



Article

Scenario Generation and Autonomous Control for High-Precision Vineyard Operations

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Abstract: Precision Farming (PF) in vineyards represents an innovative approach to vine cultivation that leverages the advantages of the latest technologies to optimize resource use and improve overall field management. This study investigates the application of PF techniques in a vineyard, focusing on sensor-based decision-making for autonomous driving. The goal of this research is to define a repeatable methodology for virtual testing of autonomous driving operations in a vineyard, considering realistic scenarios, efficient control architectures, and reliable sensors. The simulation scenario was created to replicate the conditions of a real vineyard, including elevation, banking profiles, and vine positioning. This provides a safe environment for training operators and testing tools such as sensors, algorithms, or controllers. This study also proposes an efficient control scheme, implemented as a state machine, to autonomously drive the tractor during two distinct phases of the navigation process: between rows and out of the field. The implementation demonstrates improvements in trajectory-following precision while reducing the intervention required by the farmer. The proposed system was extensively tested in a virtual environment, with a particular focus on evaluating the effects of micro and macro terrain irregularities on the results. A key feature of the control framework is its ability to achieve adequate accuracy while minimizing the number of sensors used, relying on a configuration of a Global Navigation Satellite System (GNSS) and an Inertial Measurement Unit (IMU) as a cost-effective solution. This minimal-sensor approach, which includes a state machine designed to seamlessly transition between in-field and out-of-field operations, balances performance and cost efficiency. The system was validated through a wide range of simulations, highlighting its robustness and adaptability to various terrain conditions. The main contributions of this work include the high fidelity of the simulation scenario, the efficient integration of the control algorithm and sensors for the two navigation phases, and the detailed analysis of terrain conditions. Together, these elements form a robust framework for testing autonomous tractor operations in vineyards.

Keywords: Precision Farming; vineyard; simulator; MPC; autonomous driving; CarMaker



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1. Introduction

Throughout history, viticulturists have faced the significant challenges inherent to grape cultivation. However, in recent decades, an agricultural revolution powered by technological advancements has enabled faster, more precise, and safer management of plant health. This transformation has spurred research into new approaches to further accelerate progress in the field. The agricultural market is rapidly evolving to meet global demands,

with Precision Farming (PF) leading the way. Specifically, PF focuses on maximizing output while minimizing input [1], addressing critical issues such as population growth [2], environmental impact [3], and the effects of geopolitical events [4]. Furthermore, it tackles the urgent need to reduce energy consumption, water usage [5,6], gas emissions [7] labor requirements [8], and the use of chemicals [9,10]. In essence, PF is an agricultural approach aimed at increasing productivity and account for labor shortages [11] while minimizing energy, chemical inputs, land use, and overall resource consumption.

In this context, agricultural tractors play a pivotal role in inspecting vineyards and providing farmers with accurate yield estimations. Sensors are essential tools for achieving this goal. For instance, the VinBot system employs 2D laser sensors and cameras [12], while the VineRobot combines ultrasonic, fluorescence, and camera sensors with Artificial Intelligence [13]. “VineSLAM” [14] proposes a hybrid Simultaneous Localization and Mapping (SLAM) method using low-cost landmarks to enhance localization accuracy and robustness in steep-slope vineyards, mitigating GPS limitations. Other examples include Liu et al. [15], who use 3D vision, Light Detection and Ranging (LiDAR), and ultrasonic sensors, and Bernard et al. [16], who focus exclusively on LiDAR technology.

The success of PF also hinges on the ability to autonomously navigate fields, reducing farmer intervention and improving application precision by minimizing the unpredictability of human behavior. Autonomous driving performance depends on the choice of controller algorithms and the sensors used for feedback. Various methods are proposed in the literature for row-following and headland turns. Liu et al. [15] introduce a path-following navigation system using Model Predictive Control (MPC) based on Direct Yaw Moment Control (DYC) for a Four-Wheel Independent-Drive (4WID) self-steering system, with tracking provided by GPS sensors. Rovira-Mas et al. [17] propose a reactive inside-row guidance system utilizing 3D vision, LiDAR, and ultrasonic sensors. Similarly, Bernard et al. [16] present three infield navigation systems relying solely on LiDAR sensors. Bertoglio et al. [18] develop a navigation system combining LiDAR and wheel encoders for precise in-row and end-row turns. Hybrid approaches, such as those in VinBot [12] and VineRobot [13], integrate GPS, IMU, 2D lasers, ultrasonic sensors, and GPS to achieve reactive navigation. Recent studies have also explored mechanical control strategies to enhance implement positioning during autonomous navigation, with a particular focus on adaptive stubble avoidance mechanisms. For instance, Ref. [19] investigates side-shift control using a fuzzy PID approach, while [20] develops a deflection adjustment system optimized through PID tuning, both contributing to advancements in PF control techniques.

Developing autonomous driving algorithms through field testing is risky, time consuming, and costly. Consequently, simulation technology has emerged as a transformative tool in vineyard management, overcoming seasonal limitations and providing a safe environment for precise scenario testing [21]. Simulation offers researchers a powerful resource to refine vineyard strategies, enhance efficiency, experiment with new tools, and ensure the sustainability of the wine industry. For example, the GREENSPACE Virtual Reality simulator [22] provides a safe training environment and mitigates seasonal constraints, although it does not focus on sloped terrains or vineyards. Shamshiri et al. [23] employ a fully simulated robotic platform in a virtual citrus orchard, yet terrain irregularities are not addressed. Gutierrez-Cejudo et al. [24] leverage simulation for dynamic multi-robot task allocation and vehicle routing problems in agricultural robotics.

Finally, Cheli et al. [25] propose a simulation framework utilizing CarMaker [26] and AgriSI [27], offering robust vehicle dynamics modeling, customizable scenarios, and efficient multi-physics integration. This approach significantly enhances simulation fidelity and flexibility for vineyard applications.

2. Motivation and Methodology

This paper introduces a novel approach to vineyard operations with three primary contributions: a methodology for creating realistic simulation scenarios, a state-machine algorithm for autonomous tractor driving, and an analysis of terrain irregularities' impact on performance. These contributions address the gaps identified in the literature review discussed in the previous section. Accordingly, the paper is structured as follows: the creation of simulation scenarios, the development of an autonomous driving algorithm (including feedback sensors), and a performance evaluation.

First, a simulation scenario was developed to test algorithms in a controlled, repeatable environment. This includes a digital twin of a vineyard field and an autonomous driving controller. The virtual scenario replicates the 3D features of real terrain, such as elevation, camber, and banking profiles, as well as the position and orientation of grapevine rows to ensure realism. This framework enables effective testing of sensor and controller robustness, even under uneven terrain conditions. Additionally, plant width is represented using three distinct 3D models corresponding to different levels of maturity. These models differ in leaf density and plant width, with both parameters increasing as the plants mature. The plant width directly impacts the measurements taken by the virtual ultrasonic sensors integrated into the tractor. Ultrasonic sensors were chosen for their ease of use, affordability, and suitability for the agricultural sector.

Next, Model Predictive Control (MPC) was selected as the autonomous driving algorithm due to its ability to anticipate future actions and effectively address irregularities. This algorithm is designed to enable the autonomous execution of complete driving maneuvers within any designated area, including lane adherence and lane changes. The navigation process is divided into two phases: driving straight between rows of plants and performing lane changes. During the first phase, the algorithm operates within a local reference frame, utilizing ultrasonic sensors for lateral detection to ensure the tractor maintains equal spacing from the plants on both sides. For the second phase, a GNSS-IMU sensor model is employed to track the tractor's position outside the field. This model provides precise estimates of the tractor's location and orientation, facilitating accurate lane-change maneuvers.

Finally, the algorithm was evaluated through an extensive series of realistic simulations, covering a wide range of terrain and soil conditions. These simulations incorporated various combinations of micro- and macro-terrain irregularities to comprehensively assess performance across diverse scenarios.

The paper is organized as follows: Section 3 details the modeling of a realistic simulation environment. Section 4 develops the algorithm for autonomous driving, outlining its model and control scheme. Section 5 analyzes the methodologies for position measurement within the proposed framework, focusing on relative positioning with respect to plants and global positioning based on GNSS and IMU sensors. Section 6 presents simulation tests to evaluate the effects of field irregularities and terrain slope on autonomous driving performance. Finally, Section 7 summarizes the research findings and proposes avenues for future development.

3. Scenario Creation for Simulation

This section focuses on the development of a realistic virtual simulation environment designed to mimic the behavior of a real tractor equipped with sensors operating in a vineyard. The process begins with the user selecting a geo-referenced field from a 2D map. Based on this input, the algorithm generates the elevation profile of the cultivated terrain by leveraging the Google Maps API, which provides the altitude data for points within the selected field. Additionally, using the field's corner positions, the start and end points

of the first vine row, and the distance between rows as inputs, the algorithm accurately positions the vine plants within the field. Figure 1 compares the real plant distribution to the computed vine placement, demonstrating the accuracy of the spin generation.

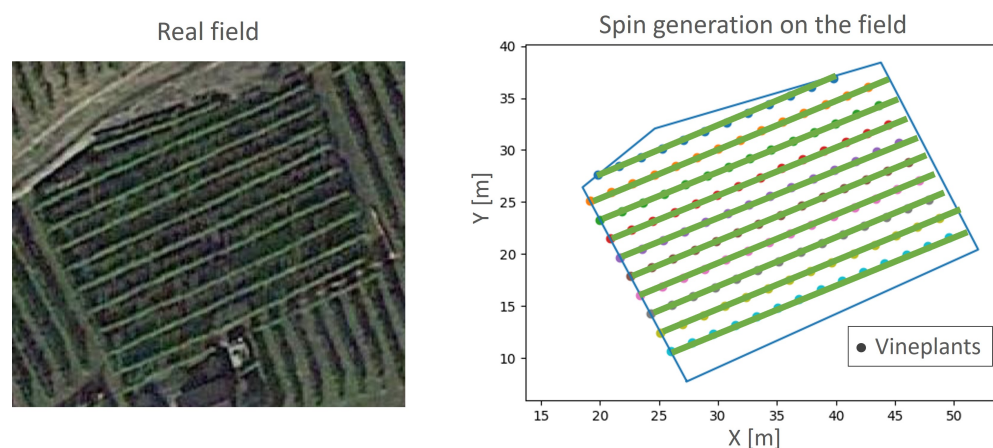


Figure 1. Comparison of the real plant distribution with the spin generation.

Once the 2D plant positions are determined, their heights are assigned using the elevation data from the Google API. Figure 2 illustrates the crop field's elevation profile and the corresponding plant altitude distribution.

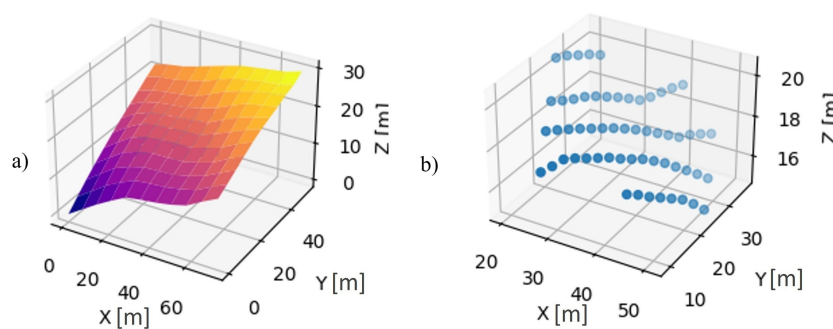


Figure 2. Elevation profile (a) and plant altitude distribution (b).

An example of the created environment is shown in Figure 3, which provides a perspective view of the digital twin generated in TruckMaker.

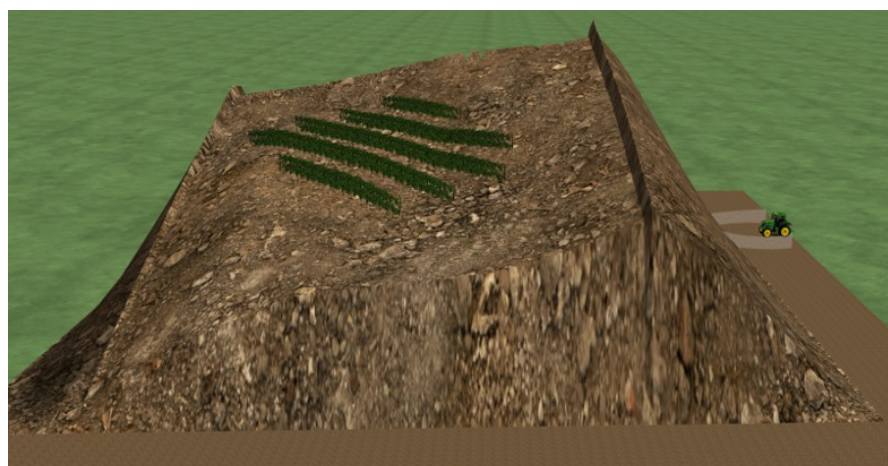


Figure 3. Perspective view of the digital twin in TruckMaker [26].

The simulations are conducted using TruckMaker by IPG [26] and AgriSI [27], as referenced in [25]. These tools incorporate a highly realistic 18-DOF vehicle model, simulate tire-soil interactions, and mimic sensor behavior. The virtual vineyard includes vines modeled with three distinct maturity levels. As plants mature, their width increases, as depicted in Figure 4.

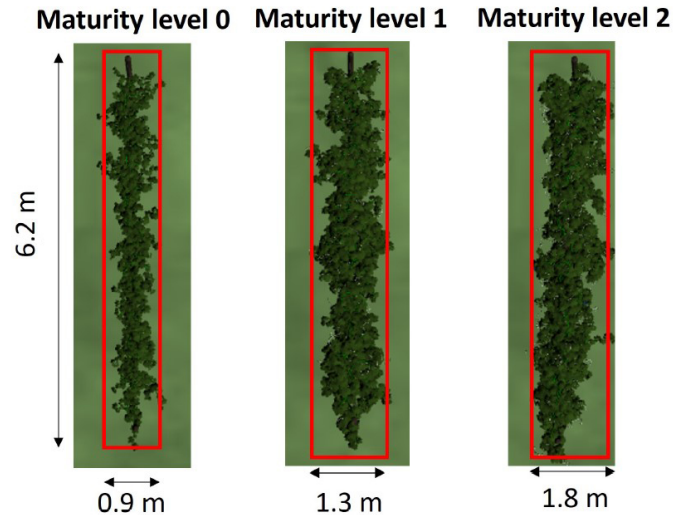


Figure 4. Increase in plant width as a function of maturity level.

To evaluate the proposed control architecture under realistic conditions, a simulation scenario was created in TruckMaker to replicate a challenging vineyard environment. The vine rows are arranged following a parabolic distribution to introduce a more demanding reference trajectory, which tests the MPC controller's tracking performance. Additionally, the simulation incorporates plants with varying maturity levels, randomly distributed throughout the field. Figure 5 illustrates the plant distribution (in red) and the optimal trajectory (in blue) that the tractor is expected to follow. The trajectory accounts for variations due to plant maturity and optimally positions the tractor between rows, with U-turns oriented based on the endpoints of each straight segment (as detailed in Section 4).

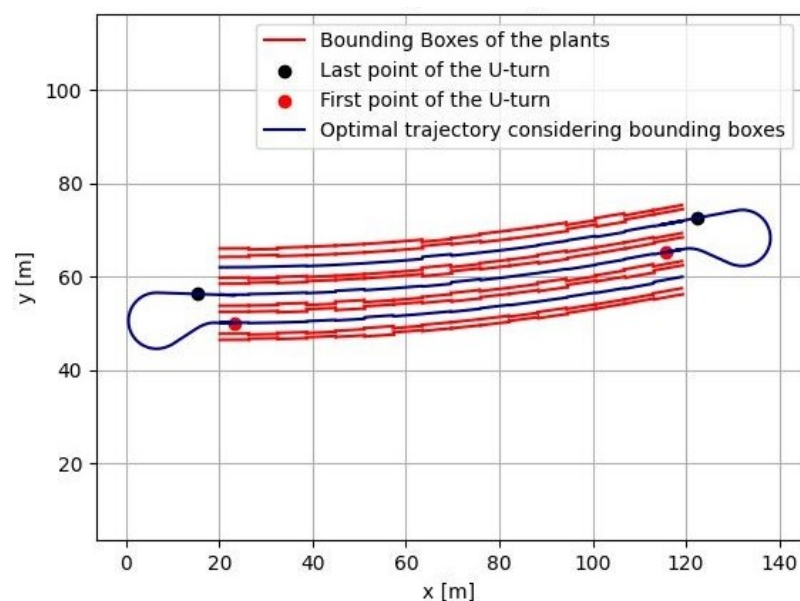


Figure 5. Complete trajectory to be followed in the testing scenario.

A 3D terrain morphology is generated by combining elevation, slope, and camber profiles, as shown in Figure 6. The elevation profile represents vertical height changes along the longitudinal axis (X), ranging from 0 to 10 meters to simulate realistic field variations. The slope profile describes the gradient or incline of the terrain along the lateral axis (Y), starting from an initial elevation (A) and modifying the terrain, reaching a maximum value of 0.05 m/m. The camber profile represents the transverse tilt of the terrain, simulating the inclination from the center-line to the edge, with a maximum value of 0.0005 m/m².

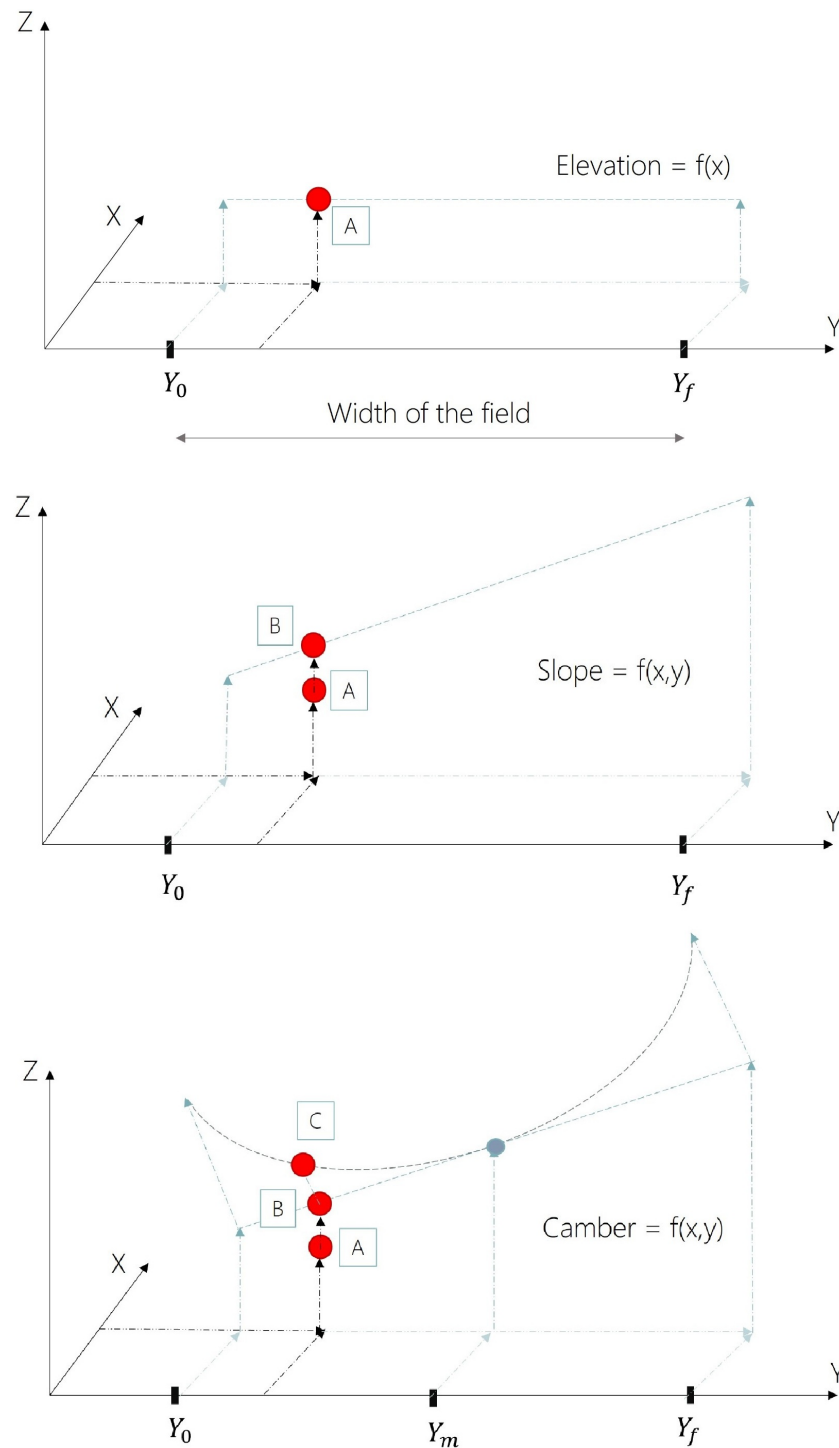


Figure 6. Schematic of the elevation, slope and camber profiles applied in the simulation environment.

These three parameters (elevation, slope, and camber) are collectively referred to as terrain macro-irregularities. The resulting 3D terrain morphology, shown in Figure 7, represents a challenging environment characterized by significant slopes and altitude variations, rigorously testing the robustness of the controller.

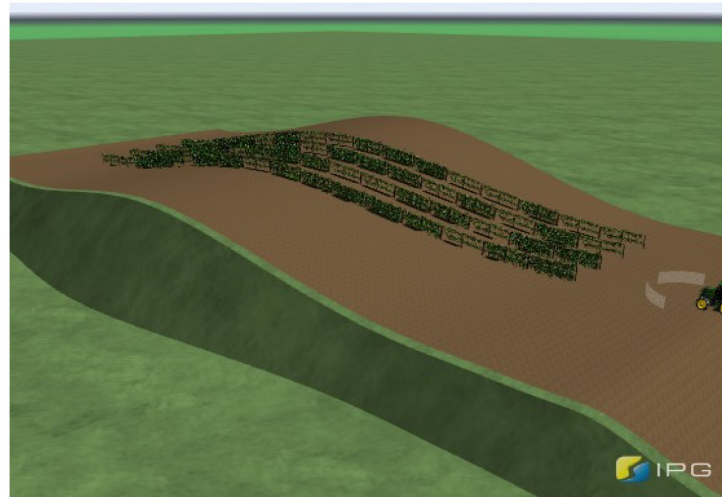


Figure 7. Complete 3D trajectory in the testing scenario.

Additionally, variations in road roughness were introduced to analyze the impact of micro-irregularities on control performance. These micro-irregularities are modeled as sinusoidal waves applied throughout the field, rotated by 60 degrees to generate lateral forces on the vehicle. The wave period is set to 1 m to mimic typical terrain unevenness. Amplitude values range from 0.025 to 0.065 m to test the effect of varying roughness profiles. Table 1 summarizes these parameters.

Table 1. Parameters of the sinusoidal wave roughness.

Parameter	Value
Rotation around z direction [deg]	60
Height in z direction [m]	0.025 to 0.05
Wave period [m]	1

Considering, for example, the amplitude equal to 0.025, the roughness can be expressed as in Equation (1):

$$Z(X, Y) = 0.025 \sin(2\pi[X \cos(60^\circ) + Y \sin(60^\circ)]) \quad (1)$$

4. MPC Controller

This section outlines the development of a control framework designed to autonomously navigate a tractor along vineyard rows and execute U-turn maneuvers to transition between rows. Additionally, the control architecture accounts for the impact of uneven terrain by utilizing feedback measurements from onboard sensors.

The control framework employs a Model Predictive Control (MPC) approach [28], implemented using MATLAB/ Simulink (R2023a), and validated in AgriSI (v2.1). The framework accommodates varying maturity levels of vine plants. To compute optimal control actions, the MPC leverages a 3DOF vehicle model, which is well-suited for vineyard navigation due to the tractor's low operational speeds. The real vehicle used as a reference for this research is the "John Deere 6R 120" tractor [29].

Table 2 illustrates the main parameters of the real vehicle implemented in the simplified 3 DOF vehicle model described in the next subsection.

Table 2. Vehicle model parameters.

Parameters of the Vehicle Model	Symbol	Value
Total mass [kg]	m	6200
Yaw moment of inertia [kgm^2]	I_Z	8549.216
Longitudinal acceleration tracking time constant [s]	τ	0.5
Longitudinal distance from COG to front tires [m]	L_F	1.52306
Longitudinal distance from COG to rear tires [m]	L_R	1.0574
Vertical distance from COG to axle plane [m]	h_f	0.95
Front width track [m]	w_F	1.95
Rear width track [m]	w_R	1.85
Wheel base [m]	W_B	2.58
Traction	-	Rear
Steering system	-	Front Wheel Driving

4.1. Vehicle Model

In this research, the linearized vehicle model utilized within the controller is represented using general state-space equations:

$$\dot{s} = As + Bu \quad (2)$$

$$q = Cs \quad (3)$$

where, s , u and q represent the states, inputs and outputs of the model, while A , B and C are the state, input and output matrices, respectively. $\dot{s}$ is the derivative of state variables with respect to time.

Building upon the general state-space formulation presented above, the state-space model describing the combined lateral and longitudinal dynamics of the vehicle can be expressed as

$$\frac{d}{dt} \begin{bmatrix} V_y \\ \dot{\psi} \\ V_x \\ \dot{V}_x \end{bmatrix} = \begin{bmatrix} -\frac{2C_f+2C_r}{mV_x} & -V_x - \frac{2C_f l_f - 2C_r l_r}{mV_x} & 0 & 0 \\ -\frac{2C_f l_f - 2C_r l_r}{I_z V_x} & -\frac{2C_f l_f^2 + 2C_r l_r^2}{I_z V_x} & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & -\frac{1}{\tau} \end{bmatrix} \begin{bmatrix} V_y \\ \dot{\psi} \\ V_x \\ \dot{V}_x \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 0 \\ \frac{1}{\tau} \end{bmatrix} \begin{bmatrix} \frac{2C_f}{m} \\ \frac{2C_f l_f}{I_z} \\ 0 \\ 0 \end{bmatrix} \begin{bmatrix} a_x \\ \delta \end{bmatrix} \quad (4)$$

$$\begin{bmatrix} V_y \\ \dot{\psi} \\ V_x \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} V_y \\ \dot{\psi} \\ V_x \\ \dot{V}_x \end{bmatrix} \quad (5)$$

The state, output and input are, respectively, equal to $s = \begin{bmatrix} V_y \\ \dot{\psi} \\ V_x \\ \dot{V}_x \end{bmatrix}$, $q = \begin{bmatrix} V_y \\ \dot{\psi} \\ V_x \end{bmatrix}$, and

$u = \begin{bmatrix} a_x \\ \delta \end{bmatrix}$. Where, a_x is the longitudinal acceleration in m/s^2 and δ is the steering angle in rad. V_x is the longitudinal velocity in m/s , V_y is the lateral velocity in m/s and $\dot{\psi}$ yaw angle rate in rad/s . The longitudinal acceleration tracking time constant τ is an dimensionless scalar that ranges from 0 to 1. It represents the time it takes for a vehicle's actual acceleration $\dot{V}_x$ to reach a desired one, accounting for system dynamics delays (a smaller τ indicates

faster response). C_F and C_R are the corner stiffness of the front and rear tires parameter, respectively, in N/rad. τ , C_F and C_R values were obtained from CarMaker and AgriSI simulator, which represent a typical commercial tractor, while the other parameters were derived from a real tractor as mentioned in Table 2.

4.2. Control Scheme

In order to navigate the vineyard field, the overall decision-making algorithm is divided into three distinct tasks in the form of a state machine (schematized in Figure 8):

- Idle: This phase lasts for a few meters to ensure that the environment is fully loaded and that the tractor is positioned correctly. During this state, the MPC is inactive, and the steering angle remains zero.
- Straight: In this phase, the tractor autonomously drives between the plant rows while maintaining an equal lateral distance from both sides of the tractor.
- U-turn: This phase is responsible for executing the lane-change maneuver.

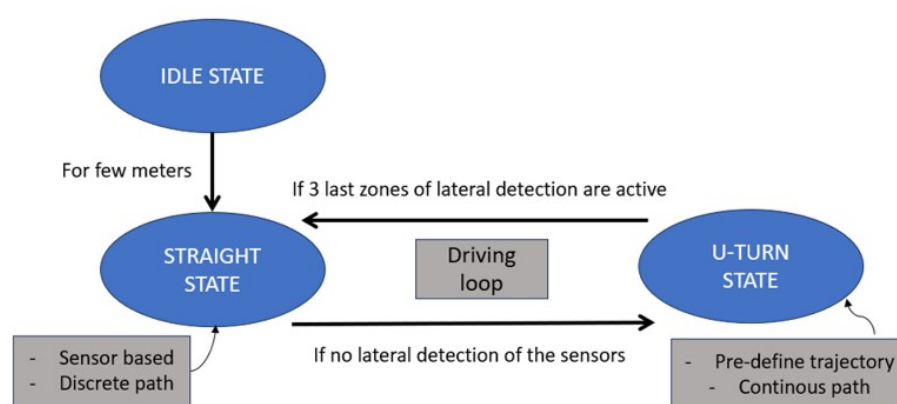


Figure 8. States of the overall decision making algorithm.

In the straight state, the tractor, equipped with two ultrasonic sensors, calculates the lateral distances from the plants relative to the vehicle. To create a reference trajectory, the sensor's detection range is divided into seven longitudinal zones in front of the tractor on each side, generating a discrete path to be followed by calculating the mean position. Refer to Figure 9.

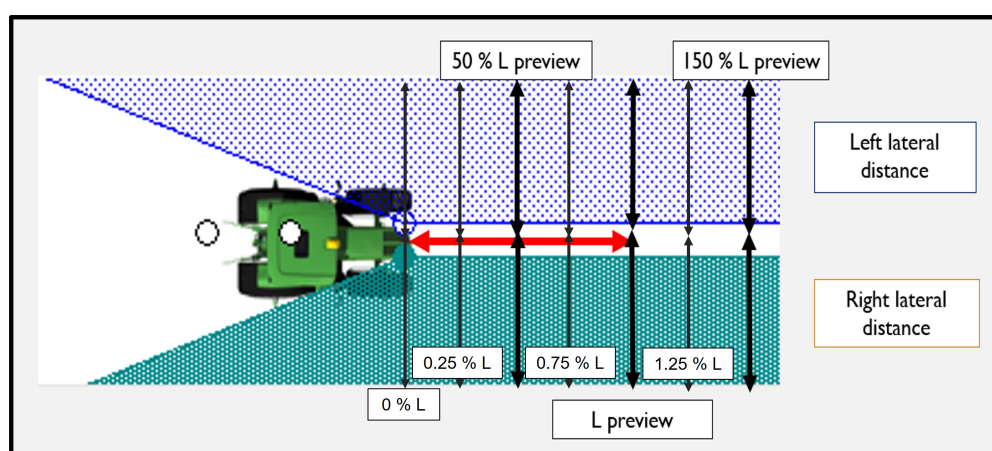


Figure 9. Seven detection zones.

In this state, the controller's output is solely the steering angle, as the longitudinal velocity is maintained constant at 15 km/h. The MPC is executed via the Simulink "Lane

Keeping Aid System" (LKA) toolbox [30]. This system takes the vehicle's longitudinal speed and desired trajectory information as input, such as the current curvature, lateral deviation, and relative yaw angle of the vehicle with respect to the trajectory. The LKA system's ability to maintain the vehicle's trajectory is utilized by continuously adjusting the steering angle based on sensor inputs, using MPC to adjust the lateral dynamics model accordingly. The goal of lane-keeping control is to minimize both lateral deviation (from the reference trajectory) and relative yaw angle (from the reference curvature). Figure 10 represents a simplified scheme of the MPC controller's working principle. The positions of the left and right lanes are measured by the sensors, from which a centerline is interpolated, and the lateral deviation and relative yaw angle of the vehicle with respect to this line (e_1 and e_2 respectively) are computed.

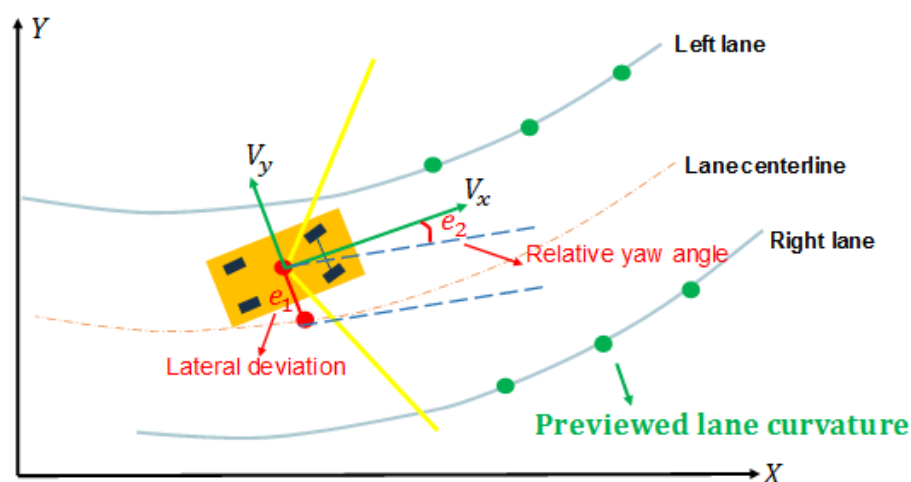


Figure 10. Scheme of the MPC states and feedback errors [30].

The transition from the straight to the turning state is triggered when the sensors no longer detect anything on either side of the tractor. The goal of the turn state control is to follow a trajectory based on the distance between consecutive lanes and the minimum turning radius of the tractor, as shown in Figure 11. The path will be located and oriented according to the last point of the in-row straight state.

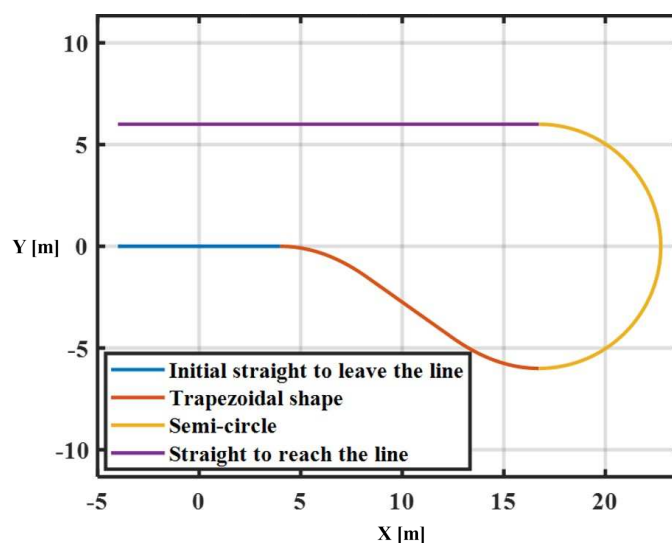


Figure 11. Reference X-Y trajectory to be followed during the U-turn maneuver.

To execute this path, it is crucial to know the position and orientation of the tractor during the maneuver. Additionally, the speed must be reduced to approximately 5 km/h to perform the turn with a small radius. Consequently, the MPC must also account for the longitudinal model. For this state, the Simulink “Path Following Control System” toolbox [31] is used. This block combines the LKA and “Adaptive Control System” to navigate the desired trajectory by adjusting both the steering angle and longitudinal acceleration of the tractor using MPC. The optimal outputs are determined by considering the combined lateral and longitudinal model, with the goal of minimizing the lateral deviation and relative yaw angle of the vehicle relative to the predefined path. In this case, the scheme of the MPC algorithm at the U-turn is represented in Figure 10, with the centerline now representing the U-turn trajectory defined in Figure 11.

The turn is considered complete when the three detection zones furthest from the tractor are active, ensuring that the system has reached the beginning of the next lane, thus enabling the transition back to the straight state. The main parameters of the MPC controller used in the simulation are shown in Table 3.

Table 3. Control parameters for straight and U-turn states.

Variables	Control Parameters	Straight State	U-Turn State
T_s	Sample time [s]	0.5	0.5
p	Prediction horizon [steps]	12	20
c_h	Control horizon [steps]	-	6
cb	Controller behavior	0.5	-
w_v	Weight on velocity tracking	0.1	-
w_a	Weight on change of longitudinal acceleration	0.1	-
w_e	Weight on lateral error	1	-
w_{st}	Weight on change of steering angle	0.1	-

The first four parameters are related to the definition of MPC prediction and control horizons. In particular, c_b is a scalar between 0 and 1; smaller values result in a more robust controller with smoother control actions, while larger values produce a more aggressive one. The last four parameters represent the weights used in the standard MPC cost function. These weights penalize deviations in system states, control inputs, and their rates of change to balance the trade-off between performance and control effort.

5. Sensors

This section analyzes the implementation and performance of sensors for detecting the position of the plants with respect to the tractor in a local reference frame, which is crucial for straight-state control, and for measuring the global position of the vehicle in the field, which is fundamental for the U-turn.

5.1. Local Sensors

Currently, the most commonly used ranging sensors in outdoor environments are Lidar and ultrasonic sensors. Due to the high cost of Lidar, ultrasonic sensors were selected for this analysis as they are both affordable and easy to use. In the AgriSI simulation environment, a set of features is available to emulate real the functionality of an ultrasonic sensor, in this work based on [32]. The Free Space sensor was chosen for this analysis as it detects the bounding box that limits the 3D image of the plant. Figure 12 shows the lateral distance measurements obtained from a simulation of an ideal tractor driving perfectly along the centerline compared to the real values obtained by the sensors. Moreover, knowing the tractor’s geo-referenced position allows the recreation of the position and width of the plants in the field, as illustrated in Figure 13.

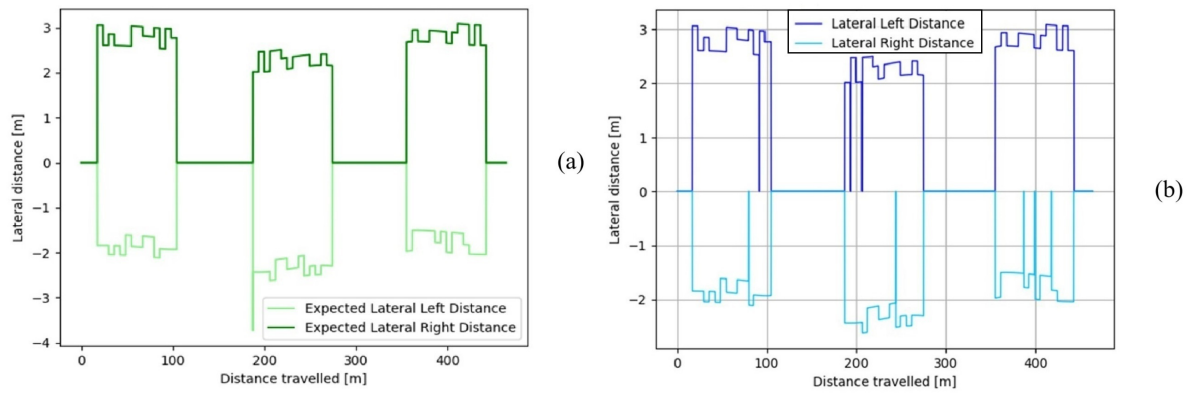


Figure 12. Lateral distances measured by Free Space sensors (b) versus expected ones (a).

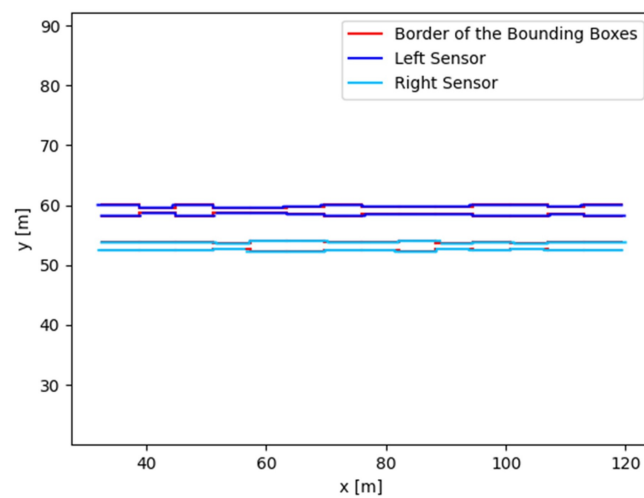


Figure 13. Recreated field using Free Space sensor over the actual bounding box positions of the plants.

The generated map evaluates sensor precision by calculating the percentage of correct width estimations, as defined in Equation (6). The map is compared to the “ground truth”, represented by the actual plant widths and positions in the simulation environment. In this context, P_i represents the percentage of correct estimations for each width “level” (dependent on the maturity of the plant), where subscript $i = 1, 2$, or 3 . N_{M_i} denotes the number of vine plants at the i width value, i is the number of detections made by the sensor per length of the plant. and NCR_{M_i} indicates the number of correct recreations of the width x .

$$P_i = \frac{NCR_{M_i}}{N_{M_i} \times ds} \times 100\% \quad (6)$$

The map generated by the Free Space sensor achieves detection performances of 89%, 92%, and 94% for the three different plant maturity levels (1, 2, and 3, respectively), providing an accurate overview of the field.

Thus, the exact knowledge of the tractor’s global position was used to evaluate plant widths and recreate the field map, assessing the precision of the local sensors. However, this assumption will be omitted in subsequent sections to evaluate the proposed autonomous driving algorithm’s performance in the presence of measurement errors in the tractor’s global position.

5.2. Global Sensors

This section introduces three methodologies for estimating the vehicle's position and orientation, which are essential for controller design and for performing the U-turn at the end of a row.

The first method simulates vehicle behavior using an analytical 3DOF dynamic model of the tractor in open loop. While it provides accurate results during the early stages of the simulation, accumulated errors due to unmodeled effects, noise, and terrain irregularities degrade performance over time, as shown in Figure 14.

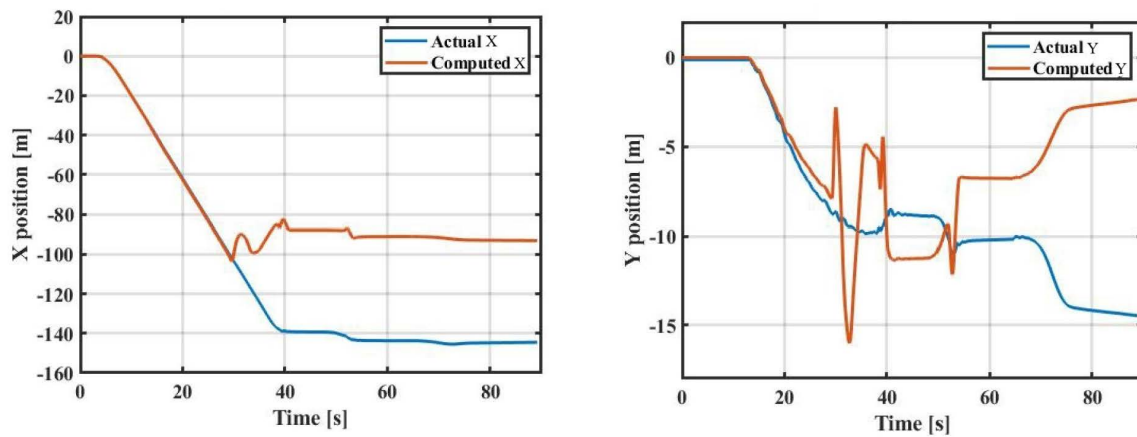


Figure 14. Comparison of the actual X and Y positions with the ones obtained with the blind model.

The second approach uses a GNSS sensor to measure the tractor's absolute X-Y position. However, to fully locate the vehicle, its orientation must also be determined. The yaw angle γ can be roughly estimated by evaluating the angle between two closely spaced points. To limit noise, a moving average filter with a window of 10 measurements is applied. The points are divided into two subsets of five points each then, X and Y coordinate of each point is used to calculate the mean X and Y position of each subset: $(Y_{\text{mean_group1}}, Y_{\text{mean_group2}}, X_{\text{mean_group1}}, X_{\text{mean_group2}})$. Then, the yaw angle can be estimated as reported in Equation (7):

$$\gamma(t) = \arctan\left(\frac{Y_{\text{mean_group1}} - Y_{\text{mean_group2}}}{X_{\text{mean_group1}} - X_{\text{mean_group2}}}\right) \quad (7)$$

This method estimates the tractor's position with reasonable accuracy, as shown in Figure 15. However, it provides a noisy and biased yaw angle estimation, as seen in Figure 16.

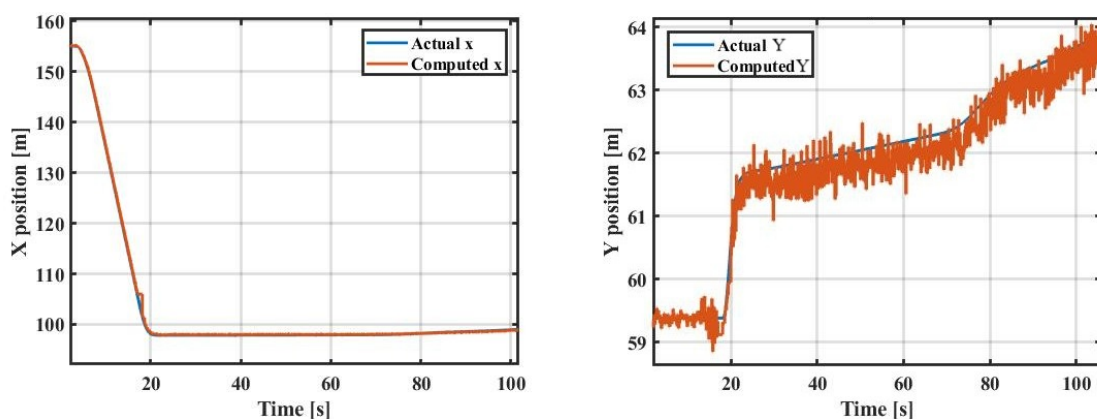


Figure 15. Comparison of the actual X position with the one computed by the GNSS.

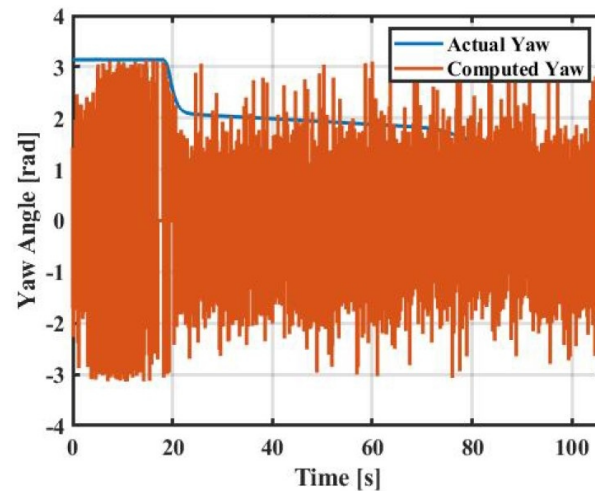


Figure 16. Comparison of the actual orientation with the one computed by the GNSS.

The limited accuracy of this positioning technique is attributable to different error sources, including: satellite errors, propagation errors and receiver errors [33]. Thus, estimation accuracy is influenced by the simulation environment's ability to replicate the intrinsic noise of real sensors, thereby enhancing simulation realism. Since yaw angle estimation based solely on GNSS data proves to be extremely noisy, an additional Inertial Measurement Unit (IMU) sensor is proposed to improve orientation approximation. While the angular velocity measured along the axis orthogonal to the tractor does not typically match the yaw rate of the vehicle, this assumption holds reasonably well under the specific operational conditions of a tractor operating at low speeds within a vineyard. In such cases, the yaw angle can be integrated using the equation reported in Equation (8).

$$\gamma(t) = \gamma_0 + \int_0^t \dot{\gamma}(t) dt \approx \gamma_0 + \dot{\gamma}(t)t \quad (8)$$

The comparison between the IMU-based estimation and the real yaw angle provided by AgriSI is shown in Figure 17.

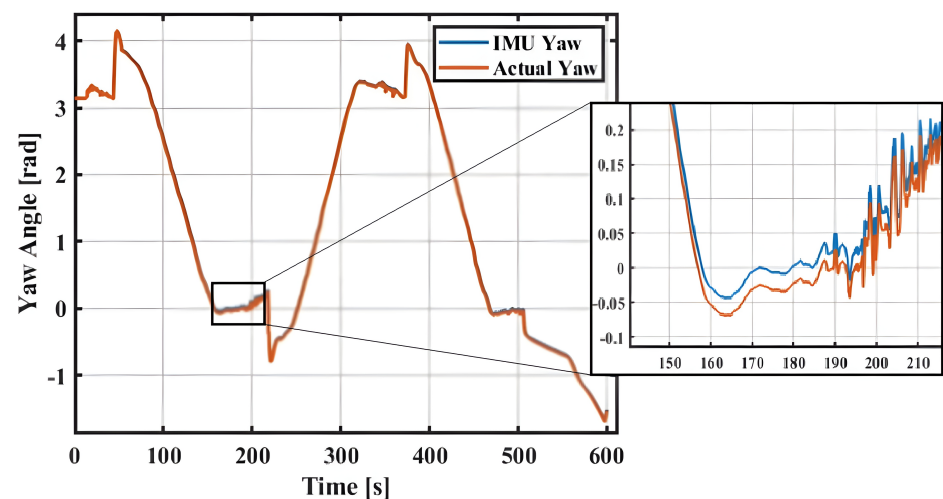


Figure 17. Comparison between the real yaw angle and the computed with IMU sensor.

Future work could explore more refined estimators, such as Kalman filters as in [34], to mitigate sensor noise and disturbances from soil roughness. However, noise reduction is beyond the scope of this paper. Considering the terrain unevenness parameters reported in

Section 3, the satisfactory accuracy achieved with Equation (8) supports its exclusive use in subsequent simulations.

6. Performance Evaluation

Referring to the testing scenario described in Section 3, the lateral deviation of the vehicle from the reference position (the centerline of the reference trajectory shown in Figure 5) at the i -th point of the simulated trajectory is computed using Equation (9):

$$\epsilon = y_{\text{reference}} - y_{\text{real}} \quad (9)$$

To evaluate the effectiveness of trajectory tracking, the Root Mean Square Error (RMS) is calculated using Equation (10).

$$\text{RMS} = \sqrt{\frac{1}{n}(\epsilon_1^2 + \epsilon_2^2 + \dots + \epsilon_n^2)} \quad (10)$$

6.1. Influence of Sensors

This section evaluates the significance of vehicle localization accuracy by comparing it to the controller's performance under the assumption that the tractor's position and orientation are perfectly known. This "ideal" scenario represents the best possible outcome for the MPC model developed in Section 4. Notably, the RMS error in this case is not zero, as the control algorithm cannot perfectly follow the reference trajectory due to its complexity, which arises from the varying maturity levels (widths) of the plants. These differences result in a piecewise-defined reference trajectory, as illustrated in Figure 5.

An initial set of simulations is conducted in a simplified virtual environment that excludes the effects of 3D terrain profiles and soil roughness, thereby neglecting macro and micro irregularities. The comparison aims to evaluate the impact of localization errors on the overall controller performance. Results are presented separately for two driving phases: straight-line performance and U-turn performance. Figure 18 clearly highlights how the simplified tractor model and absolute state estimation errors significantly affect U-turn performance, while their impact on straight-line performance is negligible.

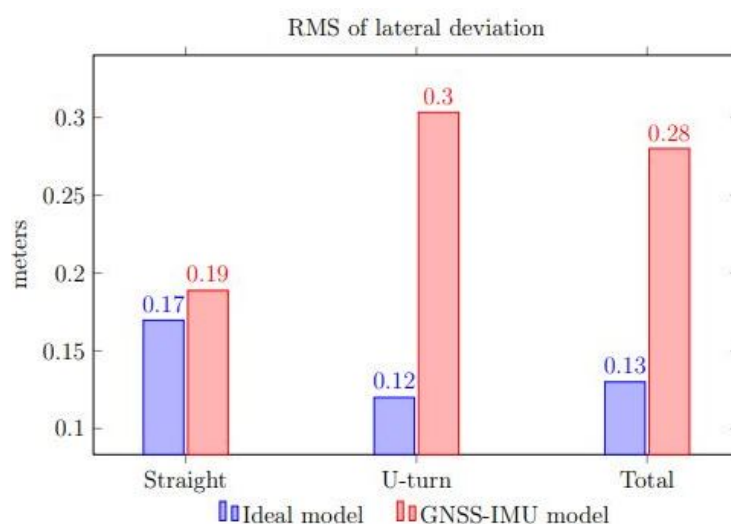


Figure 18. Comparison between the ideal and the GNSS-IMU model performance in terms of RMS of lateral deviation with respect to testing trajectory in Figure 5.

Although straight-line control (within lanes) depends solely on relative measurements provided by ultrasonic sensors and not on absolute vehicle position, an unexpected increase in lateral RMS error is observed. This behavior stems from errors during the U-turn phase,

which introduce an initial lateral deviation when the tractor enters the next lane at the beginning of the straight-line phase.

The U-turn controller strategy, which relies on a pre-defined trajectory, is highly sensitive to position estimation errors, as demonstrated by the simulation results.

6.2. Influence of Roughness

The second analysis examines the effect of micro-irregularities on the road surface, assuming a flat terrain scenario that neglects macro-irregularities. From this point forward, state estimation using GNSS-IMU sensors is consistently adopted as the baseline case. This choice ensures that the analysis focuses exclusively on the impact of varying micro-waviness heights. As shown in Figure 19, an expected trend emerges: as road imperfections increase, the accuracy of the results decreases.

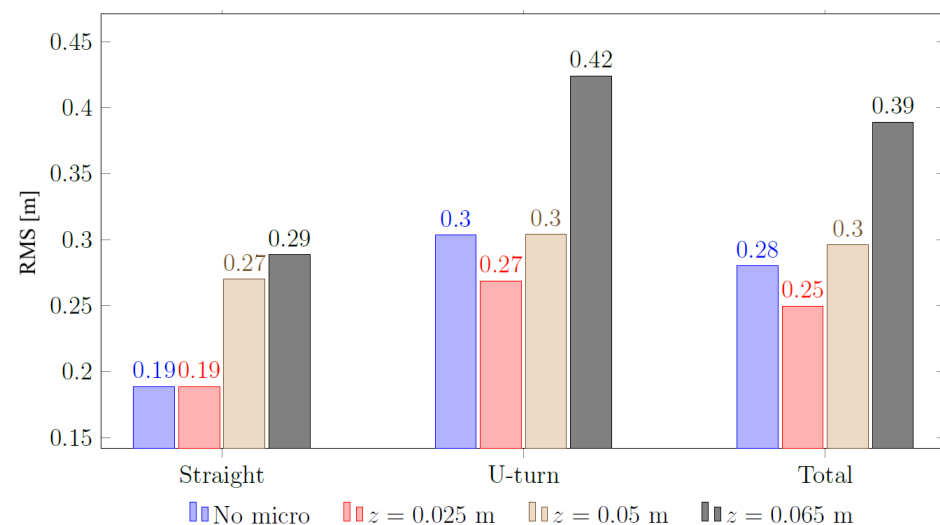


Figure 19. Analysis of the effect of micro-irregularities, in the GNSS-IMU model, on the RMS of lateral deviation from the testing trajectory in Figure 5.

Typically, an accurate representation of a vineyard field includes simulating greater roughness heights in the field's center and lower values in the U-turn areas, reflecting the wear and tear in those regions. The results obtained in this section align with these expectations. The expected waviness outside the field ranges from 0.025 to 0.065 meters. For such imperfections, the U-turn errors exhibit minimal deviation from the ideal case, while the straight-line errors are expected to average around 0.05 meters, which is considered acceptable.

6.3. Influence of 3D Shape

The third comparison incorporates the elevation and banking profiles, as previously defined in Figure 7, while neglecting terrain roughness.

Figure 20 illustrates the impact of elevation and slope profiles on the performance of the control architecture compared to plain terrain conditions (represented in red in Figure 18). The results demonstrate a strong correlation between tracking errors and macro irregularities.

Unlike the case of micro irregularities, the greater magnitude of macro irregularities causes a more uniform reduction in performance. This diminishes the disparity between U-turns and straight-line maneuvers, leading to a comparable level of performance degradation in both scenarios.

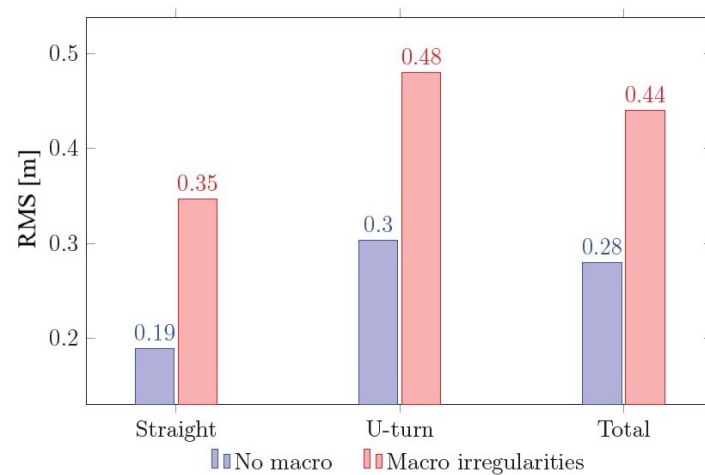


Figure 20. Analysis of the effect of macro-irregularities, in the GNSS-IMU model, on the RMS of lateral deviation from the testing trajectory in Figure 5.

6.4. Combined Influence of Micro and Macro Irregularities

To evaluate the MPC controller's effectiveness in a realistic scenario, the simulation includes a field with both micro- and macro-irregularities. Figure 21 compares tracking performance using the RMS lateral deviation under three conditions: combined macro and micro irregularities (roughness amplitude 0.025 m and 0.05 m), macro irregularities only, and flat terrain.

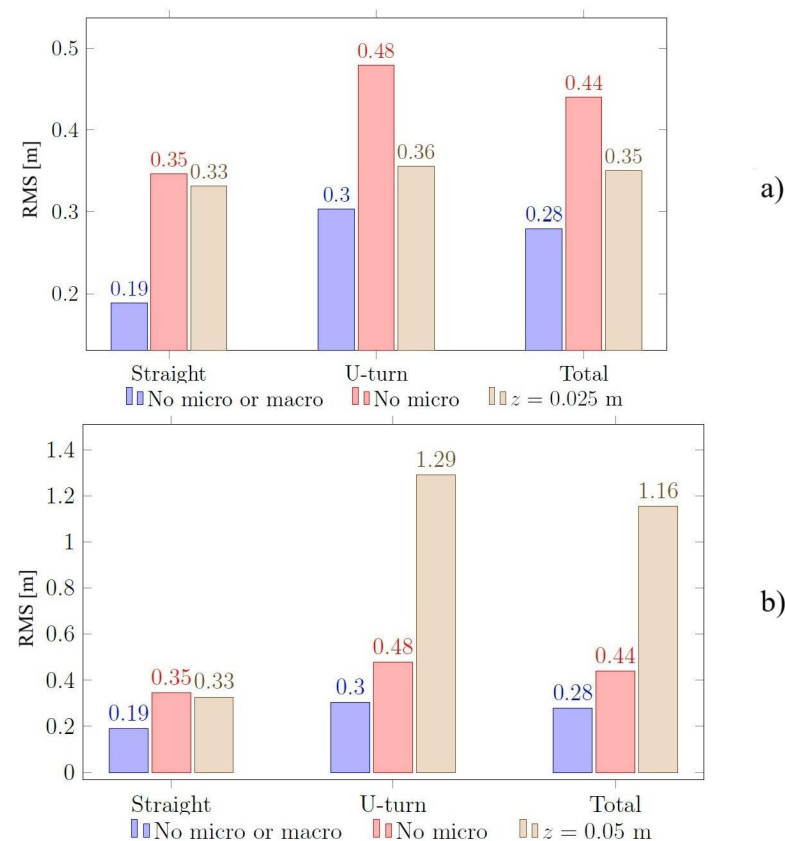


Figure 21. Analysis of the combined effect of roughness and macro irregularities, in the GNSS-IMU model, on the RMS of lateral deviation from the testing trajectory in Figure 5. Considering low roughness (a) and high roughness (b) levels.

Surprisingly, the introduction of low-level micro-irregularities (amplitude 0.025 m) improves performance during both straight line and turning maneuvers, probably due to enhanced grip and traction. This phenomenon warrants further investigation as a future research direction.

In contrast, when the tractor encounters high ground roughness (amplitude 0.05 m), significant trajectory deviations occur during U turns, while straight-line phases remain largely unaffected, as shown in Figure 21. This difference arises because straight-line control relies on local lateral deviations, while U-turn control depends on a predefined trajectory, making it more sensitive to disturbances.

7. Conclusions

This work proposes a methodology and a virtual tool for designing a digital twin of a real vineyard and a control architecture for autonomous driving both inside and outside the field as its main contributions. Specifically, the selected simulation software, in conjunction with the developed scripts, has proven to be a suitable tool for creating a virtual environment for the development and testing of advanced algorithms. This system can reproduce the altitude profile, banking, camber, and the precise positions of the vineyard rows. Additionally, it enables the detection of plant widths using virtual sensors (e.g., ultrasonic sensors, GNSS, and IMU).

Furthermore, the paper introduces a control architecture based on a state machine, where two distinct states are modeled using an MPC algorithm to define the optimal control actions. The first state controls the tractor within the plant rows, relying on local lateral detection from sensors. The second state governs the tractor outside the field, using GNSS and IMU measurements for position and orientation estimation during the U-turn maneuver. The overall control architecture demonstrates appropriate performance under both ideal conditions and in the presence of irregularities and measurement noise.

The impact of irregularities depends on the trajectory-following approach. In the straight-line case, the system shows a slight dependence on micro-irregularities but a high sensitivity to lateral slopes. In contrast, during the U-turn, the system is significantly influenced by high micro-irregularities, while its sensitivity to low roughness and the 3D road shape remains relatively constant. Moreover, the simulation results are highly sensitive to the accuracy of localization sensor data, especially since the U-turn is based on a pre-defined reference trajectory.

This paper represents a significant first step toward developing a comprehensive and realistic framework for simulating tractors in vineyards. As promising research directions, exploring advanced filtering techniques would provide valuable insights into better handling 3D dynamics and incorporating cameras. Finally, more sophisticated virtual interactions with terrain and testing the proposed system in an experimental campaign could validate the model's realism.

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Abbreviations

The following abbreviations are used in this manuscript:

2D	Two-Dimensional
3D	Three-Dimensional
API	Application Programming Interface
DOF	Degrees of Freedom
DYC	Direct Yaw Moment Control
GNSS	Global Navigation Satellite System
IMU	Inertial Measurement Unit
IPG	IPG Automotive GmbH
km/h	Kilometers per hour
LIDAR	Light Detection and Ranging
LKA	Lane Keeping Aid System
MPC	Model Predictive Control
PF	Precision Farming
RMS	Root Mean Square
SLAM	Simultaneous Localization and Mapping

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