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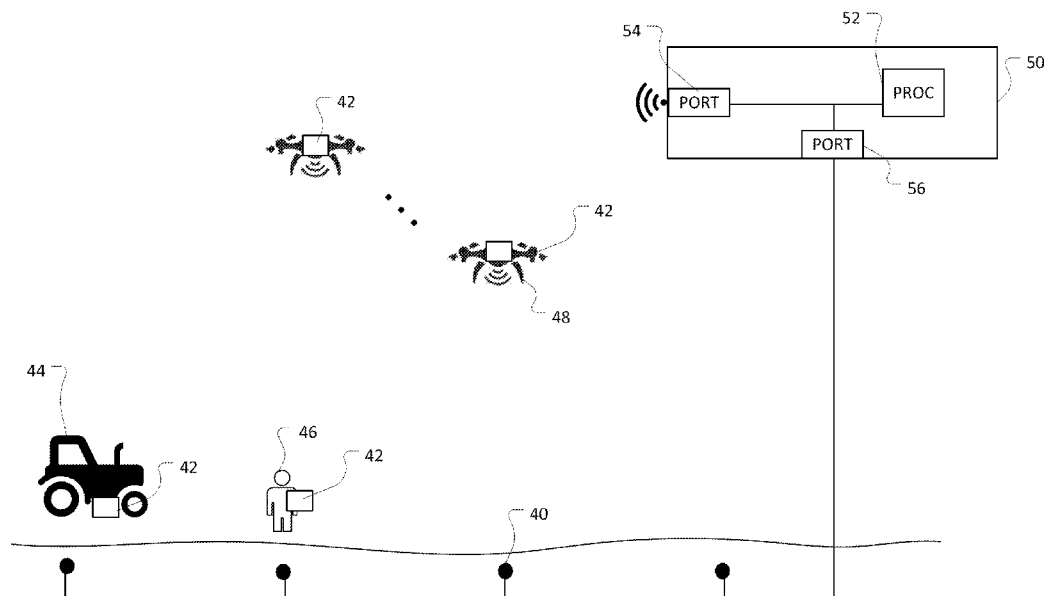


FIG. 11

(57) Abstract: A system to monitor soil data includes an array of sensors, each sensor positioned such that any overlap between adjacent sensors is minimized and coverage of a field is maximized, and one or more readers configured to gather data from the sensors and provide the data to a computing device. A method includes representing an agricultural field as a set of field pixels, placing an initial sensor at a random pixel location, selecting a selected pixel from the set of field pixels, determining if a sensor placed at a location of the selected pixel would overlap with any other sensor already placed in the field, placing a sensor at the location, if the sensor would not overlap any other sensors, to become part of a design, computing a score for the design, and repeating the method until the agricultural field has maximum sensor coverage with minimal overlap between sensors.

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**PLACEMENT AND DRONE FLIGHT PATH MAPPING OF
AGRICULTURAL SOIL SENSORS USING MACHINE LEARNING**

RELATED APPLICATIONS

[0001] This disclosure is a non-provisional of and claims benefit from US Provisional Application No. 63/512,738, titled “PLACEMENT AND DRONE FLIGHT PATH MAPPING OF AGRICULTURAL SOIL SENSORS USING MACHINE LEARNING,” filed on July 10, 2023, the disclosure of which is incorporated herein by reference in its entirety.

STATEMENT REGARDING FEDERALLY SPONSORED RESEARCH AND
DEVELOPMENT

[0001] This invention was made with Government support under award number DE-AR0001013 awarded by the US Department of Energy, and award number 2020-67021-32855 awarded by the US Dept. of Agriculture. The Government has certain rights in this invention.

TECHNICAL FIELD

[0002] This disclosure relates to precision agriculture, more particularly to precision agriculture using drones in conjunction with soil sensors.

BACKGROUND

[0003] Precision agriculture offers a pathway to increase crop yield while reducing water consumption, carbon footprint, and chemicals leaching into groundwater. Precision agriculture comprises the practice of collecting spatial and temporal data in an agricultural field to match the inputs to the site-specific conditions. While industrial agriculture seeks to maximize crop yield, one needs also to consider maintaining a healthy ecosystem. Fortunately, these are not competing interests; numerous case studies have demonstrated that

adopting precision agriculture techniques increases crop yield while lessening detrimental environmental effects (Diacono, M., Rubino, P., Montemurro, F., 2013. Precision nitrogen management of wheat. A review. *Agron. Sustain. Dev.* 33 (1), 219–241. Ahrens, T., Lobell, D., Ortiz-Monasterio, J., Li, Y., Matson, P., 2010. Narrowing the agronomic yield gap with improved nitrogen use efficiency: a modeling approach. *Ecol. Appl.* 20 (1), 91–100. Sela, S., Woodbury, P., Van Es, H., 2018. Dynamic model-based N management reduces surplus nitrogen and improves the environmental performance of corn production. *Environ. Res. Lett.* 13 (5), 054010.)

[0004] Consider the first the use of irrigation in agriculture, which accounts for approximately 36.7% of the freshwater consumption in the U.S., 65% in China, and 77% in New Zealand. This is in part because crops need a large amount of water to grow. For example, high-production maize crops require 600,000 gallons of water per acre per season—about the same volume as an Olympic swimming pool. However, adopting precision agriculture practices such as variable-rate irrigation methods has been proven to reduce water consumption by 26.3%. Meanwhile, fixing nitrogen from the air to produce fertilizers is an extraordinarily energy-intensive process and accounts for nearly 2% of the U.S.’s annual CO₂ emissions. Crop plants recover only 30%–50% of nitrogen in fertilizers, which means that over half of the nitrogen becomes a potential source of environmental pollution, such as groundwater contamination, eutrophication, acid rain, ammonia redeposition, and greenhouse gases. Fortunately, precision agriculture practices have demonstrated an increase in nitrogen use efficiency, thereby reducing both the production volume of fertilizer and the amount that is polluted into the environment.

[0005] Accurate soil data represents crucial information for precision agriculture. In particular, the moisture content and the concentration of various chemical analytes in soil have a significant influence on crop health and yield. These properties vary considerably over

short distances. A need exists for accurate placement of sensors in the soil, as well as a way to gather the sensor data.

BRIEF DESCRIPTION OF THE DRAWINGS

[0006] FIG. 1 shows graphical representations of definitions of agricultural fields.

[0007] FIG. 2 shows a flowchart of an embodiment of a sequential gap reduction process for placing sensors in a digitized agricultural field.

[0008] FIG. 3 shows schematics of a single-agent model and a two-agent, three-objective system.

[0009] FIG. 4 shows embodiments of sensor placements and effective field coverage.

[0010] FIG. 5 shows embodiments of different data sampling strategies.

[0011] FIG. 6 shows embodiments of flight paths of drones for scanning sensors.

[0012] FIG. 7 shows split-axis plots showing total distance traveled and the flight time.

[0013] FIG. 8 shows a box-whisker plot showing the variance of energy consumption per sensor scanned.

[0014] FIG. 9 show sequences of flight paths in a center-pivot irrigation field for a four-agent swarm.

[0015] FIG. 10 shows an embodiment of flight paths for a four-agent swarm.

[0016] FIG. 11 shows a diagram of an embodiment of an agriculture sensor system.

DETAILED DESCRIPTION OF THE EMBODIMENTS

[0017] The embodiments herein involve a system for detection of information from agricultural soil sensors having placement of the sensors based upon the variability of soil properties and the characteristics of the sensors. The sensors may gather and communicate different types of data about the soil, including, but not limited to the moisture content, amount of fertilizer, and presence of a particular analyte such as that resulting from the use of pesticides or fertilizers including nitrogen.

[0018] In placing sensors, one can use half the spatial range, referred to herein as the ‘half variogram range,’ as a “rule-of-thumb” to account for the spatial dependency of agricultural measurements. The variance of a measurand, z , as a function of distance is empirically given by:

$$\hat{\gamma}(\vec{h}) = \frac{1}{2} \cdot \frac{1}{N(\vec{h})} \sum_{i=1}^{N(\vec{h})} [z(\vec{x}_i + \vec{h}) - z(\vec{x}_i)]^2 \quad (1)$$

where $\hat{\gamma}$ is the variance, $z(\vec{x}_i)$ and $z(\vec{x}_i + \vec{h})$ are the measured values of the measurand z at $N(\vec{h})$ pairs of comparisons separated by the vector $\vec{h}$. Numerous studies have determined the spatial range of various soil properties in various soil conditions, which demonstrates the fact that the half-variogram range itself varies depending on the geographic location and sampling method. Recently, Longchamps & Khosla analyzed and tabulated the spatial ranges of numerous soil properties reported in literature (Longchamps, L., Khosla, R., 2017.

Precision maize cultivation techniques. In: Achieving Sustainable Cultivation of Maize Volume 2. Burleigh Dodds Science Publishing, pp. 127–157.), which can be used as informed estimates for spacing sensors when no other information about the soil is known.

[0019] Geostatistically representative soil data can be collected with agricultural sensors spaced at the half-variogram range. The data gathered from these sensors can inform management techniques such as variable-rate technologies, which adapt to the heterogeneities of an agricultural field and thus enable site-specific management. For example, farmers could tailor their nitrogen and water management to site-specific conditions, which would, in turn, reduce nitric oxide emissions, increase yields, and reduce fertilizer use. Other researchers have investigated the use of machine-learning algorithms as tools for decision-making in precision agriculture. However, as far as the inventors know, no others have optimized agricultural soil sensor placement using the half-variogram range to inform the placement of sensors.

[0020] Because many sensors need to be distributed across an agricultural field to acquire granular enough data to capture soil variability, drones offer a unique advantage over other existing methods to sample data from the sensors. With drones and drone accessories becoming less expensive, using multiple drones to simultaneously map sensors has become an attractive route to efficiently gather data. Machine-learning algorithms provide a promising approach for generating flight path maps due to their ability to solve highly non-convex problems rapidly and even operate in real-time as a digital twin.

[0021] The embodiments here employ a sequential gap reduction (SGR) algorithm that determines an optimal distribution of soil sensors across an agricultural field. The SGR process solves optimal sensor distribution using the half-variogram range as the basis in four field geometries: a circular field, a rectangular field, a field with both circular and rectangular features, and a field shape determined from an image. The embodiments provide a methodology for sampling the sensor measurements using UAV swarms.

[0022] Similar to definitions of an agricultural field as a geographic area at a location in the real world, one can define a digital representation, or 'simulation,' of an agricultural field as some number of discrete pixels, where each pixel position corresponds to a geographic coordinate, and its size corresponds to an area. The embodiments discuss three methods of expressing an agricultural field in a digital format.

[0023] Approximating some agricultural fields, such as a rectangular field or a center-pivot irrigation field, digitally becomes trivial. For a rectangular-shaped field, one can discretize the space into a grid of uniform pixels with dimensions proportional to the length and width of the physical field. For a center-pivot irrigation field, bounding the field uses a square grid of uniform pixels. Then, the process can test each pixel in the grid to determine if the pixel coordinates are equal to or less than the physical field radius. FIG. 1A demonstrates this technique for a rectangular-shaped field and FIG. 1B for a center-pivot irrigation field.

[0024] When an agriculture field has irregular boundaries, the field is defined by a list of consecutive coordinate points that form an enclosed shape when piecewise connected by polynomial curves. A ray tracing algorithm can determine whether or not a pixel lies inside or outside of this boundary. Given an enclosed boundary and a point in space, if one draws an infinite vector in any direction originating from that point, it will intersect the boundary an odd-numbered of times if-and-only if the point lies within the enclosed space, shown in FIG. 1C. This holds for all points in space except for points on the boundary, which must be determined explicitly. This way, the coordinates of each pixel are used as a point to determine if a pixel is inside the boundary and append it to a list.

[0025] Finally, satellite or drone visible-spectra images of agricultural land are already stored in a digital, pixelized format. Such images and datasets are widely available from Google Earth, NASA Earth Observatory, or the USDA cropland data layer, to name a few. Computer vision techniques can differentiate the arable land on a field from obstructions, such as roads, buildings, trees, and ponds, and store those pixels in a list. FIG. 1D shows this process.

[0026] In all cases, one should note the physical dimensions that a single pixel represents. One should also note that because each method requires discretization of the field, the results comprise approximations, the accuracy of which increases proportionally to the number of pixels used.

[0027] The optimal layout of sensors in an agricultural field occurs when, using the fewest number of sensors possible, all points in the field are statistically represented by the data collected by sensors in that field. For a given sensor, the data collected from that sensor is statistically significant for all points within a radial distance equal to the half-variogram range of that sensor. If one considers an agricultural field as a two-dimensional collection of pixels described previously, one can model sensors as circles with a radius equal to the half-variogram range. Using this definition for optimal sensor placement, the problem becomes

similar to the circle packing problem. Circle packing, or more broadly, “object packing,” is a well-researched area in mathematics that has many practical applications.

[0028] Object packing aims to fit as many objects within a domain as possible without any overlap between the objects. Several algorithms aim to optimize object packing, such as random sequential addition, the Metropolis algorithm, and various particle growth schemes. The limit of packing efficiency for equal-size circles in two dimensions is about 91% for a hexagonal grid. While circle-packing nearly describes the model problem, it has one major caveat: no physical justification prevents the circles (sensors) from overlapping. This ‘soft boundary’ makes it possible to achieve 100% coverage of the domain by allowing overlap. If the only objective was to maximize the effective areal coverage of the field, then one could simply distribute sensors next to one another without discretion. However, the monetary cost of sensors, sensor operation, and sensor maintenance makes this approach unreasonable, which motivates the stated objective of maximizing field coverage with the fewest sensors possible. This leads to the goal of providing the maximum field coverage with minimal overlap between the sensors, as that results in the fewest number of sensors needed to cover the field. The score for the design has a threshold, so there is a little flexibility to

[0029] The SGR algorithm was developed and applied to place sensors within the field to minimize the overlap of each sensor’s coverage radius. The general process is as follows:

INITIALIZE: Select a random pixel in the field and place a sensor there,

GENERATE: Select a random pixel in the field,

TEST: Check to see if a sensor placed at that pixel will overlap with any other sensor already placed in the field. If not, append that pixel to the list of placed sensors within the field,

SCORE: Compute the score of the design,

ITERATE: If the score is below the threshold, iterate through the algorithm.

[0030] This algorithm results in sensors placed throughout the field such that sensors are placed in the largest gaps between sensors. This is done by increasing the acceptable distance between sensors by a small amount, then making many attempts at placing a sensor before repeating the process. The fitness of each placement design was scored by the ratio of the number of field pixels within the half-variogram range of a sensor to the total number of pixels in the field. In other words, the process determines what percentage of the field area lies within the half-variogram range of one or more sensors. This process repeats until it is impossible to place a sensor outside the range of all other sensors in the design, or until the field is completely covered. FIG. 2A shows the flowchart of an embodiment of this algorithm, and FIG. 2B shows a schematic depicting the evolution of sensor placement in an arbitrary field shape.

[0031] In FIG. 2A, the process starts at 10 with the placement of an initial sensor in the field. At 12, the process selects a pixel. The process checks to see if the pixel is in range at 14. If the pixel is in range of at least one other sensor, a sensor is placed at that pixel in 16. The fitness of the design is determined at 18, and tested to see if it is still above the tolerance threshold at 20. If the design score, discussed above and represented by the cost function Π , less than the tolerance threshold (TOL), the process ends. Returning to 16, if the pixel is out of range at 16, the process checks to see if the number of times the process has failed, FAIL COUNT, has exceeded the tolerance at 26. If FAIL COUNT is less than the tolerance, a new pixel is selected and the process repeats. If the tolerance has been exceeded at 26, the range of each sensor is reduced at 28 to increase the acceptable distance between sensors, FAIL COUNT is reset, and the process continues.

[0032] To make informed decisions about allocating resources for treating the soil, one must sample or collect the soil sensor data periodically throughout the growing season. When deployed, soil sensors lie partially or completely buried under the soil using common farming

equipment such as post augers or portable excavators. FIG. 11 shows sensors such as 40 buried under the surface of an agricultural field.

[0033] Depending on the design of the sensor, communication of the data may take several forms. One method would be through a hardwire connection, such as a USB or Serial cable. An underground cable network would interfere with regular farming activities, but the sensors could be sampled by a temporary connection through a data port. However, this would require a data-reading device to directly contact with the sensor and a moderate level of precision to plug into the port.

[0034] In one embodiment, the data reading device may comprise a computing device such as 50, having one or more processors such as 52 configured to execute code that causes the one or more processors to communicate with the sensor such as 40, or the computing device may communicate with one or more mobile readers such as 42.

[0035] A simpler data transfer solution would integrate a transceiver into the sensor 40 and transmit the data wirelessly using RFID, Bluetooth Low Energy (BLE), Wi-Fi, or similar technologies. In this case, the data reading device would only need to be within the transmission radius of the sensor to sample the sensor data. Generally speaking, the cost and complexity of the sensor increase dramatically as the transmission radius increases. For the technology to be practical for agricultural field operations, the associated costs of the sensor need to be minimal, so short-range transmission technologies are more feasible at scale.

[0036] One can choose from several options to sample or gather the sensor data. One option uses a human 46, riding or walking along the sensor locations with one or more readers 42. Another option includes various types of ground machinery, such as tractor 44, fitted with one or more readers 40 to receive sensor data as it traverses above them. Tractors are well suited to traverse through muddy or uneven ground; however, they can become costly as they may have poor fuel economy. A typical Fendt 1050 tractor model may consume eight gallons

of diesel per hour and cover a large agricultural field may take the majority of a day. This does not include the cost of a staffed operator. A much more attractive option would be to incorporate unmanned vehicles, such as unmanned aerial vehicles (UAVs) such as 48, or unmanned ground vehicles (UGVs).

[0037] Unmanned vehicles typically have lower energy consumption than typical ground farm machinery and, as the name suggests, operate remotely, minimizing labor and operational costs. There are important distinctions to make between deploying ground-based and air-based vehicles. UGVs can typically withstand a larger range of weather conditions than UAVs but are limited to driving along the field rows to avoid damaging the crops. On the other hand, UAVs can traverse directly from sensor to sensor above the crop canopy. Because small UAVs and UGVs have similar energy consumption, the ability to traverse freely throughout a field makes UAVs more energy efficient than UGVs. Assuming the soil sensors have a wireless transceiver integrated, the UAVs can sample data from the sensor from anywhere within the transmission radius, meaning the UAVs' positioning around the sensor does not have to be precise, and slight perturbations to the UAVs' position caused by weather will have a minor effect on the overall performance.

[0038] A coordinated effort of multiple drones may possibly further reduce the time and energy required to sample data from each sensor in the field. Furthermore, it may be difficult for a single UAV to scan all sensors due to battery life limitations. For these reasons, the embodiments have developed a flight path optimization model for single-drone and multi-drone swarms to investigate their trade-offs.

[0039] The embodiments developed a robust agent-based model that generates flight paths for each drone within a swarm to scan all sensors within a simulated agriculture field. The simulations determine each drone's aerial route for optimal flight path planning. Each drone within the simulated framework, referred to as an 'agent,' has unique characteristics that

determine how it interacts with its surroundings, such as its environment and other drones.

These characteristic parameters take inspiration from the physics of molecular dynamics, where each agent is modeled as a point-mass particle that is attracted and repelled by other objects within the system. The framework inputs are the field's shape, the number of agents, and the sensor locations (targets).

[0040] Depending on the field geometry and the locations of sensors within that field, the framework will output several suggestions of each drone's trajectory. Agents follow some simplified assumptions, such as that the process may neglect the effects of buoyancy, lift, drag, and gravity as they have secondary importance. Other assumptions include that the agents may propel themselves in any direction in 3D space, may be idealized as point masses, and the agents know the locations of all targets, obstacles, and other agents.

[0041] This framework is modeled in a fixed Cartesian basis in e_1 , e_2 , and e_3 where the position $\mathbf{r}$, velocity $\mathbf{v}$, and acceleration $\mathbf{a}$ of a drone are described as:

$$\begin{aligned} \mathbf{r} &= r_1 \mathbf{e}_1 + r_2 \mathbf{e}_2 + r_3 \mathbf{e}_3, \\ \mathbf{v} = \dot{\mathbf{r}} &= \dot{r}_1 \mathbf{e}_1 + \dot{r}_2 \mathbf{e}_2 + \dot{r}_3 \mathbf{e}_3, \\ \mathbf{a} = \ddot{\mathbf{r}} &= \ddot{r}_1 \mathbf{e}_1 + \ddot{r}_2 \mathbf{e}_2 + \ddot{r}_3 \mathbf{e}_3, \end{aligned} \tag{2}$$

respectively. FIG. 3A shows a schematic of this framework. The only force, $\mathbf{F}$, imposed on each agent, i , is the agent's propulsion, which is assumed to be of constant magnitude. Hence each agent's equation of motion is described using Newton's second law:

$$m_i \mathbf{a}_i = \mathbf{F}_{p,i} = F \mathbf{n}_i^*, \tag{3}$$

where m_i is the agent's mass, $\mathbf{a}_i$ is the agent's acceleration, and $\mathbf{n}_i^*$ is the agent's propulsion vector.

[0042] The distance between an agent and other agents or sensors, hereafter referred to as 'objects,' is imperative to calculate the propulsion's vector $\mathbf{n}_i^*$. At each time step, the model

calculates the Euclidean distance between objects, defined between agent i with position $\mathbf{r}_i$ and another object j in the system at $\mathbf{A}_j$, as:

$$d_{i,j} \stackrel{\text{def}}{=} \|\sqrt{(\mathbf{r}_{i1} - \mathbf{A}_{j1})^2 + (\mathbf{r}_{i2} - \mathbf{A}_{j2})^2 + (\mathbf{r}_{i3} - \mathbf{A}_{j3})^2}\|. \quad (4)$$

[0043] The distance between an agent and other objects influences the magnitude of the attraction or repulsion force it has towards that particular object; Distant objects should have a weaker influence than near objects. Therefore, an exponentially decaying function is used to calculate the interaction vector between an agent and an object:

$$\hat{\mathbf{n}}_{i \rightarrow j} = (w_{att} e^{-c_{att} d_{ij}} - w_{rep} e^{-c_{rep} d_{ij}}) \mathbf{n}_{i \rightarrow j}. \quad (5)$$

where w_{att} and c_{att} are the weight and exponential decay coefficients of the attraction term, and w_{rep} and c_{rep} are the weight and exponential decay coefficients of the repulsion term, respectively. $\hat{\mathbf{n}}_{i \rightarrow j}$ is calculated for each type of object within the system, therefore agents and sensors will have their own values associated with w_{att} , c_{att} , w_{rep} , and c_{rep} . The direction $\mathbf{n}_{i \rightarrow j}$ is the unit normal vector in the direction of the object j relative to agent i and is given by:

$$\mathbf{n}_{i \rightarrow j} = \frac{\mathbf{A}_j - \mathbf{r}_i}{\|\mathbf{A}_j - \mathbf{r}_i\|}. \quad (6)$$

[0044] Generally, a larger attraction term relative to the repulsion term causes net propulsion towards sensor objects. The total interaction vector between agent i and all objects of a particular type is the sum of all their interaction vectors, such as those shown in FIG. 3B. For instance, the total interaction vector given by all sensors on agent i is:

$$\mathbf{N}_i^S = \sum_{j=1}^{N_{sensors}} \hat{\mathbf{n}}_{i \rightarrow j}^S \quad (7)$$

where $N_{sensors}$ is the total number of sensors in the system. A similar calculation is used for the finding the interaction vector influenced by all other agents, $\mathbf{N}_i^A$. A weighted sum of the total interaction forces of sensors and agents is normalized to give the final direction of propulsion:

$$\mathbf{n}_i^* = \frac{W_s N_i^s + W_a N_i^a}{\|W_s N_i^s + W_a N_i^a\|}. \quad (8)$$

[0045] Using this framework, one embodiment of an algorithm determines the flight paths:

INITIALIZE: Load in the sensor location data within the simulated domain and position agents along one edge of the domain. Assign weight and exponential decay coefficients for each object's attraction and repulsion terms in Eq. (5).

OBSERVE: Each agent observes its surroundings to calculate the attraction and repulsion terms and the optimal direction of propulsion as described in Eqs. (3)–(8).

STEP: Each agent will apply its thrust and accelerate toward the optimal direction.

TEST: If an agent is within the transmission range of a sensor, the sensor is considered scanned and removed from the domain. If an agent is within a 'crash radii of another agent, both will be removed from the domain.

ITERATE: If there are unscanned sensors in the domain, iterate through the algorithm.

[0046] In one embodiment, the magnitude and range of the interactive vectors between the agents and the targets were varied to optimize the flight paths, and the results were simulated. In this simulation, the number of mapped sensors were maximized while flight time and the number of collisions were minimized. Written as a cost function:

$$\Pi = W_1 \frac{N_{sensors} - N_{mapped}}{N_{sensors}} + W_2 \frac{t_{actual}}{t_{actual}} + W_3 \frac{N_{crashed}}{N_{drones}} \quad (9)$$

where $N_{sensors}$ is the total number of sensors in the field, N_{mapped} is the number of sensors that were mapped by the drones, t_{actual} is the time it takes for the drones to map the sensors, t_{max} is the maximum allowed time for the mapping to take place, N_{drones} is the number of drones in the swarm, and $N_{crashed}$ is the number of drones that crashed into one another during the simulation. W_1 , W_2 , and W_3 are the user-defined weights given to each cost term.

[0047] One embodiment employs a genetic algorithm to minimize the cost function, using the magnitude and range of the interaction vectors as the design strings.

[0048] One embodiment encoded the two-dimensional problem for an agricultural field in a geographic coordinate system. First, the domain of the problem is expressed as $\tilde{D}$, a $N_{dp} \times 2$ vector of values where N_{dp} is the number of pixels within the domain of consideration and the two columns are the longitudinal and latitudinal coordinates, respectively. Similarly, the agricultural field is expressed as F , a $N_{fp} \times 2$ vector of values where N_{fp} is the number of pixels within the bounds of the field and the two columns are the longitudinal and latitudinal coordinates, respectively.

[0049] Sensor optimization throughout a field is achieved using the SGR algorithm. One embodiment uses the following algorithm:

INITIALIZE: For a given vector of field pixels, F , select a random pixel within it and append it to $\tilde{S}$, a $N_{sensors} \times 2$ vector of sensor coordinates, where $N_{sensors}$ is the number of sensors in the field.

GENERATE: Select a random pixel, $P = (p_x, p_y)$, within the field F

TEST: For all S_i where $S_i = (s_x, s_y)$, if $\|P - S_i\| \geq R_{hv}$, where R_{hv} is the half-variogram range of the sensor, then append P to $\tilde{S}$

SCORE: Calculate fitness as the ratio of N_r to N_{fp} , where N_r is the number of pixels within distance R from any sensor pixel N_c . S_i . $f(\mathcal{A}) = N_r / N_{fp}$

ITERATE: If $f \leq TOL$, loop to Step 2.

[0050] The algorithm for optimizing the system parameters for flight paths for each drone is as follows:

POPULATION GENERATION: For a given number of drones, N_{drones} , randomly generate a population of G genetic strings, Λ^i , ($i = 1, 2, 3, \dots, G$):

$$\Lambda^i \stackrel{\text{def}}{=} \{\lambda_1, \lambda_2, \lambda_3, \lambda_4, \dots, \lambda_G^i\} \stackrel{\text{def}}{=} \{\lambda_1, \lambda_2, \lambda_3, \lambda_4, \dots, \lambda_G\}^i$$

$$\Lambda^i \stackrel{\text{def}}{=} \{w_{att}, w_{rep}, c_{att}, c_{rep}\}^i$$

PERFORMANCE EVALUATION: Compute fitness of each string, $\Pi(A^i)$, ($i=1, \dots, G$):

$$\Pi(\Lambda^i) \stackrel{\text{def}}{=} W_1 \frac{N_{sensors} - N_{mapped}}{N_{sensors}} + W_2 \frac{t_{actual}}{t_{actual}} + W_3 \frac{N_{crashed}}{N_{drones}}$$

RANK: Rank each string based on their cost output Π , where Rank 1 is the best performing design string that produced the lowest cost and Rank G the worst performing string:

$$\Pi(\Lambda^i, i = 1, \dots, G)$$

$$\Pi(\Lambda^1) \leq \Pi(\Lambda^2) \leq \dots \leq \Pi(\Lambda^G)$$

MATE: Mate design strings to produce offspring:

$$\Lambda^i \stackrel{\text{def}}{=} \phi^1 \Lambda^i + (1 - \phi^{(1)}) \Lambda^{i+1}$$

$$\text{where } 0 \leq \phi \leq 1$$

GENE ELIMINATION: Eliminate poorly performing genetic strings, keep top parents and generated offspring.

POPULATION REGENERATION: Repeat the process with the new gene pool and new *random* genetic strings.

[0051] This process repeats until the performance of a genetic string, $\Pi(\Lambda^i)$, falls below the tolerance limit, indicating that the cost function has been minimized. The minimization of the cost function Π is guaranteed to be monotone with increasing generations if the parent strengths are retained, i.e., $\Pi(\Lambda^{\text{opt},I}) \geq \Pi(\Lambda^{\text{opt},I+1})$ where $\Lambda^{\text{opt},I+1}$ and $\Lambda^{\text{opt},I}$ are guaranteed to be monotone with increasing generations if the parent strings are the best genetic strings from generations $I+1$ and I , respectively. If one does not retain the parents in the algorithm above, it is possible that inferior-performing offspring may replace superior parents. Top parents were kept for the subsequent generation.

[0052] One embodiment generates digital expressions of four types of agricultural fields to show the flexibility and range of the SGR sensor placement method. First, a 50-ha circular field with a half-mile (400 m) radius was generated. Second, a rectangular-shaped 93-ha field was generated. Third, a 22-ha field with straight and curved boundaries was generated. Finally, a field from an image of pixels was generated. For all simulations, the pixel size was set to one square meter.

[0053] Next, for each field type, optimal sensor placement was found using the SGR algorithm with 40 m as the half-variogram range, which is a conservative value for soil nitrate. The optimized locations of soil sensors in a center-pivot irrigation field were then inserted into the agent-based model to determine flight paths for UAV drone swarms of varying sizes. The simulation parameters are shown in Table 1. In this simulation, the transmission radius of the sensors was assumed to be 2 m, corresponding to the transmission radius of an RFID tag, which has been shown recently in other agricultural monitoring applications.

Symbol	Units	Value	Description
R_{field}	m	400	Radius of the center-pivot irrigation field
R_{hv}	m	40	Half-variogram range
$R_{transmission}$	m	2	Sensor transmission radius
N_{drones}	None	1-8	Number of drones in simulation
W_a	None	[1, 10]	Search bounds of interaction weights for agents
W_s	None	[1, 10]	Search bounds for interaction weights for sensors
w_{att}^-, w_{att}^+	None	[0, 1]	Search bounds for attraction term weight coefficient
c_{att}^-, c_{att}^+	None	[0, 1]	Search bounds for attraction term decay coefficient
w_{rep}^-, w_{rep}^+	None	[0, 1]	Search bounds for repulsion term weight coefficient
c_{rep}^-, c_{rep}^+	None	[0, 1]	Search bounds for repulsion term decay coefficient
F	N	100	Drone magnitude of propulsion force
M	Kg	5	Drone mass
V_{max}	m/s	10	Drone max velocity
R_{crash}	m	2	Crash radius
W_1	None	0.6	Cost function weight associated with mapping sensors
W_2	None	0.1	Cost function weight associated with mapping speed
W_3	None	0.3	Cost function weight associated with crashed drones
TOL	None	0.5	Cost tolerance for GA

Table 1: Flight path simulation parameters (all types are scalar)

[0054] To test the hypothesis that a swarm of drones would outperform a single drone, the simulation was executed for swarm sizes of 1–8 drones.

[0055] FIG. 4A-D shows the placement of sensors determined by the SGR algorithm. In FIG. 4A, the placement of sensors in a circular field with a 400 m radius, which is a common length for a center-pivot irrigation arm, was determined. FIG. 4B shows the optimal placement of sensors for a rectangular farm field with dimensions corresponding to the average small-family U.S. farm. As of 2017, small family farms make up 89% of farms in the U.S. FIG. 4C demonstrates that the SGR algorithm could adapt and generate sensor placement for an arbitrary field shape defined by several boundary points. In FIG. 4D, the SGR algorithm distributed sensors in a field generated from a digital image. One embodiment places the sensors efficiently such that they cover all of the pixels of the image while ignoring the islands of non-field pixels, such as those in the ‘a’ and ‘l.’ In real-world applications, the satellite image could capture this image, such as those available on Google Earth, ArcGIS, or other publicly available data sets.

[0056] A hexagonal-grid sensor distribution scheme is shown in FIG. 4E-H. Hexagonal packing provides the most efficient packing method to date, and circles can be packed in two dimensions to completely cover an area when staggered by a distance of $R\sqrt{3}$ in the *x-direction* and $3R/2$ in the *y-direction*.

[0057] The field coverage for varying numbers of sensors for the SGR and hexagonal-packing schemes are shown in FIG. 4I–L. The SGR algorithm outperformed the efficient hexagonal-grid distribution scheme when less than 95% of the field is covered for the circular and rectangular field types. In the case of total field coverage, however, the hexagonal packing method could cover the entire field with fewer sensors. Because the SGR algorithm prioritizes maximizing field coverage at each step, it makes it superior to other distribution

schemes when the domain is sufficiently spacious. However, if the field shape is relatively simple and total coverage is needed, then the hexagonal-packing approach outperforms SGR because the entire field area can be covered with fewer sensors. Distributing sensors this way could have other benefits during field operations. Sensor distribution and maintenance would be simpler than the SGR placement approach, which requires a calibrated GPS and field map for the sensors' initial placement and subsequent maintenance events. As the complexity of the field becomes high, however, the SGR algorithm becomes preferential to the hexagonal-packing method. The number of sensors required to cover the user-defined boundary type field shown in FIG. 4C and G was the same. For the field generated from an image in FIG. 4D and H, the SGR algorithm outperformed the hexagonal packing scheme for any number of sensors, as shown in FIG. 4L, and required only 52 sensors to completely cover the field compared to 59 for the hexagonal packing method.

[0058] To validate that UAVs operating with optimized flight paths are more energy efficient than a traditional sweeping method or a UGV, the paths for all three were simulated for a 400 m center pivot irrigation field with sensors distributed using the SGR algorithm, shown in FIG. 5. FIG. 5A shows the path for a UGV, which is constrained to traversing through the concentric crop rows to avoid damaging the growing crop. Row spacing varies, though it is typically around 0.5–0.75 m for corn and generally less for smaller row crops. Since this is less than the transmission radius of the sensors, the UGV does not have to traverse every row of the field. Instead, the effective row spacing was set to 4 m to minimize the number of concentric sweeps performed by the UGV, resulting in a 59.6 km path. If the sensors were paired with a stronger transceiver, such as a BLE or WiFi module, then the UGV would be able to skip more rows with each concentric sweep. However, the cost of such modules is inhibitive, and an economic analysis motivating the use of RFID is shown in the Appendix.

[0059] FIG. 5B shows the flight path for a UAV scanning the sensors using a traditional sweeping method. Because of the short transmission radius, the UAV has to make tight turns to reach all of the sensors, making for a 63.9 km flight path, which is even longer than the UGV. Finally, FIG. 5c shows the optimized flight path for a single UAV. When applying the agent-based optimization model, the total path length is reduced to 11.4 km. While the agent-based method is more energy efficient than the traditional sweeping method, the comparison is more difficult to make against the case of UGVs, which consume power at a different rate than UAVs. The energy consumption of the three scenarios was calculated from the path lengths and the average power of the vehicles while neglecting the impact of start-stop behavior and turning. The total energy consumed to scan all of the sensors in the field was 165 kWh for UGVs, 0.32 kWh for UAVs performing a traditional sweep, and 0.06 kWh for UAVs with optimized flight paths.

[0060] To determine the ideal number of drones to use for sampling data from the distributed sensors, flight paths for swarms of $n = 1-8$ on the stacked bar chart. As the number of agents increases, the time required to map all the sensors decreases. Meanwhile, as the number of drones in the swarm increased, their individual flight drones were simulated. The optimized flight paths for the varying-sized swarms are shown in FIG. 6, and the total flight path length and flight time are shown in FIG. 7.

[0061] FIG. 6A shows the flight path of a single agent. FIG. 6B and C show the flight paths for two and three agent swarms, respectively. In both cases, the agents frequently crossed each other's paths. As swarm size increases, such as for four agent swarms shown in FIG. 6D, the agents crossed paths less, and each agent subdivided the field into its own sections to scan the sensors within it, which is generally more efficient and less prone to accidental crashes in the event of interference or GPS malfunction. For swarms with five or more sensors, as shown in FIG. 6E-H, more overlapping occurred as agents began to compete over the same

sensors. These results may also depend on each drone's initial starting position. The agents in this example were placed at the edge and linearly spaced along the width of the domain. However, one may choose to have the agents start along the circumference of the field, somewhere within the field, or from a single point. A staggered start time would also vary the flight path recommendations.

[0062] The benefits of employing a multi-agent swarm of drones are highlighted in FIG. 7 where a different color indicates each agent's total energy consumed on the stacked bar chart. As the number of agents increases, the time required to map all the sensors decreases. Meanwhile, as the number of drones in the swarm increased, their individual flight path lengths decreased while the total flight path remained relatively consistent for all simulated swarm sizes. The distance traveled can be correlated with the amount of fuel or battery power a drone consumes, meaning that a swarm of drones uses a comparable amount of energy as a single drone, but performs the scan much faster.

[0063] To further analyze the trade-offs in swarm size, the drones' energy expenditure per sensor scanned as a function of swarm size was examined, as shown in FIG. 8. As the number of agents increased, the total average energy consumption per sensor scanned did not significantly change. This agrees with FIG. 7, which shows that the total flight path to scan all of the sensors in the field also did not significantly change when the number of drones was increased. However, the variance of the energy consumption per sensor scanned increased as the number of drones increased. When inspecting the simulations, it was found that this was primarily caused by a scenario where several agents would 'race' to scan the same sensor. Then, once that sensor was scanned and removed from the domain, the same agents would often continue to race one another for subsequent sensors. This 'leader-follower' behavior is wasteful as the agents consume energy, thus creating more conflict between agents instead of

collaboration. Four was the optimal number of drones for this scenario because it was the fastest scan that did not demonstrate ‘leader–follower’ behavior.

[0064] The flight paths for a four-agent drone swarm in a 400 m radius center-pivot irrigation field are shown in FIG. 9. Starting from the edge of the simulated domain, the agents traversed through the center-pivot irrigation field and sampled the distributed sensors, as seen in FIG. 9A and B. Initially, the drones seek out the nearest sensors because they have the strongest interaction force. However, as the flight paths continued to develop, as in FIG. 9C–F, the number of unscanned sensors dwindled, and the relative attraction strength of more distant sensors grew. This continued until the last sensor was scanned, as shown in FIG. 9G, and the drones returned to their initial positions.

[0065] Because the flight paths are optimized using a genetic algorithm and the initialization is random, the outcome could theoretically be different every time the simulation is executed, even when the same parameters are used. Table 2, for example, shows the optimal parameters for the top three performing design strings when the four-drone condition was simulated. For parameters such as C_{rep}^{agent} , which is the exponential decay coefficient for the repulsion term emitted by the agent, the ‘optimal value’ is practically the same for each design string.

Meanwhile, for other parameters, such as C_{att}^{sensor} , the value varies by about one-third of the search bounds across the design strings. While it may seem like this indicates that the output is unstable, when the flight paths of the top-performing design strings are simulated, as shown in FIG. 10, it becomes evident that only minor differences exist between the resulting flight paths. This is because genetic algorithms excel at solving highly multivariate problems quickly. Furthermore, the similarities between the top three flight paths indicate the robustness of the solution.

[0066] For any agricultural field geometry, the embodiments use the SGR algorithm maximizes the coverage of an agricultural field with fewer sensors than a grid-based

distribution in most cases. The proposed multi-agent flight path mapping can effectively and efficiently generate flight paths for variable numbers of drones to scan all sensors. Thus, a crop grower could use the algorithms described in this paper to determine the optimal placement of soil sensors inside their own field, the ideal number of drones to sample data from the sensors, and their flight paths. This framework can be adopted for variable-rate irrigation applications to maximize crop yield and minimize environmental pollution.

[0067] The embodiments used the aforementioned framework to determine the optimal placement of sensors for a 400 m radius center-pivot irrigation field and simulated the flight paths of drone swarms of varying sizes. Four drones provided the best balance between energy efficiency and flight time for the simulated scenario. Using multiple drones also significantly decreased the amount of the total time it takes to complete the sensor scanning task within the field compared to a single drone.

[0068] The drone flight path mapping shown here does not account for topological features or weather conditions. Further extensions of this framework include adding variations in terrain height and additional outside forces such as wind drag synchronized with weather data, to obtain a more accurate framework for digital twin capabilities.

W_s	W_a	w_{att}^{sensor}	w_{rep}^{sensor}	c_{att}^{sensor}	c_{rep}^{sensor}	w_{att}^{agent}	w_{rep}^{agent}	c_{att}^{agent}	c_{rep}^{agent}
2.38897	6.060861	0.38679	0.34980	0.41784	0.73018	0.28894	0.48590	0.69733	0.32812
2.38633	3.69574	0.36072	0.32646	0.35214	0.78264	0.29032	0.48498	0.72134	0.33702
2.42084	6.98402	0.39193	0.54399	0.69210	0.67569	0.27516	0.48624	0.68220	0.32287

Table 2: Optimal parameters for the top three performing design strings for flight paths of four drones

[0069] Agricultural drone flight path mapping applications are not limited to reading sensors. Recently, drones in precision agriculture have taken a more physical role, such as aerial application of fluids, solids, and biological control agents. In 2015, the Federal Aviation Administration approved the first crop-dusting drone capable of spraying pesticides with tanks weighing more than 55 lbs. This approval allowed the rapid deployment of drones to

spray soil amendments and seeds to precise areas indicated by the soil-embedded sensors, reducing the amount of irrigation runoff and seeds dispensed in unwanted areas. The flight path model could also be modified for tasks such as orchard harvesting, where the drone is programmed to collect fruits or nuts from trees and deposit them into boxes.

[0070] Other embodiments include determining the placement of wireless sensors at a distance within the transmission range of one or more wireless receivers. The process could assist with placement of sensors or other signal sources for optimization of signals with different radii. It could also assist with placement of sensors in a three-dimensional space. The sensors could also change position in time, and the embodiments could manage their positions to each other.

[0071] Modifications and variations exist. In one variation, the embodiments apply the process to the placement of sensors to monitor other environmental parameters in an area. In another, the embodiments apply the process to placement of sensors in an indoor farm or other indoor agricultural venue, or in an industrial setting.

[0072] Other modifications may include placing the sensors in or on a living creature, such as a farm animal, in a war zone or on a battlefield, popular outdoor venues for crowd control or security, in seismic regions to place sensors, placing sensors to monitor traffic, construction zones, and to monitor atmospheric gases. Other embodiments include placing sensors inside a device.

[0073] Additionally, this written description makes reference to particular features. It is to be understood that the disclosure in this specification includes all possible combinations of those particular features. For example, where a particular feature is disclosed in the context of a particular aspect, that feature can also be used, to the extent possible, in the context of other aspects.

[0074] All features disclosed in the specification, including the claims, abstract, and drawings, and all the steps in any method or process disclosed, may be combined in any combination, except combinations where at least some of such features and/or steps are mutually exclusive. Each feature disclosed in the specification, including the claims, abstract, and drawings, can be replaced by alternative features serving the same, equivalent, or similar purpose, unless expressly stated otherwise.

[0075] Also, when reference is made in this application to a method having two or more defined steps or operations, the defined steps or operations can be carried out in any order or simultaneously, unless the context excludes those possibilities.

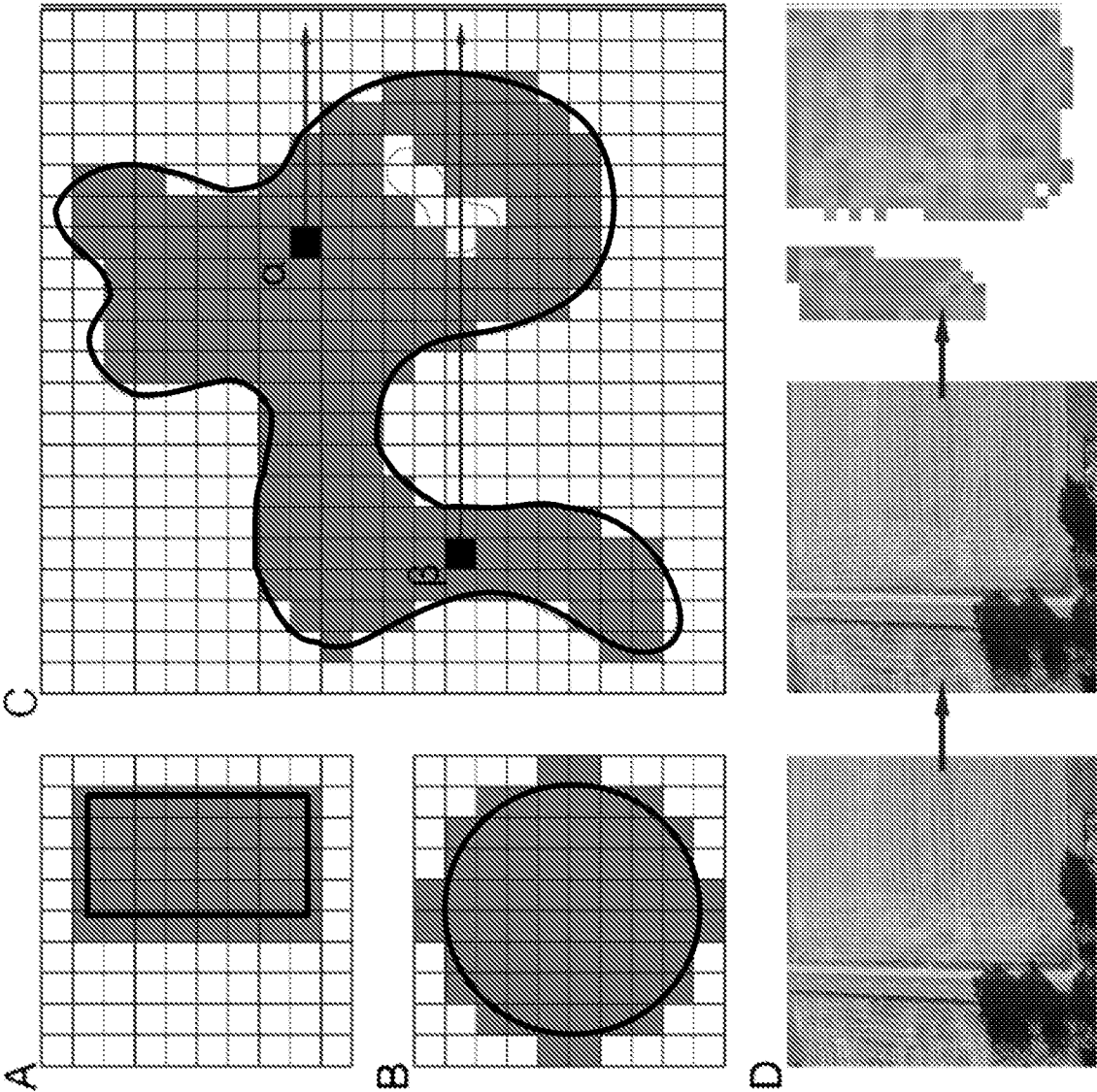
[0076] It will be appreciated that variants of the above-disclosed and other features and functions, or alternatives thereof, may be combined into many other different systems or applications. Various presently unforeseen or unanticipated alternatives, modifications, variations, or improvements therein may be subsequently made by those skilled in the art which are also intended to be encompassed by the attached claims.

WHAT IS CLAIMED IS:

1. A system to monitor soil data, comprising:
an array of sensors, each sensor positioned such that any overlap between adjacent sensors is minimized and coverage of a field is maximized; and
one or more readers configured to gather data from the sensors and provide the data to a computing device.
2. The system as claimed in claim 1, wherein the soil data comprises one or more of soil moisture content, amount of fertilizer, and concentration of a particular analyte.
3. The system as claimed in claim 1, wherein the one or more readers comprise a hardwired connection to the computing device.
4. The system as claimed in claim 3, wherein the computing device further comprises one or more processors configured to execute code that causes the one or more processors to:
represent an agricultural field as a set of pixels;
select a pixel from the set of pixels;
determine if a sensor placed at a location of the pixel would overlap with any other sensor already placed in the field;
place a sensor at the location, if the sensor would not overlap any other sensors, to become part of a design;
compute a score for the design; and
repeat the selecting, determining, placing, and computing when the score is below a threshold until the sensors are positioned such that any overlap between adjacent sensors is minimized and coverage of a field is maximized.
5. The system as claimed in claim 1, wherein each sensor comprises a transceiver.
6. The system as claimed in claim 1, wherein the one or more readers are configured to be fitted to a movable object.

7. The system as claimed in claim 6, wherein the movable object comprises a human being, ground machinery, or one or more unmanned ariel vehicles (UAV).
8. The system as claimed in claim 7, wherein the one or more UAVs comprise a swarm of UAVs, and the UAVs have one or more processors configured to execute code that cause each UAV in the swarm to fly an optimized flight path.
7. A method, comprising:
 - representing an agricultural field as a set of field pixels;
 - place an initial sensor at a random pixel location;
 - selecting a selected pixel from the set of field pixels;
 - determining if a sensor placed at a location of the selected pixel would overlap with any other sensor already placed in the field;
 - placing a sensor at the location, if the sensor would not overlap any other sensors, to become part of a design;
 - computing a score for the design; and
 - repeating the selecting, determining, placing, and computing, when the score is below a threshold, until the agricultural field has maximum sensor coverage with minimal overlap between sensors.
8. The method as claimed in claim 7, wherein placing comprises:
 - placing sensors between sensors that have a largest gap to other sensors as part of the design; and
 - increasing an acceptable distance between sensors;
9. The method as claimed in claim 7, wherein computing a score for the design comprises determining a ratio of a number of field pixels within a half-variogram range of a sensor to the total number of pixels in the agricultural field.
10. The method as claimed in claim 7, further comprising sampling data from the sensors.

11. The method as claimed in claim 10, wherein sampling the data from the sensors comprises the sensors communicating with one or more readers in a hardwired connection.
12. The method as claimed in claim 10, wherein sampling the data from the sensors comprises the sensors communicating with one or more mobile readers.
13. The method as claimed in claim 12, wherein the sensors communicating with one or more mobile readers comprises:
 - receiving, at a transceiver on each sensor, a request for data;
 - transmitting the data to the one or more mobile readers.
14. A method of determining a flight path for a swarm of drones over a field, comprising:
 - loading sensor location data for an array of sensors within a digital representation of a field;
 - positioning agents representing the drones along one edge of the digital representation of the field;
 - determining an attraction term, a repulsion term, and an optimal direction for each agent;
 - assigning weights to the attraction terms and repulsion terms for each agent;
 - accelerating each agent in the optimal direction;
 - removing sensors from the array that have any agent come within transmission range of the sensor;
 - repeat the positioning, determining, assigning, accelerating, and removing until all sensors have been removed from the array; and
 - using the resulting paths of the agents to produce a flight path for the swarm of drones.
15. The method as claimed in claim 14, further comprising removing any agent that comes into a crash range of another agent and removing the other agent.



FIGS. 1-D

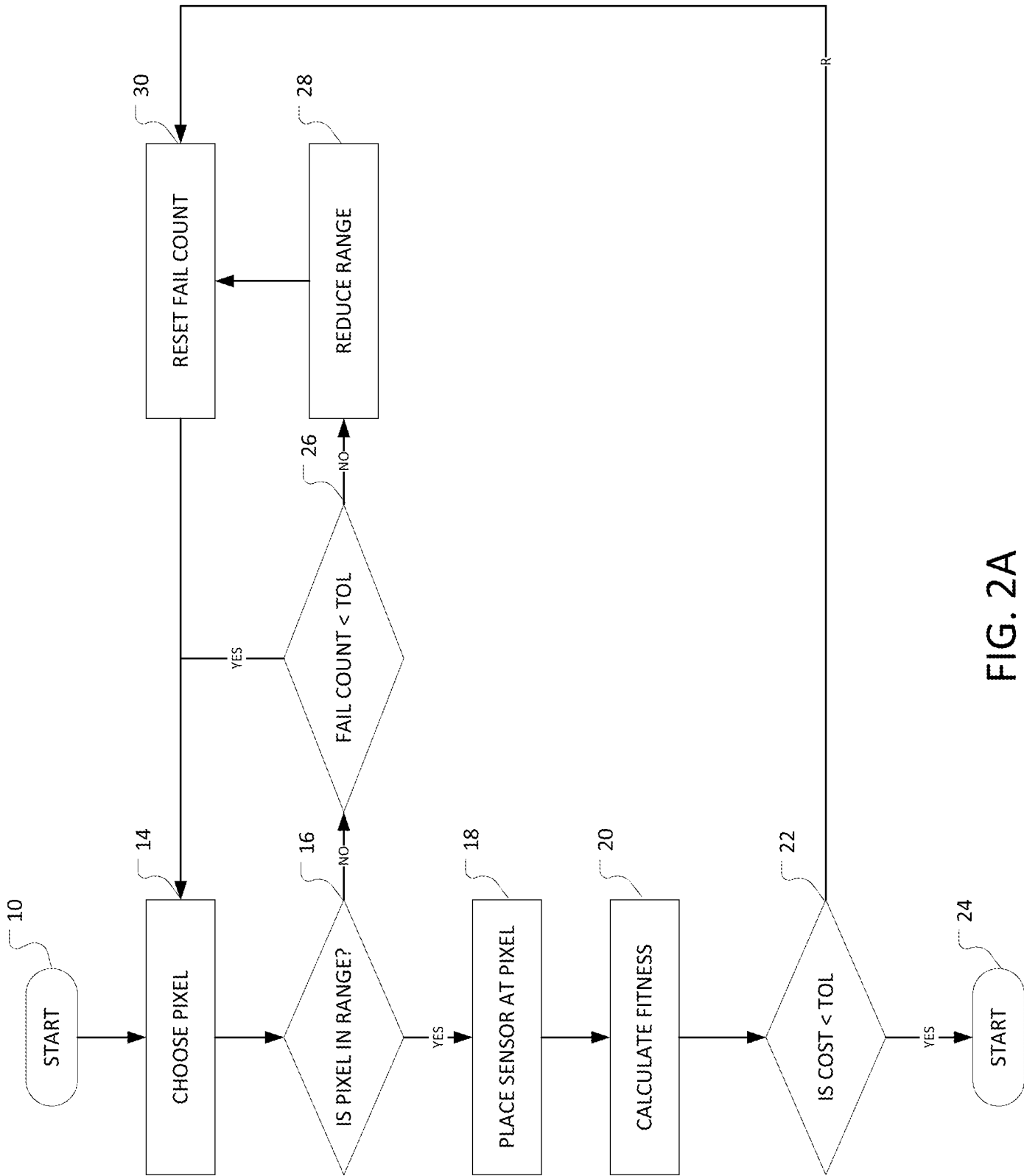


FIG. 2A

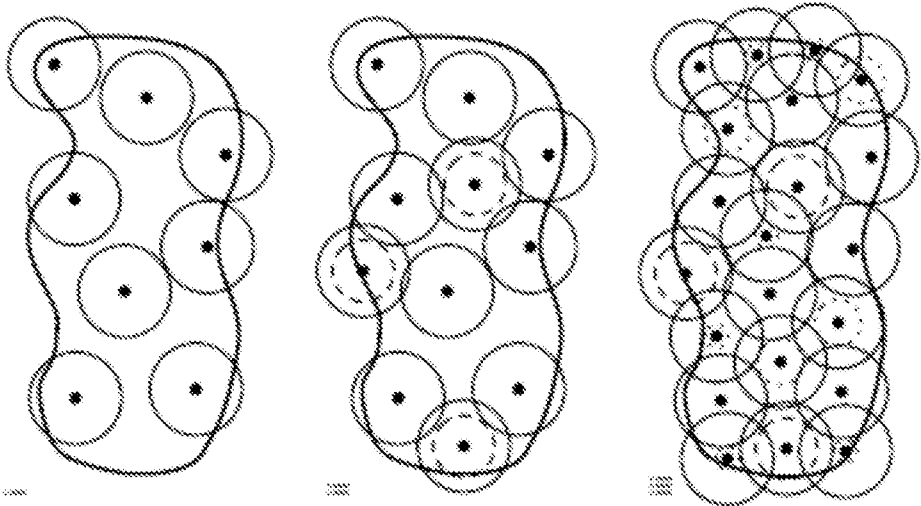
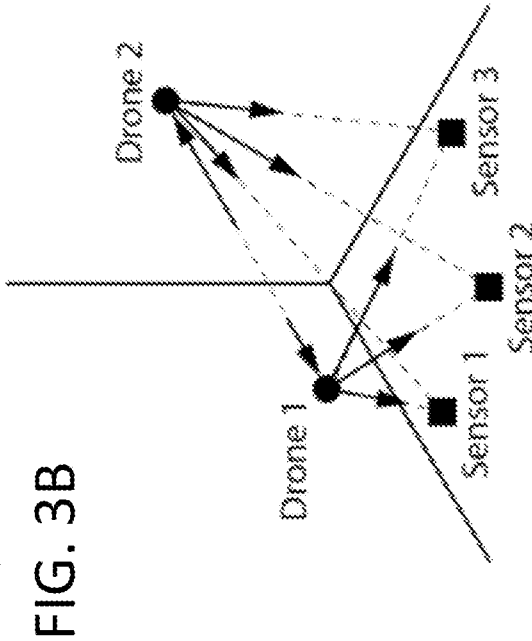
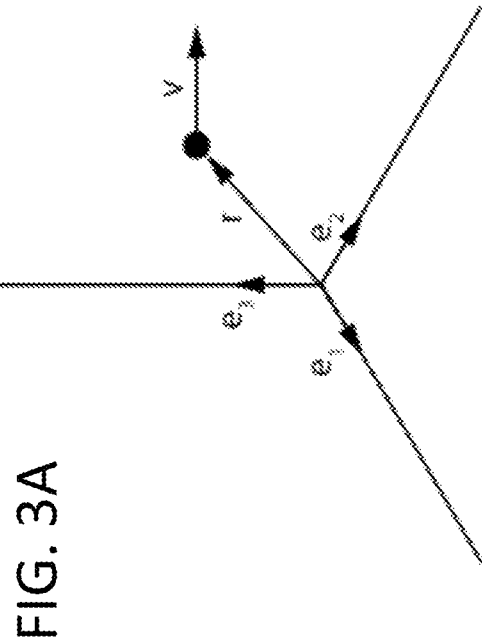
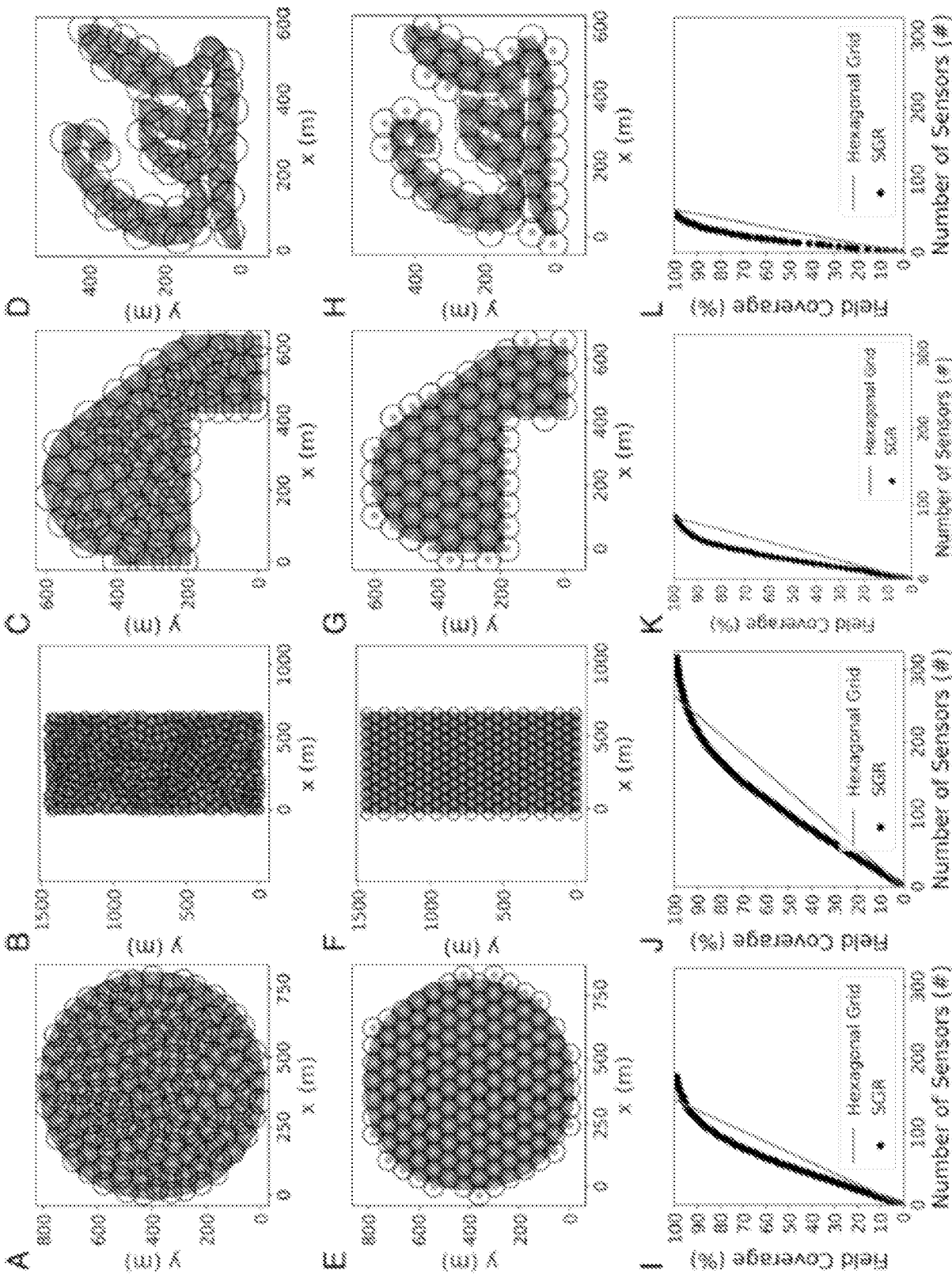


FIG. 2B



FIGS. 4A-L

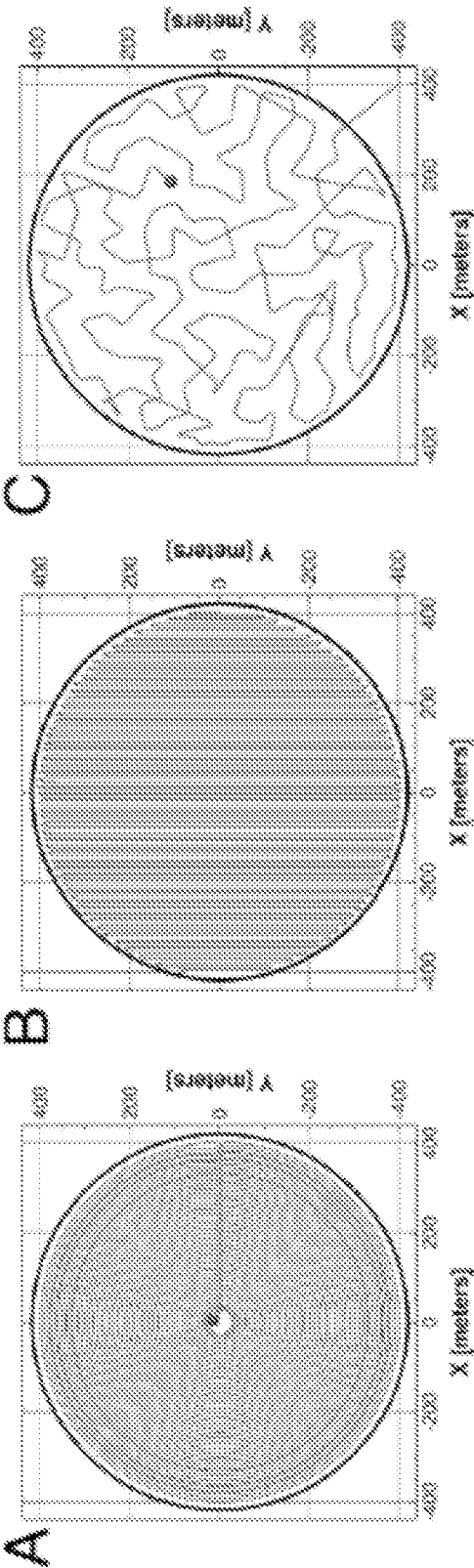


FIG. 5

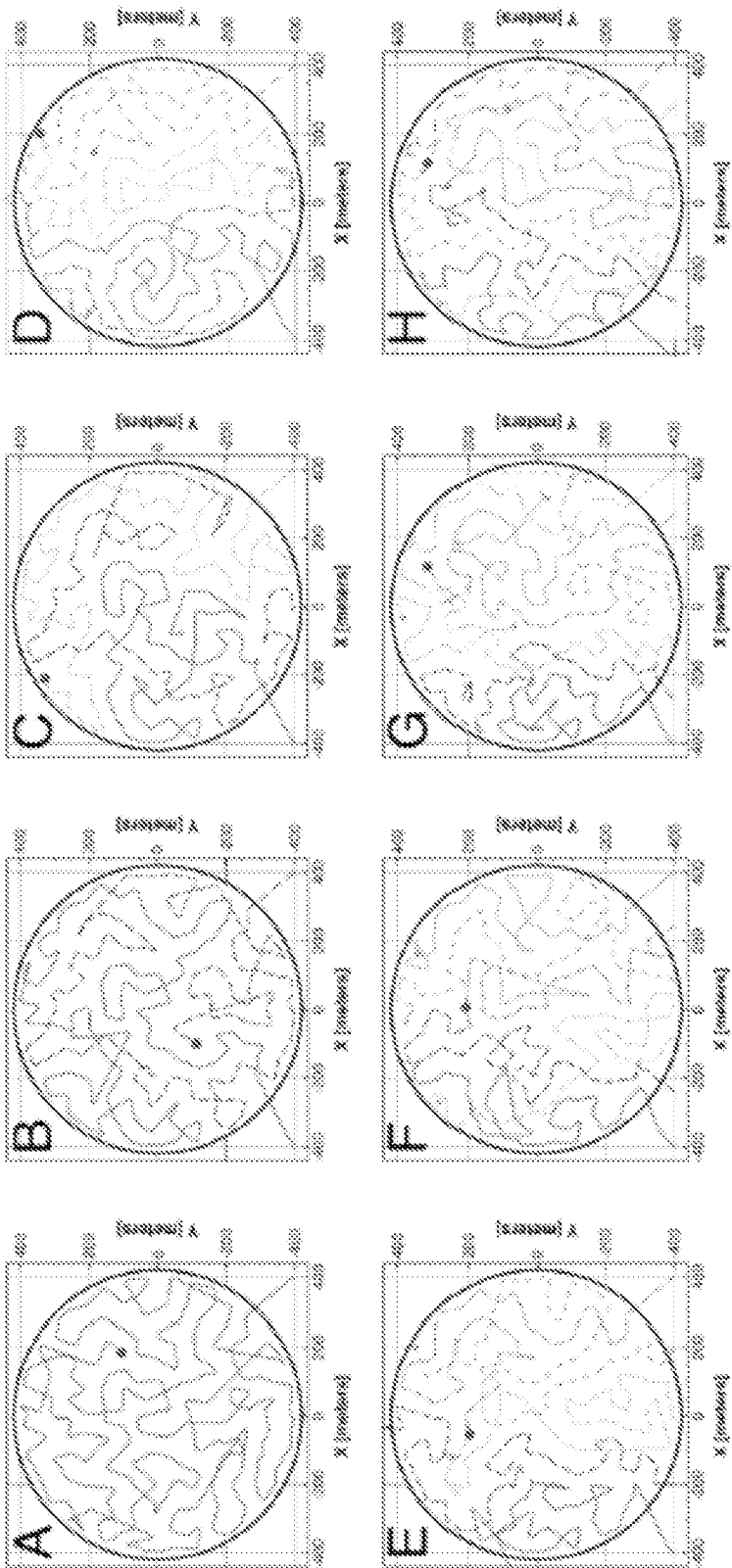


FIG. 6

FIG. 7

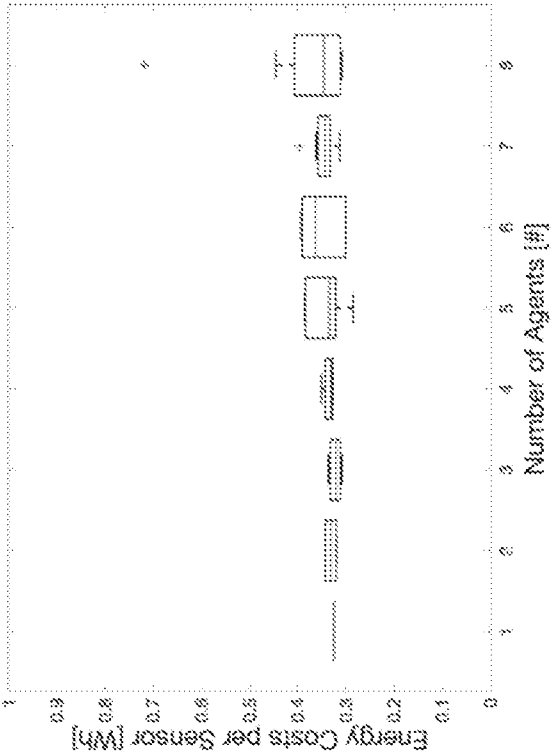
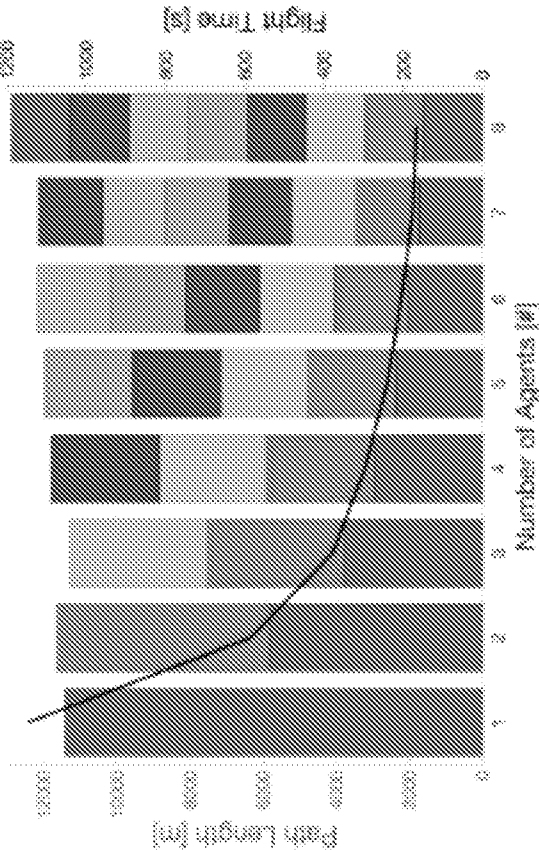


FIG. 8

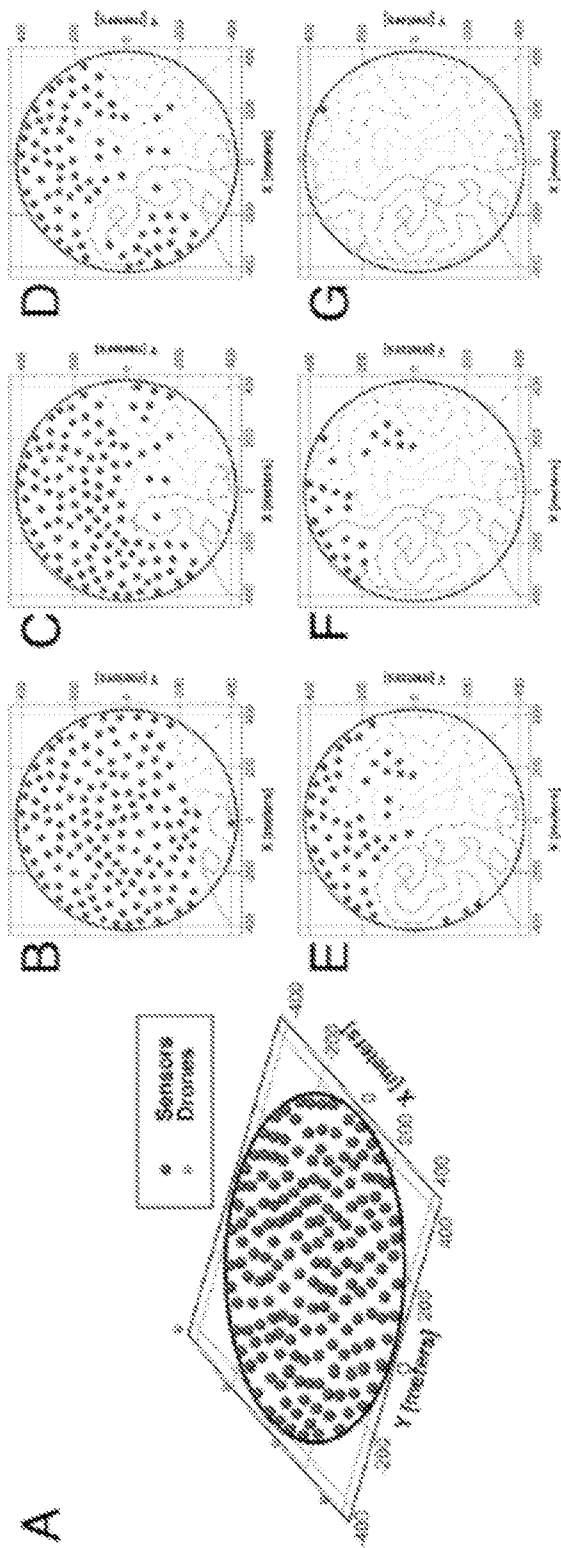


FIG. 9

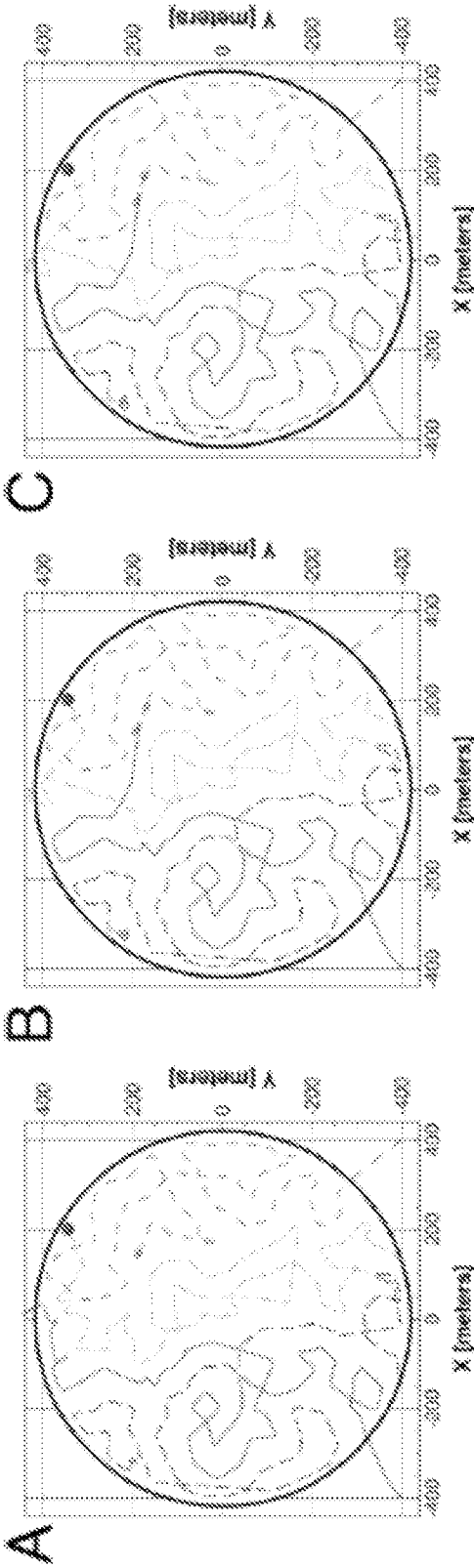


FIG. 10

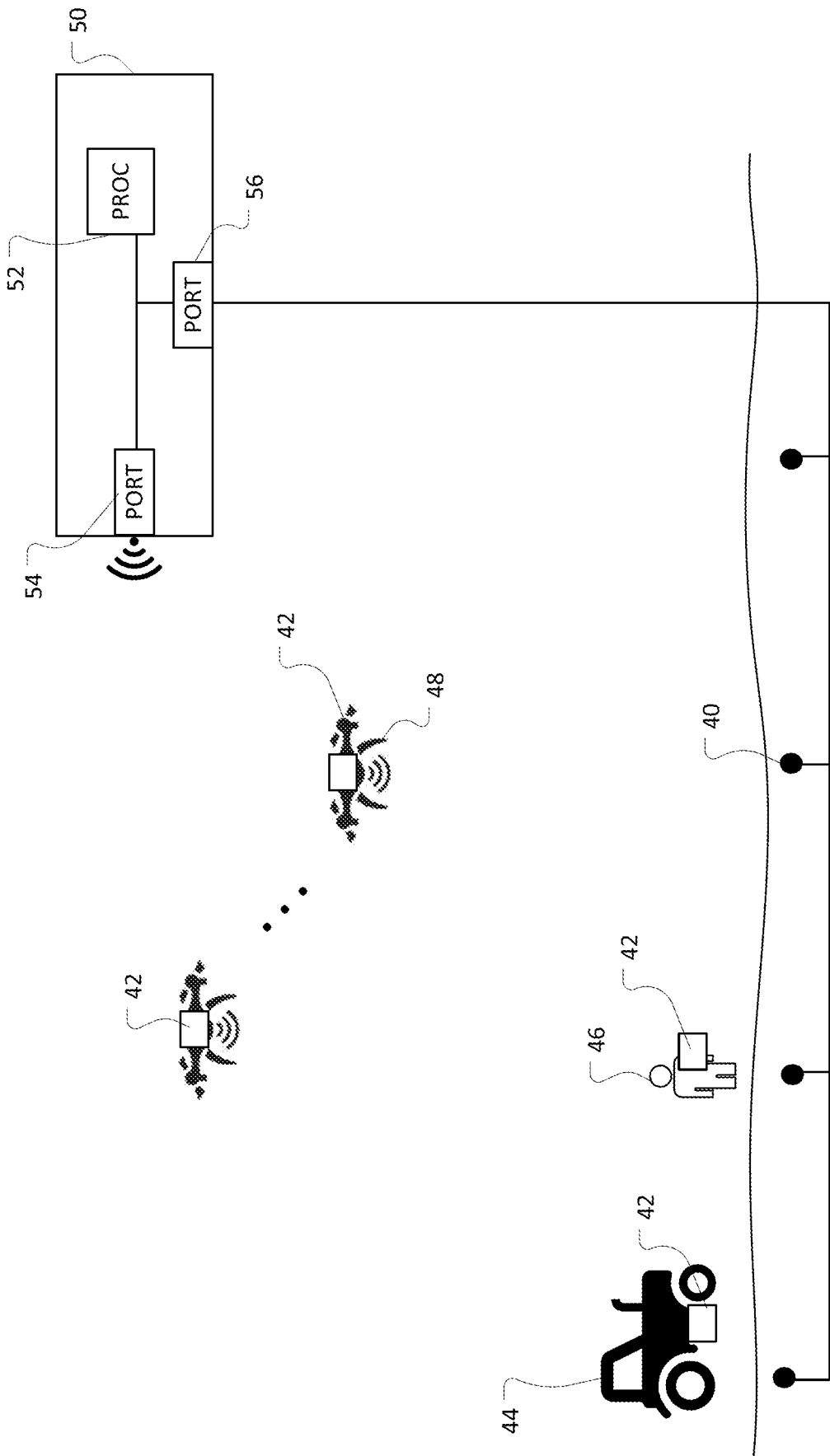


FIG. 11

INTERNATIONAL SEARCH REPORT

International application No.

PCT/US2024/037365

A. CLASSIFICATION OF SUBJECT MATTERIPC: **G01N 33/24** (2024.01); **A01B 79/00** (2024.01); **A01B 79/02** (2024.01)CPC: **G01N 33/245**; **A01B 79/005**; **G01N 33/24**; **A01B 79/02**

According to International Patent Classification (IPC) or to both national classification and IPC

B. FIELDS SEARCHED

Minimum documentation searched (classification system followed by classification symbols)

See Search History Document

Documentation searched other than minimum documentation to the extent that such documents are included in the fields searched

See Search History Document

Electronic data base consulted during the international search (name of data base and, where practicable, search terms used)

See Search History Document

C. DOCUMENTS CONSIDERED TO BE RELEVANT

Category*	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
Y	US 2007/0039745 A1 (ANDERSON ET AL.) 22 February 2007 (22.02.2007) para [0016]-[0018]	13
A	US 2019/0347836 A1 (THE CLIMATE CORPORATION) 14 November 2019 (14.11.2019) entire document	1-13
X	GOODRICH ET AL. "Placement and drone flight path mapping of agricultural soil sensors using machine learning." Computers and Electronics in Agriculture 205 (2023): 107591. [online], 27 December 2022 (27.12.2022) [retrieved on 2024-11-24]. Retrieved from the Internet: <DOI: https://doi.org/10.1016/j.compag.2022.107591 > <URL: https://www.sciencedirect.com/science/article/abs/pii/S0168169922008997 >	1-12
Y	entire document	13

☐ Further documents are listed in the continuation of Box C.☐ See patent family annex.

* Special categories of cited documents:

"A" document defining the general state of the art which is not considered to be of particular relevance

"D" document cited by the applicant in the international application

"E" earlier application or patent but published on or after the international filing date

"L" document which may throw doubts on priority claim(s) or which is cited to establish the publication date of another citation or other special reason (as specified)

"O" document referring to an oral disclosure, use, exhibition or other means

"P" document published prior to the international filing date but later than the priority date claimed

"T" later document published after the international filing date or priority date and not in conflict with the application but cited to understand the principle or theory underlying the invention

"X" document of particular relevance; the claimed invention cannot be considered novel or cannot be considered to involve an inventive step when the document is taken alone

"Y" document of particular relevance; the claimed invention cannot be considered to involve an inventive step when the document is combined with one or more other such documents, such combination being obvious to a person skilled in the art

"&" document member of the same patent family

Date of the actual completion of the international search

24 November 2024 (24.11.2024)

Date of mailing of the international search report

12 December 2024 (12.12.2024)

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Box No. III Observations where unity of invention is lacking (Continuation of item 3 of first sheet)

This International Searching Authority found multiple inventions in this international application, as follows:

This application contains the following inventions or groups of inventions which are not so linked as to form a single general inventive concept under PCT Rule 13.1.

Group I: Claims 1-13, directed to a system to monitor soil data.

Group II: Claims 14-15, directed to a method of determining a flight path for a swarm of drones.

The groups of inventions listed above do not relate to a single general inventive concept under PCT Rule 13.1 because, under PCT Rule 13.2, they lack the same or corresponding special technical features for the following reasons:

Special Technical Features:

Group I includes the special technical features of a system to monitor soil data, comprising: each sensor positioned such that any overlap between adjacent sensors is minimized and coverage of a field is maximized; and one or more readers configured to gather data from the sensors and provide the data to a computing device, not found in the other group.

Group II includes the special technical features of determining a flight path for a swarm of drones over a field, comprising: loading sensor location data for an array of sensors within a digital representation of a field; positioning agents representing the drones along one edge of the digital representation of the field; determining an attraction term, a repulsion term, and an optimal direction for each agent; assigning weights to the attraction terms and repulsion terms for each agent; accelerating each agent in the optimal direction; removing sensors from the array that have any agent come within transmission range of the sensor; repeat the positioning, determining, assigning, accelerating, and removing until all sensors have been removed from the array; and using the resulting paths of the agents to produce a flight path for the swarm of drones, not found in the other group.

Common Technical Features:

The only technical features shared by Groups I-II are a field, an array of sensors, and sensor location. However, these shared technical features do not represent a contribution over prior art, because the shared technical features are disclosed by US 2022/0092990 A1 to Rakuten Group, Inc. (hereinafter Rakuten).

Rakuten discloses a field (para [0003]), an array of sensors (para [0043], [0063]), and sensor location (para [0045]).

Accordingly, the inventions listed as Groups above lack unity of invention under PCT Rule 13 because they do not share a same or corresponding special technical feature providing contribution over prior art.

INTERNATIONAL SEARCH REPORT

International application No.

PCT/US2024/037365

Box No. III Observations where unity of invention is lacking (Continuation of item 3 of first sheet)

1. ☐ As all required additional search fees were timely paid by the applicant, this international search report covers all searchable claims.
2. ☐ As all searchable claims could be searched without effort justifying additional fees, this Authority did not invite payment of additional fees.
3. ☐ As only some of the required additional search fees were timely paid by the applicant, this international search report covers only those claims for which fees were paid, specifically claims Nos.:
4. ☒ No required additional search fees were timely paid by the applicant. Consequently, this international search report is restricted to the invention first mentioned in the claims; it is covered by claims Nos.: **1-13**

Remark on Protest

- ☐ The additional search fees were accompanied by the applicant's protest and, where applicable, the payment of a protest fee.
- ☐ The additional search fees were accompanied by the applicant's protest but the applicable protest fee was not paid within the time limit specified in the invitation.
- ☐ No protest accompanied the payment of additional search fees.