variability of the environment.

This interpretation is also reinforced by the comparative findings. Although some of the techniques can be applied identically to achieve a greater nominal coverage, they can be applied by more dense or less selective deployments, resulting in increased redundancy and reduced practical efficiency. The proposed approach, in contrast, has a more balanced trade-off between coverage, energy consumption, number of sensors, and redundancy. This means that it is not the raw coverage that is maximized in the specified framework, but the useful geographical coverage and expenditure of resources is regulated. This variation is very important in the farming environment where price, battery capacity, and service are very essential. The findings thus point

out that an efficient multi-objective performance should be used to assess optimal deployment, as opposed to a single metric of coverage.

These results are generally in line with the previous research on bio-inspired and swarm-based optimization of WSNs. Past reviews have established that evolutionary and bio-inspired approaches have been the best in handling nonlinear and constrained deployment issues since they are flexible in how they can be applied to multiple targets simultaneously [13]. In the meantime, most of the PSO-based literature on homogeneous deployment has generally considered a regular sensing space and uniformly distributed node requirements, which limits them to irregularly-bounded agricultural fields with spatially-varying terrain [14]. Recent research on the agricultural sector has emphasized localization and connectivity as important aspects of sustainable monitoring systems and determined that the position of the nodes determines the general consistency and sustainability of the agricultural sensing infrastructures [15]. It has also been demonstrated in a related literature concerning evolutionary optimization in wireless sensor scheduling that adaptive optimization schemes can be used to optimize the system level efficiency under resource constraints [16]. The present study expands on them by showing that field geometry and terrain variability must be explicitly factored into optimization of deployments in agriculture, rather than using generalized network-based formulations.

The work has wide application implications. To begin with, the proposed framework will enable a reduction in the cost of deployment since it will avoid the implementation of the unnecessary sensors in the homogenous areas. Second, event-driven communications logic into the integration allow lower transmission overhead, thus enhancing energy efficiency and possibly increasing network lifetime. Third, there is an opportunity to improve the quality of the irrigation-related decision making in accordance with the monitoring network by emphasizing on representative sensing instead of dense sensing. These advantages make the solution particularly attractive in the contextual precision agriculture where there are financial, technical and energy resource constraints. On a larger scale, the findings are worth the change in the paradigms of the deployment of generic WSNs in area-sensitive sensing systems configurations with respect to the physical and agronomic characteristics of the object of interest.

A few restrictions are to be noted as well. This paper is grounded on a simulated geospatial environment constructed using raster data and thus, it is not currently involved with field deployment of such systems in real-time or longitudinal validation of these systems as changing environmental conditions are involved. Also, the model of energy is deliberately simplified to reflect the cost of sensing and transmission on the generalized level; the real implementing deployments might be considered as more elaborate hardware usage, routing and communication patterns. The existing model is also based on terrain driven heterogeneity, and it does not explicitly include other significant agronomic factors, including soil texture, crop type or seasonal variation, which could also influence the optimal sensor density.

This work can be extended in various ways in future research. Real-field validation is one of the priorities to ascertain how the proposed deployment behaves in real-world conditions when it is applied in irrigation, the variability of weather, and the uncertainties associated with the hardware level. Second pathway involves the inclusion of additional covariates on the environment, including the allocation of soil nutrients, activity and moisture dynamics of crops to improve the agronomic sensitivity of the placement model. The third opportunity is to carry out the current optimization framework using predictive analytics or learning-based control systems in such a way, that adaptive reconfiguration during the time can be carried out. These extensions would increase the scalability and practical robustness of the framework and advance to fully autonomous and intelligent sensing systems to climate-smart agriculture.

6. CONCLUSION

In this study, a geometry-conscious and heterogeneity-driven optimization framework was proposed for sensor node placement in smart irrigation and soil monitoring systems. By integrating geospatial modeling, terrain-based zoning, and the GA-HASO optimization algorithm, the study demonstrated that sensor deployment becomes more efficient when sensor density is aligned with spatial variability rather than distributed uniformly across the field. The results indicate that the proposed approach achieves a balanced trade-off among geographical coverage, energy consumption, sensor count, and redundancy, thereby improving monitoring efficiency without compromising data quality.

From an environmental science perspective, the framework contributes to sustainable agricultural resource management by supporting more precise irrigation decisions, reducing unnecessary sensor deployment, and minimizing energy-intensive communication in wireless sensor networks. By prioritizing representative sensing in environmentally variable zones, the proposed method enhances the quality of soil and field-condition monitoring while reducing operational and ecological costs. This makes the approach particularly relevant for climate-smart agriculture, where efficient water use, energy conservation, and adaptive environmental monitoring are essential.

Although the framework shows practical potential, further validation under real field conditions is required to assess its performance under dynamic soil, crop, and weather variability. Future work should incorporate additional agronomic and environmental parameters, such as soil texture, crop type, nutrient distribution, and seasonal moisture changes, to improve deployment precision. Integrating predictive analytics and adaptive sensing mechanisms could further support autonomous, environmentally sustainable, and climate-resilient agricultural monitoring systems.

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