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Integration of Software Platforms Based on Secondary Air Quality Standards

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Abstract: *This paper presents the design and implementation of an integrated software platform that connects air quality monitoring systems with smart agriculture tools, with a focus on secondary air quality standards. The study investigates the correlation between air pollution and the development of tomato crops in the Plovdiv region of Bulgaria. The system integrates two intelligent agents: Air Agent, responsible for analysing real-time pollutant data, and Farmer Agent, which monitors the vegetation dynamics of tomato plants. Experimental results from the 2023 growing season indicate that elevated concentrations of PM2.5 and PM10 during critical growth stages significantly inhibited both plant height and stem development. The proposed platform utilises ontologies, asynchronous communication protocols, and data analytics to provide actionable insights for farmers and to support the practical application of environmental standards in agriculture. These findings underscore the importance of incorporating secondary air quality considerations into agricultural decision-making and environmental policy.*

Keywords: *intelligent agents; environmental monitoring; Plovdiv region; integrated platform; secondary air quality standards.*

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1. Introduction

Air pollution represents one of the most pressing environmental challenges of our time, exerting a significant negative impact not only on human health but also on ecosystems and agricultural productivity. Numerous scientific studies have demonstrated that poor air quality contributes to respiratory and cardiovascular diseases in humans. However, the adverse effects of air pollution extend beyond direct health implications. Airborne pollutants also have a profound indirect influence on agriculture by affecting the growth, yield, and quality of crops. This dual impact, on both human well-being and food systems, underscores the need for integrated approaches to environmental monitoring and sustainable development.

In this context, the current study focuses on investigating the potential correlation between air quality and the vegetation dynamics of crops, with an emphasis on tomato cultivation in the Plovdiv region of Bulgaria. Plovdiv is recognised as a major center for vegetable production in the country, making it a strategically important location for such research. Understanding how environmental factors like air pollution influence crop health in this region can provide critical insights for farmers, policymakers, and researchers alike.

Previously, as part of a smart agriculture initiative, we developed the ZEMELA platform, an intelligent system designed to support tomato growers through advanced vegetation monitoring. At the heart of ZEMELA lies a personalised virtual assistant capable of tracking the growth and development of tomato plants cultivated at the Maritsa Vegetable Crops Research Institute in Plovdiv. When deviations from expected vegetation patterns are detected, the assistant automatically generates alerts and sends recommendations to farmers, enabling timely interventions.

Building on this foundation, the current project introduces a complementary regional platform for real-time air quality monitoring in the Plovdiv area. This system is equipped with its intelligent assistant that continuously analyses air quality data, detects deviations from established standards, and identifies major pollutants that may pose risks to both humans and crops.

The overarching goal of this study is to develop a communication component that enables bidirectional data exchange between the two assistants, one focused on air quality and the other on crop vegetation. By enabling data exchange and collaborative analysis, this integration will allow us to explore and validate possible correlations between air pollution levels and the physiological responses of plants, particularly during sensitive stages of development.

This paper presents the outcomes of the project's first phase, focusing on the initial system architecture, integration challenges, and early findings from the correlation analysis between air quality metrics and tomato vegetation data. These results lay the groundwork for future platform enhancements and contribute to the broader vision of sustainable, data-driven agriculture in pollution-prone regions.

2. Air Quality Standards

Air Pollution and Regulatory Responses in Europe. Air pollution causes ~300,000 premature deaths annually in Europe, driven mainly by PM_{10}, $PM_{2.5}$, NO_2, and SO_2. In 2022, the European Commission revised air quality laws (Directives 2004/107/EC, 2008/50/EC), adopting stricter limits in 2024, including reducing $PM_{2.5}$ from 25 to 10 µg/m³ (near WHO's 5 µg/m³ guideline). The reforms mandate action plans for polluted areas, citizen compensation rights, and better monitoring (WHO Ambient Air Quality Database, 2024).

Air Quality Standards Framework. Air quality standards regulate ambient pollutant levels (e.g., PM, NO_x, O_3), unlike emission standards targeting sources. Based on WHO, EPA, and EEA research (Bachmann, 2012), such standards undergo periodic revision (WHO Ambient Air Quality Database, 2024).

Secondary standards, exemplified by those in the U.S. Clean Air Act, protect ecosystems and visibility (Bachmann, 2012). The EU integrates ecological thresholds via directives (2016/2284/EU, 92/43/EEC), but nitrogen deposition still exceeds safe levels (De Marco et al., 2019).

Global Challenges and Trends. Asia employs varied standards (e.g., China's Grade I/II, India's zoning) but faces monitoring gaps (Huang et al., 2021). Secondary standards have proven effective in mitigating acid rain (Lovett et al., 2009), with economic benefits ($33B/year in the U.S., €2–10B in Europe) (U.S. Environmental Protection Agency, 2020; Amann et al., 2020). Challenges include scientific complexity (Clark et al., 2019) and political resistance (Zhao et al., 2017).

Future Directions. Emerging tools (satellite data, GEO BON models) aid policymaking (Pereira, 2017). Integrating air quality and climate policies can address co-pollutants like methane (Shindell, 2017). This study aims to bridge gaps by developing a digital platform to operationalise secondary standards for real-time decision-making. Against this background, the present study aims to operationalise the concept of secondary air quality standards through the development of an integrated digital platform that connects air pollution monitoring with vegetation dynamics in agriculture. Specifically, the paper presents the design and early-stage implementation of a two-part intelligent system: one component tracks air quality metrics in real time, while the other monitors crop health and development. By enabling communication between these two assistants, the platform allows for correlation analysis between pollution levels and physiological changes in plants. The system focuses on tomato cultivation in the Plovdiv region of Bulgaria, an area of both agricultural and environmental significance.

Against this background, the present study aims to operationalise the concept of secondary air quality standards through the development of an integrated digital platform that connects air pollution monitoring with vegetation dynamics in agriculture. Specifically, the paper presents the design and early-stage implementation of a two-part intelligent system: one component tracks air quality metrics in real time, while the other monitors crop health and development. By enabling communication between these two assistants, the platform allows for correlation analysis between pollution levels and physiological changes in plants. The system focuses on tomato cultivation in the Plovdiv region of Bulgaria, an area of both agricultural and environmental significance.

This study's goal is to demonstrate how the integration of real-time environmental data and crop monitoring systems can provide early warning signals, improve decision-making for farmers, and contribute to the broader adoption of secondary air quality standards in practical, agriculture-related applications.

In designing the local platform for Plovdiv, the updated regulatory thresholds for $PM_{2.5}$ and PM_{10} were explicitly incorporated as baseline criteria for alert generation and risk assessment modules. The system was calibrated to trigger warnings when pollutant concentrations approached or exceeded the new EU 2024 standards, enabling timely interventions to protect both crops and human health. Furthermore, vegetation response models were developed to align with critical loads for nitrogen deposition, ensuring that secondary ecological thresholds were embedded into the agronomic decision-support tools. By grounding platform functionality in these updated regulatory benchmarks, the study demonstrates a practical pathway for translating European air quality reforms into localised, operational strategies for environmental management in agricultural regions.

3. General Architecture of the Integrated Platform

As part of the implementation of two research projects, we developed two software systems with largely identical architectures, which we now aim to integrate for use in the study presented in this paper (Figure 1). The two frameworks are designed to solve heterogeneous tasks, and they operate in distinct environments and use different sensor networks. The conceptual premise is that only the Air Agent from the framework ACreM supports the Farmer Agent from the framework ZEMELA in solving the task considered in this article. At the same time, both frameworks can continue to perform their main functions.

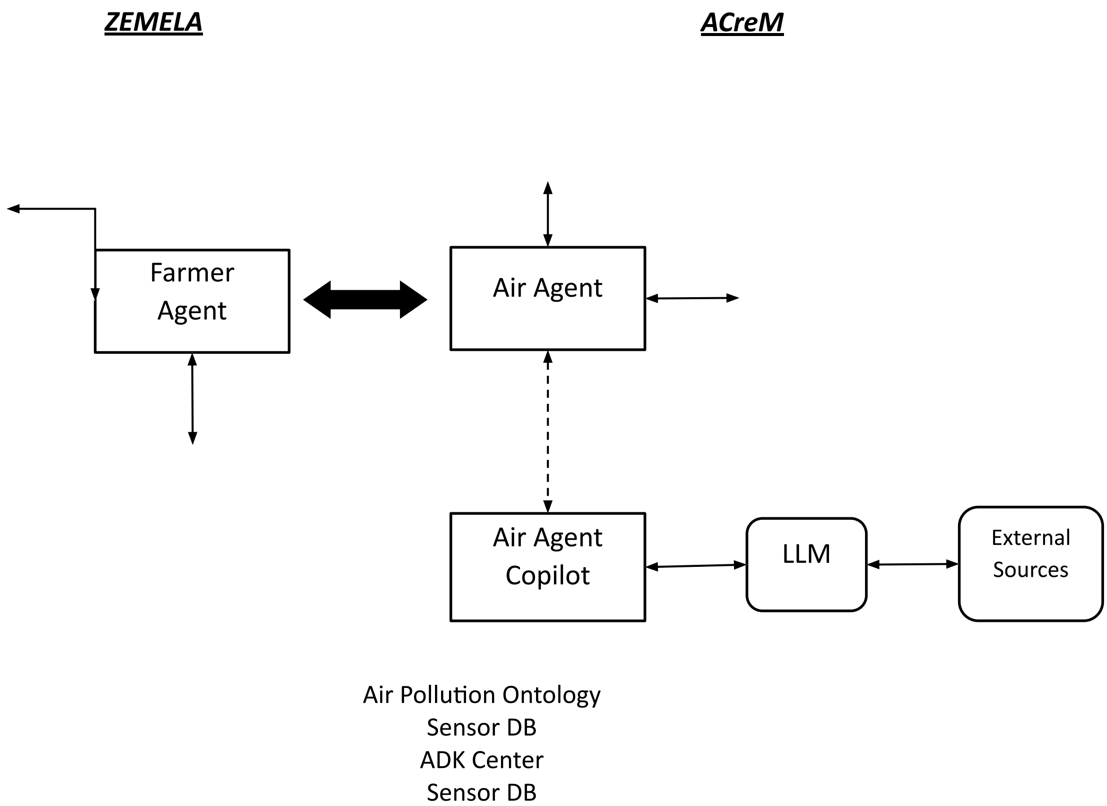

Figure 1. Architecture of the integrated platform

The ACreM (Air Credible Monitoring) platform is designed to support air quality monitoring in the Plovdiv region of Bulgaria (Stoyanov et al., 2025). Each day, various governmental and non-governmental organisations publish their measurements and analyses of local air quality. These datasets frequently differ and are sometimes contradictory, due to variations in methodology, instrumentation, or data sources. The ACreM platform was developed to address this inconsistency by providing an independent, objective assessment of air quality.

At the platform's core are two intelligent assistants, implemented as autonomous software agents, each responsible for processing and interpreting environmental data in support of real-time monitoring and analysis.

The first assistant, referred to as Air Agent, is responsible for analysing data received from internal sources, specifically, measurements of various air pollutants collected by our sensor network deployed throughout the Plovdiv region. This agent was developed using the BDI (Beliefs–Desires–Intentions) model within the JaCaMo development environment (Boissier et al., 2013). The BDI model originates from the philosophical tradition of studying practical and rational human reasoning. In this context, practical reasoning refers to the process of deciding what actions to take based on competing goals and constraints. It involves two primary steps: (1) deliberation, in which the agent determines the intended state (i.e., the goal), and (2) means–ends reasoning (or planning), in which the agent identifies how to achieve that goal given its current beliefs and capabilities (Bratman, 1990). One of the key advantages of the BDI architecture is its capacity to represent and interact with dynamic environments in a flexible and context-aware manner, an essential requirement for our study. Furthermore, Air Agent leverages domain-specific expertise in air quality monitoring, enabling it to reason over validated environmental knowledge and make context-sensitive assessments based on pollutant data.

Two main repositories are in the environment of the ACreM, which the assistant utilises during data processing. The first repository is the Air Pollution Ontology, developed under the World Health Organisation's global air quality guidelines (WHO Global Air Quality Guidelines: Particulate Matter (PM2.5 and PM10), Ozone, Nitrogen Dioxide, Sulfur Dioxide, and Carbon Monoxide, 2021). The Air Pollution Ontology captures structured knowledge about air pollutants (such as PM10, PM2.5, SO_2, O_3, CO, and NO_2), their sources, and environmental and health impacts. This ontology forms the foundation for understanding and analysing air quality data, providing a semantic framework for integrating dynamic data from our sensor network. The second repository is a relational database that stores our measurements. The databases contain high-frequency, real-time data received from various sensor nodes. The data flow commences with its inception, measurements conducted by devices within the sensor group. The recorded values are subsequently read and consolidated into a singular data package by a dedicated controller device. This controller functions as an intermediary, adapting between the diverse sensor devices, each with its specific interface, and the broader system.

The second assistant, known as Air Agent Copilot, is a cognitive assistant based on the ReAct architecture that we use to examine and evaluate air pollution data in the Plovdiv region from external sources. The ReAct framework (Yao et al., 2023) uses a combination of task decomposition, reasoning loops, and multiple issue resolution tools. The ReAct agents of the LangChain library (LangChain, n.d.) can support a complete query processing process. Using these agents, complex requests are decomposed into manageable steps and executed systematically. In the context of LangChain, dialog agents can exhibit dynamic behaviour, integrating different data sources and services. LangChain agents can use a language model as a reasoning engine. Unlike chains, where the sequence of actions is predefined, agents use language models to determine the sequence of actions based on the given context. LangChain allows us to easily integrate tools and APIs to improve the functionality of language models. This includes connecting models to external data sources and services, allowing for more dynamic and intelligent applications. By giving language models access to APIs and custom tools, developers can create more flexible and context-aware applications, ranging from data mining to performing specific actions based on model output. The current prototype version of Air Agent Copilot consists of the following three components: the AMCo Agent, AirQualityApi, and AirQualityMobile. The AMCo Agent is a Python program using the LangChain library and the OpenAI Large Language Model. The agent can analyse particle levels from unstructured data obtained from different sources of information. The agent first reads the external resources, which it uses to initialise its internal vector database. For this purpose, it performs an internal text transformation before generating the representation in the vector database. The agent's next action is to connect OpenAI to the local vector database. This completes the preparation phase, and AMCo goes into operational mode. In the test experiment, every minute, the agent generates a query to an external source to retrieve information about the current state of particulate matter in the city center of Plovdiv. If the discrepancy is detected from the previous state, a query is generated and sent to OpenAI to analyse the results, and then the result is forwarded as a query to AirQualityApi. AirQualityApi is a .NET API using MongoDB as the internal database. This AMCo component operates as a service used to store the results and provide access to them for the mobile application. In our case, it stores the current air dust status along with the analysis results from OpenAI. The AirQualityMobile application, used by AMCo, visualises these analysis results. This app makes a request to AirQualityApi for visualisation data every minute, ensuring the analysis is refreshed whenever pollution levels change.

The ZEMELA platform has been developed to support the development of smart agriculture applications (Stoyanov et al., 2021). The core of this platform is a personal assistant known as Farmer Agent, which operates as the manager ensuring the platform's functioning. The main task of the Farmer Agent is to monitor the vegetation of the observed crops and, in cases of deviations, to warn farmers. The Farmer Agent has an architecture mirroring the structure of the Air Agent and is implemented using the same technology. In the assistant's environment, the ADK Center

(Agricultural Data and Knowledge Center) is located, which acts as a central knowledge and data repository for the platform. Knowledge is stored about the so-called "natural artifacts", which include agricultural crops and the factors affecting their vegetation, such as soil, air, and water. In addition, knowledge about "artificial artifacts" is stored, such as irrigation systems, sensor networks, and ventilation systems etc. A third category of stored knowledge concerns farming activities and events occurring in agricultural scenarios and settings. The knowledge is primarily represented using mutually integrated ontologies, frames, and rules. A relational database is integrated within the Farmer Agent's environment, which stores real-time ("hot") measurements obtained from two sensor networks deployed in two agricultural institutes in the Plovdiv region.

This integration can generally be characterised as asynchronous, relying not on strictly defined interfaces but on message-based interaction between the BDI agents on the two platforms. In the BDI architecture, a standard exists for agent communication known as ACL (Agent Communication Language) (Foundation for Intelligent Physical Agents [FIPA], n.d.). According to this specification, agents communicate through messages called performatives. Typically, interaction between agents in a multi-agent system requires understanding at a higher semantic level, such as cooperation, negotiation, or plan sharing. This is supported by higher-level protocols that define specific dialogue scenarios, which can be implemented using sequences of performatives. One widely adopted protocol is the Contract Net Protocol (CNP) (Foundation for Intelligent Physical Agents [FIPA], n.d.). CNP is a high-level interaction protocol designed for task allocation in distributed multi-agent environments. It facilitates decentralised control over task execution and enables efficient communication between agents. Under this protocol, an initiator agent broadcasts a task request to multiple potential executor agents, who may respond with either offers to perform the task or rejection messages. For our research, we are developing a domain-specific implementation of such a protocol, illustrated in the diagram shown in Figure 2.

The sequence diagram illustrates asynchronous communication between two intelligent agents, namely the Farmer Agent and the Air Agent, within a system designed to explore the effects of air quality on tomato crop development. The interaction begins when the Farmer Agent sends the start and end timestamps of a specific observation period to the Air Agent. The periods that can be sent correspond to the phases of tomato vegetation, which are as follows: planting, vegetative growth, flowering, fruit formation, and ripening. Typically, the individual phases last 10-14 days, which defines the expected duration of the periods being analysed. This communication is asynchronous, meaning each agent operates independently and does not wait for immediate responses, allowing for flexible and distributed processing.

Upon receiving the time window, the Air Agent retrieves relevant information from AirOntology, a structured knowledge base containing threshold values for various air pollutants specific to the Plovdiv region. At the same time, the Farmer Agent reads meteorological data and queries TomatoEventOntology, which currently includes detailed phenological data for four tomato varieties. This ontology provides thresholds and reference values for development stages, including heat units, plant height, stem diameter, and leaf count, all tailored to cultivation conditions in the Plovdiv area.

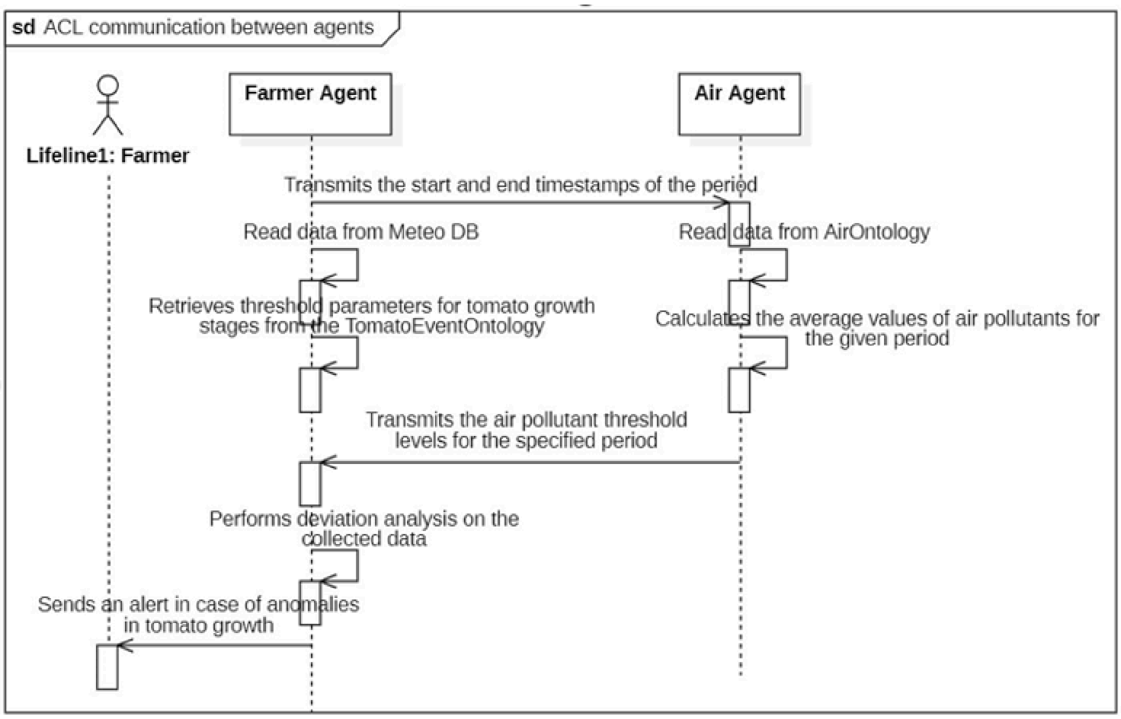

Figure 2. Agents' iteration protocol

The Air Agent then calculates the average pollutant concentrations during the given period and transmits both the values and their corresponding thresholds to the Farmer Agent. With this combined dataset, the Farmer Agent performs a deviation analysis, comparing real-world conditions against the expected physiological parameters for the tomato varieties. If significant anomalies are detected, such as pollutant levels likely to disrupt crop development, the system sends an alert to the farmer.

This asynchronous architecture allows for independent, real-time operation of both agents, enabling the system to dynamically integrate environmental and agricultural data. By leveraging domain ontologies, the platform translates complex environmental interactions into actionable insights, supporting smarter decision-making in agriculture under pollution stress.

The protocol presented above is implemented using the JaCaMo framework. The agents' behaviour is programmed as separate plans, which are stored in corresponding plan libraries. Figure 3 illustrates part of the agent code serving the interaction of the agents to establish a relationship between air pollution and deviations in a certain vegetation phase.

```
/* farmer agent’s belief base */
/* the results of the farmer agent's request to the air agent are saved here */

/* farmer agent’s plan library */

/* plan for anomaly in the vegetative growth phase */
+anomaly(Phase) : Phase = vegetative_growth
   <-  .send(air_agent,achieve,calculate_average(Start,End));
        .send(air_agent,askOne,limit_value(vegetative_growth,Y));
        .wait({+average_pollution(X)});
        .wait({+limit_value(vegetative_growth,Y)});
        if ( X>Y) {
           .print(“The average pollution from “,Start,“ to “,End,” is ”,X,”, this is the
likely cause of the anomaly in Vegetative growth phase!” )
        [ } else { true ]
        }.

/* plan for anomaly in the germination phase */
…

/* air agent’s plan library */

+!calculate_average(Start,End) : true
   <- calculate(Start,End,X) ;
       .send(farmer_agent,tell,average_pollution(X)).

+? limit_value(Phase,Y) : true <-
    ?limit_value(Phase,Y);
    .send(farmer_agent,tell, limit_value(Phase,Y)).
```

Figure 3. Section of the plan libraries of the two agents

When the Farmer agent detects an anomaly in any of the phases of tomato vegetation, it sends a message to the Air agent to achieve a goal to calculate the average pollution (particulate matter, PM10 and PM2.5) from the start to the end date. Messages in JaCaMo are completed as ".send(Receiver, IllocutionaryForce, Content)" method calls, where the IllocutionaryForce parameter indicates the type of the performative (message). In this case, the Farmer agent uses two types of Illocutionary Force, "achieve" and "askOne", which respectively ask the Air agent to achieve a goal and to share the result as a belief. The Air agent uses "tell" in this communication, which directly saves the result into the Farmer agent’s belief base (supported by JaCaMo run-time). After the first message Farmer agent sends a second message, this time to ask for the limit value of the given phase. When the Air agent receives the first message with the goal directive, it takes action to achieve the desired goal. The applicable plan calculates the average value for the period and stores the result in a variable X. Then, the Air agent sends a message to the Farmer agent to report the result, which is directly recorded as a belief in the Farmer agent's belief base. For dealing with the second message, the Air agent just checks its belief base to get the limit value that is obtained from the ontology, while the pollution calculations are based on the results obtained from the relational database. When the Farmer agent receives both results, it moves on to the next intention of the plan body, namely comparing the obtained average value with the critical value in the given phase of tomato vegetation and, if the critical value is exceeded, notifies the farmer by sending a message to his device that the anomaly in the vegetation is probably due to increased pollution.

This protocol can be embedded in the reasoning cycles of both agents, which are identical since both agents have a BDI architecture (Bordini, Hübner, & Wooldridge, 2007). First, the agents perceive their environment and update their belief bases, after which they can communicate with other agents and select so-called ‘socially acceptable’ messages. This step enables the integration of the proposed protocol for interaction between PAZ and AM. As socially acceptable, agents will identify those who belong to the protocol. Then, depending on the content of the messages, the agents first choose relevant plans and subsequently select an applicable plan from the set of relevant plans.

4. Experiment

To evaluate the viability of our integrated system under real-world conditions, we conducted a field experiment involving tomato plants in the Plovdiv region. Air pollution is known to adversely affect plant growth by disrupting physiological processes, inhibiting photosynthesis, and altering key biochemical pathways. Tomatoes (Solanum lycopersicum), one of the most widely cultivated vegetable crops globally, are particularly sensitive to air pollutants such as ozone (O_3), nitrogen dioxide (NO_2), sulfur dioxide (SO_2), and particulate matter (PM). The specific impacts of these pollutants across various stages of tomato development are summarised in Table 1.

Table 1. Influence of pollutants in different phases of tomato development

	Germination & Seedling (0–3 weeks)	Vegetative Growth (3–6 weeks)	Flowering Stage (6–9 weeks)	Fruit Development & Ripening (9+ weeks)
O_3	High ozone (O3) can stunt early root and leaf development. Poor CO2 levels affect initial photosynthesis Excess humidity or airborne pathogens can lead to damping-off disease.	Ozone exposure leads to oxidative stress, causing stunted growth and leaf damage.	Ozone damage can prevent proper pollen formation, reducing fruit yield.	High ozone can lead to premature leaf drop, reducing fruit nutrition.
NO_2, SO_2	Air pollution (SO2, NO2, O3): Can hinder seed germination by reducing oxygen availability and damaging seed coatings.	Sulfur dioxide (SO_2) and nitrogen oxides (NO_x) can cause leaf damage.	Air pollution (O_3, SO_2, NO_2): Causes leaf chlorosis, necrosis, and reduced photosynthetic efficiency, limiting plant biomass accumulation.	
CO_2		High CO2 levels (400–800 ppm) enhance growth.		Excess CO_2 can alter fruit acidity and color development.
Heavy metals like Pb, Cd, Hg, Zn	Toxic metals can inhibit root elongation, impair nutrient uptake, and reduce seedling vigor.			
Particulate Matter - PM		Airborne dust and pollutants can clog stomata, reducing gas exchange.	Particulate matter can reduce pollination efficiency.	
Soil pollution (Oil spills, Microplastics , Excess nitrogen)		Heavy metals interfere with chlorophyll production, reducing photosynthesis and causing poor root development.	Impacts microbial balance, leading to poor root function and lower nutrient uptake.	Interferes with reproductive transition by limiting phosphorus and potassium availability, which are crucial for flowering.
Water pollution (Eutrophication, Contaminated irrigation water)	High salinity and chemical contaminants can reduce water absorption and inhibit enzymatic activities crucial for germination.		Leads to nutrient imbalances, poor water absorption, and possible accumulation of toxic substances in tissues.	Can act as hormone disruptors, affecting the transition from vegetative to reproductive growth.
Water pollution (acid rain, industrial wastewater) pH		Alters pH and affects nutrient solubility, leading to deficiencies or toxicities that slow down seedling establishment.		
Volatile Organic Compounds (VOCs)				Ground-level ozone, VOCs, Dust particles: Leads to stomatal damage, reduced transpiration efficiency, and weakened plant structure.

The results from Table 1 for the Germination and Seedling phase are presented graphically in Figure 4.

Major pollutants and their effects on tomato plants are the following:

- Ozone (O_3). Damages stomata and enters plant leaves, causing oxidative stress. Impairs chlorophyll production, reducing the efficiency of photosynthesis. Visible symptoms include yellowing (chlorosis), bronzing, and necrotic spots on leaves. Studies show up to a 20–30% reduction in tomato yield at high O_3 exposure (Paoletti & Manning, 2007).
- Nitrogen dioxide (NO_2) and sulfur dioxide (SO_2). Acidification - forms nitric and sulfuric acids, damaging leaf tissues. High NO_2 reduces root and shoot biomass (growth inhibition). Exposure to SO_2 results in smaller, misshapen tomatoes, which reduces fruit quality.
- Particulate matter (PM). PM coats leave, reducing gas exchange (blocking stomata). Some particulate matter contains cadmium and lead, which accumulate in fruit, posing health risks (heavy metal toxicity).
- Physiological and biochemical effects include:
  - Oxidative stress. Pollutants generate reactive oxygen species (ROS), damaging cells.
  - Hormonal disruption. Alters auxin and ethylene levels, affecting fruit development.
  - Nutritional imbalance. Impairs nitrogen and phosphorus absorption.

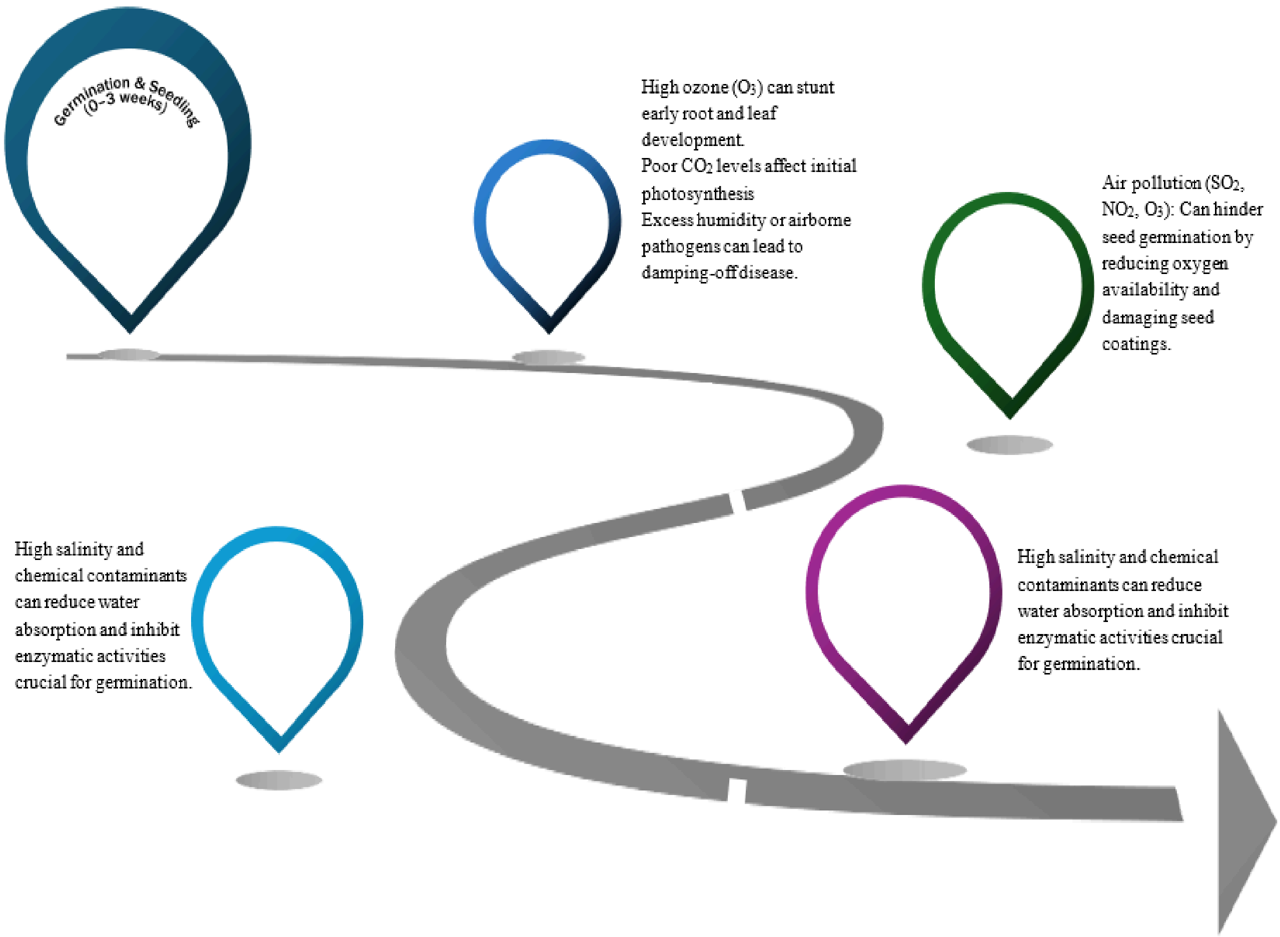

Figure 4. Influence of pollutants on the germination and seedling phase of tomatoes

In the germination phase, key growth processes are seed hydration, root emergence, and early root development. In the next phase, the seedling phase, key growth processes are root elongation, cotyledon expansion, and early leaf formation. Key growth processes are rapid leaf, stem, and root development, and crown formation. During the transition from vegetative to reproductive growth, a redistribution of nutrients occurs. The critical pollution parameters in each of the phases are shown in Table 2.

Table 2. Air pollution parameters

	Air Pollution Parameters	Soil Pollution Parameters	Water Pollution Parameters
Parameters/ Concentrations/ Exposure duration	O_3 (>50 ppb), SO_2 (>100 ppb), PM (>50 μg/m³)	Heavy metals (Cd >1 mg/kg, Pb >30 mg/kg), EC (>4 dS/m), pH (<5 or >8)	Salinity (EC >3 dS/m), pH (<5.5 or >8.5), Heavy metals (Cd >0.005 mg/L, Pb >0.01 mg/L)
Germination Phase (0-10 Days)	SO_2 > 100 ppb, NO_2 > 50 ppb (reduces oxygen availability).	Heavy metals: Cd > 1 mg/kg, Pb > 30 mg/kg (inhibits root elongation). Salinity: EC > 4 dS/m (reduces water absorption and seed viability). Pesticide residues: Glyphosate > 0.1 mg/kg (disrupts enzymatic activity). Soil pH: < 5.5 or > 8.0 (affects seed metabolism and enzyme function).	EC > 3 dS/m (osmotic stress reduces germination rate). NO_3^- > 10 mg/L (excess nitrogen can be toxic to seeds). Air Pollution: SO_2 > 100 ppb, NO_2 > 50 ppb (reduces oxygen availability).
Seedling Phase (10-30 Days)	O_3 > 50 ppb (causes leaf chlorosis, reduces photosynthesis). $PM_{2.5}$ > 50 μg/m³ (blocks stomata, lowers gas exchange).	Heavy metals: Zn > 300 mg/kg, Cd > 1 mg/kg (reduces chlorophyll production). Excess nitrogen (NO_3^- > 20 mg/kg) (causes excessive shoot growth, weak seedlings).	EC > 3.5 dS/m (affects root water uptake). pH < 5.5 or > 8.5 (nutrient deficiencies).
Vegetative Growth Phase (30-60 Days)	O_3 > 60 ppb (leaf necrosis, oxidative stress). SO_2 > 150 ppb, NO_2 > 100 ppb (reduces chlorophyll and photosynthesis). PM_{10} > 75 μg/m³ (clogs stomata, reduces transpiration).	Heavy metals: Pb > 50 mg/kg, Cd > 2 mg/kg (reduces nutrient absorption). Salinity: EC > 4.5 dS/m (causes leaf burn, wilting). Soil pH < 5.5 or > 8.0 (interferes with phosphorus and potassium uptake).	Excess nutrients: NO_3^- > 30 mg/L (causes excessive vegetative growth but weak plants). Pesticide residues > 0.05 mg/L (affects root microbiota).
Pre-Flowering and Reproductive Transition Phase (60-80 Days)	O_3 > 70 ppb (disrupts hormonal signals, delays flowering). VOCs (e.g., benzene > 0.01 mg/m³) (disrupts reproductive hormones).	Excessive nitrogen (NO_3^- > 40 mg/kg) (delays flowering). Heavy metals (Hg > 0.3 mg/kg, Cd > 2 mg/kg) (hormonal imbalance).	EC > 5 dS/m (flower drop due to water stress). pH < 5 or > 8.5 (reduces phosphorus uptake needed for flowering).

A field study was conducted in 2023 to observe the developmental phases of four tomato varieties (Stoyanov et al., 2024). The plants were cultivated in an open greenhouse at the Maritsa Institute of Vegetable Crops, under climatic conditions typical of the Plovdiv region. The study involved monitoring both expected and measured values for key growth parameters, which are critical for evaluating plant health and development. The results revealed that during the Vegetative Growth and Flowering phases, plant height was two to three times lower than the expected range. In contrast, during the Ripening phase, the plants exhibited a rapid increase in height, while the stem diameter remained relatively constant. This pattern suggests a physiological response likely driven by prior environmental stress, resulting in plants that became tall but structurally weak, as illustrated in Figure 5.

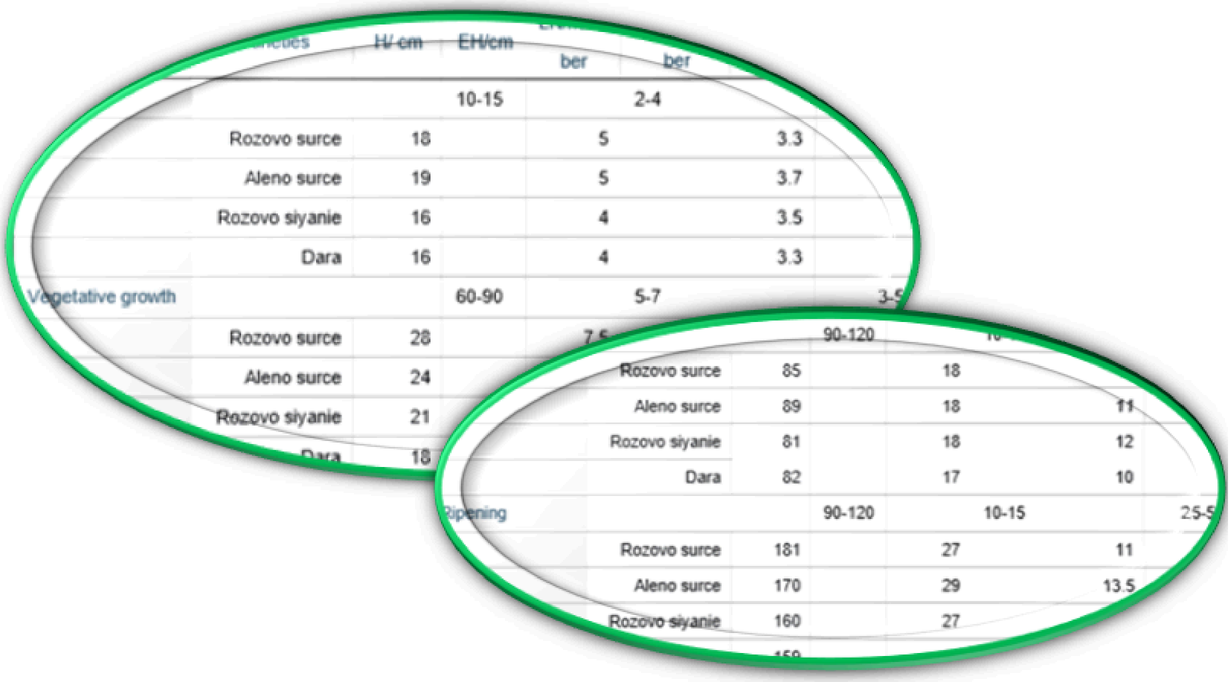

Figure 5. Plant height during different phases (expected and actual)

This study aimed to investigate the potential relationship between tomato development and air pollution in the Plovdiv region. The tomato plants were cultivated in an open greenhouse at the Maritsa Institute of Vegetable Crops, under the region's representative climate conditions. The institute operates a weather station that continuously records various meteorological parameters, including temperature, dew point, wind chill, atmospheric pressure, global radiation, wet bulb temperature, air density, wind speed, and wind direction. To assess air pollution exposure, we utilised data from a regional network of air quality sensors, specifically from the nearest monitoring station located in the Gagarin district. This sensor records measurements of PM2.5, PM10, temperature, altitude, atmospheric pressure, and gamma radiation at five-minute intervals. For analysis, the raw data were aggregated into daily averages, which were then aligned with the distinct phenological phases of tomato development. During the Vegetative Growth phase, the sensor network registered elevated concentrations of PM2.5 and PM10, coinciding with the period of active plant development. These findings are illustrated in Figure 6.

Roy et al. (2024) concluded that particulate matter pollutants can disrupt the absorption and reflection of photosynthetically active radiation and reduce gas exchange, ultimately reducing crop yield depending on the level of plant sensitivity. Upon exposure, PM inhibits lipid desaturases, which ultimately leads to modification of the cell wall and membranes and alteration of cell fluidity; thus, plants can primarily sense pollutants on cell surfaces. In the experiment shown in Daresta et al. (2015), results indicate that PM 10 has a negative effect on Solanum lycopersicum cv. Roma plants.

Date	PM2.5 [ug/m3]	PM10 [ug/m3]	P [hPa]	T [deg C]	RH [%]	DewPoint	WindChill	Gamma radiation [CPM 5 min]	Height	Growth Rate (cm/day)	Stem, diameter mm
18.4.2023 г.	15,9568	21,5128	995,5425	11,6182	92,82420028	9,763282337	10,66675939	167,9129	6,30	0,40	1,80
04.5.2023 г.	19,1977	25,8517	1003,1172	13,0583	86,76069444	10,22555556	12,26798611	167,5029	15,60	0,60	3,34
15.5.2023 г.	28,4203	45,5259	999,4231	14,8482	85,35584958	11,68642061	14,16998607	167,6817	17,40	0,10	4,31
16.5.2023 г.	27,5019	46,3083	995,4426	16,8410	85,24157932	13,13542977	15,68448637	169,3769	17,60	0,20	4,32
17.5.2023 г.	16,2704	44,9662	994,4743	14,6976	93,3011822	12,80653686	13,88574409	169,6431	17,77	0,17	4,33
02.6.2023 г.	8,8230	11,9261	996,3898	22,7124	64,73646486	12,24356298	20,06666667	169,9927	47,26	3,59	7,96
25.7.2023 г.	9,7264	13,0149	990,6321	33,0985	71,31049869	15,40629921	20,7808399	171,8435	170,63	2,16	13,32

Figure 6. Average daily values from the sensor network on days with exceedances.

Our experiment: Statistical analysis of air pollution data (PM2.5 and PM10) and the relationship with tomato vegetation. A correlation analysis was conducted between PM2.5, PM10, and other parameters. The data show measurements of PM2.5, PM10, atmospheric pressure (P), temperature (T), relative humidity (RH), and gamma radiation (CPM) for a period of 4 months (April - July 2023).

To understand how these factors are connected, a regression analysis was performed, and the results show the relationship between the dependent variable, Height, and the independent variables PM2.5 [ug/m3], T [deg C], and RH [%].

Descriptive statistics (Table 3) show significant variability in height (data are highly distributed), average pollution with moderate variability in PM2.5, temperatures that are somewhat stable with moderate changes, and humidity that is extremely variable but normally above average.

Table 3. Descriptive Statistics

	Mean	Std. Deviation	N
Height	59,368275862068960	54,918595111006960	116
PM2.5 [ug/m3]	8,815012728467382	3,790688511870295	116
T [deg C]	20,506169276777360	6,874572940976213	116
RH [%]	65,470857133830900	12,248926995336015	116

Table 4 reveals a substantial association ($r = 0.944$, $p < 0.001$) between temperature (T) and tomato plant height. Increasing the temperature by 1°C results in a height rise of around 7.52 units. RH has a moderate negative impact on height ($r = -0.479$, $p < 0.001$). Higher humidity probably causes height to decrease.

Table 4. Correlations

		Height	PM2.5 [ug/m3]	T [deg C]	RH [%]
Pearson Correlation	Height	1,000	-,140	,944	-,479
	PM2.5 [ug/m3]	-,140	1,000	-,210	,368
	T [deg C]	,944	-,210	1,000	-,498
	RH [%]	-,479	,368	-,498	1,000
Sig. (1-tailed)	Height	.	,067	,000	,000
	PM2.5 [ug/m3]	,067	.	,012	,000
	T [deg C]	,000	,012	.	,000
	RH [%]	,000	,000	,000	.
N	Height	116	116	116	116
	PM2.5 [ug/m3]	116	116	116	116
	T [deg C]	116	116	116	116
	RH [%]	116	116	116	116

PM2.5 has a slight and negligible correlation with height ($p = 0.067$). This means that pollution may not directly affect height. T and RH have a negative relationship ($r = -0.498$), which is predicted given that warmer air typically contains less moisture. PM2.5 and RH have a positive correlation ($r = 0.368$), which could be because high humidity helps to trap particles in the air.

Pearson Correlation Coefficients. The coefficients indicate the strength and direction of the linear relationship between variables. The range is from -1 to 1. Weak negative relationship Height ↔ PM2.5, coefficient is -0.140 (increase in PM2.5 may be associated with a slight decrease in height). Very strong positive relationship Height ↔ T, coefficient 0.944 (increase in temperature is associated with an increase in height). Moderate negative relationship Height ↔ RH (higher humidity is associated with lower height). Weak negative relationship PM2.5 ↔ T (higher temperatures may be associated with lower PM2.5 levels). Moderate positive relationship PM2.5 ↔ RH (higher humidity is associated with higher PM2.5 levels). Moderate negative relationship T ↔ RH (higher temperatures are associated with lower humidity).

Statistical significance (Sig. 1-tailed). Height ↔ PM2.5 has a coefficient of 0.067, insignificant ($p > 0.05$), i.e., the relationship may be random. Height ↔ T, with a coefficient of 0.000, therefore is extremely significant ($p < 0.001$), i.e., temperature strongly influences height. From Height ↔ RH, with a coefficient of 0.000, i.e., very significant ($p < 0.001$), therefore, humidity has a moderate influence. PM2.5 ↔ T has a coefficient of 0.012—significant ($p < 0.05$); therefore, temperature weakly influences PM2.5. From PM2.5 ↔ RH, with a coefficient of 0.000—very significant ($p < 0.001$)—it is seen that humidity influences PM2.5. And T ↔ RH also has a coefficient of 0.000—very significant ($p < 0.001$), i.e., temperature and humidity are related.

The regression model (Fig. 7) explains 89.6% of the variation in height ($R^2 = 0.896$), indicating very good predictive power. F-statistic: 322.808 ($p < 0.001$), confirming the significance of the model.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,947[a]	,896	,894	17.91724850	,896	322,808	3	112	<,001	,839

a. Predictors: (Constant), RH [%], PM2.5 [ug/m3], T [deg C]

b. Dependent Variable: Height

Figure 7. Regression model

Coefficients, Coefficient Correlations, Collinearity Diagnostics, Residuals Statistics were also made, from which it can be seen that PM2.5 has a significant influence ($p = 0.031$), but the effect is small (Beta = 0.072); T has a highly significant influence ($p < 0.001$) with a large effect (Beta = 0.941), and RH is not significant ($p = 0.331$). The VIF values are below 2 (1.158–1.472), which indicates the absence of serious multicollinearity. And the average value of the residuals is close to zero. There are no obvious outliers (the maximum Cook's distance is 0.264, which is below the critical threshold). The residuals are approximately normally distributed, without obvious regularities, which confirms the adequacy of the model.

It can be concluded that temperature (T) is the strongest predictor of Height, and PM2.5 has a weak but significant influence. Humidity (RH) does not contribute significantly to the model. The model is reliable and explains a large part of the variation in the data.

After the analysis, it was found that the dependence is complex, and it is necessary to consider data on other pollutants, climatic factors, and soil indicators.

Analysis of high pollution periods. The following high pollution thresholds are defined: PM2.5 > 15 μg/m³, PM10 > 45 μg/m³. High pollution periods from our data:

- On April 8 (PM2.5 - 17.3165 μg/m³).
- On April 18 (PM2.5 - 15.9568 μg/m³).

- On May 4 (PM2.5 - 19.1977 µg/m³).
- On May 15 (PM2.5 - 28.4203, PM10 - 46.3083 µg/m³).
- On May 16 (PM2.5 - 27.5019, PM10 - 45.5259 µg/m³).
- On May 17 (PM2.5 - 16.2704, PM10 - 44.9662 µg/m³).

Impact on plants. High levels of PM can block sunlight and reduce photosynthesis. The particles are deposited on the leaves, which leads to difficulty breathing and gas exchange. Relationship between pollution and tomato vegetation. Data on tomato vegetation (table) were compared with periods of high pollution. Table 5 shows the development of the plant during the individual phases.

Table 5. Plant stem height and diameter

Phase/ Varieties	Average height (H/cm)		Stem diameter (SD/mm)	
	EH/cm expected height in cm interval	H/ cm the measured average height	ESD/mm expected stem diameter	SD/mm measured mean stem diameter
Planting		10-15		1-3
Rozovo surce	18		3	
Aleno surce	19		4	
Rozovo siyanie	16		4	
Dara	16		3	
Vegetative growth		60-90		3-5
Rozovo surce	**28**		5	
Aleno surce	**24**		5	
Rozovo siyanie	**21**		5	
Dara	**18**		4	
Flowering		90-120		8-12
Rozovo surce	54		7	
Aleno surce	51		8	
Rozovo siyanie	29		7	
Dara	47		8	
Fruit formation		90-120		15-20
Rozovo surce	85		10	
Aleno surce	89		11	
Rozovo siyanie	81		12	
Dara	82		10	
Ripening		90-120		25-50
Rozovo surce	**181**		**11**	
Aleno surce	**170**		**14**	
Rozovo siyanie	**160**		**13**	
Dara	**159**		**13**	

During the period of fine dust pollution (PM2.5 and PM10) in the vegetative growth phase, a significant deviation in plant growth from the expected norms was observed. With a predicted height in the range of 60 to 90 cm, the actual measured values varied between 18 and 28 cm, depending on the tomato variety, indicating substantial growth inhibition under the influence of pollutants. After this period of heavy pollution (e.g., 15 May), during the subsequent phases of development, the plants showed rapid height growth but slow stem thickening. For example, the cultivar ‘Pink Heart’ reached 181 cm in height, but the stem diameter was only 11 mm (below the expected 25–50 mm). This phenomenon is likely attributable to pollution stress and reduced photosynthesis. The data show that PM2.5 reduces photosynthetic efficiency by blocking the stomata of leaves and leads to growth retardation in tomatoes under chronic exposure to PM10.

PM2.5 and PM10 pollution have a significant impact on tomato development, causing rapid height growth (possibly as a compensatory mechanism) alongside suboptimal stem thickening, which reduces plant stability and resistance. Measures such as PM monitoring in agricultural areas and the use of protective nets or filters can help reduce the impact.

The analysis confirms that air pollution not only affects human health but also has profound consequences for agriculture. Air pollution significantly impairs tomato growth by reducing photosynthesis, causing oxidative damage, and decreasing yield. Sustainable agricultural practices and pollution control policies are essential for maintaining crop productivity.

Air, soil, and water pollution also significantly affect tomato growth and development at all stages, from germination to ripening. Major pollutants such as ozone (O_3), sulfur dioxide (SO_2), nitrogen oxides (NO_x), heavy metals, and excessive soil and water salinity lead to reduced photosynthesis, stunted growth, chlorosis, oxidative stress, and lower yields.

To mitigate the harmful effects, measures should be taken to maintain good ventilation, control CO_2 levels, ensure soil and water purity, and monitor pollution. Implementing adaptive agricultural practices, such as treating irrigation water, reducing the use of chemical fertilisers and pesticides, and using sustainable soil improvers, will contribute to healthier tomato growth and optimal yields.

In our experiment, the farmer agent observes a deviation (anomaly) in the values for average plant height during the vegetative growth phase. This triggers the Farmer agent, which sends a message to the Air agent in order to calculate the average pollution between 01.05.2023 and 18.05.2023. The Air agent detects that PM2.5 and PM10 pollution are present during this period and notifies the Farmer agent thereof. Subsequently, the Farmer agent prepares a warning that a connection between the two deviations is possible. Figure 8 shows a screenshot of the Farmer agent's response.

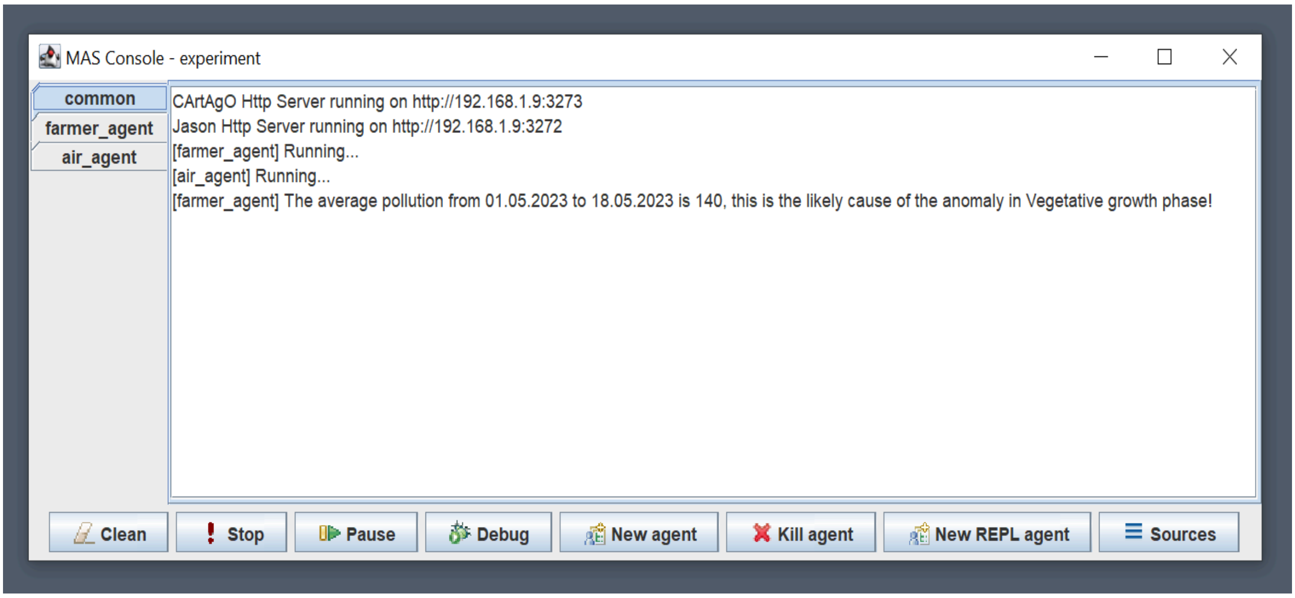

Figure 8. Example interaction session between the two agents

5. Conclusion and Future Work

This study presented the initial results from the development of an integrated digital platform designed to assess the impact of air pollutants on tomato vegetation in the Plovdiv region of Bulgaria. By enabling real-time interaction between intelligent agents responsible for air quality monitoring and crop growth analysis, the platform operationalises the concept of secondary air quality standards in the context of precision agriculture. The findings from the 2023 growing season indicate measurable negative effects of elevated particulate matter (PM2.5 and PM10) levels on tomato development, particularly during sensitive phenological stages.

While the present study offers promising insights into the integration of real-time environmental monitoring and smart agriculture tools, several limitations must be acknowledged. First, the experiment was conducted over a single growing season (2023), limiting the ability to account for interannual variability in climatic conditions, pollution patterns, and crop responses. Second, the study focused on only four tomato varieties cultivated under semi-controlled open greenhouse conditions, which constrains the generalizability of the findings. Third, air pollution data were derived from a single monitoring station (Gagarin district and sensors in Mariza Institute) near the experimental site, potentially missing microclimatic variations. Finally, although the dual-agent system architecture enables modular environmental and agricultural data analysis, its complexity warrants critical evaluation to determine whether the combination of BDI and ReAct-based agents provides significant performance advantages.

Future work will address these limitations in several key directions. First, we plan to expand the sensor network to include additional pollutants such as ozone (O_3), nitrogen oxides (NO_x), sulfur dioxide (SO_2), and volatile organic compounds (VOCs), known to affect the physiological processes of vegetable crops. Second, the analytical framework will be extended to include a wider range of vegetable species commonly cultivated in the Plovdiv region, allowing for comparative studies across plant types and varieties. Third, we intend to incorporate multi-seasonal datasets and deploy additional sensor nodes to better capture spatial and temporal heterogeneity. Furthermore, advanced statistical methods, including multivariate regression models and analysis of covariance (ANCOVA), will be applied to better isolate the effects of air pollution on crop development.

Finally, future versions of the platform will include benchmarking studies to critically assess the efficiency, scalability, and accuracy of the dual-agent architecture. In the long term, the proposed platform aims to serve as a practical tool for farmers, agronomists, and environmental policymakers by providing early warnings, supporting adaptive farming strategies, and promoting the integration of ecological air quality standards into agricultural decision-making. The fusion of multi-source environmental data with intelligent reasoning components represents a promising approach to addressing the complex challenges at the intersection of air pollution, agriculture, and sustainable development.

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