IMPACTO CIENTÍFICO
EDITORA

ARTIFICIAL INTELLIGENCE IN AGRICULTURE 4.0: ANT COLONY APPLIED TO WATER AND NITROGEN OPTIMIZATION

INTELIGÊNCIA ARTIFICIAL NA AGRICULTURA 4.0: COLÔNIA DE FORMIGAS APLICADA À OTIMIZAÇÃO HÍDRICA E DE NITROGÊNIO

INTELIGENCIA ARTIFICIAL EN LA AGRICULTURA 4.0: COLONIA DE HORMIGAS APLICADA A LA OPTIMIZACIÓN HÍDRICA Y DEL NITRÓGENO

https://doi.org/10.56238/edimpacto2025.080-008

Manoel Villas Boas Junior[1], Thiago Marlon da Conceição Esteves Damas[2], José Roberto Duarte Hegendorne[3], Gabriel Araújo dos Santos Pereira[4], Rafael Bahiense Brasão[5], Ralfh Varges Ansuattigui[6]

ABSTRACT

This study investigates Ant Colony Optimization (ACO) as an Artificial Intelligence strategy for the joint economic tuning of water and nitrogen in iceberg lettuce and melon crops, within the Agriculture 4.0 framework. Well-established agronomic production functions from the literature are replicated and embedded in a transparent two-dimensional grid formulation, in which pheromone deposition is proportional to performance and global evaporation controls the balance between exploration and intensification. The analysis focuses on solution quality, convergence dynamics, and sensitivity to key algorithm parameters and grid resolution. The economic optima obtained with ACO are consistent with results reported for existing AI/optimization-based tools and methods (such as INTELIAGRI, MBL, and Pattern Search), including a case in which the optimum lies on the boundary of the decision domain. Net revenues are computed under a uniform economic scenario, ensuring comparability across crops and approaches. The paper concludes by summarizing practical configuration guidelines for ACO and discussing their implications for the design of decision support systems in Agriculture 4.0 aimed at efficient water and nitrogen management.

[1] Dr. in Science, Technology and Innovation in Agriculture. Universidade Estácio de Sá.
E-mail: manoel.villas@professores.estacio.br Orcid: https://orcid.org/0000-0003-4610-2005
Lattes: http://lattes.cnpq.br/2694980072582390
[2] Undergraduated student in Systems Analysis and Development. Universidade Estácio de Sá.
E-mail: thimarlon@gmail.com Orcid: https://orcid.org/0009-0001-1790-4351
Lattes: https://lattes.cnpq.br/0749510077360584
[3] Undergraduated student in Systems Analysis and Development. Universidade Estácio de Sá.
E-mail: joserd@msn.com Orcid: https://orcid.org/0009-0005-1141-3454
Lattes: http://lattes.cnpq.br/3567769065936624
[4] Undergraduated student in Systems Analysis and Development. Universidade Estácio de Sá.
E-mail: araujogabrielsp@gmail.com Orcid: https://orcid.org/0009-0007-5812-0397
Lattes: https://lattes.cnpq.br/7891317381756031
[5] Graduated in nformation Systems. Universidade Estácio de Sá. E-mail: rbahiensebraptor@gmail.com
Orcid: https://orcid.org/0009-0001-1063-191X Lattes: http://lattes.cnpq.br/3545467005698660
[6] Master's degree in Technology. Universidade Estácio de Sá. E-mail: ralfh.ansuattigui@gmail.com
Orcid: 0009-0004-4122-3021 Lattes: http://lattes.cnpq.br/8581705909697288

Keywords: Productive Efficiency. Agricultural Resource Management. Production Functions. Smart Agriculture. Bio-Inspired Optimization. Decision Support Systems.

RESUMO

Este trabalho investiga a Otimização por Colônia de Formigas (ACO) como estratégia de Inteligência Artificial para o ajuste econômico conjunto de água e nitrogênio nas culturas de alface-americana e meloeiro, no contexto da Agricultura 4.0. Para isso, são replicadas funções de produção agronômicas consolidadas na literatura, às quais se aplica uma formulação em malha bidimensional, com depósito de feromônio proporcional ao desempenho e evaporação global, de modo a equilibrar exploração e intensificação da busca. Avaliam-se sistematicamente a qualidade das soluções, a dinâmica de convergência e a sensibilidade a parâmetros-chave do algoritmo e à resolução da malha. Os ótimos econômicos obtidos pela ACO mostram-se consistentes com resultados de ferramentas e métodos de IA/otimização previamente reportados (como INTELIAGRI, MBL e PS), inclusive em cenário de ótimo localizado na fronteira do domínio de decisão. As receitas líquidas são calculadas em um enquadramento econômico uniforme, o que garante a comparabilidade entre culturas e abordagens. Por fim, são sintetizadas diretrizes práticas de configuração da ACO e discutidas suas implicações para o desenho de sistemas de apoio à decisão em Agricultura 4.0 voltados ao manejo eficiente de recursos hídricos e nitrogenados.

Palavras-chave: Eficiência Produtiva. Manejo de Recursos Agrícolas. Funções de Produção. Agricultura Inteligente. Otimização Bioinspirada. Sistemas de Apoio à Decisão.

RESUMEN

Este trabajo investiga la Optimización por Colonia de Hormigas (ACO) como una estrategia de Inteligencia Artificial para el ajuste económico conjunto de agua y nitrógeno en los cultivos de lechuga iceberg y melón, en el contexto de la Agricultura 4.0. Para ello, se replican funciones de producción agronómicas consolidadas en la literatura, a las que se aplica una formulación en malla bidimensional, con depósito de feromonas proporcional al desempeño y evaporación global, con el fin de equilibrar la exploración y la intensificación de la búsqueda. Se evalúan sistemáticamente la calidad de las soluciones, la dinámica de convergencia y la sensibilidad a parámetros clave del algoritmo y a la resolución de la malla. Los óptimos económicos obtenidos mediante ACO son consistentes con los resultados de herramientas y métodos de IA/optimización previamente reportados (como INTELIAGRI, MBL y PS), incluso en escenarios en los que el óptimo se localiza en la frontera del dominio de decisión. Los ingresos netos se calculan dentro de un marco económico uniforme, lo que garantiza la comparabilidad entre cultivos y enfoques. Por último, se sintetizan directrices prácticas para la configuración de la ACO y se discuten sus implicaciones para el diseño de sistemas de apoyo a la decisión en Agricultura 4.0 orientados al manejo eficiente de los recursos hídricos y nitrogenados.

Palabras clave: Eficiencia Productiva. Manejo de Recursos Agrícolas. Funciones de Producción. Agricultura Inteligente. Optimización Bioinspirada. Sistemas de Apoyo a la Decisión.

1 INTRODUCTION

The continuous increase in global demand for food, driven by population growth and the expansion of markets, imposes on agriculture the challenge of producing more using less water and inputs. Agriculture consumes about 70% of the available fresh water, but only 0.3% of terrestrial reserves are effectively accessible for human consumption. The water crisis already affects a large part of the world's population (FAO, 2011). This scenario reinforces the need for decisions on water use that increase productivity with efficiency and sustainability. In addition to the limited volume, there is great temporal and spatial variation in water availability; More frequent droughts and competition with urban and industrial uses increase the pressure on irrigation. Traditional methods still generate waste through evaporation, leaks and uneven distribution, causing part of the water not to be used by plants. In summary, the central problem is to define how much, when and where to apply water to sustain productivity without aggravating the water situation.

Within the scope of Agriculture 4.0, Artificial Intelligence (AI) techniques, especially nature-based metaheuristics, have been explored to support irrigation and fertilization decisions. Ant Colony Optimization (ACO) is a collective search approach inspired by the self-organized behavior of social ants, in which agents cooperate indirectly through pheromone. This mechanism combines exploration and intensification of solutions through the reinforcement of successful trajectories and evaporation, which preserves the system's exploratory capacity. ACO has been shown to be efficient in continuous and discrete problems, being applicable to multivariable decision agricultural scenarios, such as the simultaneous allocation of water and nitrogen under cost constraints.

The production functions used in this work derive from widely recognized agronomic studies: **Silva et al. (2008)** for the culture of iceberg lettuce *(Lactuca sativa L.)* and **Monteiro et al. (2006)** for melon *(Cucumis melo L.)*element. "In both cases, second-order polynomial models were obtained experimentally" by varying irrigation depths and nitrogen doses, generating continuous productivity models with high explanatory power. These models allow to mathematically represent the joint effect of inputs in specific decision domains, serving as a reliable basis for investigating optimization procedures in a controlled and reproducible environment.$(w)(n)(y)$

In this study, ACO is applied directly to these production functions with the goal of maximizing net revenue under a defined pricing and cost scenario. To this end, the two-dimensional decision space is discretized, the performance of each candidate is evaluated by the economic objective function and the pheromone is updated according to the quality obtained, with global evaporation to prevent stagnation. In this configuration, it is sought to verify the feasibility of the ACO, to characterize its convergence behavior in the proposed framework and to observe, in a controlled manner, the effects of relevant parameters, preserving comparability with the original empirical functions and avoiding extrapolations beyond the experimental scope.(w, n)

2 DEVELOPMENT

2.1 LITERATURE REVIEW

Ant Colony Optimization (ACO) emerged as a metaheuristic inspired by the cooperative behavior of social ants, in which pheromone reinforcement and evaporation regulate, respectively, intensification and exploration throughout the search. The inaugural formulation was presented by **Dorigo (1992),** who introduced the idea of indirect learning (stigmergy) as a central mechanism for building solutions.

The formalization of the method and its variants, including transition rules, pheromone deposit schemes and the role of parameters , and , was systematized by $(\alpha)(\beta)(\rho)$**Dorigo and Stützle (2004).** In this synthesis, the selection of movements is driven by probabilities proportional to the historical influence (pheromone) and the heuristic visibility of the problem, mediated by exponents that adjust the balance between memory and instantaneous evidence.

For problems of a continuous nature, it is common to represent the domain by a controlled discretization (mesh), which provides transparency about computational resolution and cost, and facilitates the enforcement of constraints. Although the classic literature on population metaheuristics (such as Particle Swarm Optimization) deals with continuous space directly, **Kennedy and Eberhart's (1995)** and **Clerc's (2006)** discussions of stability, parameterization, and search sensitivity highlight the challenges of this domain. The discretization strategy can be seen as an analogous approach to the use of ACO when one wants to preserve dependencies between decision variables, offering control over resolution and computational cost.

In recent applications of Agriculture 4.0, ACO has been combined with sensors and learning models to support resource allocation and energy efficiency in connected environments. An example is the Bi-LSTM–ACO arrangement proposed by **Rathi and Gomathy (2025),** which integrates prediction (bidirectional recurrent neural network) and ant colony optimization for irrigation/energy decisions, illustrating the relevance of ACO in intelligent and automated system scenarios.

In the present study, we adopted the canonical transition rule according to **Dorigo and Stützle, 2004**. Given a state and the viable set, the probability of choosing is$(r)(M_k)(s \in M_k)$

$$P(r,s) = \frac{\tau(r,s)^{\alpha}\eta(r,s)^{\beta}}{\sum_{u\in M_k} \tau(r,u)^{\alpha}\eta(r,u)^{\beta}}, \quad s \in M_k. \qquad (1)$$

After each iteration, a deposit proportional to the quality and overall evaporation is applied, balancing exploitation-intensification:$(1-\rho)$

$$\Delta\tau_{ij}^{k} = \{\frac{Q}{L}{}_{k}, se\ (i,j)\ is\ part\ of\ the\ ant's\ path\ k\ 0, otherwise \qquad (2)$$

$$\tau_{i,j} \leftarrow (1-\rho)\,\tau_{i,j};\ \ \forall(i,j) \in A \qquad (3)$$

The combination of e-guided probabilistic choice and deposit-evaporation refresh produces a procedure that is simple to reproduce and flexible enough to incorporate penalty constraints, adjust the resolution of the discretization, and test different configurations. $\tau\eta(\alpha,\beta,\rho)$

From a conceptual point of view, ACO exemplifies the view of metaheuristics as general search strategies, with simple but effective mechanisms to guide exploration and intensification, as discussed by **Sørensen (2015)** in his critical analysis of the "metaphor" in metaheuristics.

2.2 PROBLEM MODELING

2.2.1 Production functions and domains

The production functions used reproduce, without change in shape or coefficients, the quadratic adjustments published for the crops in reference agronomic studies: iceberg lettuce in **Silva et al. (2008)** and melon in **Monteiro et al. (2006),** both obtained from experiments with variation of irrigation depth (water, mm) and nitrogen dose (nitrogen,), with domains for lettuce and melon. The equations and coefficients (with their) are:$wnkg \cdot ha^{-1}([100{,}250] \times [0{,}250])([0{,}700] \times [0{,}350])r^2$

- Iceberg lettuce

$$y_{alf}(w,n) = -12{,}490 + 388{,}1\,w - 6{,}02\,n - 1{,}042\,w^2 - 0{,}04563\,n^2 + 0{,}1564\,wn$$

$$r^2 = 0{,}8311$$

$$(w,n) \in [0{,}250] \times [100{,}240] \qquad (4)$$

Source: SILVA et al., 2008.

- Melon Tree

$y_{mel}(w,n) = 34{,}16737\,n + 70{,}77509\,w - 0{,}05781\,w^2 - 0{,}07612\,n^2$

$r^2 = 0{,}9962$

$(w,n) \in [0{,}700] \times [0{,}350]$ (5)

Source: MONTEIRO et al., 2006.

2.2.2 Objective function (economic fitness)

We defined the fitness function as the net revenue per hectare for each crop in which it is the price of the product (R$/kg), the cost of water and the cost of nitrogen (R$/kg). The option to optimize revenue, and not only, aligns the solution with the producer's economic criterion. When useful for analysis, we also report productivity as a supporting metric.$(c \in alf, mel)\left(p_y\right)(c_w)R\$ \cdot (mm \cdot ha^{-1})(c_n)(y)(y)$

$$R(w,n) = p_y^{(c)} y(w,n) - c_w^{(c)} w - c_n^{(c)} n \quad (6)$$

Where is the price of the product (R$/kg), is the cost of water (R$/) and is the cost of N. We used the same costs for each study:$\left(p_y\right)(c_w)mm \cdot ha^{-1}(c_n)(R\$/ha)$

- Iceberg lettuce: , ,

$$\left(p_y = 0{,}80\right)\frac{R\$}{kg}(c_w = 0{,}44)\frac{R\$}{(mm \cdot ha^{-1})}(c_n = 2{,}09)\frac{R\$}{kg} \quad (7)$$

Source: SILVA et al., 2008.

- Meloeiro: ,
-

$$\left(p_y = 0{,}40\right)\frac{R\$}{kg}(c_w = 0{,}134)\frac{R\$}{(mm \cdot ha^{-1})}(c_n = 2{,}33)\frac{R\$}{kg} \quad (8)$$

Source: MONTEIRO et al., 2006.

This framework is consistent with the literature on economic optimization of irrigation/fertilization (Frizzone, 1986).

2.2.3 Economic concepts (summary)

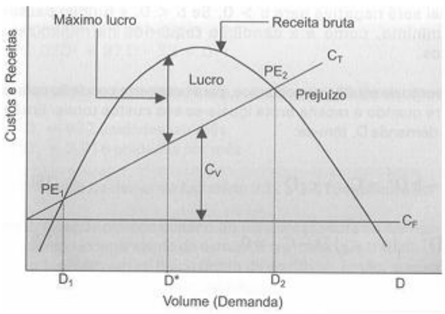
Based on **Frizzone et al. (2005),** key points of economic calculation:

- **Gross revenue**: .$RB(w,n) = p_y\, y(w,n)$ (8)
- **Variable costs**: .$CV(w,n) = c_w\, w + c_n\, n$ (9)

- **Total cost**: $.CT(w,n) = CV(w,n) + CF$ (10)
- **Objective function (net revenue):** . $R(w,n) = RB(w,n) - CT(w,n) = p_y\, y(w,n) - c_w\, w - c_n\, n - CF$ (11)

Figure 1

Cost, gross revenue and break-even point functions



Source: FRIZZONE, J.A., 2005.

Note: it is constant and does not change where the net revenue is maximized in the decision plan, it only displaces the plan, so it uses $.CFR(w,n) = p_y\, y(w,n) - c_w\, w - c_n\, n$ (12)

Interior Optimum (marginal criterion): When the Optimum is interior and without active constraints:

$$p_y \frac{\partial y}{\partial w} = c_w, \quad p_y \frac{\partial y}{\partial n} = c_n \qquad (13)$$

If the conditions point outside the experimental domain, the optimum occurs at the edge.

Break-even points and maximum profit: Break-even points (PE) satisfy (can exist and). The maximum profit point maximizes.$R = 0PE_1PE_2D^*RB - CT$

2.3 EXPERIMENTAL PROCEDURE

The implementation of ACO is simple and reproducible: (i) uniform discretization of the continuous domain (w x n); (ii) generation of solutions by sampling proportional to the entire network; (iii) global evaporation and top-k deposit proportional to performance, with elitist reinforcement in the global best; (iv) analysis of the convergence trajectory and sensitivity of and of the resolution of the mesh; (v) history logging and automatic generation of artifacts (CSV, graphs, and metadata JSON)$\tau^\alpha \eta^\beta (1-\rho)(\alpha, \beta, \rho)$

Table 1

Hyperparameters used

Parameter	Standard	Variations (ablation)
$(\boldsymbol{\alpha}, \boldsymbol{\beta})$	$(0,1;\ 0,3)$	$[0,1 \leq \alpha, \beta \leq 1,0]$
$\boldsymbol{\rho}$	$0,10$	$[0,05; 0,20]$
Ants / iteration	200	[20; 200]
Iterations	500	—
Top-k deposit	topk_fraction ,$= 0,05q = 1,0$	—
Elitist reinforcement	elitist_weight$= 1,05$	—
Early stop	Patience, tol $= 100 = 1e - 6$	—
Resolution (melon/lettuce)	$[701 \times 351]/[251 \times 241]$	—

Source: authors (2025).

3 RESULTS

3.1 MATERIALS AND TOOLS USED

The experiments were carried out in a local environment, using a Dell Vostro 15 3000 notebook, Intel® Core™ i7 processor and 32 GB of RAM. The codes were developed in Python 3.11, using the standard libraries ('numpy', 'matplotlib', 'argparse', among others).

The implementation of the ACO and the generation of the figures were carried out by the author. The convergence graphs and three-dimensional surfaces were produced with 'matplotlib', based on the numerical results of the execution. Source code and artifacts from this study are available at: [GitHub — (https://github.com/RafaelBahiense/aco-resource-optimization)]

3.2 MELOEIRO — RESULTS (NET REVENUE)

The melon evaluation used the production function and the objective function and the economic parameters described in Section 2.2. ACO showed a smooth and progressive convergence trajectory, with gradual improvement in net revenue over the iterations. The estimated optimum is around:$R_{mel}(w, n)$

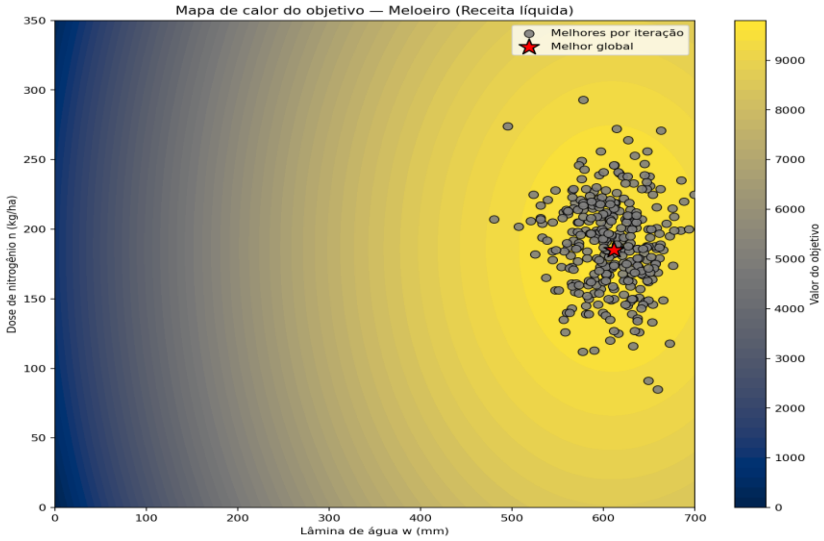
$$(w^*, n^*) \approx (612\,mm,\ 225\,kg.ha^{-1}) \quad (14)$$

> "The probability of choice combines pheromone and visibility, normalized by viable movements, ensuring valid distribution and control of the exploration-intensification balance." (DORIGO; STÜTZLE, 2004, p. 3).

In sensitivity, the evaporation parameter) proved to be adequate, preserving the exploratory capacity without loss of intensification. More values induced premature convergence, while high values increased the variability of the results. Values for how they maintained a good balance between history and heuristics. Thinner meshes raised the quality ceiling of , although with higher computational cost.$(\rho = 0{,}10(\rho < 0{,}05)(\rho > 0{,}20)(\alpha, \beta)(0{,}1; 0{,}3)R$

Figure 2

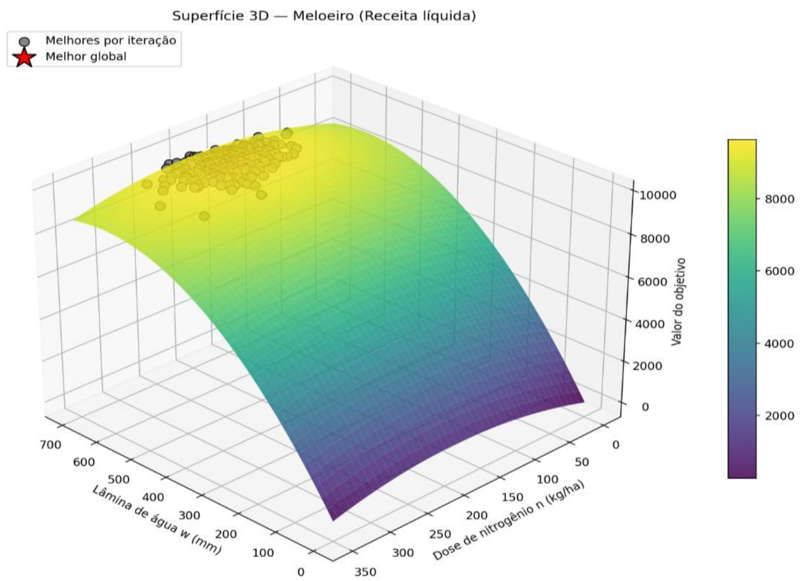
Convergence in Meloeiro



Source: authors (2025).

Figure 3

Convergence on Meloeiro on 3D surface



Source: authors (2025).

Table 2

Optimum point and metrics (ACO – melon tree)

Metric	Value
$(\boldsymbol{w}^{*})(\boldsymbol{mm})$	611,00
$(\boldsymbol{n}^{*})(\boldsymbol{kg} \cdot \boldsymbol{ha}^{-1})$	185,00
$\boldsymbol{y}(\boldsymbol{w}^{*}, \boldsymbol{n}^{*})(\boldsymbol{t} \cdot \boldsymbol{ha}^{-1})$	25.386,06
$\boldsymbol{R}(\boldsymbol{w}^{*}, \boldsymbol{n}^{*})(\boldsymbol{R\$} \cdot \boldsymbol{ha}^{-1})$	9.638.13

Source: authors (2025).

3.3 ICEBERG LETTUCE — ACO RESULTS (NET INCOME)

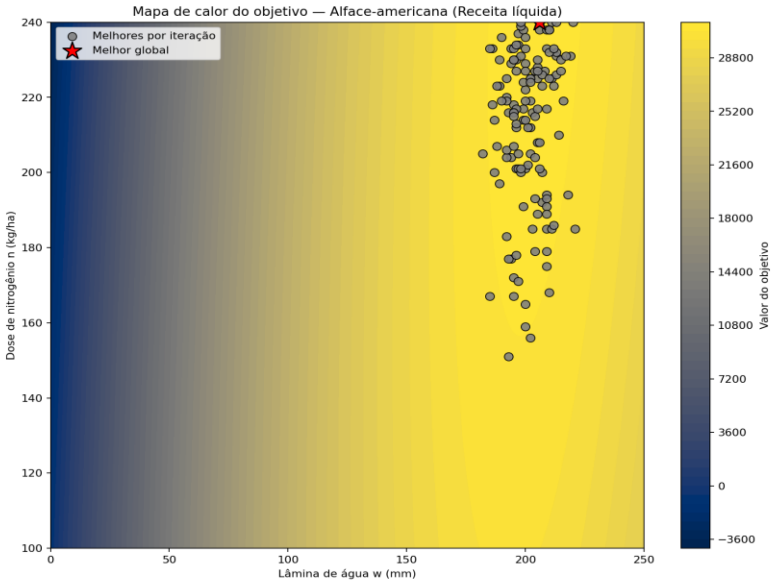
The analysis for iceberg lettuce used the production function and the objective function defined in Section 2.2. ACO showed stable convergence, with gradual improvement in net revenue over the iterations.$R_{alf}(w,n)$

Marginal conditions indicate inland optimum in , however, as it exceeds the domain boundary, the optimum occurs at the active boundary:$(w,n) \approx (204{,}240)(n)$

$$(w,n) \approx (204\,mm,\ 240\,kg \cdot ha^{-1}) \qquad (15)$$

Figure 4

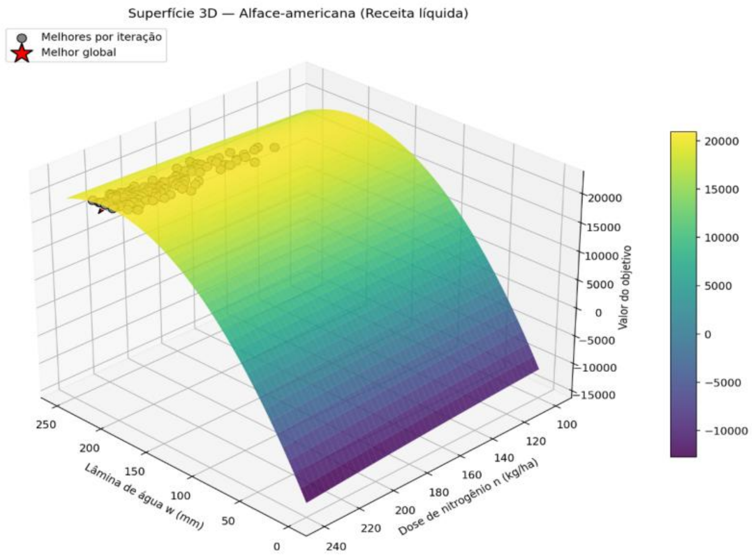
Convergence in iceberg lettuce



Source: authors (2025).

Figure 5

Convergence in iceberg lettuce on 3D surface



Source: authors (2025).

Table 3

Optimum point and metrics (ACO – lettuce)

Metric	Value
$(\boldsymbol{w}^*)(\boldsymbol{mm})$	206,00
$(\boldsymbol{n}^*)(\boldsymbol{kg}\cdot\boldsymbol{ha}^{-1})$	240.00 *(active restriction)*
$\boldsymbol{y}(\boldsymbol{w}^*,\boldsymbol{n}^*)(\boldsymbol{t}\cdot\boldsymbol{ha}^{-1})$	26.894,90
$\boldsymbol{R}(\boldsymbol{w}^*,\boldsymbol{n}^*)(\boldsymbol{R}\$\cdot\boldsymbol{ha}^{-1})$	20.927,45

Source: authors (2025).

3.4 COMPARISON WITH LITERATURE METHODS (OTIMAGRI, INTELIAGRI, MBL, PS, PBIL)

Maintaining the production functions and domains, we compared our great ACO to published results for different AI and optimization approaches (applications/systems and methods): OTIMAGRI – PSO and PS - Pattern Search (VILLAS BÔAS JÚNIOR et al., 2023), INTELIAGRI - decision support system (Cavalcante Junior, 2013), MBL - Logarithmic Barrier Method (Ventura, Sanchez Delgado and Carvalho, 2009). The values below are reported in the literature and allow us to verify the consistency of the excellent results obtained:

Table 4

Comparison of melon productivity with literature methods

Method	$(\boldsymbol{w}^*)(\boldsymbol{mm})$	$(\boldsymbol{n}^*)(\boldsymbol{kg} \cdot \boldsymbol{ha}^{-1})$	$(\boldsymbol{y}(\boldsymbol{w}^*, \boldsymbol{n}^*))\ (\boldsymbol{t} \cdot \boldsymbol{ha}^{-1})$
INTELIAGRI	630,11	234,97	25.467,00
MBL	612,30	234,97	25.469,00
PS	609,20	186,23	25.384,30
PSO (OTIMAGRI)	612,12	224,44	25.496,08
ACO (this study)	612,00	224,00	25.496,06

Source: authors (2025).

Table 5

Comparative yield of iceberg lettuce with literature methods

Method	$(\boldsymbol{w}^*)(\boldsymbol{mm})$	$(\boldsymbol{n}^*)(\boldsymbol{kg} \cdot \boldsymbol{ha}^{-1})$	$(\boldsymbol{y}(\boldsymbol{w}^*, \boldsymbol{n}^*))\ (\boldsymbol{t} \cdot \boldsymbol{ha}^{-1})$
INTELIAGRI	199,55	234,96	26.903,00
MBL	204,99	249,99	26.903,00
PS	205,26	257,14	26.959,93
PSO (OTIMAGRI)	204,35	239,97	26.902,71
ACO (this study)	207,00	240,00	26.894,90

Source: authors (2025).

In melon, the ACO optimums reproduce, within the mesh step, the values of , and reported by approaches in the literature (INTELIAGRI, MBL, PS, PBIL). In iceberg lettuce, the economic optimum is located in the active frontier of , and the ACO solution coincides with the references within the tolerance of discretization. In all comparisons, the fitness function adopted was the net revenue, recalculated in the same scenario of prices and costs to ensure uniformity between methods. In summary, ACO achieves performance equivalent to the revised alternatives, preserving control transparency (parameters and mesh resolution) and numerical robustness.$(w^*)(n^*)(y(w^*, n^*))(n)$

4 CONCLUSIONS

This study showed that a relatively simple formulation of Ant Colony Optimization (ACO), based on a two-dimensional grid with reinforcement proportional to performance and global evaporation, is not only feasible, but competitive for the joint optimization of water and nitrogen in iceberg lettuce and melon crops. The economic optimums obtained reproduce, within the discretization step adopted, the results reported by systems and methods consolidated in the literature (INTELIAGRI, MBL, PS), including in the scenario in which the optimum is located on the active frontier of the domain (iceberg lettuce). The choice of net revenue as the objective function is shown to adhere to the producer's decision criterion, while the mesh formulation provides transparency to the precision-computational cost commitment, a relevant aspect for applications in Agriculture 4.0.

From the applied point of view, the results allow us to derive objective configuration recommendations. In practical terms, it is suggested to start with evaporation values around $\rho \approx 0.5$ and exponents of pheromone and heuristic influence (α, β) in moderate ranges, adjusting them incrementally according to the observed convergence behavior. The resolution of the mesh must be compatible with the available computational budget, and it is recommended to refine the discretization only in regions close to the estimated optimum. When marginal conditions indicate a solution close to domain boundaries, it is critical to explicitly inspect boundary points to avoid mistaken conclusions as to the location of the economic optimum.

In terms of the research agenda, the results open space to deepen and sophisticate the use of ACO in agricultural management problems. As natural developments, the following stand out: (i) the investigation of elitist pheromone and adaptive discretization schemes, capable of concentrating computational effort in promising regions; (ii) the evaluation of continuous variants of ACO and hybrid approaches (e.g., combining ACO with pattern search strategies or interior point methods); and (iii) the development of multiobjective formulations that incorporate, in addition to revenue, risk and sustainability metrics. In addition, the integration of predictive productivity models — in particular sequential models — as heuristic components of ACO configures a promising line for decision support systems in Agriculture 4.0 operational environments, in which the efficient allocation of water and nitrogen is a critical condition for competitiveness and productive resilience.

ACKNOWLEDGMENTS

The authors thank Estácio (Estácio de Sá University) for the institutional support, including access to facilities, technological resources and administrative support, which were essential for the execution of the research activities and for the completion of this work.

REFERENCES

Carvalho, D. F. de, Sanchez, A. R. S. D., Oliveira, R. de, Silva, W. A. da, & Forte, V. L. do. (2009). Maximização da produção e da receita agrícola com limitações de água e nitrogênio utilizando pontos interiores. Engenharia Agrícola, 29(2), 321–327.

Cavalcante Junior, J. A. C. (2013). Ferramenta computacional inteligente aplicada à otimização do uso de recursos hídricos e aumento da receita líquida na agricultura – INTELIAGRI [Tese de doutorado, Universidade Federal Rural do Rio de Janeiro]. Repositório Institucional UFRRJ.

Clerc, M. (2006). Particle swarm optimization. ISTE; Wiley.

de Carvalho, F. D., Sanchez, A. R. S. D., Oliveira, R., Silva, W., & Forte, V. (2009). Maximização da produção e da receita agrícola com limitações de água e nitrogênio utilizando pontos interiores. Engenharia Agrícola, Jaboticabal, 29(2), 321–327.

Dorigo, M. (1992). Optimization, learning and natural algorithms [Tese de doutorado, Politecnico di Milano].

Dorigo, M., & Stützle, T. (2004). Ant colony optimization. MIT Press.

Food and Agriculture Organization of the United Nations. (2011). The state of the world's land and water resources for food and agriculture (SOLAW): Managing systems at risk. FAO; Earthscan.

Frizzone, J. A. (1986). Funções de resposta do feijoeiro (Phaseolus vulgaris L.) ao uso de nitrogênio e lâmina de irrigação [Tese de doutorado, Escola Superior de Agricultura "Luiz de Queiroz", Universidade de São Paulo].

Frizzone, J. A., Andrade Junior, A. S. de, Souza, J. L. M. de, & Zocoler, J. L. (2005). Planejamento da irrigação: Análise de decisão de investimento (1a ed.). Embrapa Informação Tecnológica.

Kennedy, J., & Eberhart, R. (1995). Particle swarm optimization. In Proceedings of the IEEE International Conference on Neural Networks (ICNN'95) (pp. 1942–1948). IEEE.

Monteiro, R. O. C., & et al. (2006). Função de resposta do meloeiro a diferentes lâminas de irrigação e doses de nitrogênio. Horticultura Brasileira, 24(4), 455–459.

Rathi, R., & Gomathy, C. (2025). Smart agriculture resource allocation and energy optimization using bidirectional long short-term memory with ant colony optimization (Bi-LSTM–ACO). Frontiers in Communications and Networks, 6, Article [número do artigo, se disponível].

Silva, P. A. M., & et al. (2008). Função de resposta da alface americana aos níveis de água e adubação nitrogenada. Ciência e Agrotecnologia, 32(4), 1266–1271.

Sorensen, K. (2015). Metaheuristics—The metaphor exposed. International Transactions in Operational Research, 22(1), 3–18. https://doi.org/10.1111/itor.12001

Villas Bôas Júnior, M. (2023). Inteligência artificial aplicada na otimização hídrica em culturas agrícolas (OTIMAGRI) [Tese de doutorado, Universidade Federal Rural do Rio de Janeiro]. Repositório Institucional UFRRJ.