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# Adaptive Planning and Scheduling of Agricultural Robotic Operations Using Intelligent Systems

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## Abstract

This manuscript addresses the development and deployment of an intelligent system dedicated to planning the operations of an agricultural robot. The core objective of this system is to independently determine the most suitable resources for performing given agricultural tasks, guided by user-defined preferences, and subsequently define and schedule the sequential order of those tasks. The practical setting is explored, including a description of the solution space for agricultural applications and how it can be bounded through specific assumptions and decisions to reduce the computational burden. The system's performance is validated by comparing specific Key Performance Indicators calculated for the choice a farmer would likely make with those for the system's proposed solution, across several scenarios.

**Keywords** Smart agriculture, Intelligent farming system, Smart planning, Agricultural task scheduling, Efficiency flexibility, Resource assignments

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## Introduction

The recent infusion of automation into arable farming has begun reshaping established practices [1, 2]. To grasp the vital role of an intelligent system adept at refining the orchestration of farming activities, one must weigh the environmental and socioeconomic dimensions of this sector. According to findings from the Food and Agriculture Organization (FAO), direct emissions tied to agricultural production represent about 10% of total greenhouse gas outputs [3], a proportion poised to climb when agriculture's links to food supply and population growth are considered. In parallel, rising labor costs and workforce scarcity jeopardize the economic viability and even the persistence of farming. Likewise, the inherently seasonal rhythm of agricultural work is vulnerable to labor shortages, unforeseen environmental and global shocks (such as COVID-19), and suboptimal planning, which can culminate in food waste, insecurity, and monetary losses [4]. Challenges stemming from volatile fertilizer prices and the fiscal strain of inflation, which are propelling the push for automation and its subsequent gains, also merit attention [4]. Breakthroughs in technology, notably in information and communication technology (ICT), have given rise to smart farming systems, including advanced or autonomous tractors and intelligent implements [5, 6], rendering their scheduling and coordination more flexible yet simultaneously more complex. A further layer of difficulty is added by the swelling demand for agricultural goods, necessitating more intensively exploited fields, tractors, and implements. These assets must operate with both time-based and spatial efficiency, exemplified by a fleet of tractors functioning simultaneously or in series, executing tasks such as spraying and weeding under varying environmental conditions, e.g., wind or rain. Consequently, devising alternative scenarios for planning

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orchestration becomes an increasingly intricate and multi-faceted challenge. An agricultural robotic system that implements dynamic route planning in four concrete real-world farming situations serves as an illustration of this, as described in Ref. [7].

All these elements point toward the essential need for a scheduling framework within the context of agricultural operations. Regarding path planning, the conventional approach favored by farmers—traversing lane by lane or alternating lanes when turning is restricted—must be accounted for. Such a pattern is depicted in **Figure 1**.

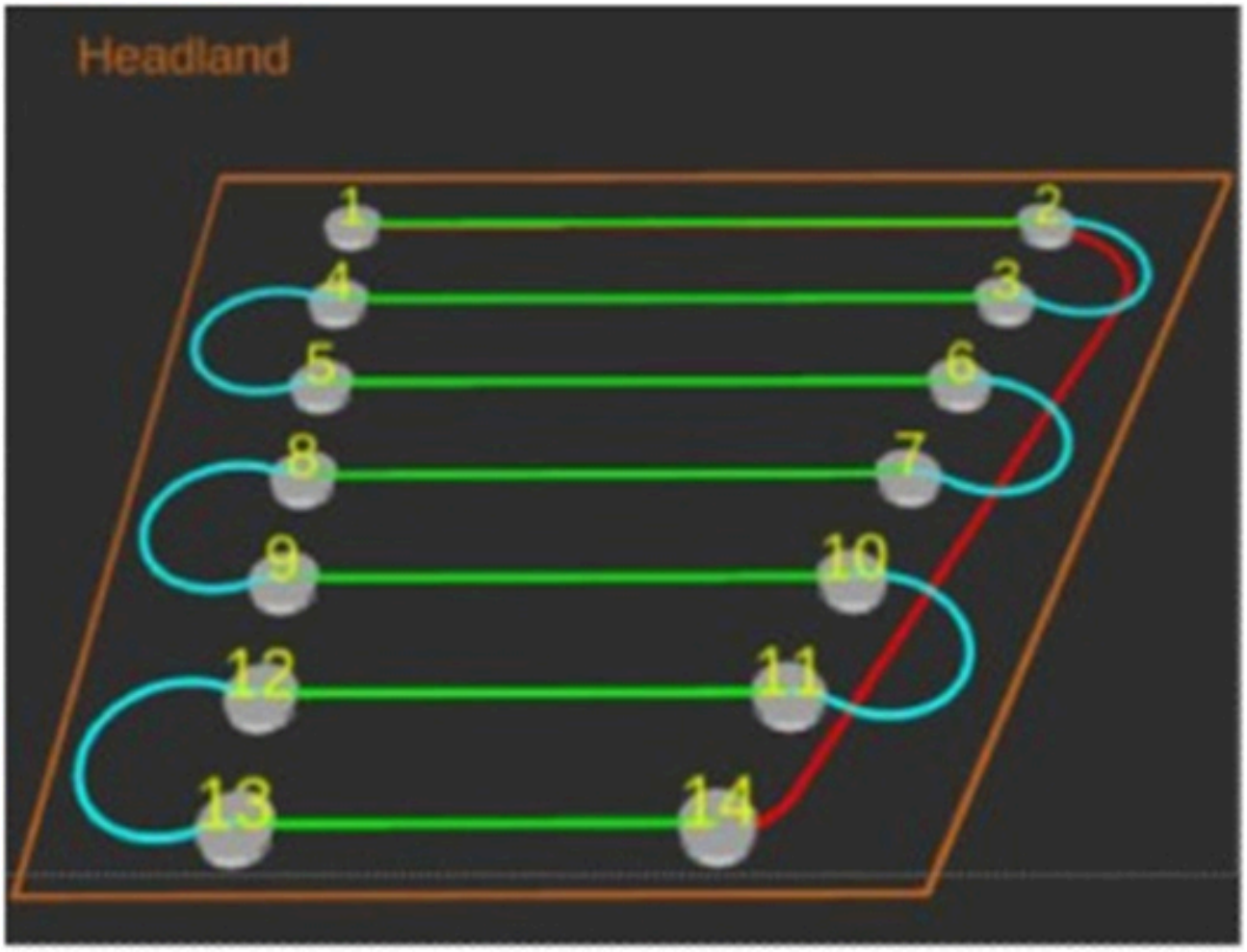


**Figure 1.** Traditional way of passing through a field. The work starts at point 1. Green indicates the working lanes where the robot performs work; blue indicates how the robot turns from one lane to the next; and red indicates how the robot returns to the starting point.

Nonetheless, mechanizing the described pattern is far from trivial; it belongs to the class of NP-Hard problems, meaning the pursuit of an optimal solution is typically unattainable [8]. An investigation by Santos *et al.* [9] dissects a range of path planning methodologies used across varied agricultural contexts, characterized by optimization criteria, system boundaries and constraints, and dynamic behavior, indicating whether the plan is generated offline or online. This scrutiny zooms in on micro-scheduling of activities, i.e., the specific manner in which a robot or tractor should traverse a field. Further approaches are documented [8, 10] from the perspective of the well-known NP-hard problem, the Traveling Salesman Problem (TSP); however, they do so without expanding the set of optimization criteria. A higher-level treatment of work schedule optimization for agricultural robots is provided by Hizatate and Noguchi [11], who employ a genetic algorithm to construct the field path for multiple robots within defined constraints.

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Although the complexity of automating path planning remains significant, various efforts have addressed it from different viewpoints, each grounded in a set of underlying assumptions. One example is the comparative evaluation between two distinct strategies performed by Filip *et al.* [12], as visualized in **Figure 2**. They examined, on one side, the method put forth by Bochtis and Vougioukas, which resolves route planning via simulated annealing [13], and on the other side, the Conesa-Munoz technique, which fuses top-performing route optimization operators into a new operator designated as mix-opt. The benchmark for their comparison is the headland distance and, by extension, the total traversed distance.

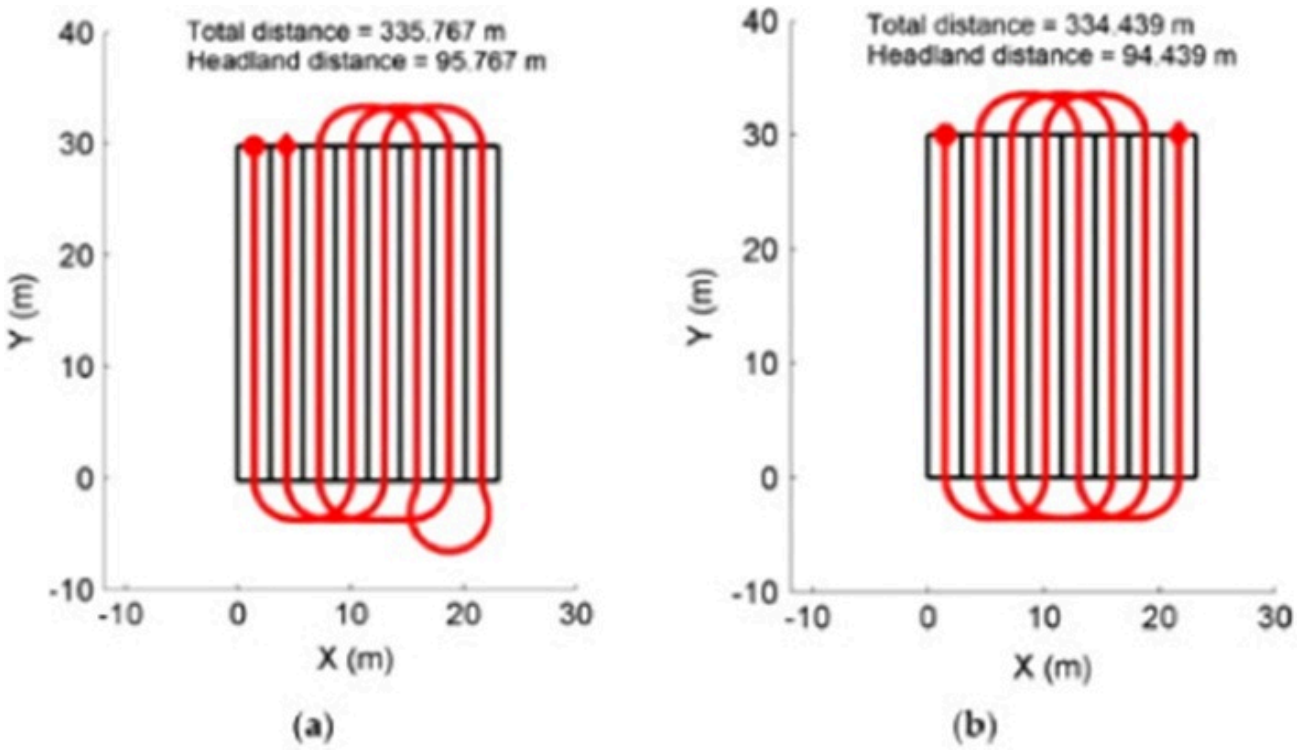


**Figure 2.** Comparison of two plans as discussed by Filip *et al.* [12] – On the left picture is the solution proposed by Bochtis and Vougioukas, and on the right picture is the solution proposed by Conesa-Muñoz *et al.* The proposed solutions yield different headland distance calculations and, consequently, different total travel distances.

Other algorithms prioritize reducing maneuver time [14] by applying the Clarke–Wright savings heuristic [15]. Utamima and Reiners [16] have presented a Fast Hybrid Algorithm (FHA) designed for the Agricultural Route Planning (ARP) problem. This algorithm blends components from disparate routing strategies and heuristic approaches, striving to curtail the non-productive distance covered by the vehicles. Their solution was tested on 5 fields situated around a central depot from which multiple vehicles originate. Each field is serviced by a single vehicle at a time. However, it may be partitioned into smaller plots, each assigned to a distinct vehicle, thereby compressing the time required to cover the entire area.

All preceding approaches address isolated fragments of a holistic agricultural planning system; none are equipped to orchestrate resource assignment and task scheduling at both macro and micro levels, while juggling multiple optimization targets and maintaining dynamic responsiveness to unexpected events. It should also be acknowledged that achieving a high degree of autonomy requires integrating supplementary hardware and software modules, such as sophisticated perception systems, motion controllers, and tracking mechanisms [17]. Nevertheless, the principal focus of this paper remains confined to the path planning architecture.

In the realm of manufacturing, the escalating complexity and heightened demand for agility and efficiency in contemporary systems call for a robust management system capable of planning multiple resources across diverse scenarios. The past few decades have witnessed substantial advancements in manufacturing, aimed squarely at these

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concerns. Chryssolouris highlighted the imperative to transition from mass production to mass customization to accommodate a wide range of manufacturing variants [18]. Michalos *et al.* [19] surveyed prevailing technologies and their associated challenges, underscoring the paramount importance of flexibility and adaptability in automotive assembly lines. Correspondingly, in sectors like aerospace manufacturing, deploying single robots would erode the system's efficiency, making a synchronized fleet of resources essential to secure optimal efficiency of the conducted operations and task parallelization [20].

In response to these difficulties, manufacturing has developed intelligent systems that leverage AI-driven techniques. One implementation involved dynamic scheduling on assembly lines, which raised throughput, reduced assembly defects, and rendered manual planning labour unnecessary [21]. In a related effort, Hu *et al.* proposed a deep reinforcement learning framework for real-time coordination of Automated Guided Vehicles (AGVs) on a flexible shop floor [22]. Liu *et al.* [23] addressed the Tree-Structured Task Allocation problem by applying Group Multirole Assignment to maintain fixed inter-task relationships, achieving highly promising results. Additionally, Feo-Flushing *et al.* [24] developed a system that jointly addresses task allocation, scheduling, and control by combining solutions from a generic mixed-integer linear program (MILP) solver with a trained genetic algorithm. In a similar vein, Wang and Gombolay [25] demonstrate a novel scheduler underpinned by a graph attention network that uses machine learning to enable near-optimal multi-robot scheduling for fleets of differing sizes and capability profiles.

The picture that emerges from the above is unmistakable: breakthroughs in Artificial Intelligence (AI), and their proven ability to resolve manufacturing problems with both effectiveness and cost-efficiency, are steadily gaining traction. Concurrently, AI applications in manufacturing processes, robotics, automation, and the design and governance of manufacturing systems have attracted significant research attention [26]. These ideas and technological strides carry promise for strengthening the manufacturing sector, which has motivated additional investigations into transferring them to the agricultural context as well.

The overarching goal of the work presented in this paper is to adapt the intelligent paradigms pioneered and applied in manufacturing to address the unique demands of agricultural planning and scheduling.

# Approach

As elaborated in the earlier section, engineering an intelligent system capable of orchestrating planning and scheduling operations across numerous fields and assets is an inherently involved endeavour. It calls for a substantial level of data structuring and readiness, along with the integration of multiple parameters that require evaluation and ultimately shape the result. A web-based interface allows the user to supply and track these parameters, which can be classified into two distinct categories:

• Field characteristics:

o Waypoints

o Working Lanes

o Non-Working Areas

o Transportation lanes

o Special zones

o Entry/Exit points of the field

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• Resource characteristics:

o Tractor info: width, weight, model, position, max working/transportation speed, fuel tank capacity/consumption/level, mechanical interface, real-time speed/position

o Implement info: width, weight, model, position, real-time speed/position, mechanical interface, consumable level

The dataset described above serves as the baseline for planning agricultural operations and is entered by the user via a custom UI. Users may also provide further details about a given field, for instance, zones that constrain the vehicle (in terms of dimensions or mass) or govern its movement (such as speed limits or permitted heading). The intelligent system does not discern the origin of these limitations—whether they arise from ground conditions (e.g., saturation) or landscape attributes (e.g., gradient)—but it factors them in exclusively through their influence on the decision metrics (e.g., duration to finish the field, minimal travelled distance, fuel conservation, etc.) during the selection of the superior plan.

To generate a planning solution, the intelligent system relies on a heuristic-based intelligent search algorithm originally formulated for manufacturing settings and described in the publication by Michalos *et al.* [27]. This algorithm operates with a suite of decision parameters that support rapid traversal of the solution space while maintaining solution quality across problems of varying magnitude. The intent of this paper is not to dissect the inner workings of this algorithm, but rather to illustrate its applicability within agriculture, beyond the manufacturing sphere where it was first deployed.

**Figure 3** offers a grid-style visual breakdown of the field, exposing a subset of the previously discussed field-level descriptors. Adopting a grid-based scheme, alongside the cell sizing proposed here, makes it possible to render the various parameters visually accessible. More precisely, each grid cell maps to a fixed spatial interval on the actual ground; a shrunken cell, however, implies a region where the resource encounters heightened “resistance,” which curtails travel speed and amplifies fuel burn. Beyond size, each cell receives a unique colour fill that flags its role within the broader field layout. The linkage between colour coding and field zone is unpacked below:

• Waypoints – Blue small boxes: Nodes that mark where a working lane starts and finishes.

• Working Lanes – Blue large boxes sandwiched between waypoints: AB strips built from a chain of oversized blue cells, across which the tractor is expected to perform a designated farming task.

• Non-Working Areas – Green boxes: The headland buffer that wraps around the working lanes on the inside of the field boundary.

• Transportation lanes – Grey boxes: Passageways lying completely outside any individual field, relied upon for tractor travel from one field to another or from a field to the barn.

• Entry/Exit points of the field – Yellow small boxes: The singular ingress/egress patch through which the tractor is permitted to move into or out of the field.

• Plants – Beige boxes: Crop-bearing zones occupied by live plants, over which the tractor is strictly forbidden from driving.

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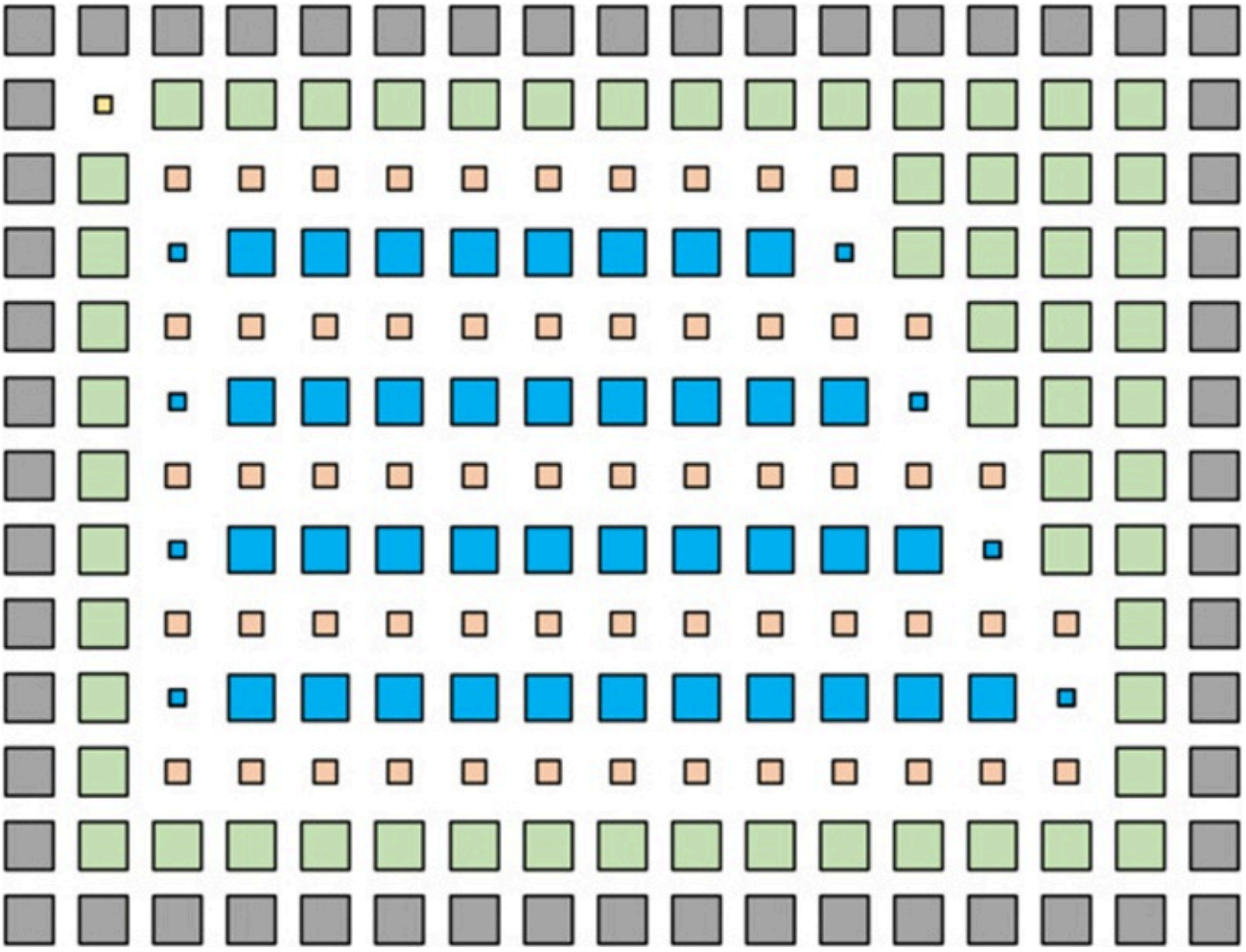

**Figure 3.** Grid-based field representation where the different colours represent the different areas.

When framed in this manner, the set of all possible solutions is shaped by a roster of spatial points demanding a purposeful ordering so that the mechanised units—tractors included—can discharge their duties productively, pushing a chosen bundle of Key Performance Indicators (KPIs) to their optimum as dictated by the operator's wishes. A given point might coincide with the opening or closing node of a work lane (a waypoint), with the field's entry or exit doorway, or with a supplementary coordinate tucked inside a non-productive (headland) or transit band. The upshot is that the search landscape sprawls wide and lacks inherent organisation, meaning a brute-force deterministic sweep is off the table. Thus, the heuristic search engine is engaged instead.

An extra simplification has been baked into the logic to reduce the computational load: once the algorithm picks a waypoint anchored to a particular lane, the twin waypoint for that same lane must also be accepted. This rule eliminates the possibility that the tractor merely tags a waypoint without genuinely committing to the lane it belongs to. Rolling past a waypoint while abandoning its partner lane, or attempting to backtrack along a lane, is not allowed under any circumstances.

Working from this foundation, the intelligent, heuristic-driven procedure has been harnessed to probe the space of strong candidate solutions, surfacing a "good-enough" pick from the elite set, selected according to a benchmark chosen beforehand by the operator. The study by Michalos *et al.* [27] documents how these intelligent algorithms achieve substantial reductions in computational footprint and turnaround time to arrive at an answer. The platform introduced throughout this article is designated the Intelligent Farming System (IFAS), and its component blueprint is sketched in **Figure 4**. Central to the platform is the backend module built around heuristic search, paired with a database that stores

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all datasets and operational states. A straightforward UI empowers users to push information into the platform and to graphically inspect the planner's recommended outcome. Once the user settles on a course of action, the implementation unit takes over, pushing commands to the physical assets to enact the plan. During live operations, telemetry streams are rendered on-screen and written to storage—subject to the sensor suite mounted on the machinery—thereby granting the farmer an unobstructed window into the fieldwork as it unfolds. Typical examples include live GPS traces and asset speeds, a raw video feed from a vehicle-mounted camera, fuel tank or spray tank gauges, and performance metrics returned from the implement, such as weeding precision or spray discharge volume, among others.

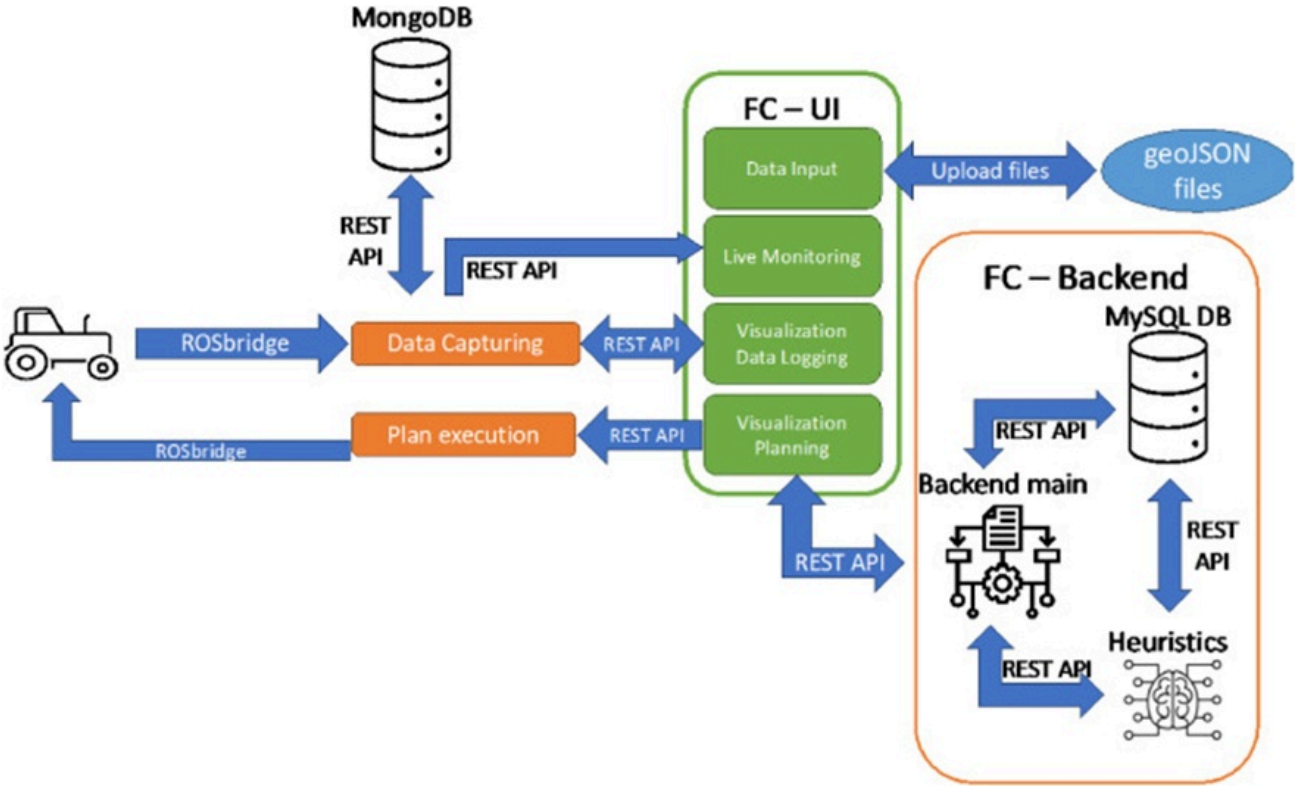


**Figure 4.** Intelligent Farming System (IFAS) architecture.

# Application Scenarios

In service of this paper's aims, a trio of adjoining fields was synthetically generated via a Python script, conforming to the modelling approach laid down in the earlier section. These form the testbed for the application scenarios **(Figure 5)**. Recapping what was stated above, each field's working lanes are communicated through blue line segments, and the enveloping headland strip is communicated via green-coloured cells. The entry-cum-exit access point of the field is likewise symbolised by a yellow cell, pulling double duty as the universal launch and return location for every traversal. Cell dimensions are calibrated to reflect the terrain's incline, effectively carving out special patches within the field where the tractor loses its ability to maintain its baseline velocity.

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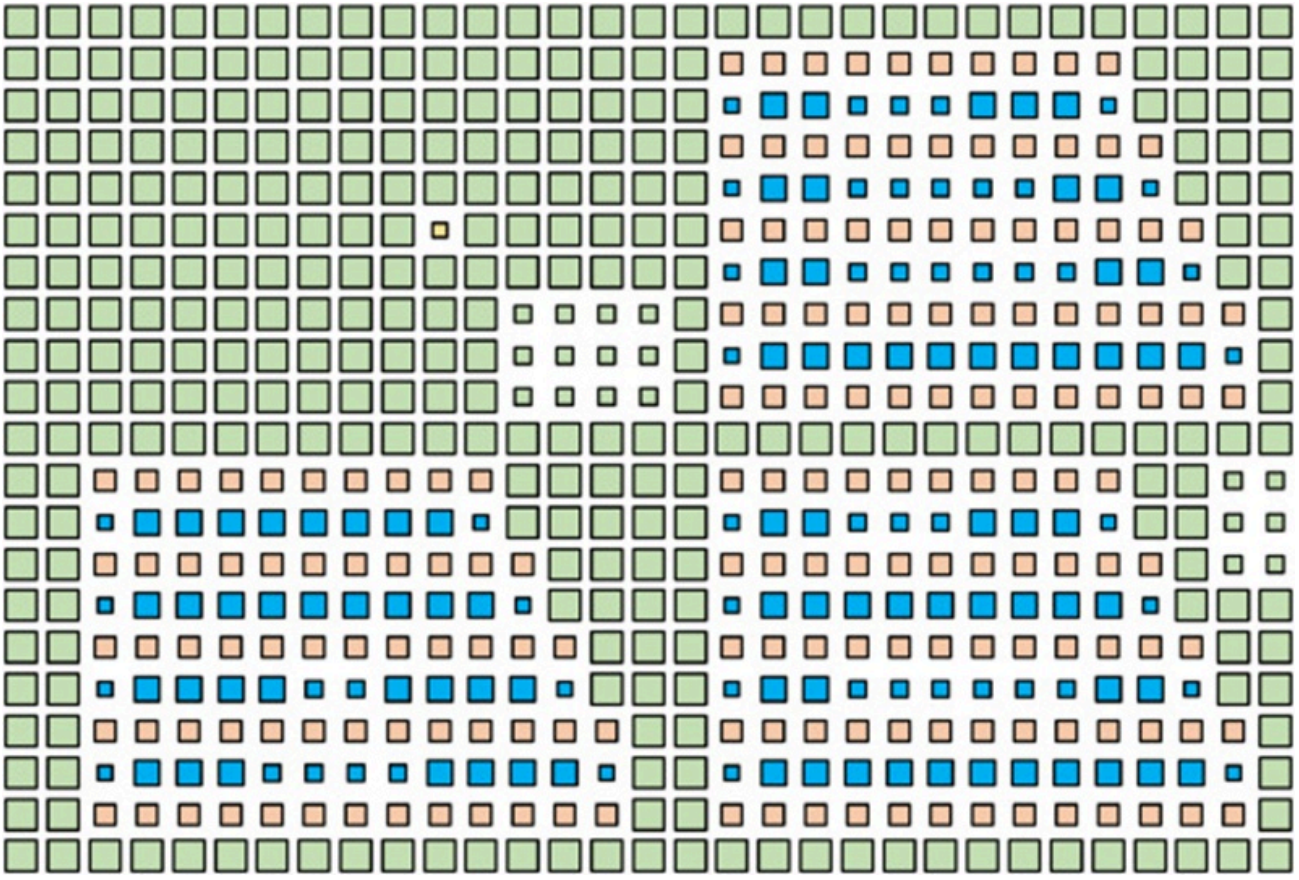

**Figure 5.** Three adjacent fields to generate alternative application scenarios where the size of each box represents the speed the tractor can have.

Upon finalising the field definitions, a set of focused KPIs—capturing travelled distance, elapsed time, and fuel burned—is determined for moving between any two coordinates across the entire field. Whether a given alternative qualifies as "good" is judged against these numerical outputs, because the central objective is to drive the KPI readings to their lowest feasible levels. The present paper puts four distinct case studies under the microscope by measuring the KPI Figures that result from a route an experienced farmer would pick by gut feeling versus the mathematically optimised route assembled by IFAS. The four case studies unpacked below are:

• A path followed by a single tractor in one field.

• A path followed by a single tractor in two fields.

• A path followed by two tractors in two fields.

• A path followed by two tractors in three fields.

To begin with, the very first scenario, which hands Field 1 over to Tractor 1 entirely, the lane-by-lane stepping pattern a farmer would organically fall into is charted in **Figure 6**; the numerals inscribed inside the cells trace the sequential footprints the farmer would leave, with every cell equivalent to a 100 m slice of the terrain.

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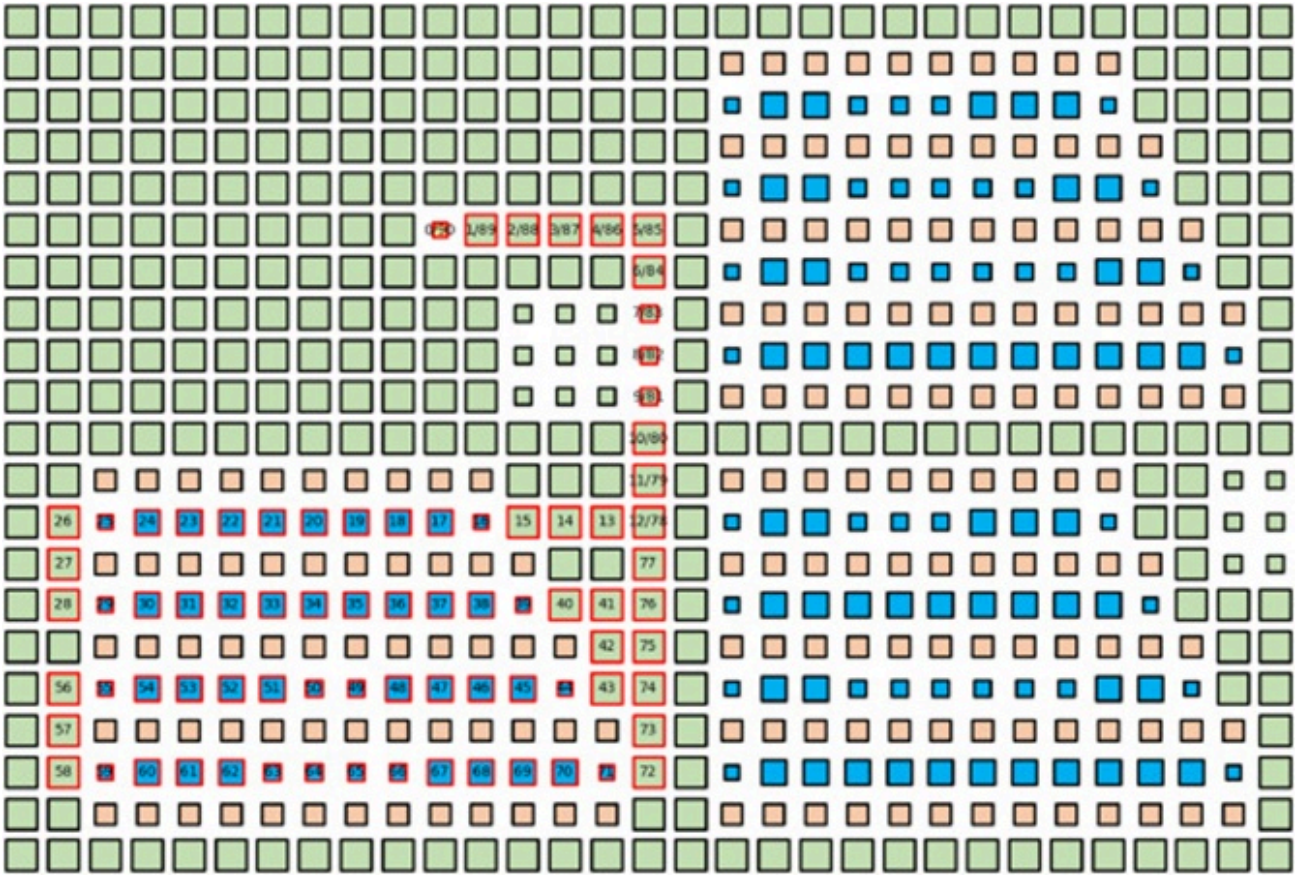

**Figure 6.** First case – Path inside the field, intuitively followed by a farmer, the numbers in the cells represent the steps the farmer would follow in the field.

Under identical conditions, the pathway synthesised by IFAS is shown in **Figure 7**.

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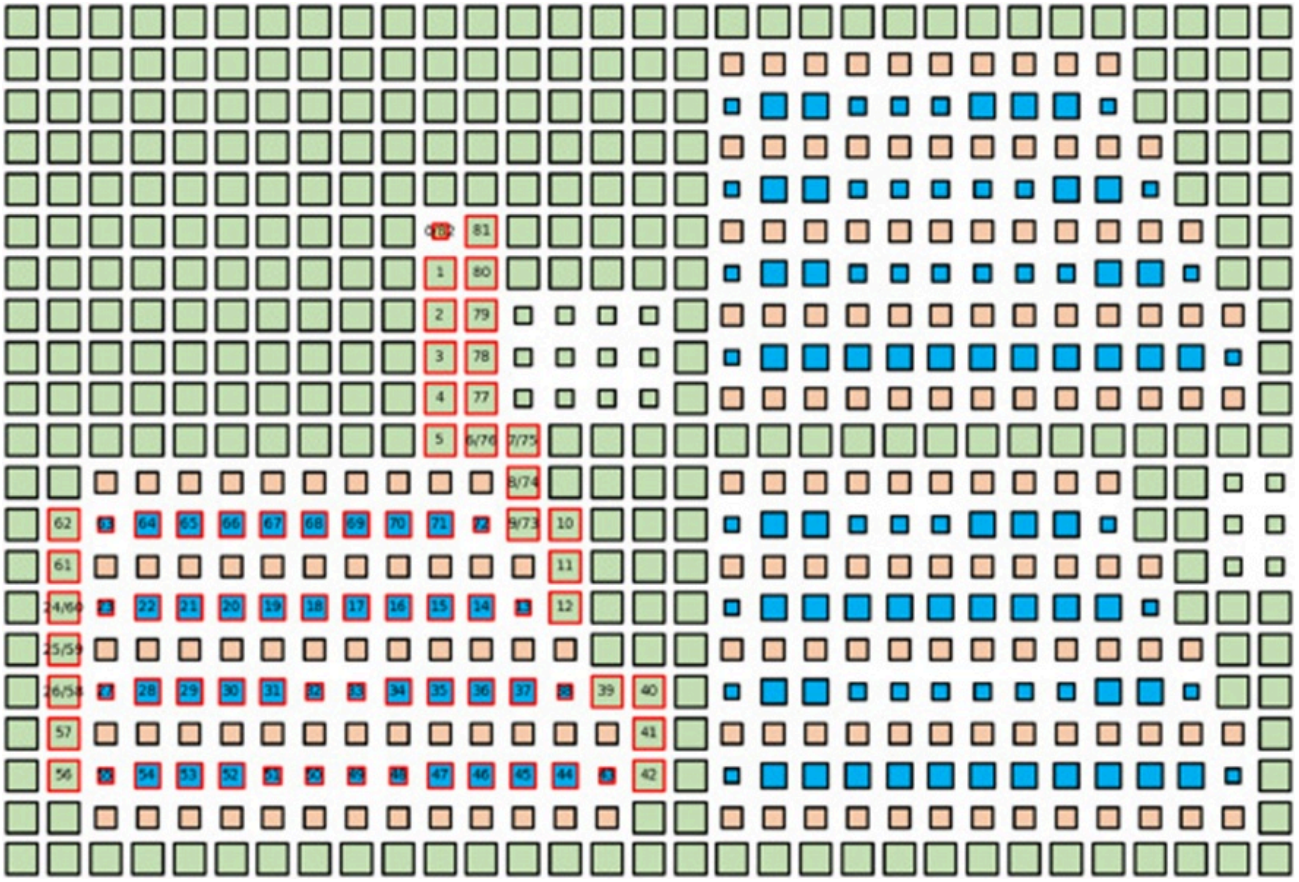

**Figure 7.** First case – Path inside the field, generated by the IFAS. The numbers in the cells represent the steps the farmer would follow in the field.

Shifting to the second scenario, in which both plots are entrusted to Tractor 1 alone, the lane order a farmer would gravitate toward is shown in **Figure 8**.

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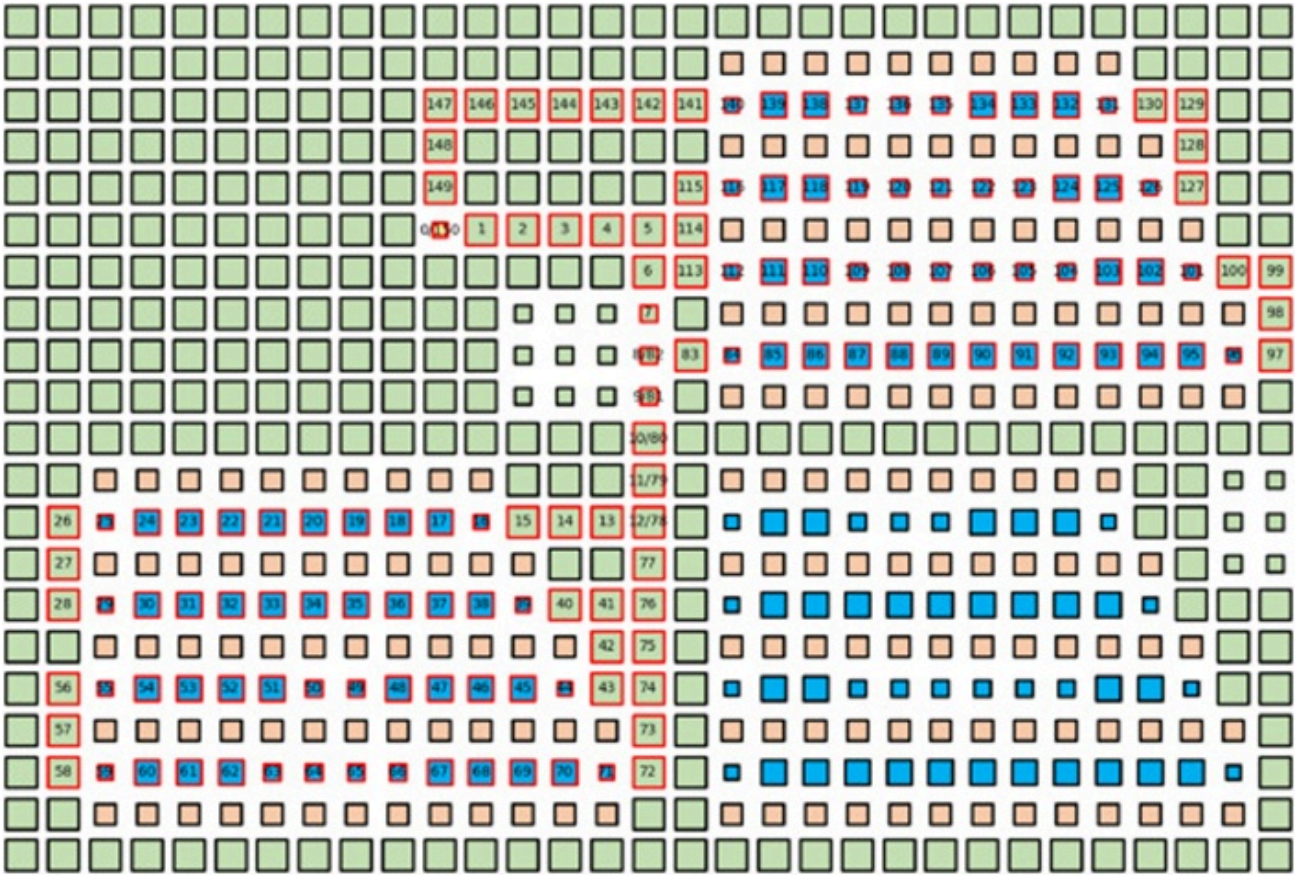

**Figure 8.** Second case – Path inside the field, intuitively followed by a farmer, the numbers in the cells represent the steps the farmer would follow in the field.

With the same inputs, IFAS's output routing is displayed in **Figure 9**.

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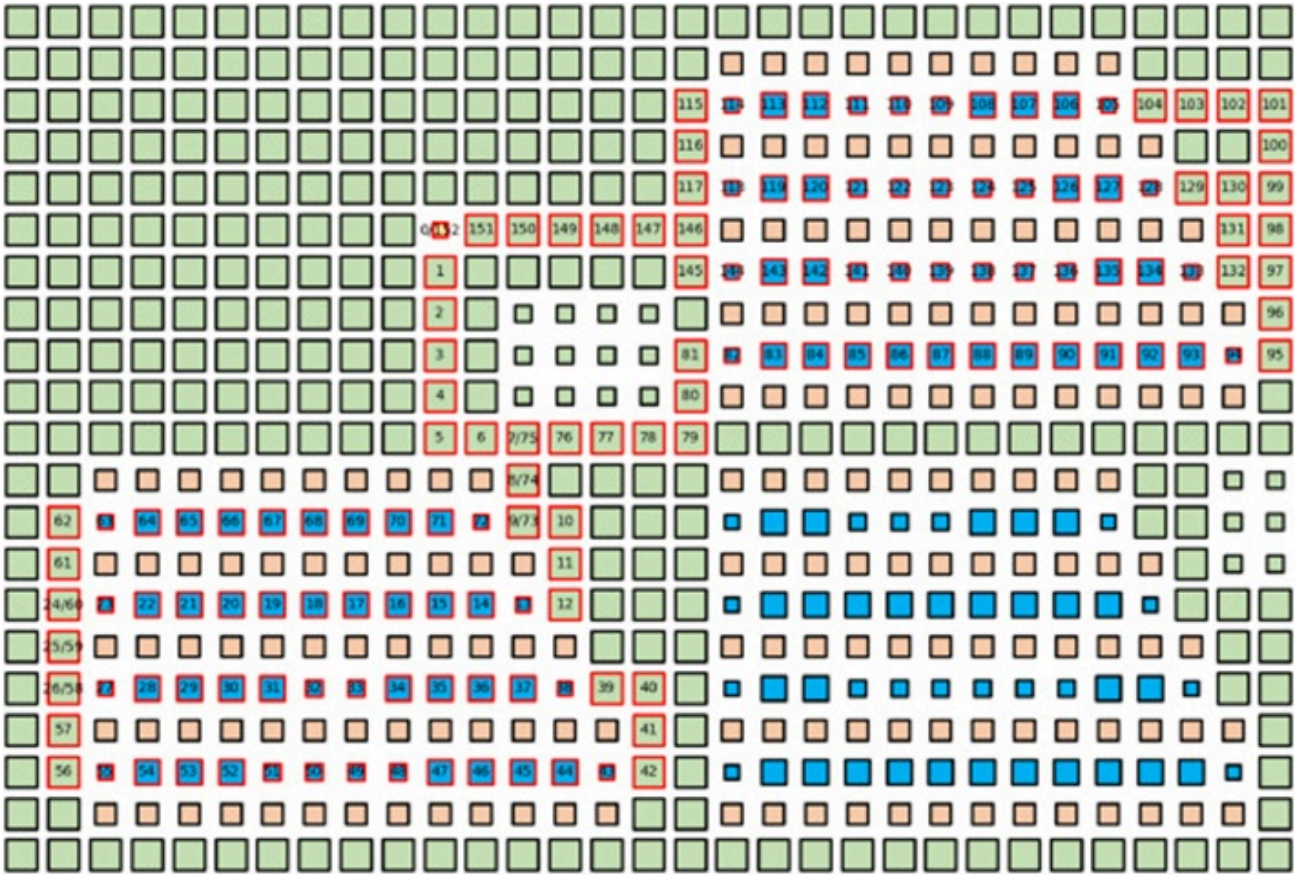

**Figure 9.** Second case – Path inside the field, generated by IFAS. The numbers in the cells represent the steps the farmer would follow in the field.

Advancing to the third scenario, where the two fields are partitioned between Tractor 1 and Tractor 2, respectively, the lane progression a farmer would settle into is illustrated through **Figures 10 and 11**.

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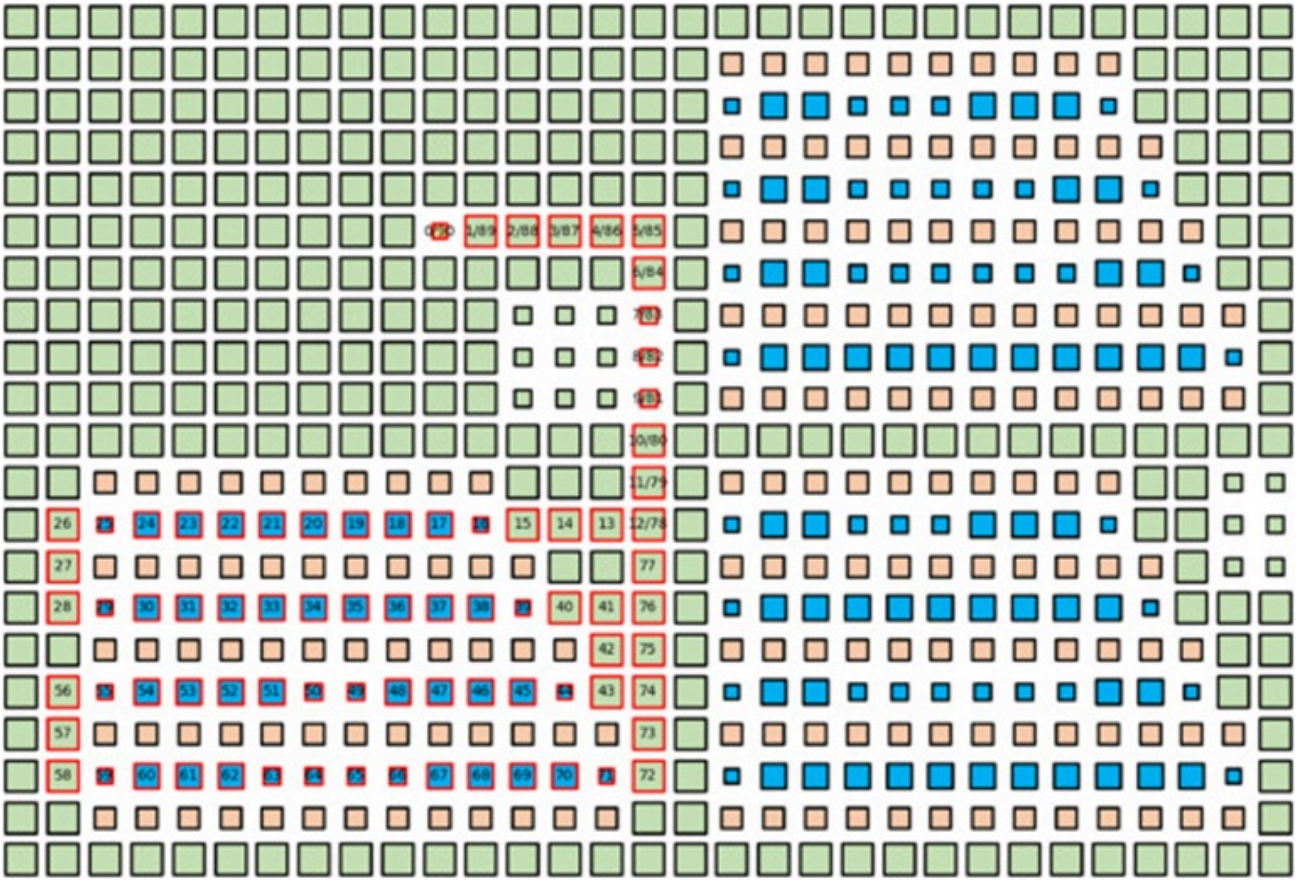

**Figure 10.** Third case: Tractor 1 – Path inside the field, intuitively followed by a farmer; the numbers in the cells represent the steps the farmer would follow in the field.

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**Figure 11.** Third case: Tractor 2 – Path inside the field, intuitively followed by a farmer; the numbers in the cells represent the steps the farmer would follow in the field.

Under the same setup, the routes generated by IFAS appear in **Figures 12 and 13**.

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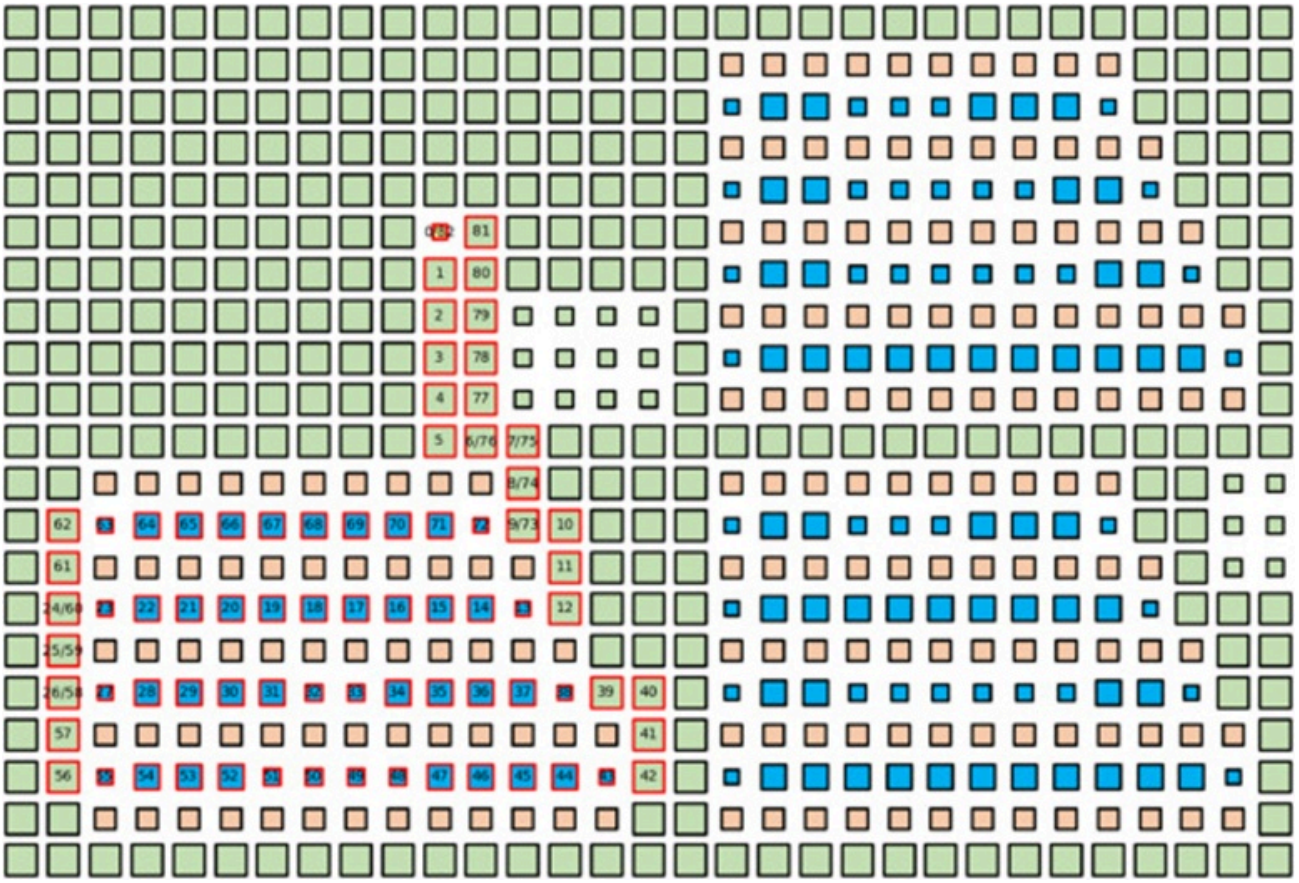

**Figure 12.** Third case: Tractor 1 – Path inside the field, generated by IFAS. The numbers in the cells represent the steps the farmer would follow in the field.

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**Figure 13.** Third case: Tractor 2 – Path inside the field, generated by IFAS. The numbers in the cells represent the steps the farmer would follow in the field.

Arriving at the fourth and final scenario, which requires three fields to be shared between Tractor 1 and Tractor 2, the stepping sequence a farmer would naturally lean on is shown in **Figures 14 and 15**.

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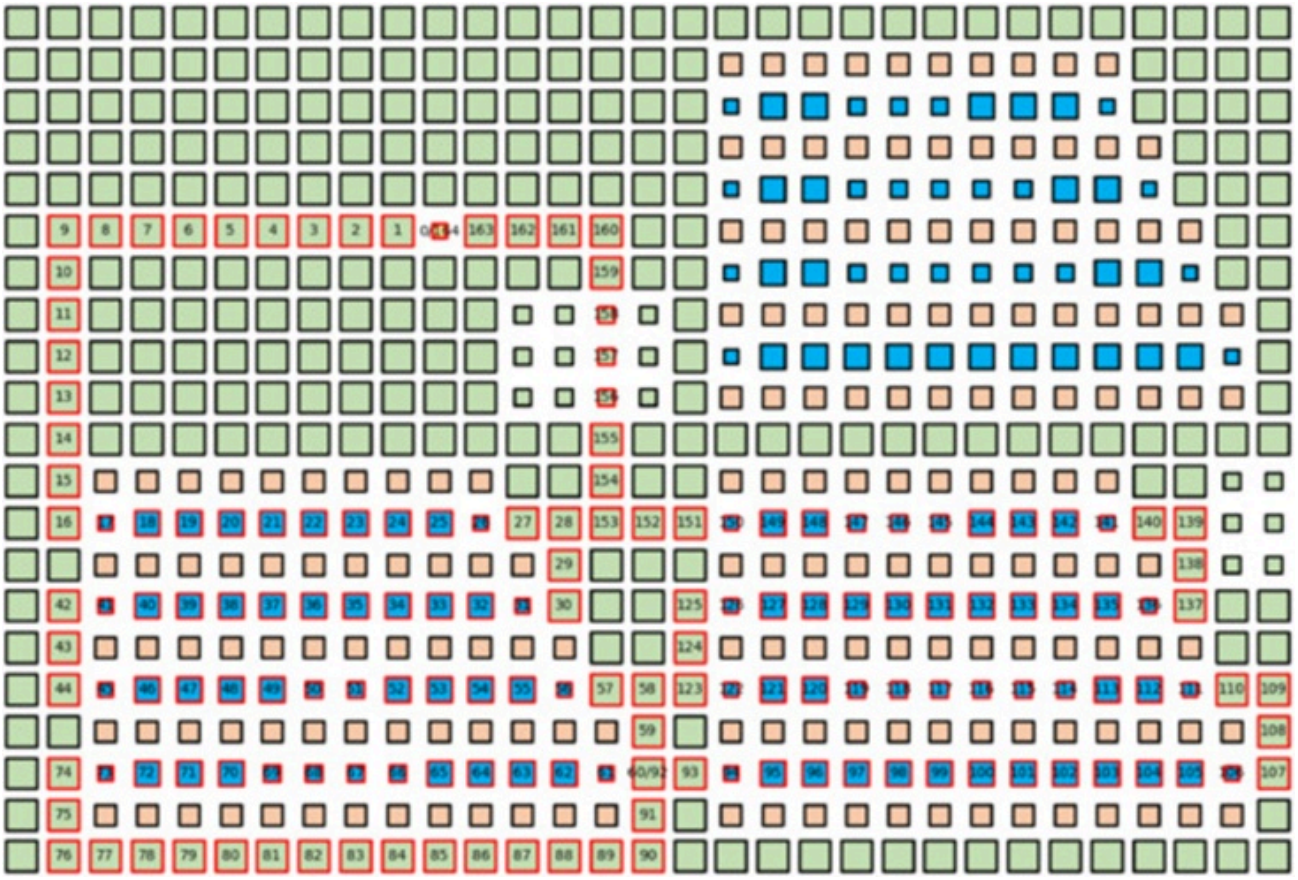

**Figure 14.** Fourth case: Tractor 1 – Path inside the field, intuitively followed by a farmer; the numbers in the cells represent the steps the farmer would follow in the field.

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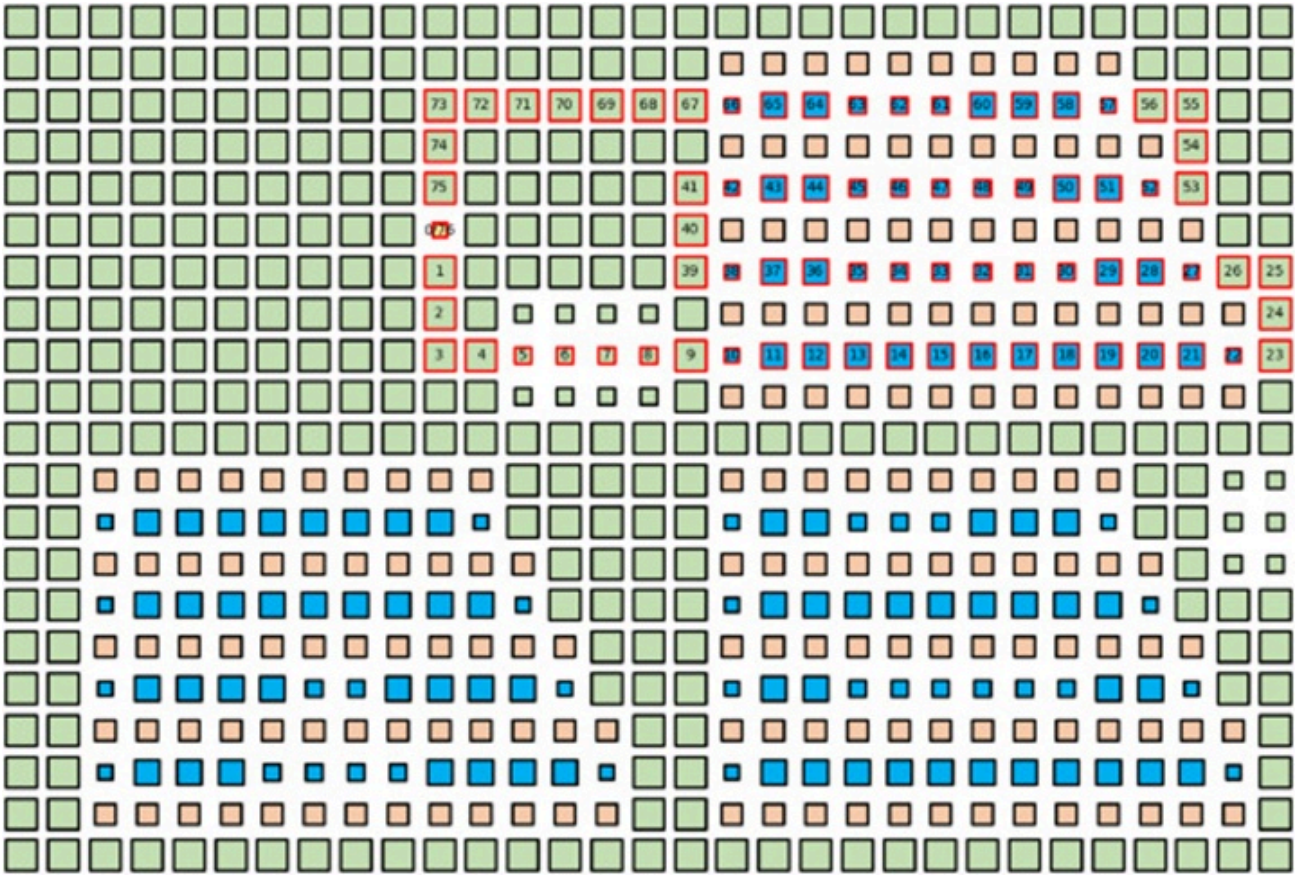


**Figure 15.** Fourth case: Tractor 2 – Path inside the field, intuitively followed by a farmer; the numbers in the cells represent the steps the farmer would follow in the field.

For this same conFigureuration, the IFAS-produced plan is presented in **Figures 16 and 17**.

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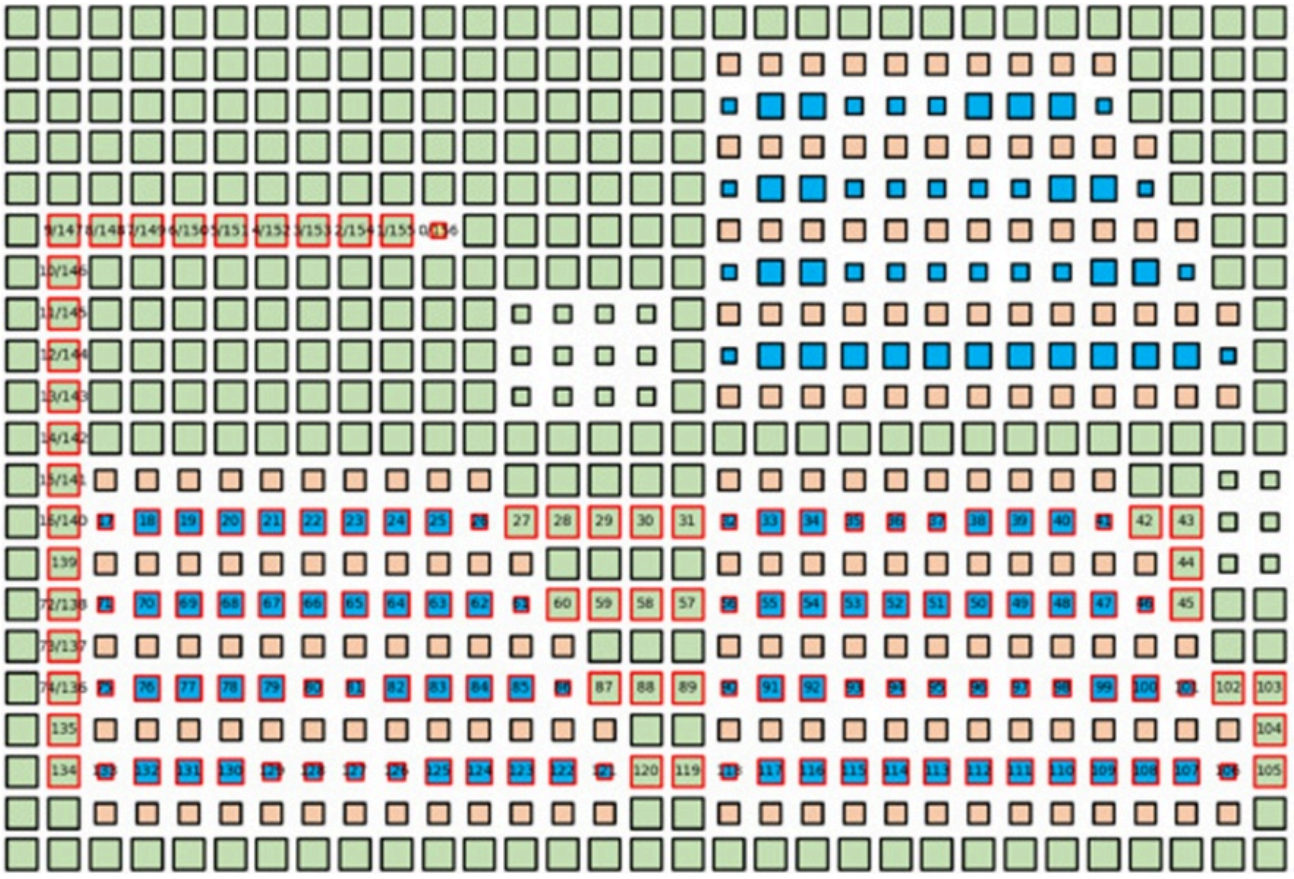

**Figure 16.** Fourth case: Tractor 1 – Path inside the field, generated by IFAS. The numbers in the cells represent the steps the farmer would follow in the field.

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**Figure 17.** Fourth case: Tractor 2 – Path inside the field, generated by IFAS. The numbers in the cells represent the steps the farmer would follow in the field.

# Results and Discussion

Through IFAS, the grower can tailor the specifications of the farming context—indicating, for instance, the quantity of plots or passes the tractors are to handle, the nature of the operation to be carried out, and the yardstick that will steer the answer, such as the speediest route clocked by duration or the most compact route gauged by length. What IFAS subsequently returns is the self-directed pairing of every pass or plot to the relevant assets and the self-directed ordering of those passes—essentially, the succession governing their execution—to land on a “good” outcome against the yardstick the grower has singled out.

Focusing on the scheduling dimension of the suggested tool, it becomes apparent that operators adopt widely differing stances, as reflected in both published research and everyday fieldwork. To be precise, most operators lean toward processing passes one after another in a rigid linear fashion, chiefly to guarantee that no strip remains untouched, while leaving unexploited the headroom for KPI uplifts that a less conventional routing pattern—of the kind sketched in **Figure 1** —might afford.

Within the academic record, an assortment of isolated recipes, and occasionally fusions thereof, can be found, each placing a premium on a separate optimisation facet, whether that be compressing the headland plus aggregate travel span, shrinking the clock time consumed by turns, or leveraging tools like the Fast Hybrid Algorithm (FHA), whose design target is to squeeze the unproductive mileage accumulated by the fleet. By comparison, the platform articulated in this manuscript pursues a markedly more integrative philosophy, with its distinctive strength being the capacity to entertain a suite of scheduling metrics simultaneously, apportioning them different weights, rather than anchoring itself to a lone

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indicator. The recipes catalogued earlier bear a loose resemblance to the one detailed here, yet they cannot match its degree of adaptability.

About the vignettes examined in this article, the computed KPIs—as already noted—are duration, traversed span, and fuel drawn. Even though several fields and pieces of equipment Figureure in the setup, every asset departs from a shared origin, and the sole optimisation directive applied is the curtailment of non-productive traversal distance, setting aside, for the moment, other KPIs like clock time or fuel throughput. The derived KPI values for each vignette are consolidated in the accompanying table, with granular commentary provided for each. Distance was reckoned by tallying the cells crossed, where each cell maps to a 100 m increment as previously specified in Section 3; duration was deduced from the locale-specific velocity caps (working rate: 2.52 m/s, non-working rate: 4 m/s, and capped-zone limit: 1.64 m/s); and fuel draw was inferred from the terrain category (working strips: 9 l/h, non-working strips: 4 l/h, and capped zones: 13 l/h).

As the Figureures assembled in **Table 1** attest, IFAS unfailingly generates a routing scheme whose KPI profile—spanning time, distance, and fuel—proves superior when benchmarked against the habitual sequential logic that farmers tend to apply, and this holds even for heavily intertwined situations like case 4, which demands the simultaneous coordination of numerous fields and vehicles. Looking more closely, the execution time is consistently reduced across the two runs, though on some occasions the margin remains slim. On the distance front, in contrast, the gulf is substantially wider, swelling to 800 m in places, a delta that carries potential knock-on effects for considerations such as topsoil packing. As time went on, fuel draw was invariably suppressed, at times delivering a saving of over 1 litre.

**Table 1.** KPIs for all the cases.

| Scenario | Farmer’s approach | IFAS |
|---|---|---|
| Case 1: 1 field – 1 Tractor | Time: 2947 s<br>Distance: 9100 m<br>Fuel consumption: 7 litres | Time: 2567 s<br>Distance: 8300 m<br>Fuel consumption: 5.8 litres |
| Case 2: 2 fields – 1 Tractor | Time: 5067 s<br>Distance: 15,100 m<br>Fuel consumption: 12.6 litres | Time: 4938 s<br>Distance: 15,300 m<br>Fuel consumption: 11.7 litres |
| Case 3: 2 fields – 2 Tractors | Tractor 1<br>Time: 2947 s<br>Path length: 9100 m<br>Fuel consumption: 7 litres<br>Tractor 2<br>Time: 2675 s<br>Distance: 7700 m<br>Fuel consumption: 7 litres | Tractor 1<br>Time: 2567 s<br>Path length: 8300 m<br>Fuel consumption: 5.8 litres<br>Tractor 2<br>Time: 2531 s<br>Distance: 7700 m<br>Fuel consumption: 6.3 litres |
| Case 4: 3 fields – 2 Tractors | Tractor 1<br>Time: 5346 s<br>Path length: 16,500 m<br>Fuel consumption: 12.6 litres<br>Tractor 2<br>Time: 2675 s<br>Path length: 7700 m<br>Fuel consumption: 7 litres | Tractor 1<br>Time: 5038.027 s<br>Path length: 15,700 m<br>Fuel consumption: 11.8 litres<br>Tractor 2<br>Time: 2531 s<br>Path length: 7700 m<br>Fuel consumption: 6.3 litres |

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In the second vignette, improvements are recorded for clock time and fuel use, yet the distance metric fails to shrink. This dynamic grants the operator the leeway to, in line with shifting priorities, opt for a different viable schedule or to elevate one KPI over another—speed above brevity, or vice versa. In a related observation, in vignettes three and four, Tractor 2 records an unchanged path length, yet both time expenditure and fuel throughput are trimmed under the IFAS-generated plan. The reason is that spatial routing had already reached its lower bound, thereby channeling the optimisation effect into the remaining two dimensions.

Drawing on the evidence marshalled above, the upside of the intelligent scheduler comes through unambiguously, with its premier attribute being the remarkable breadth of adaptability it places in the grower's hands. The operator feeds in a signal indicating which KPI to place at the top of the hierarchy, and the engine responds by proposing a conFigureuration that aligns with those expressed wishes. Growers who forgo any form of automated decision support habitually re-tread the identical course every time a field operation becomes due, blind to the type of intervention required and oblivious to other variables rooted in the field's situation—such as substrate moisture, climatic influences, the tally of plots or passes, among others. A reasoning system capable of absorbing such variables is positioned to deliver a scheme that dovetails far more closely with the operator's genuine requirements.

The reasoning prowess of IFAS is visually portrayed in the pair of graphs below **(Figures 18 and 19)**, which charts the draw travel speed. These graphs originate from the opening vignette and reveal that the farmer's path cuts across anomalous-speed patches four times, introducing corresponding perturbations in the time and fuel traces, whereas the IFAS-suggested trajectory threads through such patches only three times, culminating in an improved showing on distance, duration, and fuel economy alike.

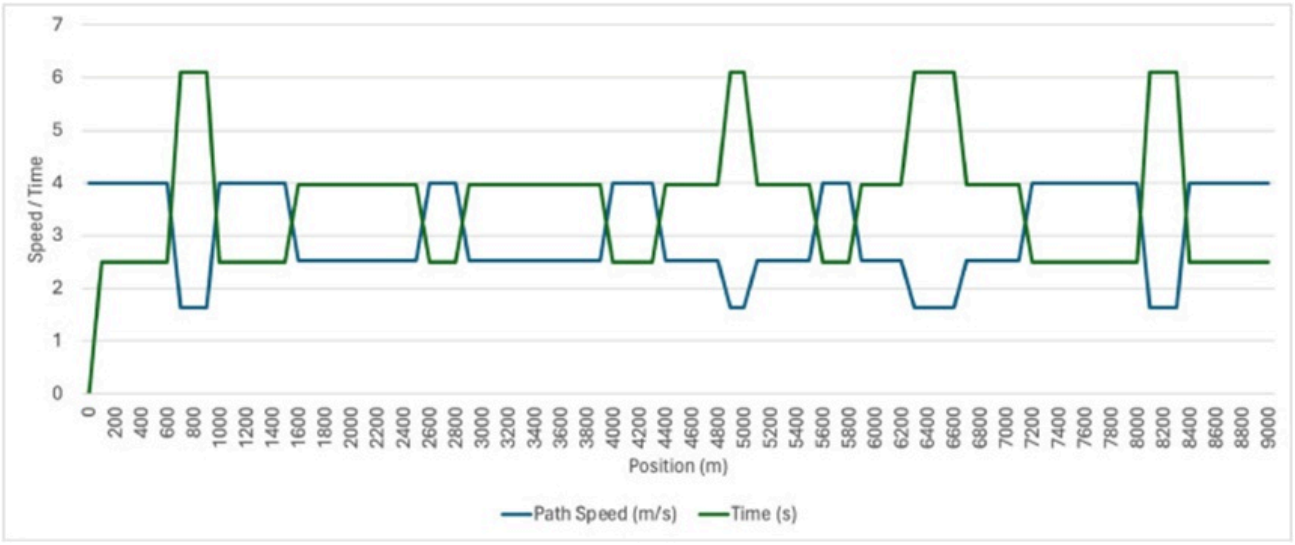


**Figure 18.** Diagram showing how the different metrics change every 100 m in the field - Manually followed by a farmer.

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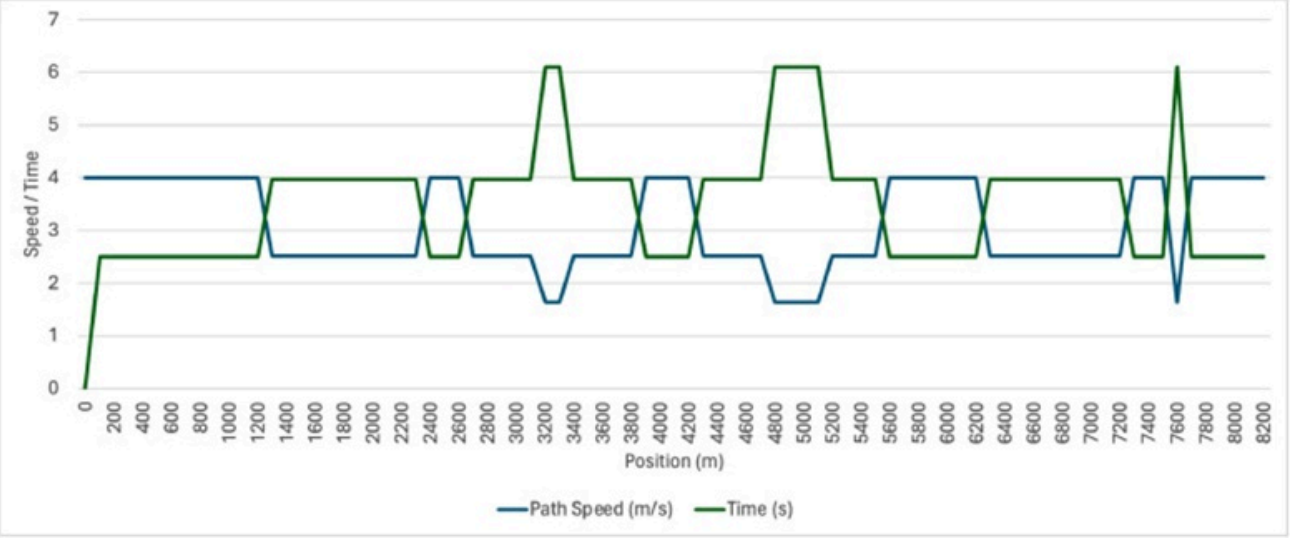


**Figure 19.** Diagram showing how the different metrics change every 100 m in the field - Generated by IFAS.

One more pillar of IFAS's advantage is its unified treatment of both the resource-to-task mapping and the temporal ordering of those tasks in an agricultural setting—a pairing that the published record has so far left untouched. This dual focus yields a more sweeping perspective on the scheduling puzzle inherent in crop operations, offloading the mental sorting that a farmer would otherwise have to shoulder after the fact, were they dependent on prior art, before any field activity could physically start.

Concerning the sequencing of operations, the current best-in-class frameworks typically drill into a narrow band of metrics—to illustrate, chasing the most compact or the fastest corridor—thereby confronting the user with a spartan set of alternatives and erasing the possibility of blending, as in hunting down the sweet spot that reconciles path brevity with minimal fuel burn. From this angle, the room for generating individually tailored outputs appears decidedly cramped. Under the apparatus advanced in this work, the user can introduce additional dimensions and ranks, or even fuse the heaviest among them, by adjusting the magnitudes of their contributions.

In addition, the intelligent core calculates and presents diagnostic Figures for the recommended plan, open to the farmer's scrutiny. Doing so can sharpen attentiveness toward auxiliary considerations—fuel throughput, spray fluid quantities, CO2 release, and the like—cultivating a stance that is more ecologically mindful and sustainable over the long haul. Other schemes that attempt such computations do not yet possess the depth or refinement to ingest parameters of comparable complexity to those enumerated above; their gaze stays primarily locked onto clock time and travelled span.

As a closing point, a signal merit of the presented apparatus is that it rests upon a set of simplifications that do not erode solution quality while drastically culling the universe of potential configurations. What is more, although an exhaustive brute-force sweep might theoretically unearth the global optimum, it would do so at a prohibitive cost in silicon cycles and elapsed time. The deployment of heuristic search empowers the platform to trim both computational demand and latency when delivering a "good" result within the envelope of the strongest candidates.

# Conclusion

An intelligent scheduling aid (IFAS) that provides resource allocation and the sequencing of field operations, drawing on inputs from multiple resources and plots, has been the focus of this discourse. IFAS gives the user the freedom to nominate the pool of plots and machinery they wish to engage, and to select a solution from the top-tier alternatives, guided by their own selection metrics. The defining characteristics of the described methodology are its pronounced

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versatility and all-encompassing outlook, while slated future work envisions running the intelligent engine on data pulled from a cluster of real fields and physical machinery to throw its practical payoffs into starker relief.

## Abbreviations

KPI = Key Performance Indicators

AGV = Automated Guide Vehicles

IFAS = Intelligent Farming System

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# Conflict of interest

None

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# Ethics statement

The authors ensure the following ethical statements

They have written entirely original works, and no work or words of others have been used.

Proper acknowledgment of the work of others has been given, citing their publications, which have influenced the reported work and give the work appropriate context within the larger scholarly record.

They ensure there is no plagiarism in any form.

No similar manuscripts have been published that describe essentially the same research in more than one primary journal.

No information in this manuscript has been obtained in the course of confidential services.

Authorship has been limited to those who have made a significant contribution to the conception, design, execution, or interpretation of the reported study. All those who have made substantial contributions have been listed as co-authors.

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# References

1. Bochtis DD, Sørensen CGC, Busato P. Advances in agricultural machinery management: A review. Biosyst Eng. 2014;126:69-81. https://doi.org/10.1016/j.biosystemseng.2014.07.012.

2. Tardaguila J, Stoll M, Gutiérrez S, Proffitt T, Diago MP. Smart applications and digital technologies in viticulture: a review. Smart Agric Technol. 2021;1:100005. https://doi.org/10.1016/j.atech.2021.100005.

3. Lynch J, Cain M, Frame D, Pierrehumbert R. Agriculture's contribution to climate change and role in mitigation is distinct from predominantly fossil CO2-emitting sectors. Front Sustain Food Syst. 2021;4:518039. https://doi.org/10.3389/fsufs.2020.518039.

4. Zuniga BGL, Calderon K, Ale TML. Impacts of COVID-19 on agriculture and food security. Centro Agric. 2021;48.

5. Sharipov GM, Heiß A, Bresilla T, Nieuwenhuizen AT, Hemming J, Van Evert FK, et al. Smart implements by leveraging ISOBUS: development and evaluation of field applications. Smart Agric Technol. 2023;6:100341. https://doi.org/10.1016/j.atech.2023.100341.

6. Paraforos DS, Aubé C, Athanasakos L, Avgoustakis I, Baron S, Bresilla T, et al. Connecting agricultural robots and smart implements by using ISO 11783 communication. IFAC-PapersOnLine. 2022;55:200-5. https://doi.org/10.1016/j.ifacol.2022.11.139.

7. Van Evert FK, Bresilla T, Nieuwenhuizen A, Veldhuisen B, Hemming J, Avgoustakis G, et al. Implementing a digital twin for flexible operation of agricultural robotics. In: Van Henten E, editor. Burleigh Dodds Series in Agricultural Science. Burleigh Dodds Science Publishing. 2023:185-222. https://doi.org/10.19103/AS.2023.0124.28.

8. Seyyedhasani H, Dvorak JS. Reducing field work time using fleet routing optimization. Biosyst Eng. 2018;169:1-10. https://doi.org/10.1016/j.biosystemseng.2018.01.006.

9. Santos LC, Santos FN, Solteiro Pires EJ, Valente A, Costa P, Magalhães S. Path Planning for ground robots in agriculture: a short review. In: 2020 IEEE International Conference on Autonomous Robot Systems and Competitions (ICARSC), IEEE, Ponta Delgada, Portugal. 2020:61-6. https://doi.org/10.1109/ICARSC49921.2020.9096177.

10. Bochtis DD, Sørensen CG. The vehicle routing problem in field logistics part I. Biosyst Eng. 2009;104:447-57. https://doi.org/10.1016/j.biosystemseng.2009.09.003.

11. Hizatate T, Noguchi N. Work schedule optimization for electric agricultural robots in orchards. Comput Electron Agric. 2023;210:107889. https://doi.org/10.1016/j.compag.2023.107889.

12. Filip M, Zoubek T, Bumbalek R, Cerny P, Batista CE, Olsan P, et al. Advanced computational methods for agriculture machinery movement optimization with applications in sugarcane production. Agriculture. 2020;10:434. https://doi.org/10.3390/agriculture10100434.

13. Bochtis DD, Vougioukas SG. Minimising the non-working distance travelled by machines operating in a headland field pattern. Biosyst Eng. 2008;101:1-12.

14. Spekken M, De Bruin S. Optimized routing on agricultural fields by minimizing maneuvering and servicing time. Precis Agric. 2013;14:224-44.
https://doi.org/10.1007/s11119-012-9290-5.

15. Tunnisaki F, Sutarman. Clarke and Wright savings algorithm as solutions vehicle routing problem with simultaneous pickup delivery (VRPSPD). J Phys Conf Ser. 2023;2421:012045.

16. Utamima A, Reiners T. Navigating route planning for multiple vehicles in multifield agriculture with a fast hybrid algorithm. Comput Electron Agric. 2023;212:108021.
https://doi.org/10.1016/j.compag.2023.108021.

17. Qu J, Zhang Z, Qin Z, Guo K, Li D. Applications of autonomous navigation technologies for unmanned agricultural tractors: A review. Machines. 2024;12:218.
https://doi.org/10.3390/machines12040218.

18. Chryssolouris G. Manufacturing Systems: theory and Practice. Mechanical Engineering Series. Springer-Verlag, New York. 2006.
https://doi.org/10.1007/0-387-28431-1.

19. Michalos G, Makris S, Papakostas N, Mourtzis D, Chryssolouris G. Automotive assembly technologies review: challenges and outlook for a flexible and adaptive approach. CIRP J Manuf Sci Technol. 2010;2:81-91.
https://doi.org/10.1016/j.cirpj.2009.12.001.

20. Liu S, Shen J, Tian W, Lin J, Li P, Li B. Balanced task allocation and collision-free scheduling of multi-robot systems in large spacecraft structure manufacturing. Robot Auton Syst. 2023;159:104289.
https://doi.org/10.1016/j.robot.2022.104289.

21. Kousi N, Koukas S, Michalos G, Makris S. Scheduling of smart intra-factory material supply operations using mobile robots. Int J Prod Res. 2019;57:801-14.

22. Hu H, Jia X, He Q, Fu S, Liu K. Deep reinforcement learning based AGVs real-time scheduling with mixed rule for flexible shop floor in industry 4.0. Comput Ind Eng. 2020;149:106749.
https://doi.org/10.1016/j.cie.2020.106749.

23. Liu D, Huang B, Zhu H. Solving the tree-structured task allocation problem via group multirole assignment. IEEE Trans Autom Sci Eng. 2020;17:41-55.
https://doi.org/10.1109/TASE.2019.2908762.

24. Feo-Flushing E, Gambardella LM, Caro GAD. Spatially-distributed missions with heterogeneous multi-robot teams. IEEE Access. 2021;9:67327-48.
https://doi.org/10.1109/ACCESS.2021.3076919.

25. Wang Z, Gombolay M. Learning scheduling policies for multi-robot coordination with graph attention networks. IEEE Robot Autom Lett. 2020;5:4509-16.
https://doi.org/10.1109/LRA.2020.3002198.

26. Chryssolouris G, Alexopoulos K, Arkouli Z. A Perspective on Artificial Intelligence in Manufacturing. Studies in Systems, Decision and Control. Springer International Publishing, Cham. 2023.
https://doi.org/10.1007/978-3-031-21828-6.

27. Michalos G, Makris S, Mourtzis D. An intelligent search algorithm-based method to derive assembly line design alternatives. Int J Comput Integr Manuf. 2012;25:211-29.

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https://doi.org/10.1080/0951192X.2011.627949.

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