Coordination and Control of Distributed Networks of Actuated Sensors

Kevin L. Moore, Director

Center for Self-Organizing and Intelligent Systems
Utah State University
Logan, Utah

6 March 2003

Outline

- Introduction
- A Motivating Example
- Control-Theoretic Problem Formulation
- Adding Actuated Actuators
- Other Application Scenarios
- What Next?

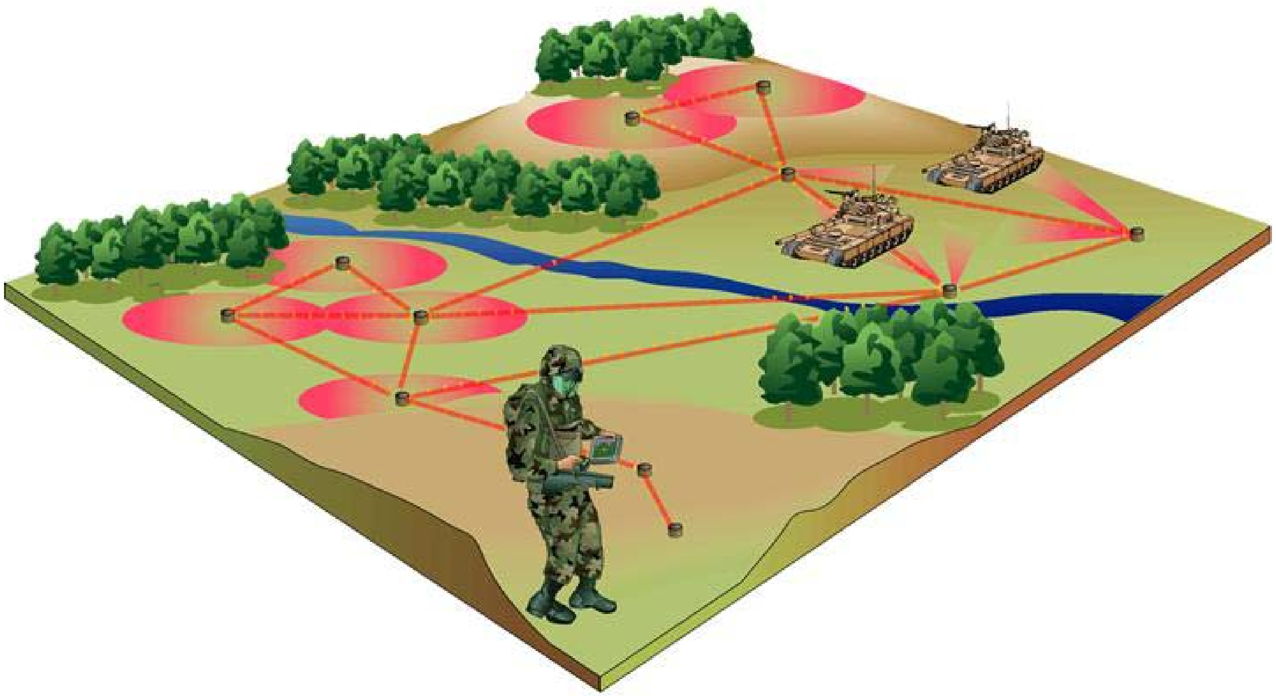
Networked Sensors

- Through history, many technologies have become ubiquitous:
  - Motors
  - Microprocessors
- Today a new technology has the same promise;
  - Networked sensors
- Due to advances in in biology, electronics, nanotechnology, wireless communications, computing, networking, and robotics, we can now:
  - Design *advanced sensors and sensor system*
  - Use *wireless communications*, or telemetry, to more effectively communicate sensor data from a distance than ever before
  - Build *networks of sensors*, using wireless communications and computer networking technology, that can provide the capability to obtain spatially-distributed measurements from low-power sensors which communicate and relay information between each other
  - Develop *reconfigurable, or adaptable, networks of distributed sensors* by providing mobility or actuation to the individual sensors in the network

Utah State University

CSOIS
CENTER FOR SELF-ORGANIZING AND INTELLIGENT SYSTEMS

Example Sensor Network



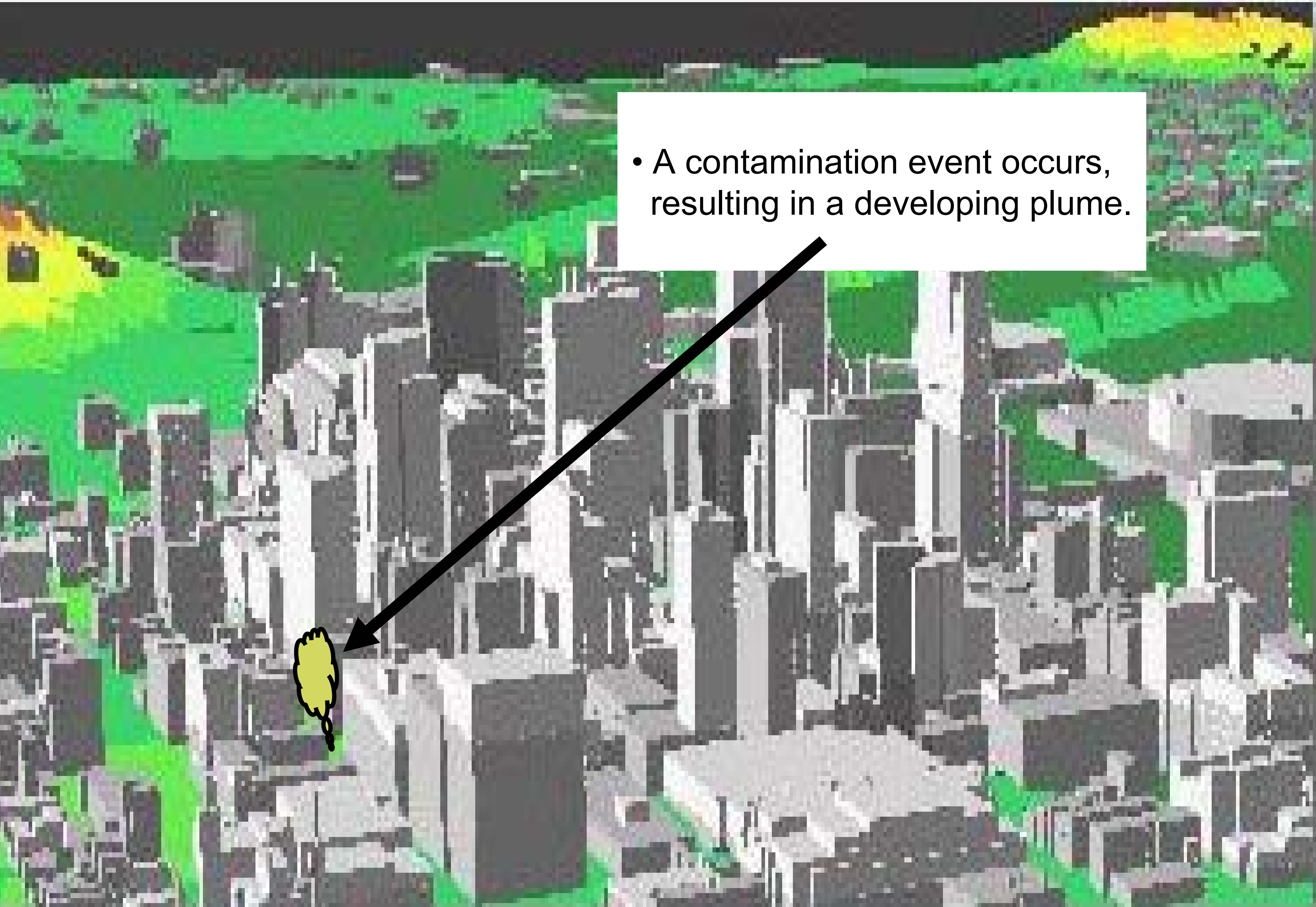
Distributed Sensor Network

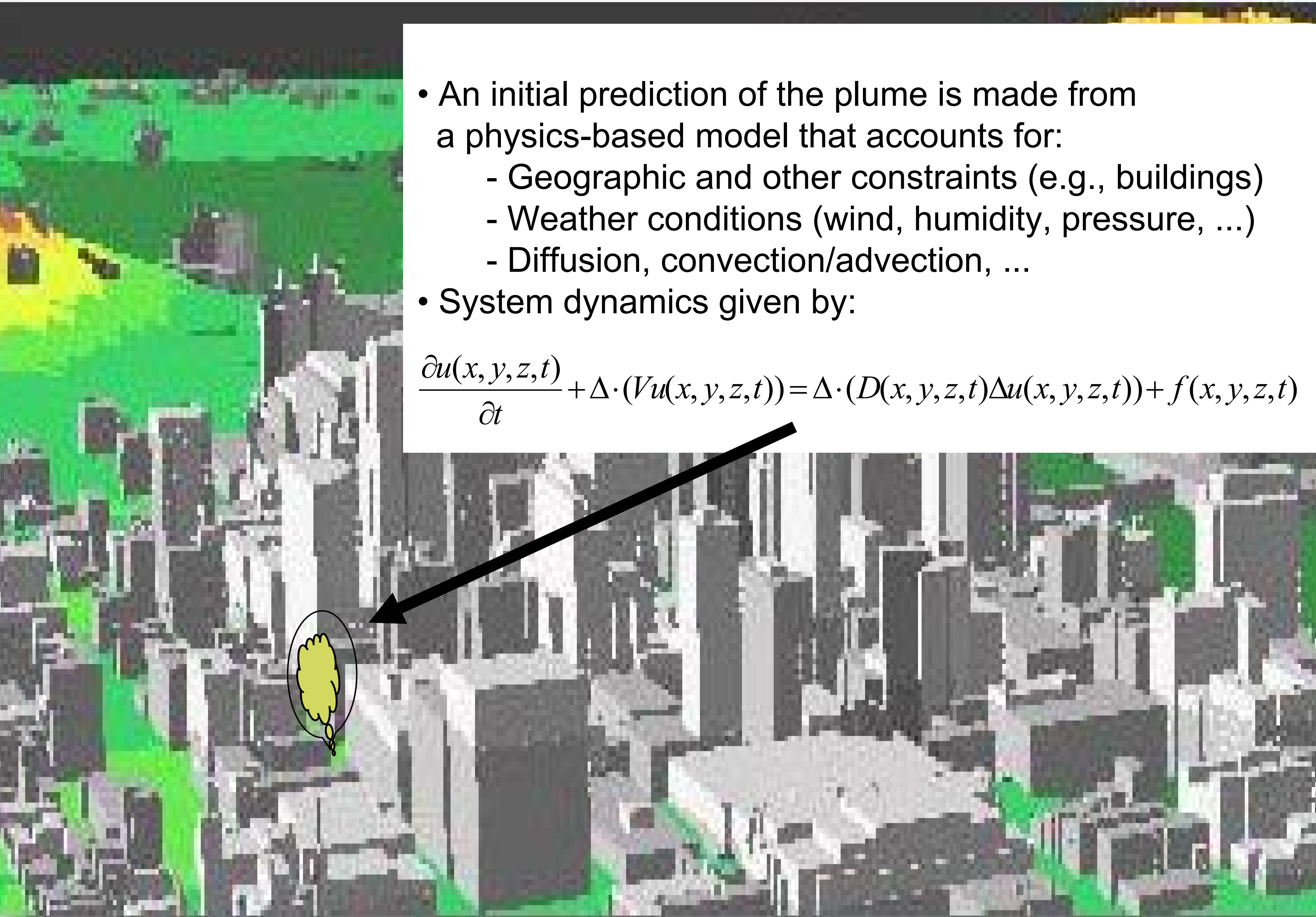
To implement a distributed sensor network, we need

- A *sensor* relevant to the application at hand
- Some type of (typically wireless) *communication* capability
- Suitable *communication and data flow control protocols*
- Algorithms for *sensor placement and data interpretation and use* (including multi-modal data fusion)
- Further, a presumption of the question, "where should the sensors be placed," is that they can indeed be placed, either
  - Manually (human-in-the-loop)
  - Robotically
- In what follows we consider robotically-deployed sensors

Distributed Actuated Sensor Network

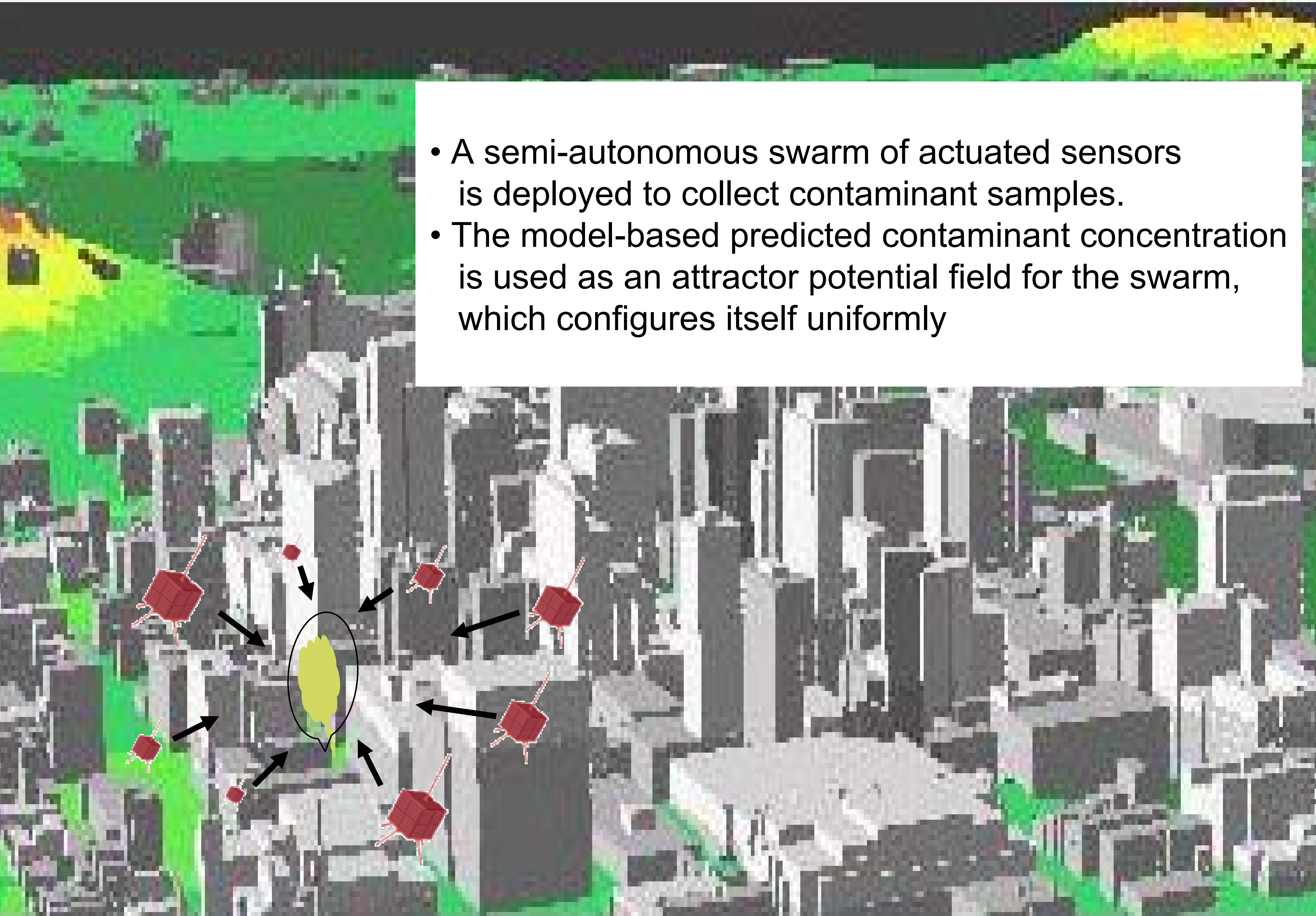
- Let us define:
  - An actuated sensor is a sensor that can move in space, either through self-logic or in response to a command from a supervisor.
  - An (actuated sensor) network is a networked collection of actuated sensors, which are working together to achieve some type of information collection and processing.
- Notes:
  - Use term “actuated” rather than “mobile”
  - Also distinguish between “autonomous” and “actuated”
- Consider an example to illustrate the use of such a network: real-time atmospheric plume identification


• A contamination event occurs, resulting in a developing plume.



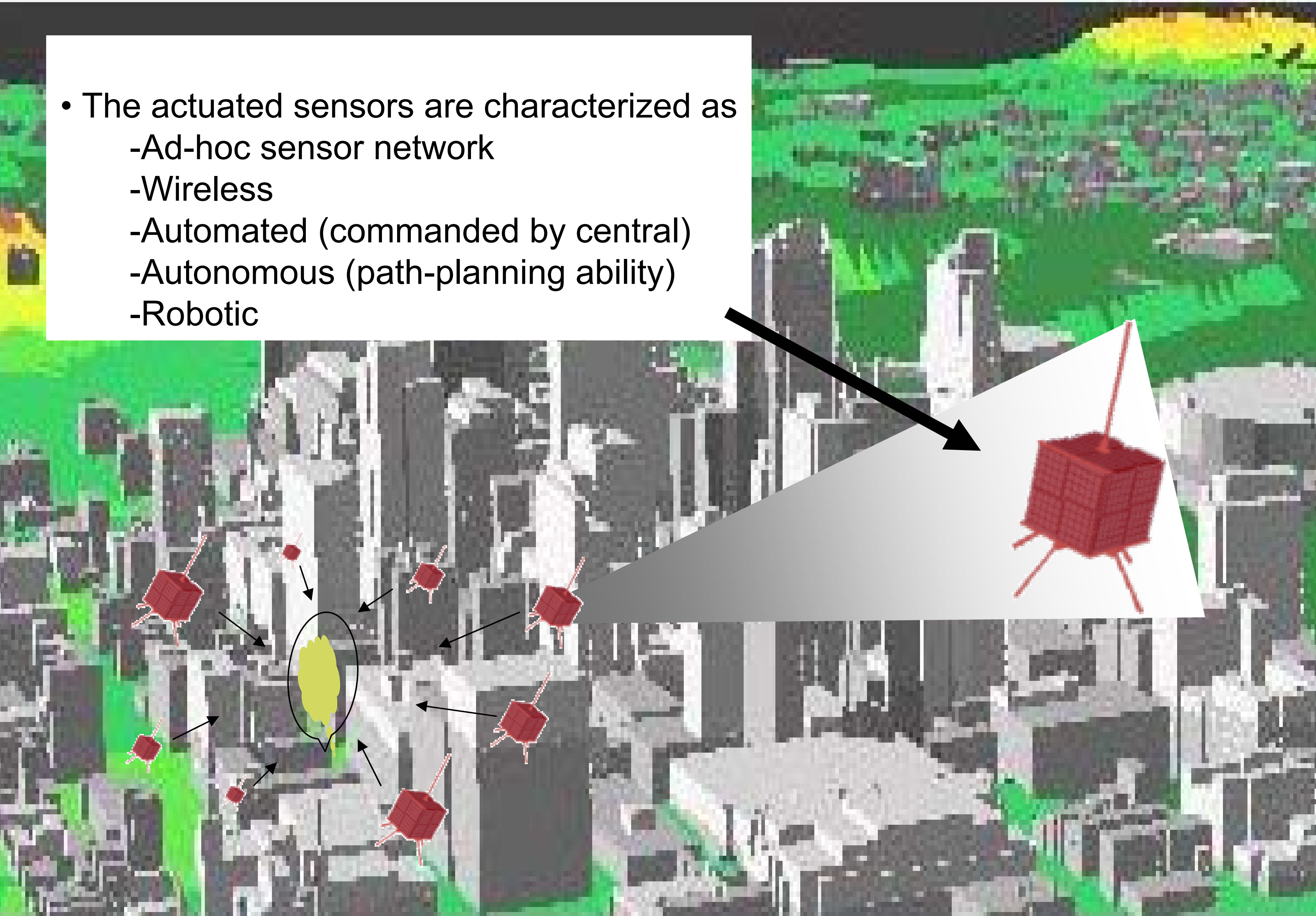
- An initial prediction of the plume is made from a physics-based model that accounts for:
  - Geographic and other constraints (e.g., buildings)
  - Weather conditions (wind, humidity, pressure, ...)
  - Diffusion, convection/advection, ...
- System dynamics given by:

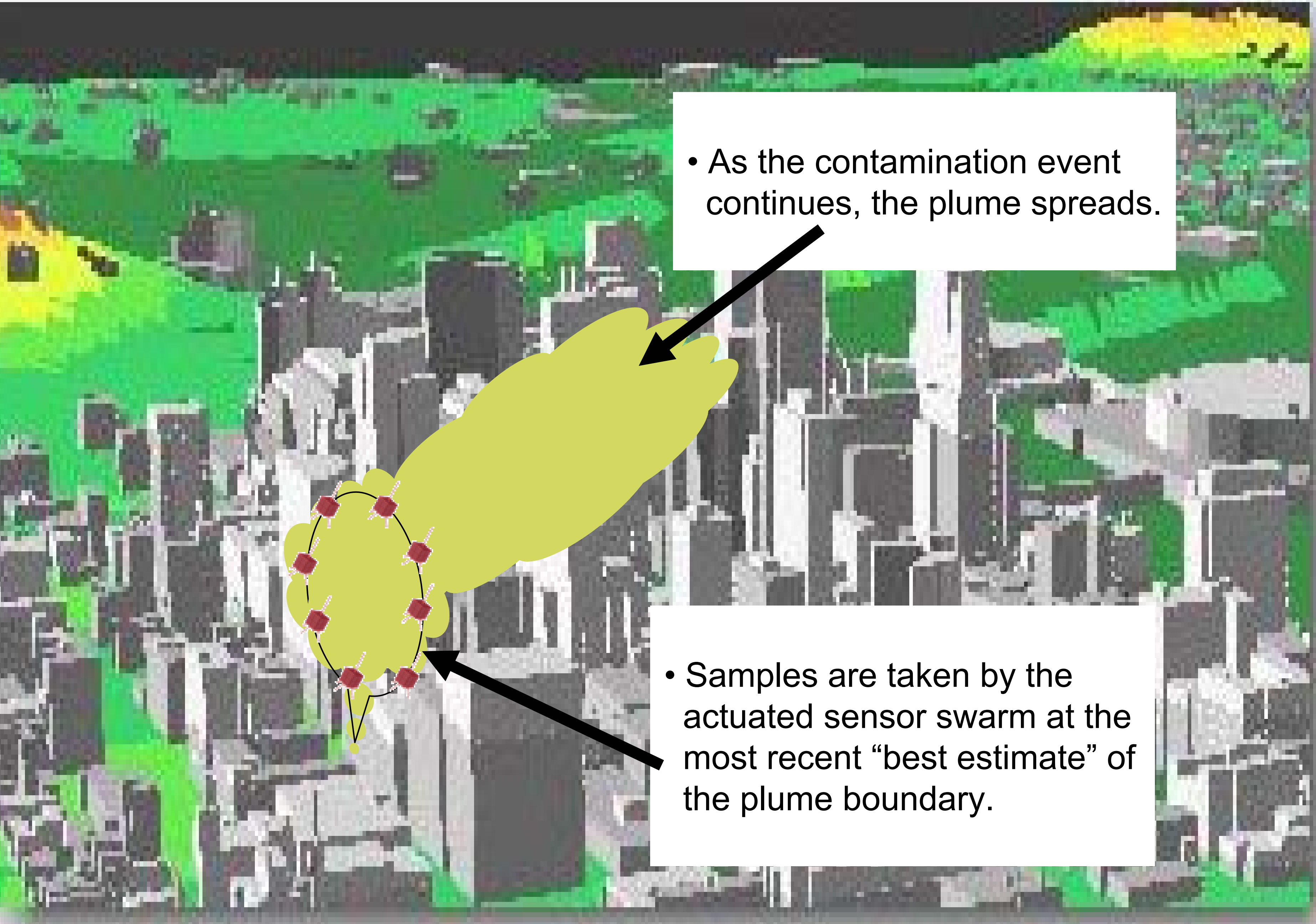
$$\frac{\partial u(x,y,z,t)}{\partial t} + \Delta \cdot (Vu(x,y,z,t)) = \Delta \cdot (D(x,y,z,t)\Delta u(x,y,z,t)) + f(x,y,z,t)$$

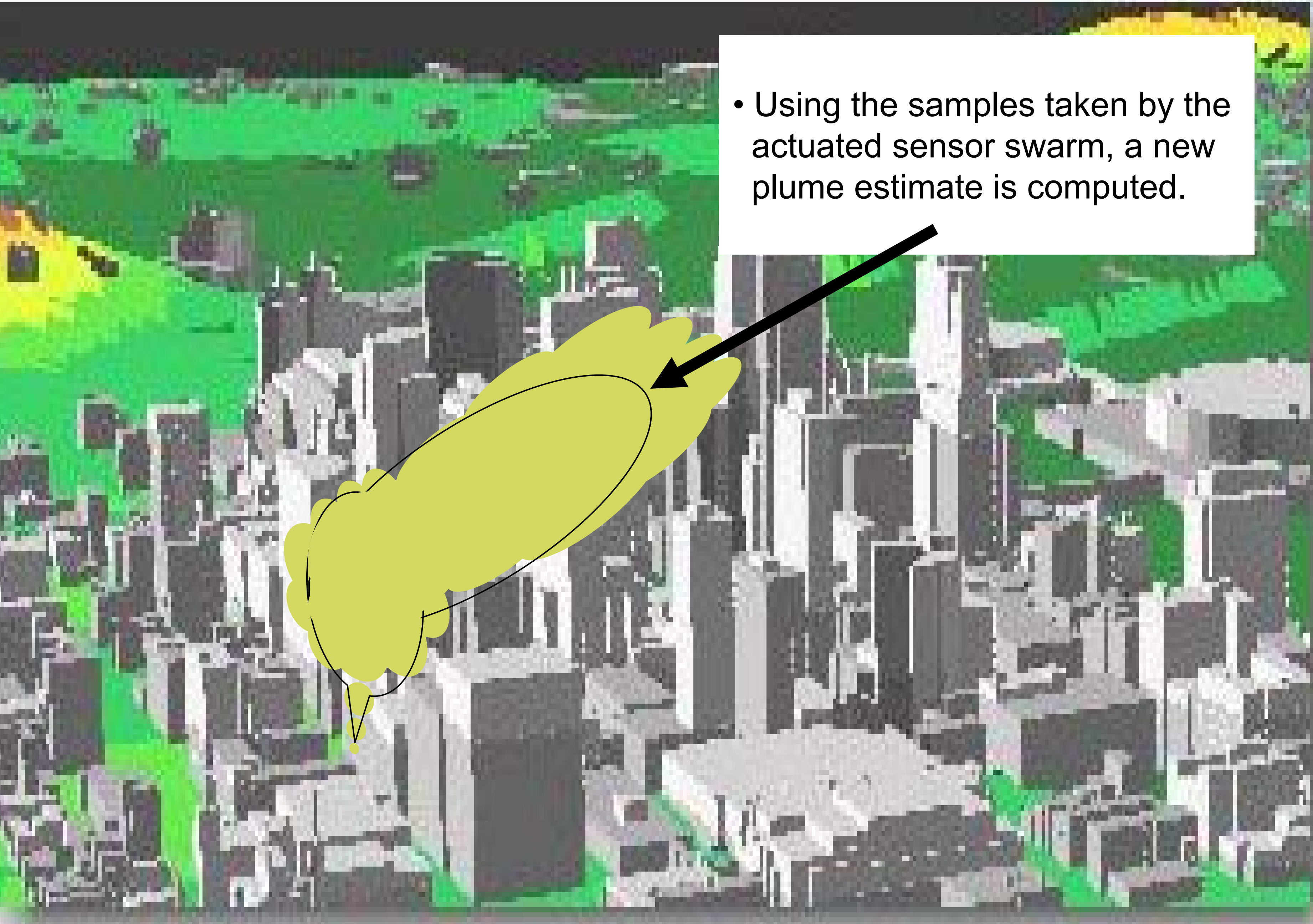


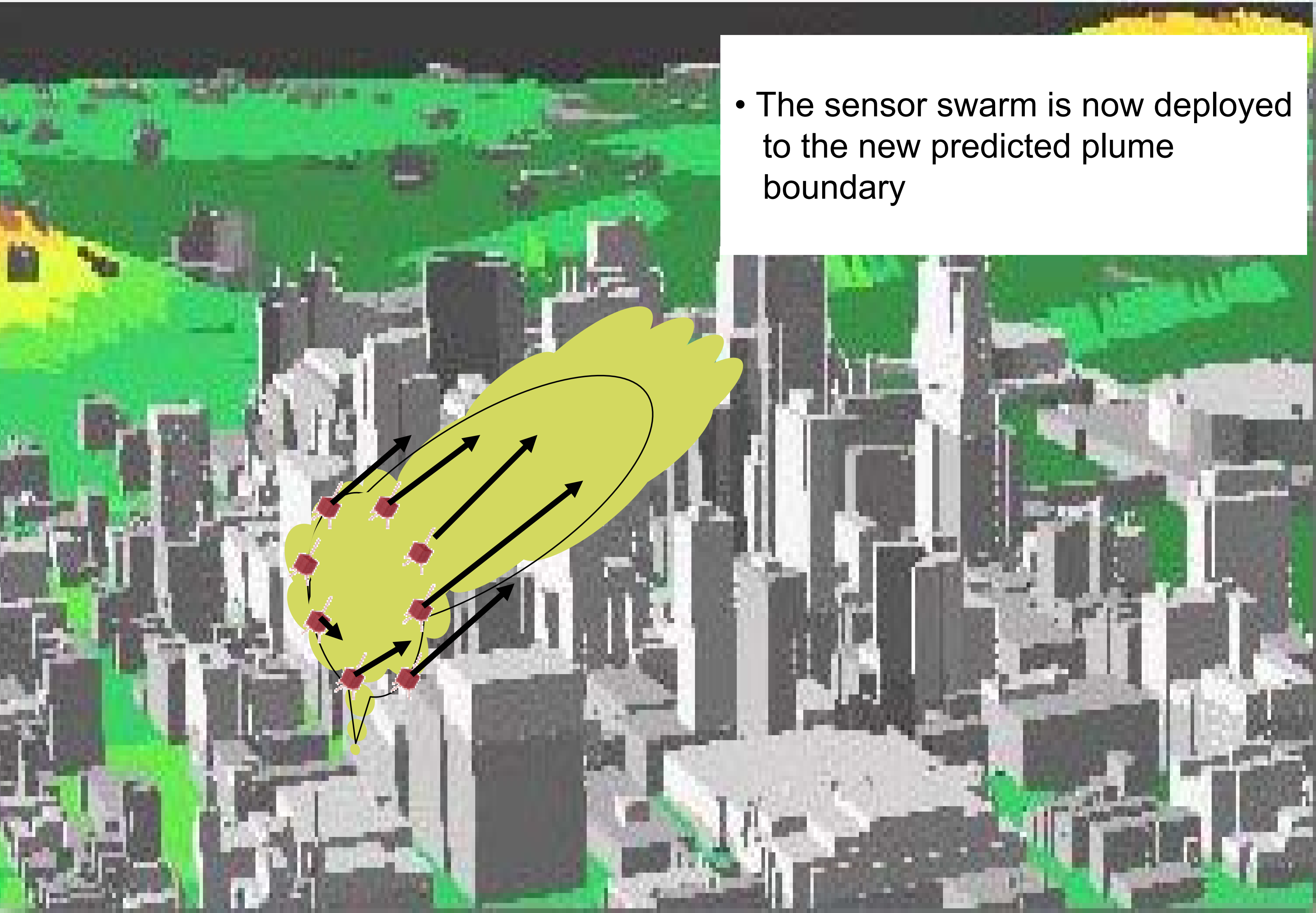
- A semi-autonomous swarm of actuated sensors is deployed to collect contaminant samples.
- The model-based predicted contaminant concentration is used as an attractor potential field for the swarm, which configures itself uniformly

- The actuated sensors are characterized as
  - -Ad-hoc sensor network
  - -Wireless
  - -Automated (commanded by central)
  - -Autonomous (path-planning ability)
  - -Robotic

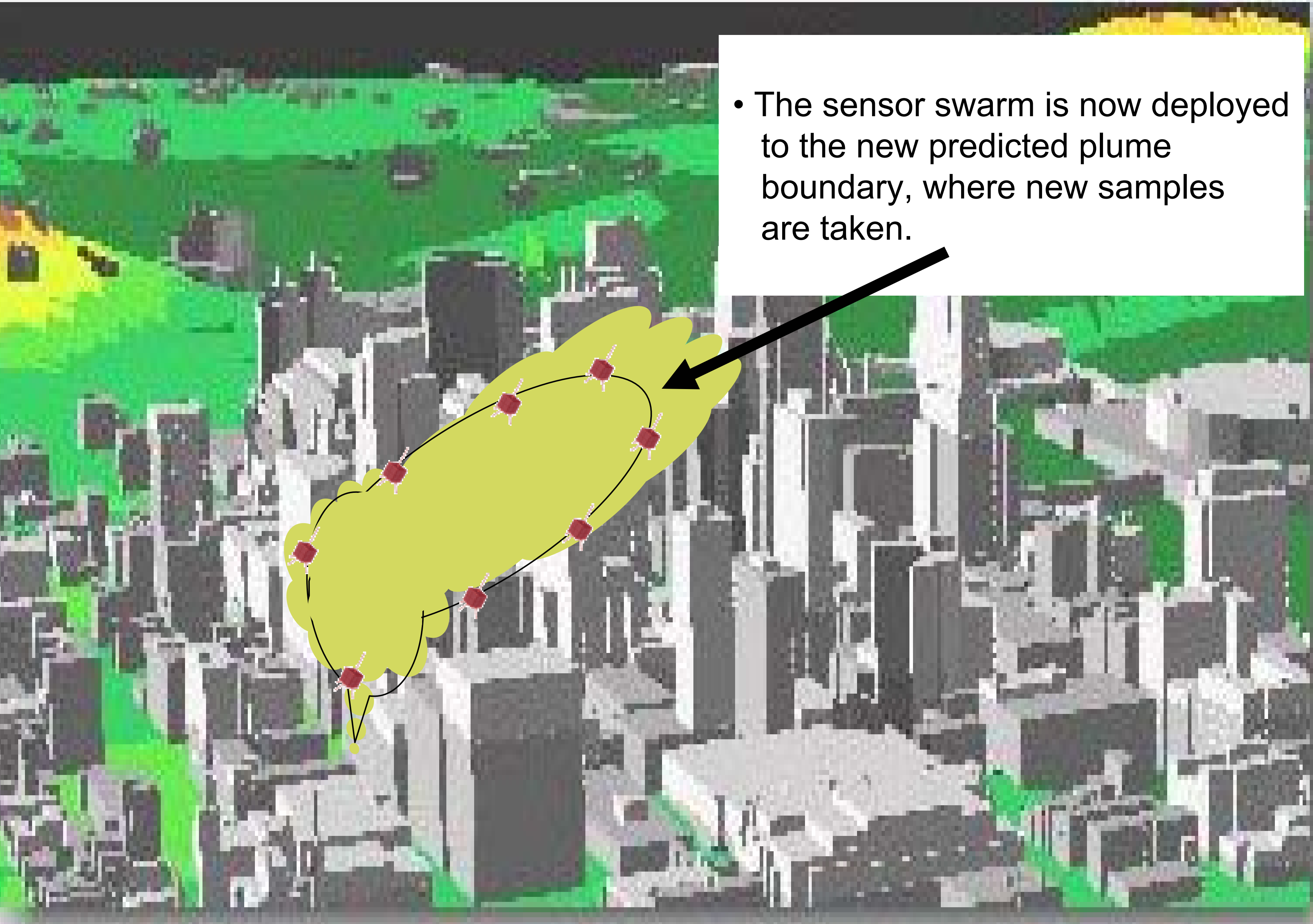



• As the contamination event continues, the plume spreads.
• Samples are taken by the actuated sensor swarm at the most recent “best estimate” of the plume boundary.


• Using the samples taken by the actuated sensor swarm, a new plume estimate is computed.



- The sensor swarm is now deployed to the new predicted plume boundary



• The sensor swarm is now deployed to the new predicted plume boundary, where new samples are taken.

Issues Related to Distributed Sensor Network Development

- If we consider issues related to developing a network of actuated sensors, we can identify the following:
    1. Appropriate sensor
    2. Communication hardware
    3. Communication and data control protocols
    4. Actuation mechanisms
    5. Coordination strategies
- Here we discuss the latter: how does one decide where to deploy a distributed network of sensors?

Problem Formulation - 1

- Formulate the general problem of
  - Coordination of distributed networks of actuated sensors
  - For real-time spatial diffusion characterization.
- Most existing related work on coordination strategies for swarm-type networks
  - Based on the idea of individual sensors following some type of a-priori energy function or gradient.
- We propose a new idea: model-based coordination strategy:
  - Models are becoming increasingly well-developed in a variety of application arenas.
  - One should use all the information that is available when trying to solve a problem.

Problem Formulation - 2

Sensor Net: We begin by assuming we are given a network of actuated sensors, NS^A, made up of a collection of individual sensors that are defined as follows:

$S_i^A(q_i)$: an actuated sensor with the following characteristics:

- located in space at $q_i(t) = (x_i, y_i, z_i)^T \in R^3$
- can communicate with all others and with a supervisor.
- can generate a measurement of interest to the application, defined by $s_i(q_i, t)$, which is assumed to be a function of both space and time as defined below.
- can move freely in three dimensions with dynamics given by

$$\dot{q}_i = f_i(q_i, u_i)$$

where $u_i(t)$ is the motion control input for sensor $S_i^A(q)$.

Problem Formulation - 3

System to be Characterized: Next, we assume that there exists a space-time distribution of interest that we wish to characterize with the distributed actuated sensor network. We denote the distribution as $V(q,t)$, which is assumed to be the solution a known PDE with a known initial condition $V(q_0, t_0)$. The plant dynamics are assumed to be of the following form (which takes into account diffusion and transport phenomena effects such as convention/advection), expressed in standard vector calculus:

$$\frac{\partial V(q,t)}{\partial t} + \Delta \cdot (FV(q,t)) = \Delta \cdot (D(q,t)\Delta V(q,t)) + g(q,t)$$

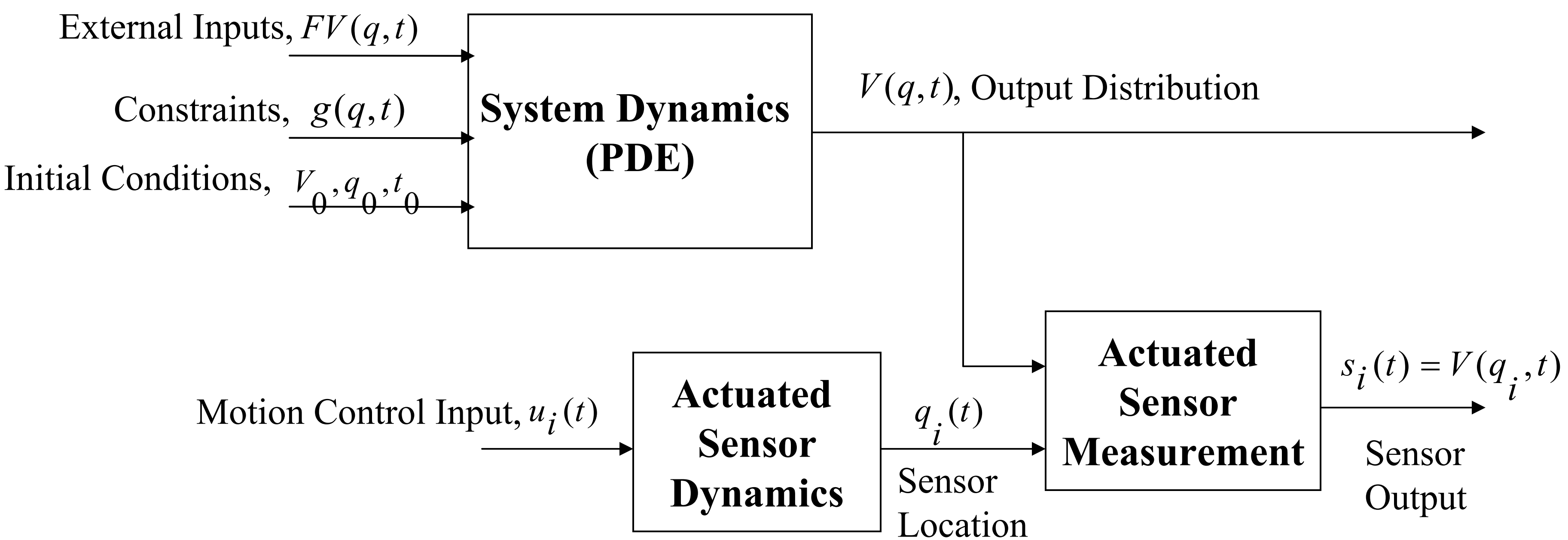
$$V(q_0, t_0) = V_0$$

where $FV(q,t)$ denotes the effect of external, possibly variable, "inputs" on the plant dynamics (e.g., wind, rain, dust, humidity, etc.), $D(q,t)$ is the diffusion function for the specific problem, $g(q,t)$ reflects the effects of constraints (e.g., gravity, building, terrain, etc.), and V_0, q_0, t_0 denote the initial conditions.

Problem Formulation - 4

Sampling Action: It is assumed that the output of the sensor $S_i^A(q)$, defined above as s_i, is a measurement of the distribution of interest at wherever the sensor is located in space. Thus we can write:

$$s_i(q_i, t) = V(q_i, t)$$



Problem Formulation - 5

Prediction: The next step in the problem formulation is to define the prediction. Of course, if we had perfect knowledge, the problem would be trivial. However, in fact we only have estimates of the initial conditions, of the external inputs, and of the constraints. Let is define these estimates as $\hat{F}\hat{V}(q,t)$, $\hat{g}(q,t)$, and $\hat{V}_0$, respectively (of course, there are other sources of uncertainty, such as parameters in the diffusion function $D(q,t)$, but for now we will assume these are known). Then we can compute the estimated diffusion $\hat{V}(q,t)$ as the solution of

$$\frac{\partial \hat{V}(q,t)}{\partial t} + \Delta \cdot (\hat{F}\hat{V}(q,t)) = \Delta \cdot (D(q,t)\Delta\hat{V}(q,t)) + \hat{g}(q,t)$$

$$\hat{V}(q_0, t_0) = \hat{V}_0$$

$$\hat{V}(q_i, t_{s_i}) = s_i(q_i, t_s) = V(q_i, t_{s_i}) \text{ for all } i \text{ and all } t_{s_i}$$

Notice the introduction of the actual sensor measurements at sample points and sample times (q_i, t_{s_i}) as constraints for the partial differential equation.

Problem Formulation - 6

Control: The next piece we add in this section is the motion control of the actuated sensor. There are various ways to approach this piece. For instance, one could take control actions to be a function of the error between the predicted samples and the actual samples. That is, given a set of samples, we make a prediction about the distribution. We then move to a new point in space and take new samples. The error between what we expect to measure and what we actually measure determines where we take our next samples. However, for the moment we consider a simpler approach. We simply move the sensors so they are uniformly distributed relative to the predicted distribution. Thus, we can write

$$q_i^{sp} = H(\hat{V}(q,t))$$

$$\dot{u}_i = h_i(q_i^{sp} - q_i)$$

where H denotes a type of feed-forward energy function that has the effect of computing a set of uniformly distributed locations around the distribution and h is the control law used to drive the actuated senor to its new setpoint q_i^{sp} .

Problem Formulation - 7

Goal Statement: Finally, we need to define the goal of the control action. Ideally, one would like to achieve

$$\lim_{t \to \infty} \hat{V}(q,t) = V(q,t) \text{ for all } q$$

However, this is quite ambitious. Instead, it may be better to hope for making the prediction match at the sample points. Thus, we can define a cost function

$$J = \lim_{t \to \infty} \sum_i h_g((\hat{V}(q_i,t) - V(q_i,t)))$$

where $h_g(\cdot)$ is a positive function

$$\min_{H,h} J = \lim_{t \to \infty} \sum_i (V(q_i,t) - \hat{V}(q_i,t))$$

subject to :

1a) $$\frac{\partial V(q,t)}{\partial t} + \Delta \cdot (FV(q,t)) = \Delta \cdot (D(q,t)\Delta V(q,t)) + g(q,t)$$

1b) $$V(q_0,t_0) = V_0$$

2a) $$\frac{\partial \hat{V}(q,t)}{\partial t} + \Delta \cdot (\hat{F}\hat{V}(q,t)) = \Delta \cdot (D(q,t)\Delta \hat{V}(q,t)) + \hat{g}(q,t)$$

2b) $$\hat{V}(q_0,t_0) = \hat{V}_0$$

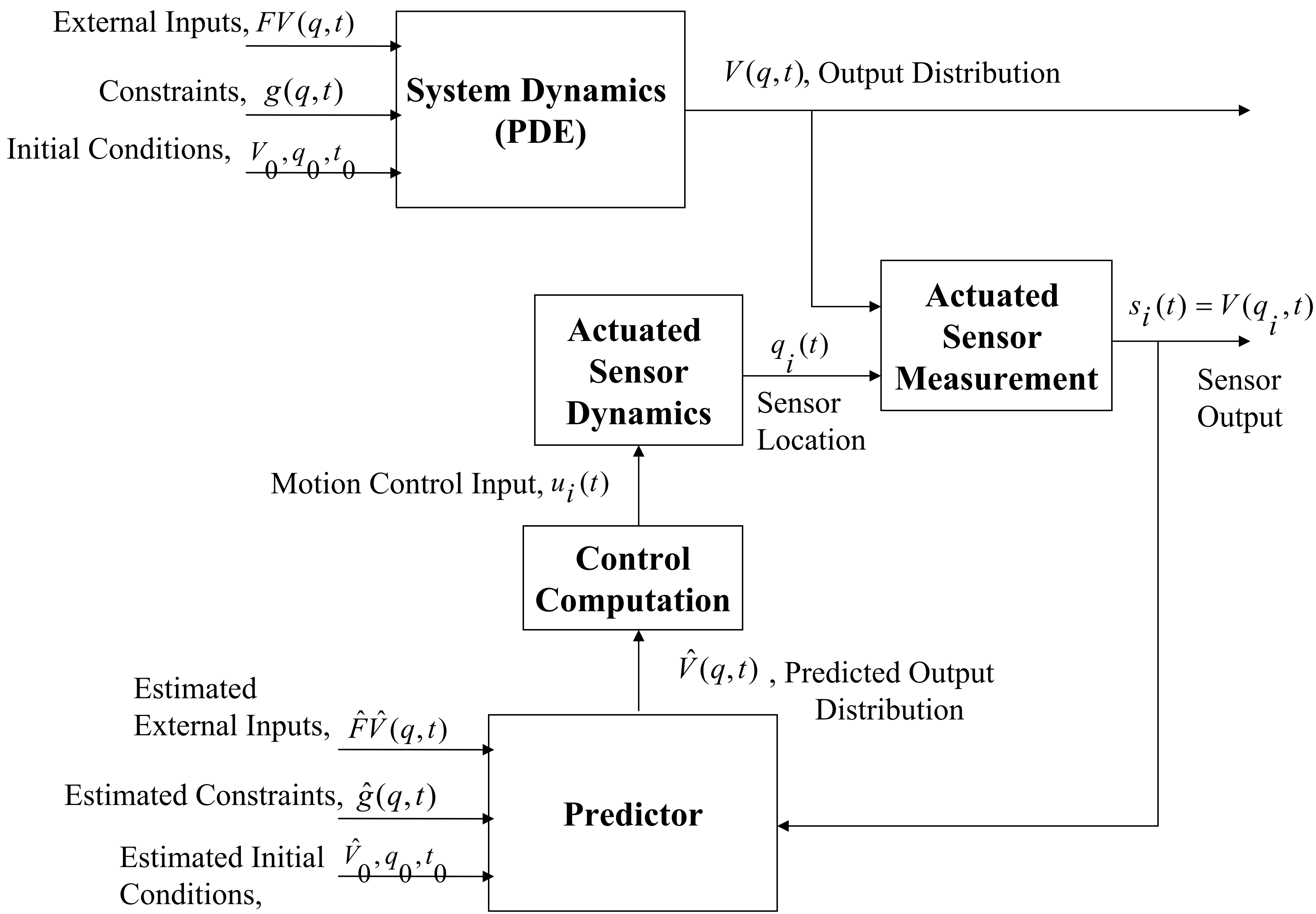
2c) $$\hat{V}(q_i,t_{s_i}) = s_i(q_i,t_{s_i}) = V(q_i,t_{s_i}) \text{ for all } i \text{ and all } t_{s_i}$$

3a) $$\dot{q}_i = f_i(q_i,u_i)$$

3b) $$s_i(q_i,t_{s_i}) = V(q_i,t_{s_i})$$

4a) $$q_i^{sp} = H(\hat{V}(q,t))$$

4b) $$\dot{u}_i = h_i(q_i^{sp} - q_i)$$


External Inputs, $FV(q,t)$
Constraints, $g(q,t)$
Initial Conditions, V_0, q_0, t_0
System Dynamics (PDE)
$V(q,t)$, Output Distribution
Actuated Sensor Measurement
$s_i(t) = V(q_i, t)$
Sensor Output
Actuated Sensor Dynamics
$q_i(t)$
Sensor Location
Motion Control Input, $u_i(t)$
Control Computation
$\hat{V}(q,t)$, Predicted Output Distribution
Estimated External Inputs, $\hat{F}\hat{V}(q,t)$
Estimated Constraints, $\hat{g}(q,t)$
Estimated Initial Conditions, $\hat{V}_0, q_0, t_0$
Predictor

One Other Idea

- We would like to go one step further:
  - Suppose we can actuate an actuator
  - I.e., There is a robot that can impact the diffusion of the plume
- Suppose

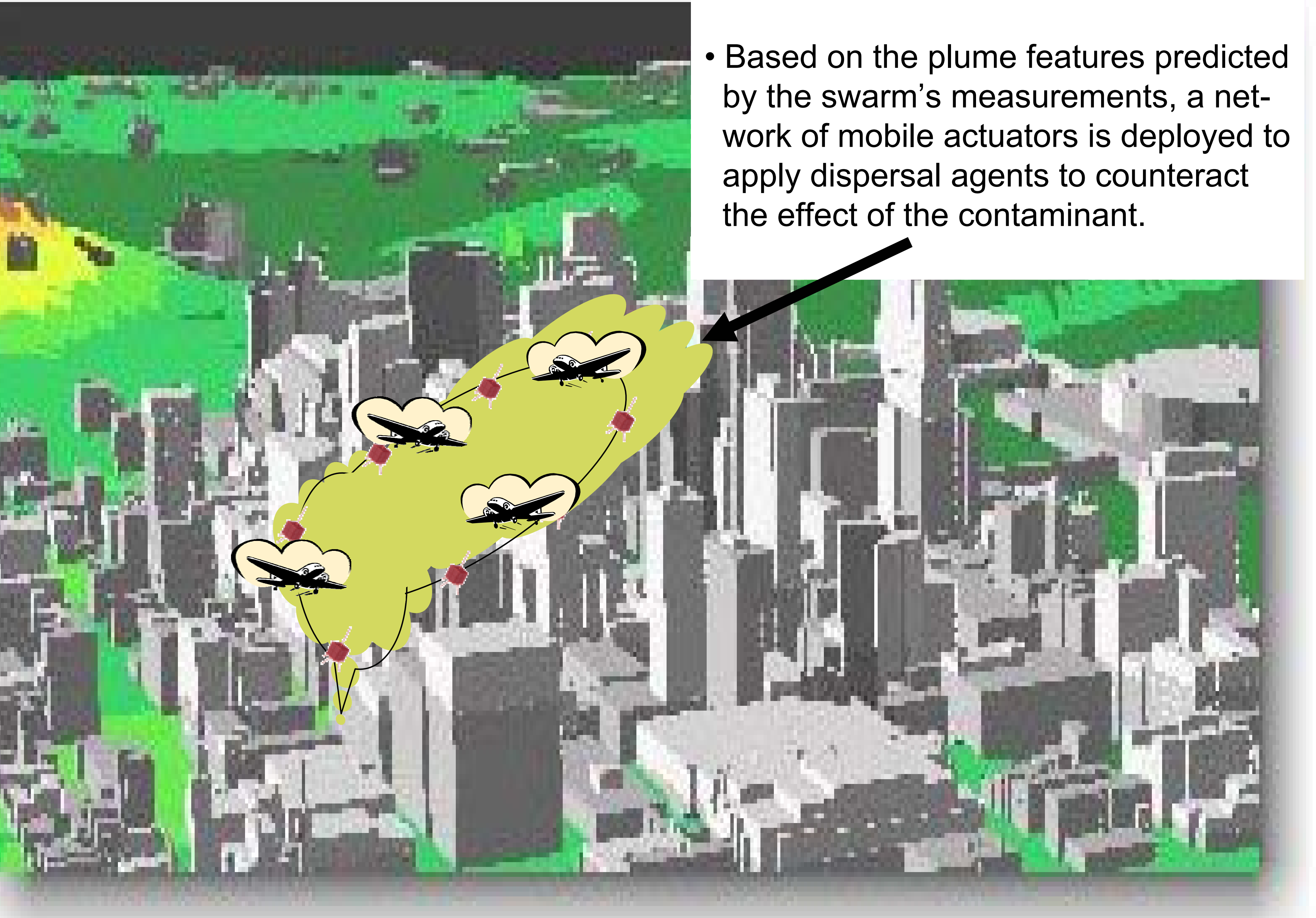
$A_j^A(q_j)$: an actuated actuator with the following characteristics

- located in space at $q_j(t) = (x_j, y_j, z_j)^T \in R^3$
- can communicate with all others, with all sensors, and with a supervisor.
- can generate an effect of interest to the application, defined by $d_j^a(q_j, t)$, which is assumed to be a function of both space and time.
- can move freely in three dimensions with dynamics given by

$$\dot{q}_j = f_j^a(q_j, u_j^a)$$

where $u_j^a(t)$ is the motion control input for actuator $A_j^A(q_j)$.

- Based on the plume features predicted by the swarm's measurements, a net-work of mobile actuators is deployed to apply dispersal agents to counteract the effect of the contaminant.



Actuator Motion: For this set of actuators we define a motion controller given by

$$q_j^{sp} = H^a(V^d(q,t) - \hat{V}(q,t))$$

$$\dot{u}_j^a = h_j^a(q_j^{sp} - q_j)$$

We point out that in the case of an actuated actuator, the function H^a is primarily a comparator and $V^d(q,t)$, the desired distribution, can typically be taken as zero (i.e., we don't want any contaminant!).

Control Goal: Without going into the details, we propose the following cost function for the design of the functions H^a and h_j^a

$$J^c = \lim_{t \to \infty} \int (V^d(q,t) - \hat{V}(q,t))dq$$

This costs seeks to drive the predicted distribution to the final distribution everywhere in space.

Final Architecture and Problem Statement: The equations below give the final form of the problem. Notice that we have actually stated two coupled problems. The sensor motion control problem is based on the output of the prediction. But the effect of the actuated actuators is shown in the diffusion function used in the prediction. We denote this as function

$$w(D(d,t), d_j^a(q_j,t))$$

because in general the effect of a dispersal agent may not necessarily be linear. At this time the effect of this coupling is not clear. One would hope to see the standard separation principle emerge, but that may not be possible. Deep research is needed to understand this problem. Figure 13 shows the complete architecture.

$$\min_{H,h} J^p = \lim_{t \to \infty} \sum_i h_g((V(q_i,t) - \hat{V}(q_i,t)))$$

$$\min_{H^a,h^a} J^c = \lim_{t \to \infty} \int (V^d(q,t) - \hat{V}(q,t))dq$$

subject to :

1a) $$\frac{\partial V(q,t)}{\partial t} + \Delta \cdot (FV(q,t)) = \Delta \cdot (D(q,t)\Delta V(q,t)) + g(q,t)$$

1b) $$V(q_0,t_0) = V_0$$

2a) $$\frac{\partial \hat{V}(q,t)}{\partial t} + \Delta \cdot (\hat{F}\hat{V}(q,t)) = \Delta \cdot (w(D(q,t), d_j^j(q_j,t))\Delta \hat{V}(q,t)) + \hat{g}(q,t)$$

2b) $$\hat{V}(q_0,t_0) = \hat{V}_0$$

2c) $$\hat{V}(q_i,t_{s_i}) = s_i(q_i,t_{s_i}) = V(q_i,t_{s_i}) \text{ for all } i \text{ and all } t_{s_i}$$

3a) $$\dot{q}_i = f_i(q_i,u_i)$$

3b) $$s_i(q_i,t_{s_i}) = V(q_i,t_{s_i})$$

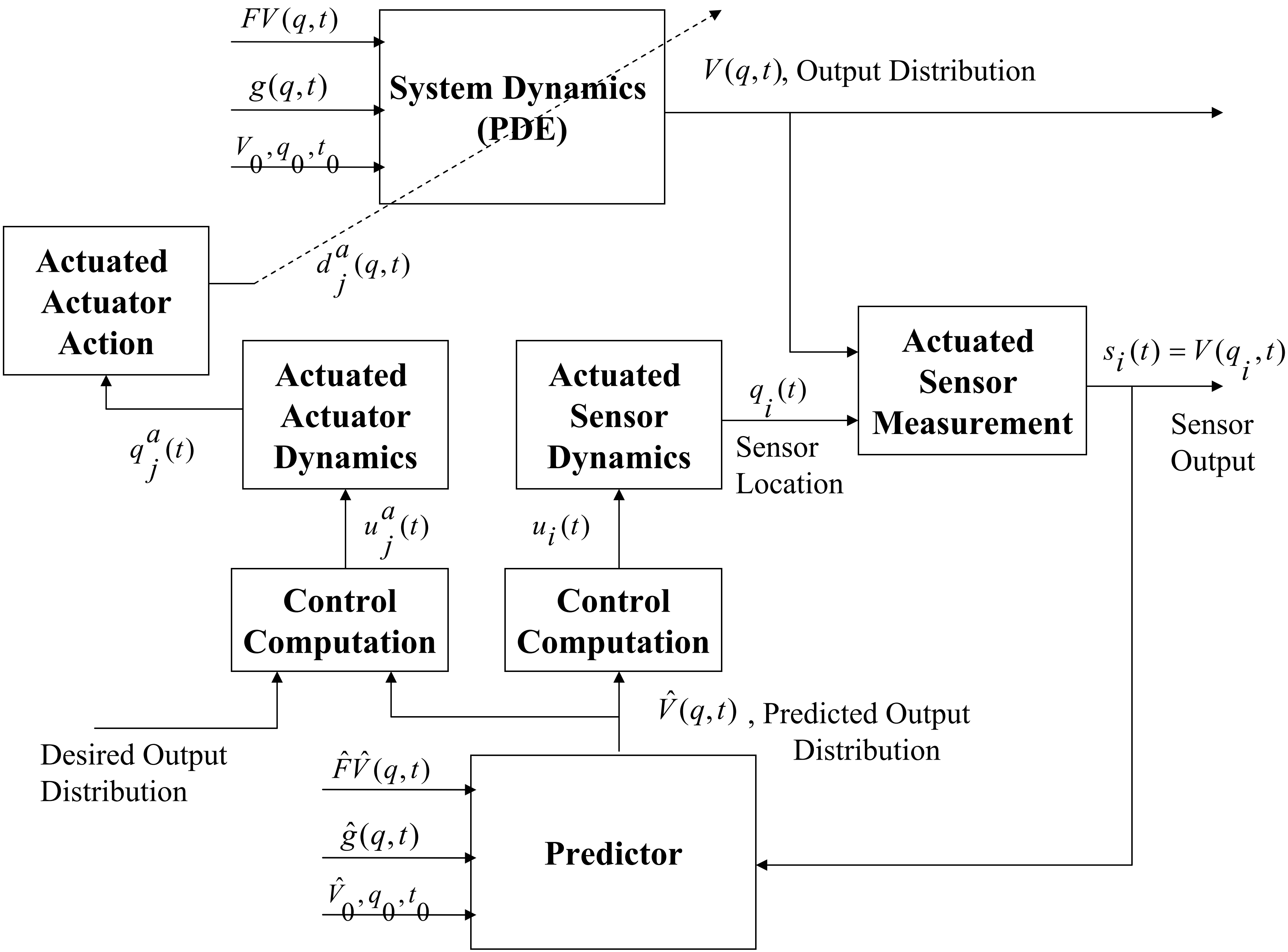
4a) $$q_i^{sp} = H(\hat{V}(q,t))$$

4b) $$\dot{u}_i = h_i(q_i^{sp} - q_i)$$

5a) $$\dot{q}_j = f_j^a(q_j,u_j^a)$$

5b) $$q_j^{sp} = H^a(V^d(q,t) - \hat{V}(q,t))$$

5c) $$\dot{u}_j^a = h_j^a(q_j^{sp} - q_j)$$



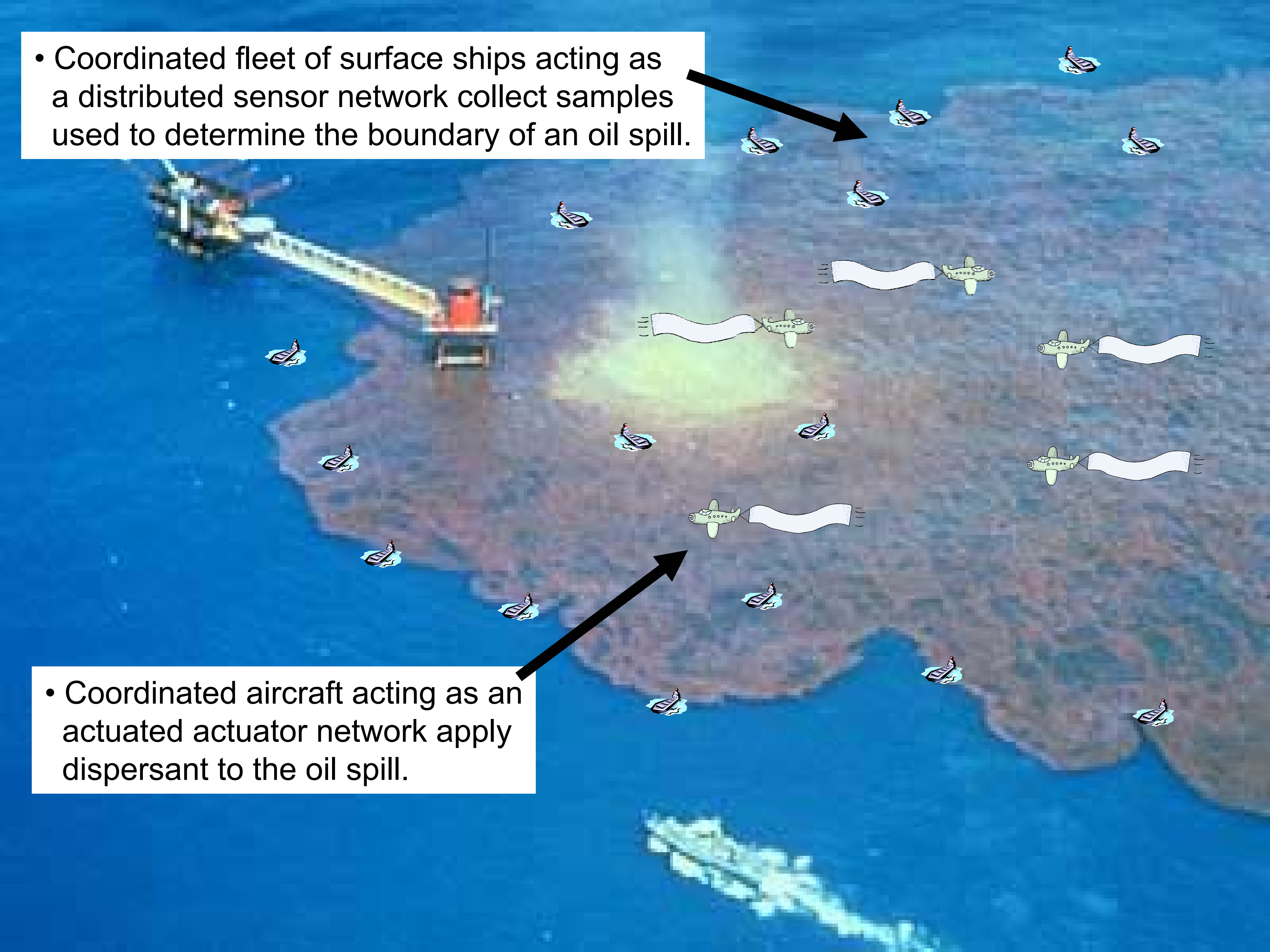
$FV(q,t)$
$g(q,t)$
V_0, q_0, t_0
System Dynamics (PDE)
$V(q,t)$, Output Distribution
Actuated Actuator Action
$d_j^a(q,t)$
Actuated Actuator Dynamics
$q_j^a(t)$
Actuated Sensor Dynamics
$q_i(t)$
Sensor Location
Actuated Sensor Measurement
$s_i(t) = V(q_i, t)$
Sensor Output
$u_j^a(t)$
$u_i(t)$
Control Computation
Control Computation
$\hat{V}(q,t)$, Predicted Output Distribution
Desired Output Distribution
$\hat{F}\hat{V}(q,t)$
$\hat{g}(q,t)$
$\hat{V}_0, q_0, t_0$
Predictor

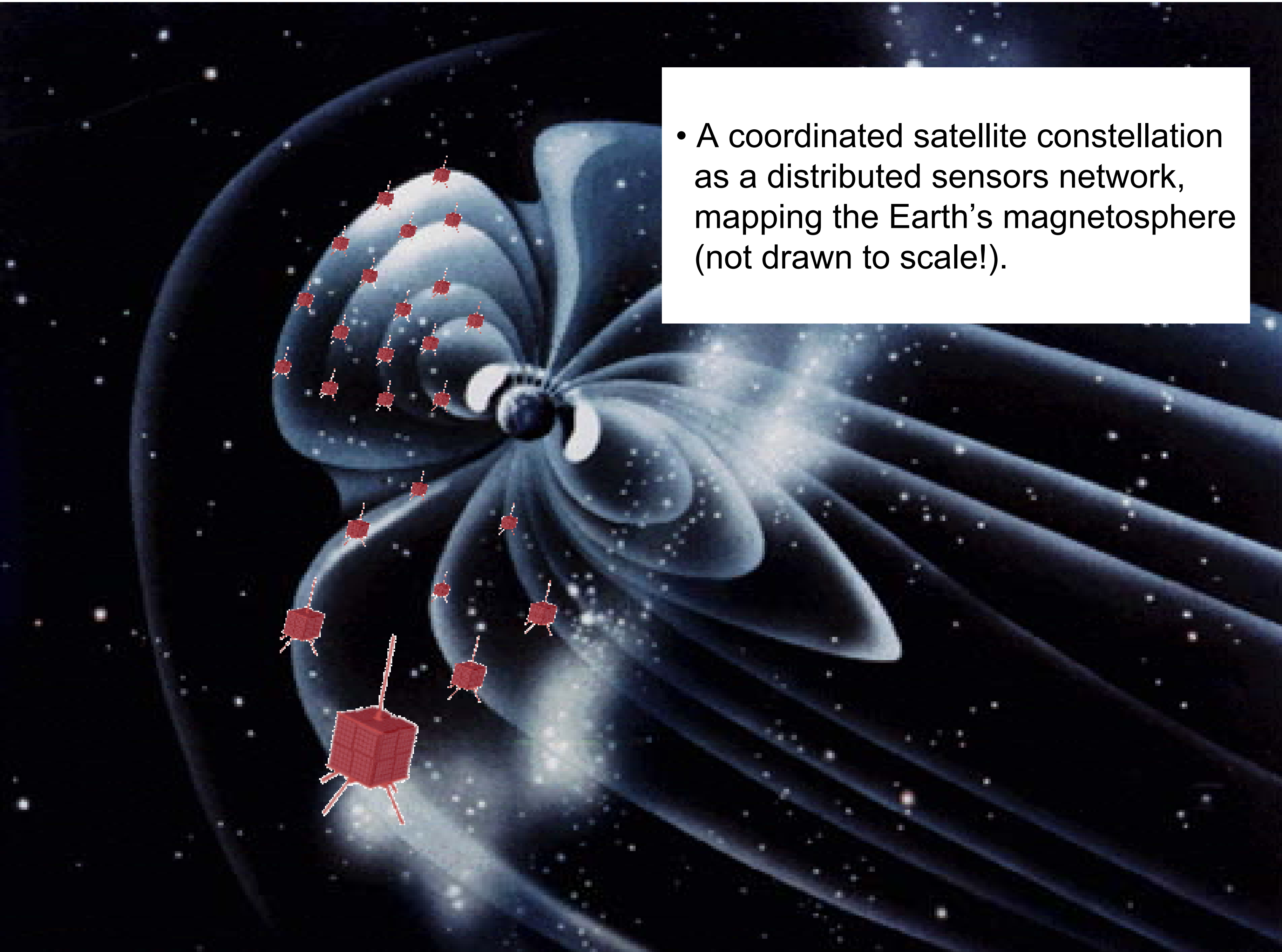
Other Applications

We believe that the ideas presented here are widely applicable to a large number of applications. In general the framework can be applied to any problem where there is a spatial diffusion process for which there is an interest in prediction and control and where there are a limited number of samples and/or actuation points available. Such applications could include, for example, mapping the diffusion of airborne contaminants as we have described, mapping the spread of water-borne contaminants, or the mapping of atmospheric and space-based features of the earth. Similarly, we can consider problems such as spatial vibration suppression on airplane wings or weed management in an agricultural setting. Figures 14-16 show several such applications.

Other Applications

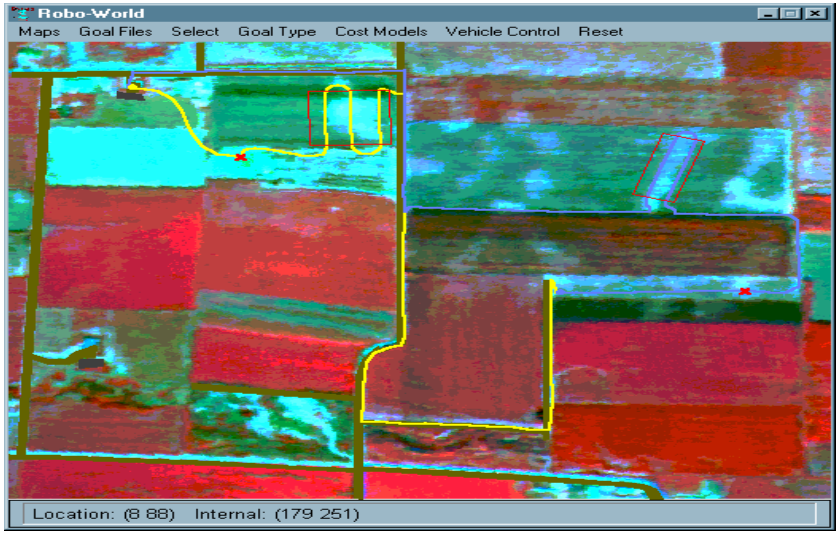
- The ideas presented here are widely applicable to a large number of applications.
- Framework can be applied to any problem where there is a spatial diffusion process for which there is an interest in prediction and control and where there are a limited number of samples and/or actuation points available.
- Such applications could include, for example,
  - Mapping the diffusion of airborne contaminants,
  - Mapping the spread of water-borne contaminants
  - Mapping of atmospheric and space-based features of the earth
  - Problems such as spatial vibration suppression on airplane wings
  - Weed management in an agricultural setting
  - Antenna array coverage
  - Etc.


• Coordinated fleet of surface ships acting as a distributed sensor network collect samples used to determine the boundary of an oil spill.
• Coordinated aircraft acting as an actuated actuator network apply dispersant to the oil spill.



- A coordinated satellite constellation as a distributed sensors network, mapping the Earth's magnetosphere (not drawn to scale!).

Weed Management Application



- Optimal Intelligent and Co-operative path and mission planning
- Using an aircraft or satellite map of the region, user assigned tasks are optimized using the intelligent path and mission planner
- The system adapts to unexpected obstacles or terrain features by re-planning optimal mission and path assignments

- Technology developed for use on various autonomously controlled vehicles using dGPS navigation
- Prototypes equipped with soil sampling equipment, chemical applicators, radiation detectors, etc.

Experimental Testbed Idea