UNIVERSIDADE ESTADUAL PAULISTA – UNESP
CÂMPUS DE JABOTICABAL

DON'T FORGET THE BELOW-GROUND CROPS: INTRODUCING SWEET POTATOES INTO THE CONCEPT OF DIGITAL AGRICULTURE

Danilo Tedesco de Oliveira
Mestre em Agronomia

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Danilo Tedesco de Oliveira
Prof. Dr. Rouverson Pereira da Silva

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TÍTULO DA TESE: DON'T FORGET THE BELOW-GROUND CROPS: INTRODUCING SWEET POTATOES INTO THE CONCEPT OF DIGITAL AGRICULTURE

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DADOS CURRICULARES DO AUTOR

Danilo Tedesco de Oliveira, filho de Lourival Bruno de Oliveira e Roseli Martins Tedesco de Oliveira, nasceu em Tupã no dia 11 de junho de 1995, município localizado no interior do Estado de São Paulo. Cursou ensino fundamental e médio no município de Quintana, São Paulo, no período entre 2002 a 2012. Durante o ensino médio cursou Técnico em Mecânica no SENAI "Shunji Nishimura" concluindo no ano de 2013. Em 2014 iniciou o curso de graduação em Tecnologia em Mecanização em Agricultura de Precisão na FATEC "Shunji Nishimura". Durante o curso foi membro do Grupo de Estudos de Colheita Mecanizada (GECOM), onde realizou trabalhos e pesquisas em campo, relacionadas a qualidade de operações agrícolas de semeadura e colheita, sob supervisão do Prof. Me. Edson Massão Tanaka. Obteve o título de Tecnólogo em Mecanização em Agricultura de Precisão no ano de 2016. Em 2017 inicio o mestrado no Programa de Pós-graduação em Agronomia (Ciência do Solo) na Universidade Estadual Paulista "Júlio de Mesquita Filho" Faculdade de Ciências Agrarias e Veterinárias Campus Jaboticabal (Unesp/FCAV), sobe a orientação do Prof. Dr. Rouverson Pereira da Silva, onde desenvolveu projetos de pesquisas relacionados a agricultura de precisão, sensoriamento remoto e uso de técnicas de inteligência artificial na agricultura, obtendo o título de Mestre em Agronomia (Ciência do Solo) em fevereiro de 2019. No mesmo ano ingressou o curso de Doutorado em Agronomia (Produção Vegetal) na mesma universidade, sob a mesma orientação. Onde dedicou seu tempo para realizar pesquisas relacionadas ao desenvolvimento de ferramentas para avaliar remotamente o crescimento, desenvolvimento, produtividade e qualidade de culturas com a implementação de técnicas de sensoriamento remoto e inteligência artificial. Durante o tempo de pós-graduação realizou dezenas de cursos, treinamentos e palestras relacionadas ao uso de imagens na agricultura de precisão e sistemas de informações geográficas (SIG). No dia de 16 de dezembro de 2021, submeteu esta Tese à banca examinadora para obtenção do título de Doutor em Agronomia (Produção Vegetal).

"Eis que estou à porta e bato. Se alguém ouvir a minha voz, e abrir a porta, entrarei em sua casa, e com ele cearei, e ele comigo."

Apocalipse 3:20

"A verdadeira ciência descobre Deus esperando atrás de cada porta."

Papa Pio XII

"Fizeste-nos, Senhor, para ti, e o nosso coração anda inquieto enquanto não descansar em ti...

Santo Agostinho

Que alegria ter buscado a ciência em Jaboticabal
e encontrado Deus esperando "atrás da porta".

Aos meus Pais, meus Avós e meus Irmãos.

Dedico!

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CONTENTS

NÃO ESQUEÇAM DAS CULTURAS SUBTERRÂNEAS: INTRODUZINDO A BATATA-DOCE NO CONTEXTO DA AGRICULTURA DIGITAL

RESUMO – Produzir alimentos de qualidade para atender a demanda global, em meio às incertezas climáticas com práticas de manejo sustentáveis é um dos maiores desafios das próximas décadas. Se realmente queremos atender a essa demanda, as ferramentas digitais são a chave para tornar a produção de alimentos mais segura. No entanto, os esforços para desenvolvimento dessas ferramentas estão totalmente focados para as culturas de maior interesse comercial, deixando de lado as de menor interesse, como as culturas subterrâneas. Grande parte das culturas subterrâneas são cultivadas por pequenos produtores rurais. Eles não possuem recursos ou conhecimento necessários para desenvolver ou adaptar essas ferramentas para suas necessidades. Devido a importância do seu valor nutricional na alimentação diária, nesta tese mostramos que não podemos esquecer das culturas subterrâneas. Para contribuir com a solução desse problema, nós desenvolvemos métodos para avaliar o padrão de crescimento, produção e qualidade da batata-doce. Mostramos que dados de clima e de satélites podem ser usados para detectar mudanças em estágios de crescimento e predizer características da cultura. Nosso trabalho introduz a cultura da batata-doce no contexto atual da agricultura conectada.

Palavras-chave: agricultura de precisão, agricultura inteligente, colheita inteligente, *Ipomoea batatas*, predição de produtividade, sensoriamento remoto

DON'T FORGET THE BELOW-GROUND CROPS: INTRODUCING SWEET POTATOES INTO THE CONCEPT OF DIGITAL AGRICULTURE

ABSTRACT – To produce quality food to meet global demand amidst climate uncertainty with sustainable management practices is one of the major challenges of the coming decades. If we truly want to meet this demand, digital tools are the key to making food production safer. However, efforts to develop such tools are entirely focused on the crops of greatest commercial interest, while leaving aside crops of minor interest, such as below-ground crops. Most below-ground crops are grown by smallholder's farmers. These farmers do usually do not have the necessary resources or knowledge to develop or adapt these tools to their needs. Due to the importance of these crops' nutritional value in day-to-day diets, in this dissertation we show that we cannot forget below-ground crops. To contribute to the solution of this problem, we developed methods to assess the pattern of growth, yield, and quality of sweet potatoes. We show that weather and satellite data can be used to detect some changes in growth stages and predict crop traits. Our efforts introduce the sweet potato crop in the current context of e-farming agriculture.

Keywords: precision agriculture, smart farming, smart harvesting, yield prediction, remote sensing, *Ipomoea batatas*

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CHAPTER 1 – General considerations

1.1 Introduction

Digital technologies are transforming the way society, farmers, and decision-makers look at the agricultural sector and food production. Increasingly accessible climate data and satellite images have enabled the creation of tools to assess the characteristics of the development of many crops. Large-scale crop assessment ensures food security for many families because it makes it possible to determine the impacts of field interventions and direct efforts to inspect and solve problems on-site. Such a comprehensive approach makes production more sustainable and boosts productivity gains.

Scientists and companies are focusing on the development of digital tools for the assessment of major crops such as cotton, soybeans, corn, and sugarcane. While this development is promising and the benefits are immeasurable, they forget about minor crops such as fruits, legumes, and vegetables, which are often grown by smallholders farmers. Traditionally, smallholders farmers contribute a significant amount of food to supply the city and regional economy. However, they do not have sufficient resources or training to adapt the use of digital tools to their realities. Moreover, to develop such tools, it is necessary to know how to program, working using databases, and with complex statistical analysis. The challenge for developing these tools is doubled when the crop grown has the development of its raw material of main economic interest undergrounds, such as roots, rhizomes, and tubers. Therefore, when developing digital tools, we cannot forget about the below-ground crops.

Sweet potato is an example of such a crop, because its roots grow below ground. Its management, therefore, requires farmers or decision-makers to look closely at the characteristics that determine its productive performance. But to look closely at these characteristics requires intensive fieldwork, due to the need to dig up the soil to visualize the production pattern of the roots. Such practice, increases production costs and does not allow for a detailed understanding of the spatio-temporal dynamics of root development. Against this background, we believe, therefore, that establishing potential relationships between vegetation growth characteristics (above ground) from remotely sensed and weather data with the pattern of root production (below ground) would allow site-specific management strategies to be set. Thus, we propose the elaboration of this dissertation. Our objective is to generate knowledge to assist smallholders farmers and decision-makers in the assessment of sweet potato development characteristics during the crop cycle. Such an approach will allow the introduction of this crop in the current context of e-farming agriculture.

1.2 An overview of thesis structure

We present in this first chapter the reasons for our concerns about the lack of research for the development of digital tools capable of assessing the performance of below-ground crops. Next, we show what was the main idea for the elaboration of each chapter of this thesis.

Chapter 2: In this chapter, our idea was to review the current status of sweet potato cultivation and to outline a profile for sustainable management of the entire production chain. We identified that the crop is rich in anthocyanins and carotenoids, beneficial for human health. That dual-purpose genotypes are in demand, to avoid the conflict between food vs. energy production. Source organic inputs are as effective for crop management as inorganic inputs. Finally, we provide insights for the digitalization of farming tasks, the building of databases based on geo-information's, and for traceability of the supply-chain production.

Chapter 3: Our idea for this chapter, was to verify whether a relationship between crop growth characteristics exists, and modelling the dynamics of this growth using orbital remote sensing and weather data. We found that vegetation indices based on canopy sensing follow the phenological trend of sweet potato growth. We were able to differentiate when phenological changes occur during the crop cycle. We find the best times to predict yield. Finally, we provide insights on how to use our results to determine site-specific management strategies.

Chapter 4: Since higher yields do not always represent higher quality, in this chapter we pursued an approach to predict crop yields by quality standard. For this purpose, an innovative methodology has been proposed and validated. Our approach detects the location of areas with higher quality roots, a practice that can increase the profitability of sweet potato growers.

Chapter 5: In the last chapter, we show how far we have come with the knowledge acquired for the development of digital tools, which are capable of evaluating crops that have their main raw material of economic interest located below ground. Such an approach introduces the sweet potato crop in the context of connected agriculture. Finally, we provide some promising directions where efforts should be directed to improve the management of this emerging but particularly promising crop.

CHAPTER 2 – Sustainable management of sweet potato: resilience-building practices for nutrition-sensitive agriculture, energy security and quality of life

2.1 Abstract

Keywords: farming systems; food security; highly nutritive edible roots.

2.2 Background

Public and private entities around the world have warned that if changes are not made, 840 million people will go hungry by 2030 (DIJK et al., 2021). Therefore, policy-makers must make every effort to ensure equitable access to healthy food, reducing undernourishment. An option to reverse undernourishment and improve human health, is the sweet potato crop (*Ipomoea batatas* [L.] Lam.). Sweet potato is nutritive and offers an exceptional option of health-promoting staple food to people living in vulnerable zones, where extreme events (e.g., heatwaves, floods, droughts), civil conflicts (e.g., wars), expansion of biofuels and financial speculation often make healthy and nutritious diets inaccessible. Biochemical composition of either orange/ yellow/ purple sweet potato provides essential micronutrients to women at childbearing age or pregnant, and pre-school children. Beta-carotene and retinol (vitamin A) can prevent progressive blindness by xerophthalmia. Purple-flesh sweet potato is an organic source of anthocyanins capable of protecting elderly patients against malignant tumor causing bladder, colorectal and stomachal cancers (HAGIWARA et al., 2002; HAYASHI et al., 2006; LIM et al., 2013; LI et al., 2018). Symptoms of bladder cancer include blood in the urine and pain during urination, and the regular consumption of purple-flesh sweet potato can potentially reduce them (LI et al., 2018). Anthocyanins also are natural colorants and can replace synthetic colorants in the food, drug, and textile industries, thus broadening health-promoting functions of sweet potato. The awareness of over-reliance of fossil fuels and global warming drives the development and implementation of sources of renewable and sustainable energy. Industrial sweet potato is one of the world's richest sources of starch, which is suitable for making bioethanol. It has the potential to produce 8.05 t ha^{-1} biofuel at 500 t^{-1}, making it cheaper than cassava, maize, and sorghum (LI; WANG; SHEN, 2010). Another benefit refers to the potential abatement of about 260 thousand metric tons of CO_2 yearly. Thus, industrial sweet potato can potentially drive the emerging global no-grain bioethanol market, reduce emission of greenhouse gases and is strategic to building community resilience (MUSSOLINE et al., 2017). However, because it is an edible crop it is prone to the 'food vs fuel' dilemma. Bioethanol or any other biofuel derived from industrial sweet potato must not hinder the access of people to basic food. Instead, it must support the energy security without threatening human health. Vines and 'rootlets' are suitable for making bioethanol and biogas via anaerobic digestion, thus preserving starchy roots for food (MUSSOLINE; WILKIE, 2015). If the trend of recovering energy from inedible parts (e.g., vines and 'rootlets') of sweet potato continues, debate on 'food vs fuel' is not likely to be significant.

The largest portion of the world's production of sweet potato arises from the People's Republic of China (FAO, 2019). The Chinese crop is versatile. Well over half of the production serves as animal feed, while the destinations for the remaining fraction are popular street food for human consumption and raw material for bioethanol (0.30 million L yr^{-1}) (QIU et al., 2010). African nations of Nigeria and Tanzania rank next in the world's production of sweet potato, focusing on nutritious edible roots and vines for food-secure community (BOUIS; WELCH, 2010). While the popularization of sweet potato as a specialty of starch-rich vegetable increases continuously across the Asia, Africa and America, technological development is lagging and at an embryonic stage of research. The global sweet potato sector unfolds into multiple actors, actions, and farm-business models. Prevalence of farmers in People's Republic of China and sub-Saharan Africa is smallholders (LAURIE et al., 2015). They usually base farming systems on roots for subsistence and synergistic interactions with rural people to promote health and strengthen agriculture in target regions, where technological, financial, and educational aspects of community is poor and make it vulnerable (BASHIR; SCHILIZZI, 2013; FETUGA et al., 2013). Small-scale smallholder farming systems are resource-limited and need high yielding cultivars/varieties (e.g., stress-tolerant landraces, biofortified sweet potato and OFSP), improved agronomic practices and the availability of agricultural inputs to produce cost-effectively, be profitable (BASHIR; SCHILIZZI, 2013; FETUGA et al., 2013), and address food and nutrition security at household, local, regional, and national scales (LAURIE et al., 2015).

By contrast, an industrial farming system focusing on making sweet potato into first-generation bioethanol unfolds into the interdependent operating units, namely on-field production, transportation, and processing (ZHANG et al., 2017). The on-field producing consists of planting, fertilizing, protecting, and harvesting, while no life cycle-inventory exists for irrigation. It can demand about 160 kg N, 80 kg P_2O_5 and 250 kg K_2O, and 2 kg ha^{-1} pesticide to enable the function of every hectare, where agricultural machinery heavily traffic to improve operationality throughout, even if topography is hilly. The transportation consists of moving the cargo via heavy truck from the field to the enterprise, where generation of every 1-tonne biofuel (analytical purity $\approx$ 99.5%) requires processing 7.5 tonnes of fresh feedstock. The manufacturer is 30 km distant from the farmer, so the journey consumes 0.06 L km^{-1} t^{-1} diesel as a fuel fossil. Another socio-environmental trade-off refers to the generation of waste, which fortunately is recyclable into an organic biofertilizer to spread onto field or, most appealing, electricity to power the manufacturer with autonomy. Overall, industrial sweet potato proves useful as an option of starchy material to bioethanol. It is flexible and fits anywhere in conventional, cogeneration and circular facilities (ZHANG et al., 2017).

On-field management of sweet potato requires farmers to closely yet holistically 'look at' processes to increase cost-effectiveness. Healthy propagative material, organic fertilization, biological control, genetic breeding, remote sensing, and traceability are resilience-building practices to help them engage in systems more profitable yet societally and environmentally responsible. Access to quality planting material and the willingness of farmers are instrumental to produce health-promoting sweet potato. If farmers continue multiplying neighborhoodlike health vines, they will be able to diffuse sweet potato through rural community, while caring for to do not build-up a suitable microenvironment where pests and diseases could thrive and limit the future production. Biofertilizers (e.g., animal manure) can support growth and development of sweet potato as effectively as synthetic fertilizers (NICOLETTO et al., 2017). They are cheaper, safer to microbiota and cleaner, as they generate lower volume of nitrogen oxide (NO_X) into the environment. Therefore, they can contribute to the reduction of greenhouse gases emission into the atmosphere. Genetic breeding of drought-resistant and nutrient-rich accessions, as well as methods of sorting/classifying market-grade roots can be of great importance to ensure sweet potato production is feasible in limiting environments. Finally, remotely monitoring and mapping sweet potato-growing areas can help farmers protect ownership rights to land, suitably and sustainably manage soil, water, and other instrumental inputs while engaging in 'green' payment by storing carbon, hence, meeting environmental and climate goals (JAIN et al., 2019). Green payment schemes will reward farmers for preserving resources and providing public goods. To fulfill the agenda of food and energy security, as well as human health, we must promote it across programs that disseminate knowledge, innovation, and technology.

2.3 Food security and human health: “Empowering” sweetness

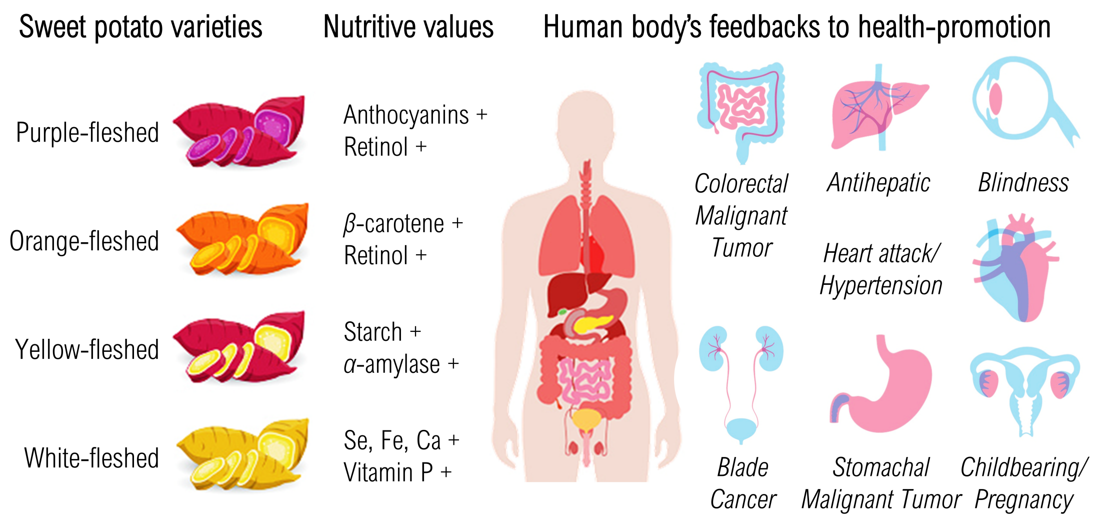
The World Food Programme’s expects the number of chronically hungry people to reach about 840 million by 2030 (DIJK et al., 2021). Food insecurity should serve as an incentive for policymakers to remain committed to reduce malnutrition. To end hunger and malnutrition and achieve food security, we (e.g., scientific community, policymakers, farmers, community etc.) must be conscious and rethink the production and supply of health-promoting food to be fair and sustainable (WARYOBA; JING, 2019). If not, we will continue to record deaths and diseases due to imbalances and deficiencies in daily intake of energy and/or nutrients by people living in societally vulnerable tropical and subtropical zones, primarily in South America and Africa (GALVAO et al., 2021). An option to reverse malnutrition is sweet potato (Figure 2.1). Sweet potato produces nutritive roots (TANG et al., 2021), and offer an exceptional alternative of starch-rich food to address security and nutrition in vulnerable regions, such as East and Southern Africa (WARYOBA; JING, 2019).

Vitamin A deficiency affects approximately 190 million pregnant women and 20 million preschool children worldwide. The biochemical composition of orange-flesh sweet potato can prevent at-risk people from retinol-deficient nutrition (Figure 2.1), making it an option to promote human health and quality of life (SAKALA; KUNNEKE; FABER, 2017). The crop is richer in beta-carotene than mango, papaya, and pumpkin (HOTZ et al., 2011). Children growing with no critical nutritional deficiency are less likely to die or suffer from immunological disruption, compared to retinol-deficient children (MAZIYA-DIXON et al., 2006). Another clinical complication due retinol deficiency is progressive blindness caused by xerophthalmia. Seven out of ten Mozambican five-year-old children and two out of ten Zambian women of childbearing age are retinol-deficient (SAKALA; KUNNEKE; FABER, 2017). Thus, the introduction of orange-flesh sweet potato as an organic precursor of vitamin A into diets is timely and relevant to reduce malnutrition and broaden the range of locally available health-promoting basic food (SAKALA; KUNNEKE; FABER, 2017). Plainly, OFSP can mitigate vitamin A deficiency. However, deploying an innovation such as OFSP into the rea world is challenging and require multiple actors and actions. By reviewing the study by Low e Thiele (2020), we can identify the major periods in the history of developing and scaling OFSP, namely (I) emergence of the idea (1991-1996); proving the potential of the innovation to the nutrition community (1997-2005); (III) evaluation of the potential to scale cost-effectively (2006-2009); (IV) heavily pushing investment in research to address breeding and launching of Sweetpotato for Profit and Health Initiative (SPHI) (2010-2014); and massive dissemination at scale (2015-mid-2019). The process should be complex and unfolds into extricable technical, organizational, institutional and leadership ramifications.

They can prove useful by providing learnable, transferable information about, for instance, drivers of innovative design and how it evolves over time to address needs of end-users; strategic, catalytic, and competence-building actions to catch funding sponsors; the role of generating an innovative idea to move it into implementation; structure and diversity of authorities both publicly and privately and how they shape the expanding, adapting, and sustaining policies, programs, and projects. A relevant organization shaping the development and scaling of OFSP is CGIAR (Consultative Group on International Agricultural Research) and another refers to IPC (International Potato Center). Both commit to restlessly elaborate, design, and coordinate actionable projects (e.g., Sweet Potato for Security and Health in Africa – SASHA, Rooting Out Hunger – ROH, and Dissemination of New Agricultural Technologies – DONATA) to develop, promote and perpetuate OFSP to address an increasing pressure to produce an option of nutritious (pro-vitamin A) and accessible food to all (MCEWAN et al., 2015). Hence, they can reduce rural poverty and improve human health and nutrition towards a food-secure future particularly for vulnerable zones, such as sub-Saharan Africa, South America, and Asia (LOW; THIELE, 2020). Genetic breeding to biofortify orange-flesh or yellow-flesh sweet potato can improve the nutrition of women of reproductive age.

The regular intake of 400-500 g of an iron-rich meal from yellow-fleshed sweet potato by Peruvian women can help them to absorb up to 33% of the daily requirement (JONGSTRA et al., 2020). The contribution of orange-flesh sweet potato to daily iron requirements for Malawian women is lower, up to 20%, because of the ability for polyphenols to inhibit adsorption of Fe, and thus decreasing the concentration of erythrocytes in the blood (JONGSTRA et al., 2020). Biofortification is an eco-compatible, cost-effective complementary strategy of delivering essential nutrients (e.g., Ca, Fe, Na, Se) to people in low-income rural zones, where they have no access to meals and thus self-sustaining intervention or supplementation can be necessary (JENKINS et al., 2018; TANG et al., 2021). Other than Fe, K, Mg and Se, vitamin C, soluble sugars and amino acids also make sweet potato an appreciable source of phytochemicals to promote health and quality of life by biofortification (GALVAO et al., 2021).

Bladder cancer is the world's leader of malignant disease in elderly patients and is prevalent across North America and Western Europe. Males are more likely to bladder cancer than females (LI et al., 2018). Treatment of bladder cancer often is complex and requires investments in infrastructure. Thus, development of an economically sustainable and year-around available alternative is necessary. Anthocyanins, coumarins, flavonoids, lignans, stilbenes and tannins are powerful antioxidant polyphenolic compounds and can act similarly to antitumoral agents in mammals (SUN et al., 2018). Purple-flesh sweet potato is one of the richest horticultural vegetables in anthocyanins



Contribution (%) of sweet potato to adults' and children's daily needs of nutrients

by consuming 100 grams of roots	Adults	Childs	Adults	Childs	Adults	Childs	Adults	Childs
Vitamin A	n.d	n.d	13.50	24.05	1.11	1.97	0.95	1.65
Vitamin C	146.50	320.60	119.55	269.05	36.55	82.00	93.80	211.25
Ca	8.55	10.45	8.80	10.15	6.83	7.38	6.95	8.25
Cl	2.25	2.10	2.25	2.50	2.13	2.40	2.10	2.20
K	8.25	16.10	8.90	17.20	9.55	18.60	9.65	18.70
Mg	18.65	21.75	21.60	25.75	20.4	23.80	23.10	26.70
Na	3.55	4.10	3.50	4.15	3.30	3.88	3.20	3.80
P	6.80	8.50	6.80	8.50	7.21	9.01	6.50	8.10

Figure 2.1: Human body's feedbacks to health-promotion sweet potato and percentage of the contribution of sweet potato varieties to adults' and children's daily needs of nutrients based 100 g fresh roots. Percentage of daily consumption according to Galvao et al. (2021).

(515–1747 mg/kg wb) (IM; KIM; LEE, 2021). Humans can absorb and concentrate purple-flesh sweet potato's anthocyanins (e.g., peonidin 3-sophoroside-5-glucoside and cyanidin 3-sophoroside-5-glucoside), which can function as antihypertensives, protectives of liver and retina , and preventives of malignant tumors (Figure 2.1), causing bladder, stomachal and colorectal cancers (LI et al., 2018). Signs and symptoms of bladder cancer include blood in the urine and pain during urination, and the regular consumption of purple-flesh sweet potato can potentially reduce them (LI et al., 2018). Its benefits are more likely for smokers. Smoking affects the urothelial cells and consequently increases the risk of bladder cancer, which also can happen in the kidney and ureter. The outer layer of purple-flesh sweet potato contains more anthocyanins and is healthier than the inner layer. Additionally, caffeoylquinic (25-85 mg kg^{-1}) and chlorogenic (6,715-20,650 mg kg^{-1}) acids are non-anthocyanins compounds capable of protecting against diabetes, cardiovascular and neurodegenerative diseases (IM; KIM; LEE, 2021). Anthocyanins also are natural colorants and can replace synthetic colorants in the food, drug, and textile industries. However, they are not stable and require supplemental acyl groups to be processable (IM; KIM; LEE, 2021).

To strengthen adoption, retention and dissemination, factors such as nutritional value, organoleptic quality and cooking of the product; availability and accessibility of propagative material; genetic resistance to stressful abiotic and biotic agents; transportability, storability and processability; competitiveness and scalability; ability of the farmer to access capital for inputs and labor; stability of market and volatility of price need to be taken into account (JENKINS et al., 2018). For instance, farmer's willingness to pay for planting material depends upon a wide range of factors, from technical to financial information (OKUMU et al., 2021). Particularly in Mozambique, they are willing to pay for premiums for OFSP by the production of dry matter, while the provision of information about health and nutrition to rural consumers are not relevant (NAICO; LUSK, 2010). Furthermore, features of vines impacting both positively and negatively the Nigeria's farmers' willingness to pay for OFSP potentially include maturity, productivity, and nutritional quality (-carotene) (ADESINA et al., 2017). Other relevant features refer to sanity (free of pests, diseases) (MWITI et al., 2020), available services (ULIMWENGU; SANYAL et al., 2011) and multiplier's reliability (OKUMU et al., 2021). Sweet potato can generate a new plant from a reproductive structure. Hence, it makes it easy for farmers to access, share and retain planting material (MCEWAN et al., 2015). By contrast, vegetative reproduction is less appealing to private enterprises, as they only could recover a portion of investment into varietal promotion through sales (LOW; THIELE, 2020). Plainly, farmers can easily multiplicate sweet potato into new ownership fields or proactively diffuse it throughout the neighborhood (MCEWAN et al., 2015), making it faster and more agile to develop and scale up nutritious food than possible with cereals (ROGERS, 2010). However, they can be compliant of "shortage of planting material" (MCEWAN et al., 2015). Therefore, bringing about an effective propagative network is instrumental to balance market dynamics (supply and demand), especially for unimodal rainfall systems and a longer dry period, which increase the risk for loss of planting material. By contrast, bimodal rainfall systems and a longer rainy period, always making it possible for farmers to have access to a healthy planting material for longer periods of time (MCEWAN et al., 2015). However, it can further build-up a suitable microclimate for residence and reproduction of pests and diseases, and thus the plant cannot produce an optimal edible material to harvest. Ensuring farmers to have timely access to sufficient quantities of appropriate planting material is instrumental to advance the field and needs a more active stance from incentive projects and programs, such as PRAPACE (regional network for the improvement of potato and sweet potato) (MCEWAN et al., 2015).

2.4 Energy security: Do not go hungry to power the world

The awareness of overconsumption of fossil fuels, global warming and its negative impact on the planet drives the development and implementation of sources of renewable and sustainable energy. Industrial sweet potato is denser and richer in starch than standard-table sweet potato, making it an alternative feedstock to bioethanol (ZHANG et al., 2017). It can grow effectively on marginal lands and potentially produce about 8.05 tonnes of bioethanol per hectare. Its cost of about €500 per ton of biofuel makes it cheaper than sorghum and cassava for bioethanol production. Another benefit of making industrial sweet potato into bioethanol is the abatement of CO_2 over 260 thousand of metric tonnes annually, thus further contributing to energy security and carbon neutrality (MUSSOLINE et al., 2017).However, as it is edible, we should be concerning ourselves with 'food versus fuel' dilemma. By reviewing the statistical database from Food and Agriculture Organization (FAO, 2019), on Global Sweet Potato Market – Perspectives and Challenges, we can picture where food-fuel divide will likely be "tense". We might not expect a tensing sub-Saharan Africa. Malawi, Nigeria, Tanzania, Uganda, Ethiopia, and Angola are amongst world's top 10 largest sweetpotato-producing countries. They are low-income countries and focus on producing sweet potato, besides maize and cassava, as an option of nutritious and accessible food to all towards mitigating hunger and malnutrition (LAREO; FERRARI, 2019). Thereby, they are not likely to dispute over the impact of biomass biofuel sector on food security (Figure 2.2). By contrast, People's Republic of China (1^{st} world's largest producer) and US (9^{th} world's largest producer) are likely to transform a portion of sweet potato as an edible crop into biofuel in competition with food production over land, water, and other resources (WEBER; TRIERWEILER; TRIERWEILER, 2020).

North America, European Union, and Asia hotspot the world's most active stock exchanges. Price movements of securities are highly frequent and volatile in People's Republic of China and US, making them economically appealing to catch stock market speculators. For instance, buyers and sellers of commodities can be of any assistance in strengthening availability, accessibility, utilization, and stability of global food security sector. However, excessive stock market speculation could cross sustainable food-fuel divide by heavily pushing financial capital to enable the function of making first-generation resource into biofuel. Therefore, it would be harder than ever for smallholder farming systems from Sichuan and Shandong, People's Republic of China, and near North Carolina, Carolina, Mississippi and Louisiana, US, to produce and distribute sufficient quantities of sweet potato as an affordable nutrient-dense food to all via domestic supply chains (MUSSOLINE et al., 2017). Drivers other than stock market speculation to ”food vs fuel” debate include policies and incentives (ECKERT et al., 2018). For instance, subsidies, import tariffs and fuel-blending mandates empower People's Republic of China, US, and Brazil (16^{th} world's largest producer) to convert sugary or starchy feedstock into bioethanol, biogas, or any other first-generation biofuel at lower price at industrial scale (HALDER et al., 2019; SAKAI et al., 2020; SILVA et al., 2018). If such mechanisms do not exist, impact of biofuel production on food production would be lower (QIU et al., 2010; WIDODO; WAHYUNINGSIH; UEDA, 2015).

Furthermore, Republic of Indonesia is a rising producer of sweet potato in Southeast Asia and Oceania. However, we might not expect it to cross the sustainable food-fuel divide. Because provinces of Indonesia, such as Jambi, Sumatera, Barat, Jawa Timur, and Jawa Barat, base regional full-scale production of bioethanol and biodiesel on molasses and oil-palm biomass, respectively (WIDODO; WAHYUNINGSIH; UEDA, 2015). Hence, they are likely to preserve cultivars/verities of sweet potato, namely Cilembu, Borobudur, Prambanan, Mendut, Kalasan, Muara Takus, Cangkuang, and Sewu, as staple food to feed people and build resilience by improving income (cash), livelihood (informal job), infrastructure and agriculture environment arrangement (WIDODO; WAHYUNINGSIH; UEDA, 2015). By contrast, a tensing scenario would arise from Vietnam, where numerous industrial factories processing starchy feedstock (e.g., cassava and sweet potato) into bioethanol are likely to spread across the provinces, namely Vinh Phu, Ha Bac, Hoa Binh, Thanh Hoa, Quang Nam, Vung Tau, Vinh Long, and An Giang. The Regional Center of Central Tuber Crops Research Institute (CTCRI), by breeding landraces/indigenous sweet potato, enable smallholder farmers to enhance rural livelihood security in India. Industrialization of sweet potation is yet at an embryonic stage in India. However, it can negatively impact the self-sufficiency in food security by destabilizing agricultural production and increasing price (ATTALURI; JANARDHAN; LIGHT, 2010), similar to what we might expect on People's Republic of China.

If investors continue to purchase millions of hectares to grow sweet potato or any other similar renewable energy crop for bioenergy, supply of food will decline, and people will go to hungry. Therefore, bioethanol or any other biofuel from industrial sweet potato must not hinder the access of people to basic nutrition. Instead, it must support energy security without threatening food security and human health. Food must remain the priority for edible sustainable energy crops, especially in vulnerable areas where hunger and malnutrition regrettably can take lives away. Accomplishment of either innovative agricultural practices or selection of dual-purpose genotypes of sweet potato will be necessary to balance its application between fuel and food (Figure 2.2). Since sweet potato can thrive and produce an appreciable volume of above-ground material in

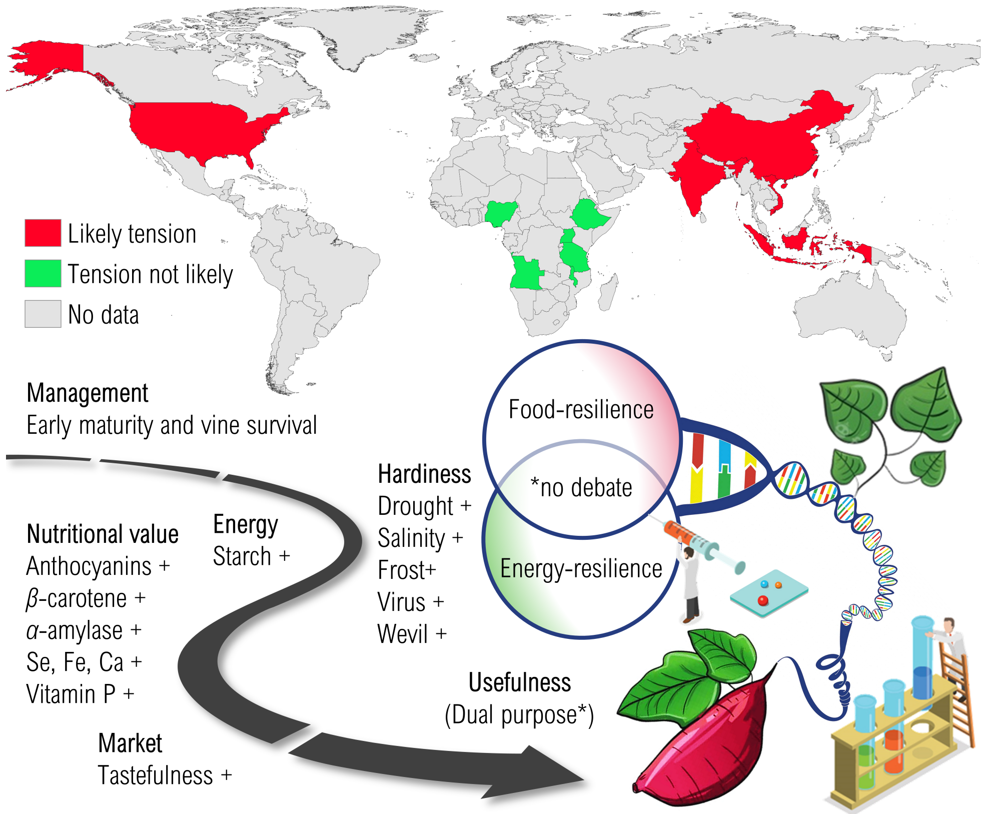


Figure 2.2: Breeding is an enabler for boosting the sweet potato to challenging climate and no debate on "energy vs food".

low-fertility soils with minimal fertilization and irrigation. Strategically introducing stems and leaves in the process of fermenting bioethanol can compensate for the utilization of its starchy roots for food. Other than the vines, rootlets also are feasible to both bioethanol and biogas via anaerobic digestion. Harnessing by-products can improve the energetic output of sweet potato-growing areas and further contributes to avoid the debate on 'food vs energy'. Another advantage potentially includes the support of no-grain bioethanol.

2.5 On-field management

2.5.1 Pre-harvest, harvest, and post-harvest: A holistic look at processes

Sweet potato is essentially geocarpic and sets its roots below ground. If temperature and moisture are optimal, roots grow effectively. If not, they never really 'mature'. Farmers able to directly sell sweet potato to consumers can do that every time they dig roots up. Harvest can be delayed from 120 up to 150-180 days of cultivation to achieve starch-rich roots promoting profitability (ALBUQUERQUE et al., 2019; SIMÕES et al., 2020). Sweet potato is tropical and usually stops growing upon freezing. Thus, harvest before freezing can improve quality. The skinning and bruising are other limiting factors pre-harvest. Often, excessive skinning and bruising cause roots to spoil or shrivel, making them unappealing for the consumer. Therefore, farmers must make every effort to minimize them. If not, they will shorten the shelf-life and reduce the acceptance of the product at the market. Removal of vines seven or more days before harvesting is the most popular cultural practice among growers worldwide to reduce skinning or bruising when digging roots up, and also can improve starch, beta-carotene and alpha-amylase in the total mass of roots (SUGRI et al., 2019); alpha-amylase catalyzes the industrial conversion of starch into bioethanol. Smallholder farmers usually rely on a cutter tool (e.g., hedge or string trimmer or scythe) to remove the excessive foliage and disc coulter to cut stems. As for large growers, they use either a mower or snatcher. Benefits of 'dehaulming' are greater in areas where the soil is dry and intensifies both skinning and bruising by sticking onto the surface of the root, exposing it to further abrasion. Smallholder farmers often harvest the sweet potato by hand. Manual harvest is selective and can prevent some loss of material to the environment. However, it is labor-intensive, time-consuming, and often intuitive rather than analytic, potentially reducing both productivity and quality. Therefore, mechanization can help them to improve efficiency and scale up.

A digger machine picks up the roots and moves them to the sieving unit (i.e., chain or roller). The role of the sieving unit is to separate the soil from the roots, which falls to the ground. As the harvester passes and the roots drop on top of the bed, a crew of workers grades and stores them by size in large boxes or bins. At post-harvest, curing is necessary to prevent injuries and preserve sweetness, flavor, aroma, texture and other relevant culinary attributes (SUGRI et al., 2019). The farmer who wishes to cure sweet potato must conduct it shortly after harvesting in an appropriate facility at 25-30 °C and 85-90% relative humidity for 5-7 days. The curing process will not happen if the product is stored outside the optimum conditions (KROCHMAL-MARCZAK et al., 2020). Any delay in curing can cause unappealing scars on the root, as the wound dries. Distribution of warm/humid air and oxygenation inside the warehouse also are of importance to prevent shriveling and reduce the risk of post-harvest pathogenic fungi causing rot during storage (WANG et al., 2019). Small farmers incapable of investing in specific storage structures can adapt the storage environment, however, to 25-30°C. They should plan the structure to support the curing of a one-week harvest. Cooling is important after the curing process levels off, however, temperatures should never drop below 15 °C. Sweet potato is sensitive to chilling, and thus low temperatures can be detrimental to quality. Hard-to-cook sweet potato is unappealing for the consumer and its price is not competitive (KROCHMAL-MARCZAK et al., 2020). Minimal processing can aggregate value to sweet potato. However, peeling, slicing, dicing, shredding or grating can accelerate the deterioration of the product (NIU et al., 2019; SIMÕES et al., 2020).

If storage conditions are favorable (15 °C and 80-90% relative humidity), sweet potato is not likely to sprout or rot. If, however, temperature is above 15 °C, sprouting can start and rootborne, soilborne or airborne fungal spores can become active. Relative humidity control is reasonable to promote healing of wounds and toughness of the skin before washing and packing for delivery to the market. However, it must not be neither too early to preserve critical mass nor too late to prevent the creation of microclimate for diseases. Additionally, storage must not exceed six weeks; otherwise, it can reduce beta-carotene levels by 25-35% and also expose the product to pathogens for longer period of time (ATUNA et al., 2018). Sweet potato is degradable by pathogenic fungi, making its transportation, storage, and marketing rather complex.

One of the most severe post-harvest diseases of sweet potato is *Rhizopus stolonifer*. Often, temperatures above 5 °C enable its spores to germinate and spread on roots, irreversibly rotting them (KROCHMAL-MARCZAK et al., 2020). Synthetic fungicides are the primary method for controlling *R. stolonifer*. They are effective and can ensure sweet potato is suitable for commercialization and consumption. However, they are not environmentally responsible and expose people to any harmful or potentially harmful residuals. Another disadvantage refers to the risk of microbial resistance to antibiotic. Thermochemical treatment by hot water is completely safe and can kill *R. stolonifer* primarily by denaturation of proteins. An integrative ultrasonic technology can further inactivate *R. stolonifer* by disruption of cellular membrane and leakage of the cytoplasm. Ultrasonic is non-toxic to human and can inhibit browning while preserving the original quality of in natura or fresh-cut sweet potato. Hot water with auxiliary ultrasonic pulse is an effective and reliable method of sterilization of soft rot. It is useful to store ready-to-eat sweet potato and improves its lifespan and safeness. However, it demands drinking water and can be costly (LI et al., 2016).

Another pathogenic fungus of economic importance to sweet potato is *Ceratocystis fimbriata*. Losses by infection of *C. fimbriata* are estimated to be around 10-20% at post-harvest (FERREIRA et al., 2017; LI et al., 2016). Nerol vapor can effectively limit the development of black rot caused by *C. fimbriata*. It acts similarly to an antiseptic by depolarizing the mitochondrial membrane and blocking the repair of oxidative damage by the pathogen. Therefore, the primary assumption for the control of *C. fimbriata* by Nerol is elicitation of a non-enzymatic defensive system of the host. Another reasonable hypothesis is its antagonistic interaction with the fungus (LI et al., 2016). An on-field practice to assist with control of post-harvest diseases is ‘dehaulming’. Removal of foliage to dig roots by hand or mechanically can reduce the transportation of organic (e.g., vegetal impurity) and inorganic (e.g., soil) sources of pathogens by human or machinery from the area of cultivation to the ambient of curing/storage.

Therefore, management of sweet potato during pre-harvest, harvest and post-harvest is crucial and requires growers to closely, yet holistically, look at the processes and adapt as needed towards improving sustainability. They can explore locally available resources to maximize productivity, quality, and profitability, while minimizing costs, losses, and societal and environmental impacts. How farmers manage sweet potato enable industrialization and in natura consumption as well as its market acceptance. Sweet potato is an important horticultural crop and its sustainable production can help us make progress towards aligning agriculture with changes in landscapes, ecosystems, and/or introducing resilience-building practices or technologies across rural value chains (i.e., delivery of goods and/or services for low-incoming communities). We must not ignore its relevance to fulfill the agenda of food/energy security and human health.

2.5.2 Planting systems

Sweet potato is not easy for planting. Production of vines for planting is vegetative and starts with the selection of visually appealing vines in the field. The practice is rather subjective, and the next steps are to bury seedlings up to the top leaves and press the soil down gently yet firmly to ensure they are in contact enough with the soil. Removal and disposal of any excess material is of importance, as they can harbor pathogens. The planting vine is shock-sensitive and requires careful handling to prevent wounds and diseases. Shoots will sprout and vines will emerge spreading on the top and sides of the bed. Thereby, lifting longer vines to keep them from the rooting at the leafy buds occasionally is necessary for preventing off-grade tubers and intraspecific competition. However, vines should not be removed because they can help preserve moisture and temperature in the soil, filter harmful sunrays, and compete with weeds. Traditional planting is simple but labor-intensive and time-consuming. Preparation of cuts for planting requires one-third of total hours of normal production, and it is not mechanizable. Therefore, an alternative system is necessary. Planting energy-storing roots as alternatives to vines could improve the “seed system”. They can more effectively recover from damage by pests and infection by viruses such as SPCSV (sweet potato chlorotic stunt virus) and SPFMV (sweet potato feathery mottle virus) (ADIKINI et al., 2019). Hence, they become an option to implement sweet potato in unimodal rainfall system and a long dry season, whether for harvesting material for consumption or industrialization. Sweet potato for processing is cheaper to produce than standard-table sweet potato, compensating for the high variable cost of its planting (ZHANG et al., 2017). Therefore, the grower who wishes to implement mechanization can expect a lower incidence of disease, maximization of yield, and savings in labor and time. Remote sensors are likely to improve mechanically planting roots by enabling end-to-end monitoring of spatial-temporal variability at the field level throughout the season. If mechanical propagation of roots with an auxiliary technology solution, entities must consider enabling smallholder farmers access to technology, training, and assistance.

Asia, Africa, and Pacific lead the world's production of sweet potato and usually grow it for food. Thereby, they generate significant quantities of vines as by-products upon harvesting. Stems and leaves can contribute to soil's health. However, they can also harbor vectors and pathogens harmful to the next crop, thus potentially decreasing both productivity and quality of roots. The nutritional composition (e.g., proteins and carbohydrates) of vines allows them to be fed to ruminants, however, without competing with human needs as traditional grain crops (e.g., maize and soy) do, thus further contributing to food safety. If, however, they are not palatable and digestible enough, they become unuseful sources of animal feed to farmyards and the farmer must strategically consider other cost-effective alternatives. Vines are considerably moist and can deteriorate easily if environmental conditions (e.g., temperature and relative humidity) are not suitable. Ensiling is an effective way to convert them into forage, preserve nutrients and reduce cost. The process is anaerobic, where fermenting bacteria enzymatically decompose carbohydrates into organic acids, primarily lactic acid. As pH decreases, forage becomes acid and unsuitable for rotten-promoting microorganisms (LI et al., 2016). Thus, ensiling can compensate for the complexities and expenditures of feeding ruminants with in natura vines, adding profit and competitiveness to smallholder farmers. The sweet potato foliage can also be used in valuable phytomedicinal bioproducts (IM; KIM; LEE, 2021), broadening its functions.

2.5.3 Fertilization and irrigation: Use locally available resources and put water in the heart of the field

Sweet potato is nutrient-consuming. The plant requires approximately 10 kg of K for every 1,000 kg of roots (dry basis) (GEORGE; LU; ZHOU, 2002), which is higher than cereals, pulses and oilseeds. Deficiency in K or any other essential mineral can limit sweet potato yields to only 4.5 t ha^{-1}, compared to attainable yields of 45-50 and 25 t ha^{-1} in Uganda and Mozambique, respectively, if fertility is reasonable (ANDRADE et al., 2016; MUKHONGO et al., 2017). About 22.5 million hectares of arable land in People's Republic of China are deficient in K (WU et al., 2011), limiting yield in the country. Nitrogen fertilization promotes higher yields, but excess N can cause rapid shoot growth at the expense of root production (DUAN et al., 2018b), especially in tropical regions. Hence, sweet potato with excessive N produces lushy vegetation, considerably reducing tuberization and affecting subsequent yield (DUAN et al., 2018a). Therefore, genotypes capable of tolerating N-rich soils could be to avoid overgrowth and underperformance in systems either focusing on food or energy. Thus, breeders must continue efforts to select adapted genotypes, and farmers must be conscious of plant requirements to realize synergistic nutrition. Integration of genetic breeding to higher-efficiency formulas can further improve the tuberization. Combination of humic acid and urea into an organic-inorganic framework increases the efficiency of fertilizer by the crop (CHEN et al., 2017). Most importantly, this process chemically stabilizes the N limiting its conversion into NH_3 and NO_X. Ammonia and nitrous oxide are volatiles and can easily escape from the farm into the environment as air polluting compounds and precursors of global warming (DING et al., 2020). Another eco-friendly alternative to reduce sweet potato reliance on synthetic N refers to diazotrophic bacteria (DING et al., 2020). They sequester N_2 from atmosphere convert it into ions ($N\text{-}NO_3^-$ and $N\text{-}NH_4^+$) ready for plant uptake. However, data on benefits of N-fixing endophytes in sweet potato are not conclusive. Thus, further in-depth studies on the ecological nature, and formulation are necessary.

The role of orange-flesh sweet potato breeding programs in Africa is significant and must continue to address traits such as earliness, resistance to drought and upregulation of beta-carotene (VUGT; FRANKE, 2018).The orange-fleshed sweet potato is highly productive and requires fertilization to thrive through the agroecosystem and ensure good yields for the current and next crop (e.g., cassava and maize) (CONZ et al., 2021; LOW et al., 2017). Smallholder farmers from Africa and South America usually cannot afford synthetic fertilizers. In Mozambique, only about 5% of farmers use synthetic fertilizers for application on farm (BENSON et al., 2012). Therefore, organic fertilization with locally available resources can be an eco-compatible, cost-effective option to agricultural systems. Biofertilizers (e.g., animal manure) benefit plant growth and development as effectively as synthetic fertilizers (MUKHONGO et al., 2017). They are cheaper, safer to microbiota and cleaner, as they release less NO_X into the environment. Therefore, they improve sustainability of sweet potato production systems and contribute to the reduction in greenhouse gas emissions (MUKHONGO et al., 2017).

Moisture in the soil is key for sweet potato production. Seedlings are highly sensitive to drought and need water daily. As they develop longer roots, however, they become capable of uptaking water and nutrients at deeper layers. Hence, after rooting levels off, irrigation is only necessary every 3-5 days to avoid any morphophysiological anomaly. When scheduling irrigation farmers can adopt fertirrigation, which captures the advantages of irrigation and fertilization by synchronically delivering water and fertilizer. It reduces labor, time, and inputs. Most importantly, it reduces N volatization by incorporating it in the soil, therefore an environmentally friendly solution to sustainably manage sweet potato, especially for tropical zones. If fertirrigation is not possible, producers must consider incorporating the fertilizer with irrigation for similar reduction of volatilization and run-off. This also helps move nutrients closer to the roots and auxiliary hairy fibers, facilitating uptake. An adequate irrigation can enable sweet potato to yield up to 50 t ha^{-1} roots compared to 4.5^{-1} t ha^{-1} under dry environments (KARAKAS; KURUNC; DINCER, 2020). While underwatering can reduce yields, overwatering saturates the soil blocking root respiration, promote vegetation-to-tuberization overlapping and rotting of roots, create microclimate to pathogens and weeds, and causes leaching, all of which can have a negative impact on yield. Therefore, monitoring of soil moisture is the key to ensure adequate irrigation of sweet potato (KARAKAS; KURUNC; DINCER, 2020).

Furthermore, extreme climate change will likely make it harder than ever to feed/power a rising world's population sustainably. Therefore, deploying climate-ready crops into the real world is instrumental to thrive through an ever-challenging scenario over the coming few years. A critical review by Heider et al. (2020) on intraspecific diversity timely elaborates how cutting-edge genetic breeding can push sweet potato to endure harsher environments. Thermotolerant and drought-tolerant genotypes (CHALLINOR et al., 2014; WARREN, 2018) can empower farmers to develop strategic, catalytic, and competence-building actions towards adapting agricultural frameworks to climatic stresses (LAURIE et al., 2020; YANG et al., 2020). For instance, the gene bank at the International Potato Center is diverse and consists of over well 6150 accessions of sweet potato from about 60 countries. Thereby, landraces, cultivars, breeding lines and commercial varieties at the IPC can enable stakeholders to address an increasing need to build resilient farming systems towards a thriving and responsive agriculture food security sector (HEIDER et al., 2020). Most notably, they are disruptive solutions to radically reshape the society, environment, and economy at the 2030 agenda for sustainable development. Fortunately, they can enhance producing and distributing sufficient quantities of appropriate food to prevent hunger and malnutrition in vulnerable geolocations (SDG2] across South America, Africa and Asia, while vastly reducing the generation of waste [SDG12]. Furthermore, they can protect and restore agroecosystems (KASSALI, 2011; OMOTOBORA et al., 2014), making them arable rather than inaccessible and unsuitable to support producing food. However, real potential of sweet potato to tolerate environmental conditions warmer and drier than normal is yet not clear. Thus, the scientific community and science policymakers must be aware of the commitment, cooperation, and coordination they need to elaborate if they are to effectively advance the field's prominence in engineering future-ready sweet potato-producing areas.

2.5.4 Pest Control: Propagate healthy material, make natural barriers and "be biological"

Insect, pathogen, and weed outbreaks make it extremely challenging for farmers to effectively grow sweet potato, especially for tropical zones. Thereby, they need to control them to ensure successful production of material adequate for commercialization and propagation. Chemicals can control pests effectively, however, the options are limited for sweet potato and effectiveness and selectiveness knowledge for this crop are not often available from official regulatory agencies (SANTOS et al., 2018), forcing producers to use off-label products to protect the crop. Off-label use of chemicals is illegal and environmentally irresponsible because it can pollute ecosystems and harm beneficial non-target living organisms (DUDLEY et al., 2017), such pollinizers (TRAYNOR et al., 2021) and mammals (KIM; KABIR; JAHAN, 2017; LARSEN; PATTON; MARTIN, 2019).

The application of chemicals into sweet potato is not usual in sub-Saharan Africa. The oldest weed control method is the removal by hand. Weeding until vegetation completely covers the soil around 45 days after planting can prevent about 85% yield loss (KUMAR; NEDUNCHEZHIYAN; S., 2020). It is effective, however, it is time-consuming and labor-intensive, and can damage roots by skinning, making them unappealing for the consumer. Another limitation of manual weeding refers to scalability. A large area will usually make manual weeding impossible, thus the conscious use of pre-emergent herbicides can be implemented (KUMAR; NEDUNCHEZHIYAN; S., 2020). This will prevent weed emergence and competition with the sweet potato crop. Since chemicals are limited, producers must consider planting genotypes capable of co-existing with weeds and tolerating insects and pathogens the system.

Producers must strive to obtain healthy mature vines or roots from trusted retailers or institutions for access to material free of harmful bacteria, fungi and virus. If the sweet potato crop dries out in the field it is not suitable propagative material (KAGIMBO; SHIMELIS; SIBIYA, 2017). In such cases farmers must allow roots the time necessary to sprout and generate healthier vines. Although planting late, healthy starting material will ensure it is more resilient to outside pathogens. Disease vector control (e.g., *Bemisia tabaci*) is also important and reduces accumulation and perpetuation of viral agents, thus improving longevity of the crop as well as the yield and quality of roots.

The weevil (*Cylas formicarius*) is the most economically relevant insect of sweet potato. It can reduce yields by 50%, if its population is above the economic threshold (HUA et al., 2020). Weevil can damage the crop in the field, the produce in the storage; hence, its effective control is mandatory. Weevil can feed on foliage and reduce photosynthetically active area by chewing. Also, it attacks roots, causing them to off-flavor, becoming unsuitable for human and animal consumption (GAPASIN et al., 2016; DADA et al., 2019; HUA et al., 2020). Adults can fly, however, they rarely do so. Flights are often short and low, so they cannot successfully disperse and need to harbor on the field (DADA et al., 2019). Females feed on the plant for one or more days before becoming sexually active, and the release of synthetic pheromone can prevent mating (REDDY et al., 2014). However, the simplest method of weevil control is the removal of residual vines and roots after harvesting. This method is effective but demands an appreciable amount of time and labor.

Extracts from *C. papaya*, *A. indica*, and *C. odorata* are biodegradable sources with repulsive and biocide properties to weevil and can effectively reduce its potential damage to edible energy-storing roots (IGWE et al., 2021). They are cheaper, harmless and easy to handle. Another advantage relative to chemicals, is the lower selection pressure on pests (IGWE et al., 2021). To improve efficiency of natural weevil control, producers can integrate natural barriers. Structuring plants across or at the edges of the field can harbor natural weevil enemies while physically blocking flights (DADA et al., 2019). The angle of a natural barrier must be convenient for farming and cannot interference with the sunrays (DADA et al., 2019). Moreover, the species would preferably allow the grower to profit from eventual commercialization of food, wood, fiber or any other valuable agricultural or forest product. Options of natural barriers potentially include *Z. mays*, *Eucalyptus sp.* and orchards of mango, banana, citrus, or any other fruit capable of adapting to tropical and subtropical climates. Fallow, early planting, intercropping/rotation/succession also are eco-friendly options to control weevil by changing food and habitat dynamics (KAGIMBO; SHIMELIS; SIBIYA, 2017). However, they are not as effective as entomopathogenic nematodes (ENPs). The ENPs live parasitically inside the host, and can biologically control weevil by infecting its larval or adult living form in the soil (MYERS et al., 2020). Endoparasitary suppression of weevil by ENPs is promising yet emerging. Therefore, producers are encouraged to learn how to collect, store and use EPNs. The in vitro suspension or in vivo production by culturing the host, requires almost no infrastructure to preserve the biological agent for an appreciable period of time (DUNN; BELUR; MALAN, 2020).

2.6 Reduce Risk: Equitable and fair technocentric arrangement

A key to successfully produce sweet potato is to monitor it, whether for acquiring useful information about soil, crop, and system. Remote and on-field sensors can empower farmers to streamline workflow and intervene at the right time and place on the field with greater accuracy, flexibility, and autonomy than possible with conventional agricultural management, whether for irrigation, nutrition, seeding/planting, harvesting and waste disposal (JAIN et al., 2019; LI et al., 2020; JUNG et al., 2021). However, remote sensing particularly for sweet potato is yet at an embryonic stage of research and technological development. However, studies by Tedesco et al., (2021a, 2021b) on satellites to computer predictive analytics on spatial-temporal data from smallholder farming systems underline the importance of remote sensors to seamlessly ”capture snapshots” from the actively growing field throughout the winter and summer. Hence, they can enable farmers to make accurate and scientific decisions on harvesting, planting, and fertilization. All with plant-level precision, and georeferencing to wherever on the site the inputs need to be, whether for maximizing cost-effectiveness. Orbital data-acquisition platforms and mainstream machine-learning algorithms, namely random forest, and k-nearest neighbors, are excellent mergers for predicting where in the field do exist roots of superior quality to selective harvest, both manually for low-income systems and mechanically for precision agriculture. They also could provide farmers valuable information about screening out high-quality roots for propagation into new high-throughput fields, where quantity and quality of production could potentially be greater than we might expect on farming without remote sensing to enhance and support acting with pinpoint accuracy and responsiveness.

A sound remote sensing to low-income farming systems can build-up resilience by bridging organizations and smallholder farmers (partnership), supporting management to thrive (self-sufficiency), promoting innovative strategies to reach all people (engagement) and explore agricultural data to learn from past events to strengthen future response and recovery efforts (education). Thereby, rural communities will be able to reduce risks and explore assets or resources wisely; and bounce back quickly from crises and disasters and take the opportunity to enhance health, environmental, social, and economic aspects of local arrangements. However, it will likely require for governance to tap diffusion into low-cost solutions and absorb a portion of investment for affordability (CUCHO-PADIN et al., 2019). If authors’ perspectives right, open-sourcing imagery data repositories and childhood-to-childhood adaptable multi-sensors will make it possible for small-scale sweet potato-producing frameworks to afford and benefit from low-cost remote sensing to enhance decision-making power and optimize producing starch-dense food in sub-Saharan African regions, such as Tanzania and Uganda.

As agricultural systems evolve they become more dynamic, complex, and thus increase the risk of food/energy insecurity. Therefore, development and implementation of policies and cost-effective solutions is necessary to understand, monitor and analyze vulnerabilities, especially in regions where extreme events are likely. Extreme weather (e.g., heatwaves, floods and droughts), civil conflicts (e.g., wars), and financial speculation make healthy and nutritious basic food unaffordable rather than accessible.

Weather forecasting and remote sensing can improve sustainability by allowing accurate monitoring of agricultural areas and informing about spatial and temporal loss of soil, vegetation (TEDESCO et al., 2021a; TEDESCO et al., 2021b), and even emission of greenhouse gases (i.e., CO_2, CH_4 and NOX) (JAIN et al., 2019). Public and private sectors need to collaboratively and harmonically collect and share survey-grade imagery data from remote platforms to allow the development of alert systems for farmers. Remotely monitoring and mapping sweet potato-growing areas can help farmers sustainably manage soil, water, and other inputs and engage in 'green' payment by storing carbon in tropical zones, meeting environmental and climate goals. Green payment schemes will reward farmers for preserving resources and providing public goods. Also, it can promote eco-compatible investments, traceability and blockchain for low-income countries.

Traceability is the ability to track a product through all stages of production, processing and distribution (DEMESTICHAS et al., 2020). One can reasonably hypothesize barcoding (QR coding) of sweet potato to track its movements at any point of the supply chain, from procurement of propagative material, on-field management, harvesting, curing, packing, transportation, delivery to the consumer, and disposal (Figure 2.3). Traceability will enable consumers to recall roots if needed, so producers, transporters or retailers can quickly and effectively implement corrective actions, thus minimizing disruptions to trade also benefiting food safety. If any potential risk (e.g., harmful or potentially harmful residual pesticides) to human health is identified, an effective traceability system can assist with its isolation, thus keeping customers safe. An effective traceability on blockchain to identify stakeholders, must allow recording, synchronizing, and sharing of identifying information of multiplier/ producer/ transporter/ retailer; description of inputs and product; timeline of on-field management; date of transaction or delivery; size and identification of batch; geolocalization of the field; and any other information likely to be representative to sustainable development (e.g., carbon/ water footprint).

The introduction of sweet potato in the era of digital agriculture with traceability of the supply chain seems a distant reality. However, it is provocative and will bring about numerous social and technological changes that will be beneficial to the entire production chain. To this end, farmers, researchers, and government agencies must make every effort to develop and standard the methods for collecting and storing of geoinformation on agronomic and culinary characteristics. In addition, it is instrumental to capacitate the decision-makers so that they know how to use this information. The agents should not use the available technologies to only create "colorful maps", without the required agronomic and precision knowledge. Otherwise, the use of technology in this field of study will fall into the concept of (im)precise farming (VISSER; SIPPEL;

THIEMANN, 2021), and may ”burn” the reputation of the technology and its adoption by sweet potato growers.

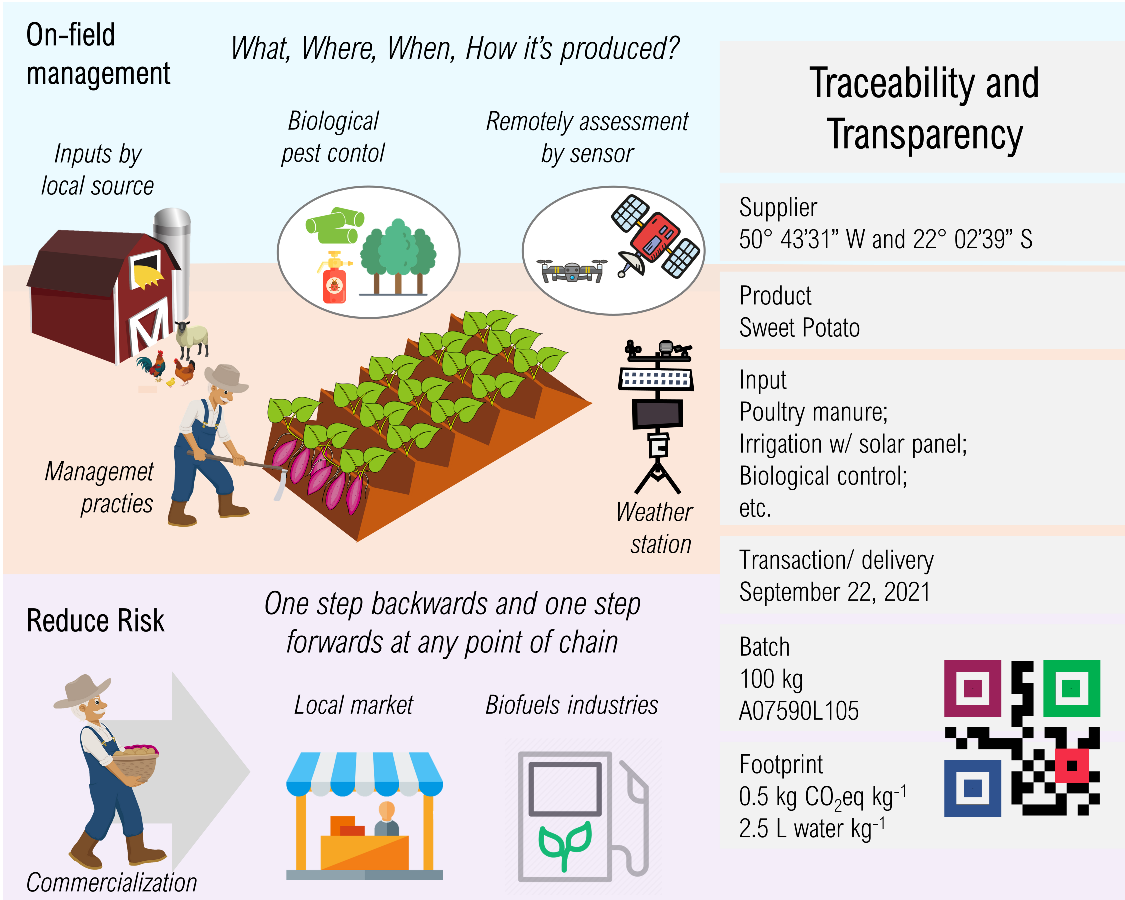


Figure 2.3: Traceable value rural food supply chain.

2.7 Future directions

Certainly, staple food can drive us towards the progress on ending hunger and malnutrition worldwide. Thereby, we profile the sustainable agricultural management of sweet potato from every angle imaginable to promote it as alternative shockingly nutritive edible root to feed the world and achieve food security. If our perspective right, we will be able to produce sweet potato sustainably and provide people feasible and equitable access to basic diets. Our insights into the resilience-building production of sweet potato are timely and valuable, especially for vulnerable geopolitical zones, where unbalances and deficiencies in diary intake of energy and nutrients make it challenging for low-income and mid-income communities to live security. We must make every commitment to reduce food unsafety and our authoritative study provide guidance for entities (e.g., policymakers, governmental organizations, and producers) to reduce hunger and malnutrition across emergency rural food supply chains.

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CHAPTER 3 – Use of remote sensing to characterize the phenological development and to predict sweet potato yield in two growing seasons

3.1 Abstract

Sweet potato is a tuberous root with versatility in food products, but also with applications in the energy industry, such as in ethanol production. Developing mechanisms to assess the performance of this crop is important, difficult, and costly, as its commercial product grows below ground. The use of remote sensing to evaluate the development of sweet potato has not yet been reported in the literature. In our study, we showed that spectral vegetation indices are good proxies to monitor the temporal dynamics of crop growth and differentiate phenological stages, regardless of the growing season. The development phases were divided into three stages according to the vegetation indices: (I) initial stage ($<$200 GDD), when vegetation has little influence on VIs; (II) growth stage (from 200 to 500 GDD), when vegetation has high influence on VIs due to its growth; and (III) stabilization stage ($>$500 GDD), when major changes in VIs no longer occur because vegetative growth has ceased. Besides that, we found that these indices can predict crop yield before harvest. In two growing seasons, the smallest errors in yield estimates occurred during the growth stage. In the summer season with NDVI at 355 GDD with errors of 2.63 t ha^{-1} and in the winter season when GNDVI at 440 GDD had errors of 3.06 t ha^{-1}.

Keywords: crop growth, digital agriculture, phenology, reflectance, smart harvesting, yield prediction.

3.2 Introduction

Sweet potato (*Ipomoea batatas* [L.] Lam.) is an important source of calories, vitamins, and minerals for humankind (CHUYEN; EUN, 2013; YANG et al., 2017). This crop plays a key role in alleviating hunger (MOLLINARI et al., 2020), especially in African and Southeast Asian countries in conditions of socioeconomic vulnerability (LOEBENSTEIN, 2009). It has relevant nutraceutical importance and is strategic in the diet when associated with other foods to combating malnutrition (SINGH et al., 2004). Besides human consumption, sweet potato can be used for animal feed and has been considered as a promising feedstock for fuel ethanol production (LAREO; FERRARI, 2019; MEGERSA, 2017; VILLORDON; GINZBERG; FIRON, 2014).

Some production aspects make sweet potato strategic for cultivation, such as its ability to grow in a wide variety of soils, with moderate to low fertility (TAYLOR; MCGREGOR; DAWSON, 2016). It also has a high variation (plasticity) in terms of yield and is very responsive to fertilization (MUKHONGO et al., 2017; YAO et al., 2020). Another advantage is the option of harvesting it progressively (IESE et al., 2018). Socially, it offers employment opportunities for and improves conditions of smallholders farmers, which account for largest part of production.

Food security has become an increasingly global concern, which should become even more evident after the COVID-19 crisis (PETETIN, 2020). Population growth has led to an increased food demands, which can be fulfilled by increasing planted area, distribution and yield, reducing wastes, and changing food consumption patterns. It is also known that the arable land per capita has decreased over the past 59 years (RITCHIE; ROSER, 2013); therefore, increasing crop yield has become essential. Higher yields can be achieved through plant breeding and improvements in cropping environment and quality of management techniques (e.g., planting, pythosanitary control, harvest, and post-harvest).

Strategic tools to monitor crop development and estimate yield and harvesting time in a non-destructive way can assist the agents of production chains in this journey. To the best of our knowledge, no studies in the literature have reported the monitoring of temporal dynamics of sweet potato growth and yield patterns by non-destructive methods. Understanding sweet potato growth and yield patterns is important for developing management techniques for trouble spots in the field. In this sense, nutritional and irrigation needs can be better defined (BARBEDO, 2019; CORBARI et al., 2019; MENDES et al., 2019; PATEL; GHOSH; SAYYAD, 2020) so that resources can then be saved through effective interventions. Moreover, the most suitable time to start harvesting can be determined. If necessary, the harvesting can be divided into several stages according to supply chain demands (MONSEF et al., 2019; AL-GAADI et al.,

2016; WENDEL; UNDERWOOD; WALSH, 2018). Harvest scheduling can also be useful for managing human resources, allocating the workforce to the sites to be harvested.

Crop phenological stages and yield can be determined through seasonal in-field inspections or extracted from remote sensing data (HE et al., 2018; VICENTE-GUIJALBA; MARTINEZ-MARIN; LOPEZ-SANCHEZ, 2014). Although in-field inspections provide quality information at any cultivation time, these may be destructive, making it a high-cost process (AL-GAADI et al., 2016). Besides, in-field monitoring demands significant time and manpower to dig and assess tuberous roots, which is inadequate in the stratification of phenological stages and yield with details at large production fields. In this sense, in crops where the commercial part is underground, such as roots (sweet potato, cassava, and carrots), rhizomes (yam) and tubers (potatoes) , it is interesting to use non-destructive and indirect strategies that allow monitoring of their development with greater efficiency.

Frequent remote sensing imagery can be employed to estimate both crop phenological stages and yields (DASH; JEGANATHAN; ATKINSON, 2010). Estimations can be based on physiological and morphological changes occurring throughout vegetation growth, as these alterations affect spectral properties of plants (USHA; SINGH, 2013) and, consequently influence crop yield (PÉREZ-PAZOS et al., 2021). This information allows understanding the dynamics of spatial and temporal vegetation growth above ground (haulm) and its relationship with crop yield (below ground), which is essential to implement local specific management measures (LI et al., 2020). Furthermore, this tool can be explored across different territorial boundaries, from small farms to government use.

Several studies have shown the potential of monitoring crop growth by associating physical scattering mechanisms of vegetation canopy to phenology (CANISIUS et al., 2018; MANDAL et al., 2020; TORBICK et al., 2017). Some studies have also used satellite images to extract vegetation indices (VIs) and estimate yields of crops that have their underground parts as the raw material of economic interest, such as carrot, potato, and cassava (AL-GAADI et al., 2016; PURNAMASARI; NOGUCHI; AHAMED, 2019; GÓMEZ et al., 2019; SUAREZ et al., 2020). Since there is a relationship between aboveground biomass accumulation and ground cover with root production (PÉREZ-PAZOS et al., 2021). However, research on the use of these images for sweet potatoes is lacking.

A clear understanding of crop growth state and phenological development can support decision-making in strategic management of production fields and thus increase yield sustainably. It can also assist in early yield estimations as a function of canopy status. Thus, our study aimed to investigate whether it is possible to characterize the phenological development and estimate the yield of sweet potatoes in two growing seasons using VIs based on crop canopy. The following questions were answered throughout our study:

1. Can VIs establish a relationship between the dynamics of canopy growth and phenological development in sweet potato?
2. Is it possible to evidence changes in the phenological development of sweet potato using VIs based on crop canopy?
3. Is it possible to estimate sweet potato yield through remote sensing based on crop canopy?

3.3 Methodology

In this section, we present information about the study areas (Subsection 2.3.1), dataset acquisition and creation (Subsection 2.3.2), approach used to measure crop growth through VIs (Subsection 2.3.3), and yield estimation and mapping (Subsection 2.3.4).

3.3.1 Study area

The study was conducted in two commercial sweet potato fields in the region of Tupã, municipality of Herculândia, State of São Paulo, Brazil. These fields were grown with the cultivar 'Canadense," irrigated by a center pivot. The regional climate is tropical, with a well-defined dry season in the winter and average annual temperatures higher than 18 ºC. The climate is classified as Aw according to Köppen's system.

The fertilization and irrigation management practices were the same for both studied fields. For planting the crop, the soil was prepared by plowing and harrowing to incorporate 4.0 t ha^{-1} of poultry manure. The beds were created with a ridger at a height of 0.30 m and spacing of 1.20 m. The fertilization at planting was 40 kg ha^{-1} N, 300 kg ha^{-1} P, and 100 kg ha^{-1} K. Planting of the branches was performed manually, with $\sim$0.25 m cuttings, spaced of 0.30 m at 0.08 m depth. The top dressing applied was 100 kg ha^{-1} N and 100 kg ha^{-1} P. The fields were irrigated twice weekly until 20 days after planting (DAP), once weekly from 20 to 40 DAP, and every other week after 40 DAP until harvest. The water demand was determined from agroclimatic data to estimate crop evapotranspiration (ETc) according to crop coefficient (Kc) values at each development stage, being Kc of 0.50, 1.05, and 0.65 for the vegetative and maturity/production stage. The study fields are close to the geographic coordinates ($W\ 50°43'31''$ and $S\ 22°02'39''$) (Figure 3.1)

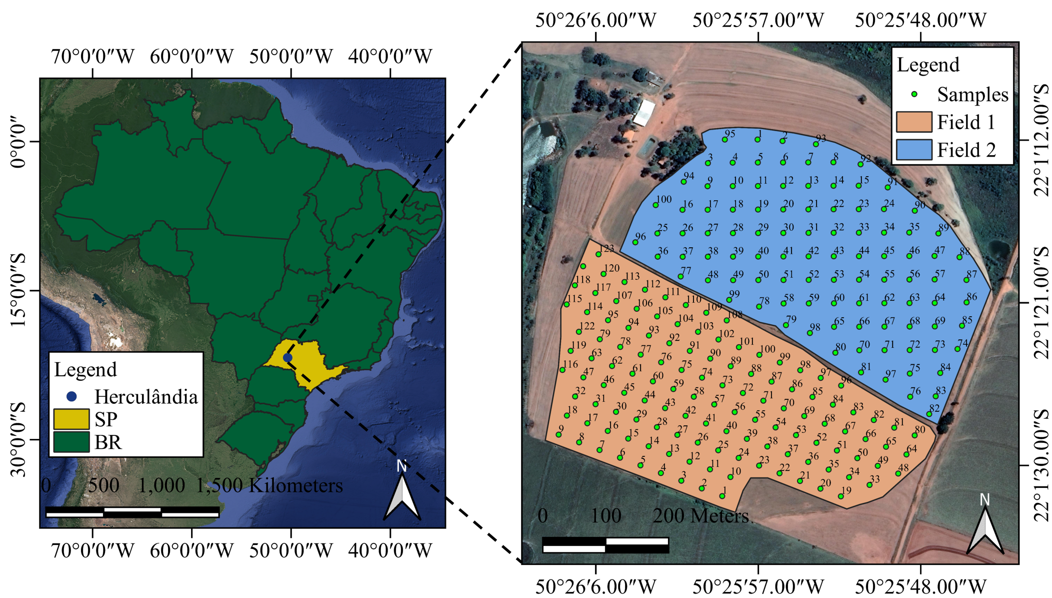


Figure 3.1: Overview of the location of the fields for trials in the summer and winter, in the municipality of Herculândia, SP, BR.

3.3.2 Data

Our database was built from information obtained in each of the georeferenced sampling points, which were distributed in a regular grid for each study area. Two study fields were used, the first was related to summer weather conditions (between February and May 2018) and the second to winter ones (from July to November 2018).The first field (summer) covered an area of 16.08 ha, wherein 123 points were distributed, spaced 35 m apart. Similarly, the second field (winter) had 16.23 ha, and 100 points were distributed in the area, 40 m apart from one another. The sampling points were located using a GPS receiver (GARMIN 60CSx). Below we show how the yield samples were collected in the field (Subsection 2.3.2.1), image acquisition and processing methods (Subsection 2.3.2.2), strategy used to combine yield data and spectral information, and database creation (Subsection 2.3.2.3).

3.3.2.1 Sweet potato yield

Sweet potato yield was determined by manual root collection within a 3-m^2 area for each sampling point. The harvested roots were cleaned to remove mineral impurities, weighed individually, and the fresh masses were converted into a common unit of measurement (t ha^{-1}).

3.3.2.2 Satellite imagery

Cloud-free satellite images were obtained for both fields throughout the sweet potato production cycle from the Sentinel-2 platform. They were downloaded using the USGS Earth Explorer. The images covered the two-seasons in 2018, one in summer with planting on February 2 and harvesting on May 31, and then another in winter with planting on July 15 and harvest on November 2.

The number of images in each field during the cropping cycle varied from 2 to 4 per month due to cloud obstruction. All images were corrected for the VI calculation using semi-automatic classification (SCP), which is a free open-source plugin for QGIS (CONGEDO, 2021), correcting the radiance into the top-of-atmosphere reflectance of the Green (525–595 nm), Red (635–695 nm), and NIR (724–957 nm) bands from the information available in the file metadata.

Among the numerous VIs available, we selected the following: NDVI (normalized difference vegetation index), GNDVI (green normalized difference vegetation index), and SAVI (soil-adjusted vegetation index). These indices were selected for their common use in assessing crop vigor, biomass, and yield. Moreover, SAVI has an adjustment factor to minimize the soil effect, which is an interesting characteristic since sweet potato takes longer to cover the soil surface with vegetation. The indices were calculated according to the equations in Table 3.1.

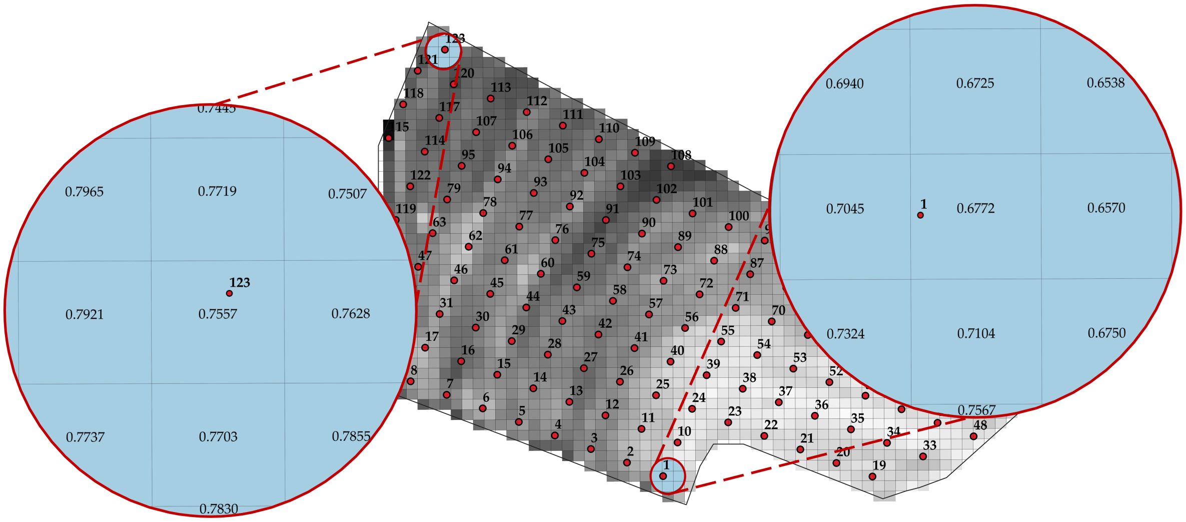
Table 3.1: List of vegetation indices used to monitor growth dynamics and estimate sweet potato yield.

Vegetation index	Equation	References
NDVI	$\frac{\rho_{\text{nir}} - \rho_{\text{red}}}{\rho_{\text{nir}} + \rho_{\text{red}}}$	(ROUSE et al., 1974)
GNDVI	$\frac{\rho_{\text{nir}} - \rho_{\text{green}}}{\rho_{\text{nir}} + \rho_{\text{green}}}$	(GITELSON; KAUFMAN; MERZLYAK, 1996)
SAVI	$(1 + 0.5)\frac{\rho_{\text{nir}} - \rho_{\text{red}}}{\rho_{\text{nir}} + \rho_{\text{red}} + 0.5}$	(HUETE et al., 1992)

ρ: reflectance, NDVI: normalized difference vegetation index, GNDVI: green normalized difference vegetation index, and SAVI: soil-adjusted vegetation index.

3.3.2.3 *Pixel extraction and database building*

All processed images were considered for this step. In each image, the VI values were extracted in each pixel in the positions of each sample point designed to collect the yield samples. For this step, a pipeline developed in Python programming language was employed. A graphic example of this extraction is illustrated in (Figure 3.2). The database for yield estimation was generated using the information from each image acquired (Figure 3.2a). The database for sweet potato growth assessment was generated using the average of the VI values from each acquisition date, converting to a sum-of-thermals measurement (Figure 3.2b).



Samples	Longitude	Latitude	VIs	Yield (t ha^{-1})
1	-50°43’30’’	-22°02’54’’	0.2449	13.33
⋮	⋮	⋮	⋮	⋮
123	-50°43’49’’	-22°02’17’’	0.1966	30.64

(a)
Example of dataset to yield prediction (NDVI at 57 GDD)

Images	Thermal Sun (GDD)	Mean of VIs each image
1	57	0.2082
⋮	⋮	⋮
14	1088	0.8119

(b)
Example of dataset to determine the growth on Gompertz approach

Figure 3.2: Example of extraction of vegetation index values at points projected in one of the study fields.

3.3.3 Definition of phenological stages using VIs

Crop phenological stage changes are usually determined by accumulated thermal sum (GDD), using cardinal temperatures, until reaching the end of the crop cycle. To determine the GDD in the sweet potato crop, we used data from a weather station located ∼20 km from the region of the production fields. The calculation (2.1) was performed according to the date of acquisition of each satellite image, following the method of ARNOLD (1959):

$$\sum GDD = [(T_{max} + T_{min})/2] - Tbase \tag{3.1}$$

Where: $\sum$GDD is the sum of degree-days, T_{max} is the maximum air temperature (°C), T_{min} is the minimum air temperature (°C), and T_{base} is the lower baseline temperature of the crop (15 °C).

Several mathematical functions have been proposed to deal with crop growth as a function of cultivation time. To date, little is known about this approach to assess crop growth using VIs. Therefore, we propose to establish a functional relationship between the growth curves of VIs and crop growth in the field. To this end, the Gompertz function was adjusted to the mean values of each VI. These means were calculated using all sampling points on all the dates of satellite image acquisition. The independent variable (X-axis) was GDD, and the dependent variable (Y-axis) was the VI (2.2).

$$W = W_o + W_f \ exp^{-exp^{-k(g-M)}} \tag{3.2}$$

Where: W represents the reflectance of the VIs in each period, W_o is the reflectance of the VIs in the first GDD value, W_f is the maximum reflectance value (upper asymptote), k is the relative growth rate in M, g is the variable (GDD), and M is the GDD at which the growth rate is maximized.

Besides using growth curves, we performed an analysis of critical points as proposed by WU et al. (2004). Two critical points were assessed, and they could be interpreted using the second derivative of Equation 2. The first critical point (*Dx*) represents the moment when the accelerated growth of the VIs is maximized, whereas the second (*Dy*) represents the moment when the slightest acceleration of growth occurs. The point of maximum growth rate (*M*) is between these two points (*Dx* and *Dy*) and represents the inflection point of the Gompertz function. Figure 3.3 shows examples of critical points on the Gompertz curve.

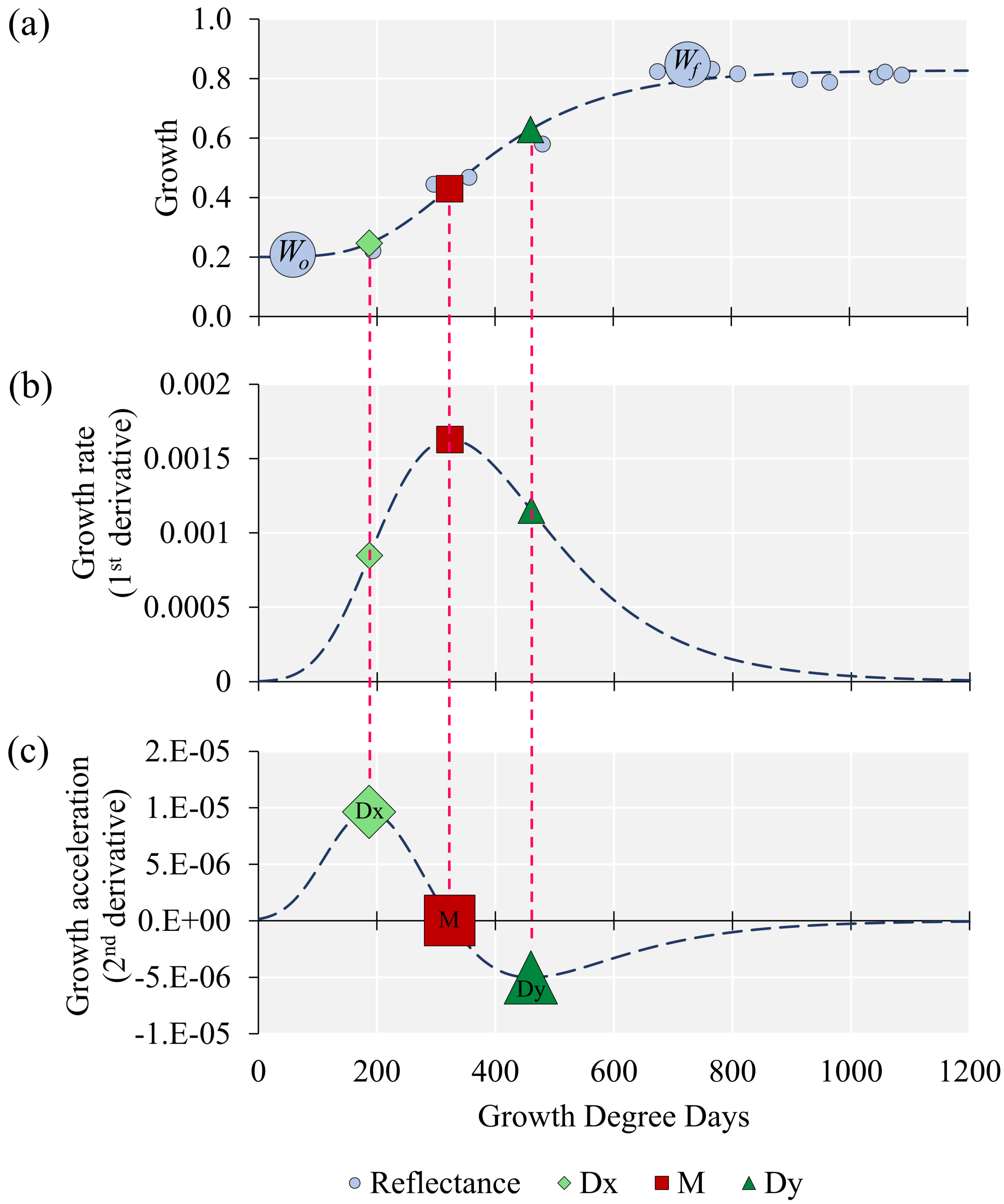


Figure 3.3: Examples of critical points as a function of growth curve (a), growth rate curve (b), and growth acceleration curve (c) of VIs. Critical points represent the moment when the accelerated growth of the VIs is maximized (Dx) and minimized (Dy), M is the GDD at which the growth rate is maximized, Wo is the reflectance of the VIs in the first GDD value and Wf is the maximum reflectance value (upper asymptote).

3.3.4 Yield estimation

In a previous study we tested a simpler approach to perform yield estimation, but the results were not satisfactory. So, for this reason, we opted to use the AutoML tool. Basically, AutoML works in three stages: (i) data preprocessing and feature engineering, (ii) model selection, hyperparameter optimization, and architecture search, and (iii) model interpretation and prediction analysis, which are optimized to obtain the best result (TRUONG et al., 2019). The advantage of using this type of tool is to speed up and facilitate all the work of developing and evaluating ML algorithms, unlike common approaches that require in-depth knowledge about algorithm architecture and manual tasks to adjust algorithm parameters.

All programming was implemented on the platform Google Colaboratory, which is a cloud service based on Jupyter Notebooks. Data acquired at sampling points were partitioned into training (80%) and testing (20%) sets. A five-fold cross-validation was performed in the training set. Estimates were made per image acquisition date, which was in turn converted into thermal sum (GDD) so that growing seasons could be compared. The process was repeated 1000 times for each estimate, and the best result was selected considering the lowest mean absolute error (MAE) in the training stage (3). This criterion was adopted because this stage has cross-validation, which results in higher robustness for assessing estimates.

$$MAE = \frac{1}{n}\sum_{j=1}^{n}|y_j - \hat{y}_j| \tag{3.3}$$

Where: n is the number of data, y_j is the yield value observed in the field, y_j is the yield value estimated by the neural network model.

3.3.4.1 Yield maps

In this section, we show how the observed and estimated yield maps were made and compared with each other. The observed yield maps were made by interpolation using the Kriging method, at a 10-m resolution (as in Sentinel-2). A spherical model was fit for both growing seasons. Semivariogram parameter values for summer cultivation were as follows: a range of 412.08 m, partial sill of 1.30 m, and nugget of 7.63 m, while in the winter a range of 80.88 m, partial sill of 6.15 m, and nugget of 1.74 m. The estimated yield maps were generated from the best results of the sweet potato yield, with the VIs in each growing season being classified as very high (values above 45 t ha^{-1}), high (35–45 t ha^{-1}), intermediate (25–35 t ha^{-1}), low (15–25 t ha^{-1}), and very low (below 15 t ha^{-1}). Finally, to show differences between observed and estimated yields, we generated an error map, which was divided into six classes (every 5 t ha^{-1}) from 0 to 30 t ha^{-1}.

3.4 Results

In this section, we present the definition of the phenological stages of sweet potato using the VIs, which were classified according to VI growth patterns (Subsection 2.4.1). Then, we selected the best periods and VI types for yield estimation (Subsection 2.4.2). Lastly, we built yield maps to visualize its variability and to compare with the observed values in the field (Subsection 2.4.3).

3.4.1 Sweet potato phenological stages

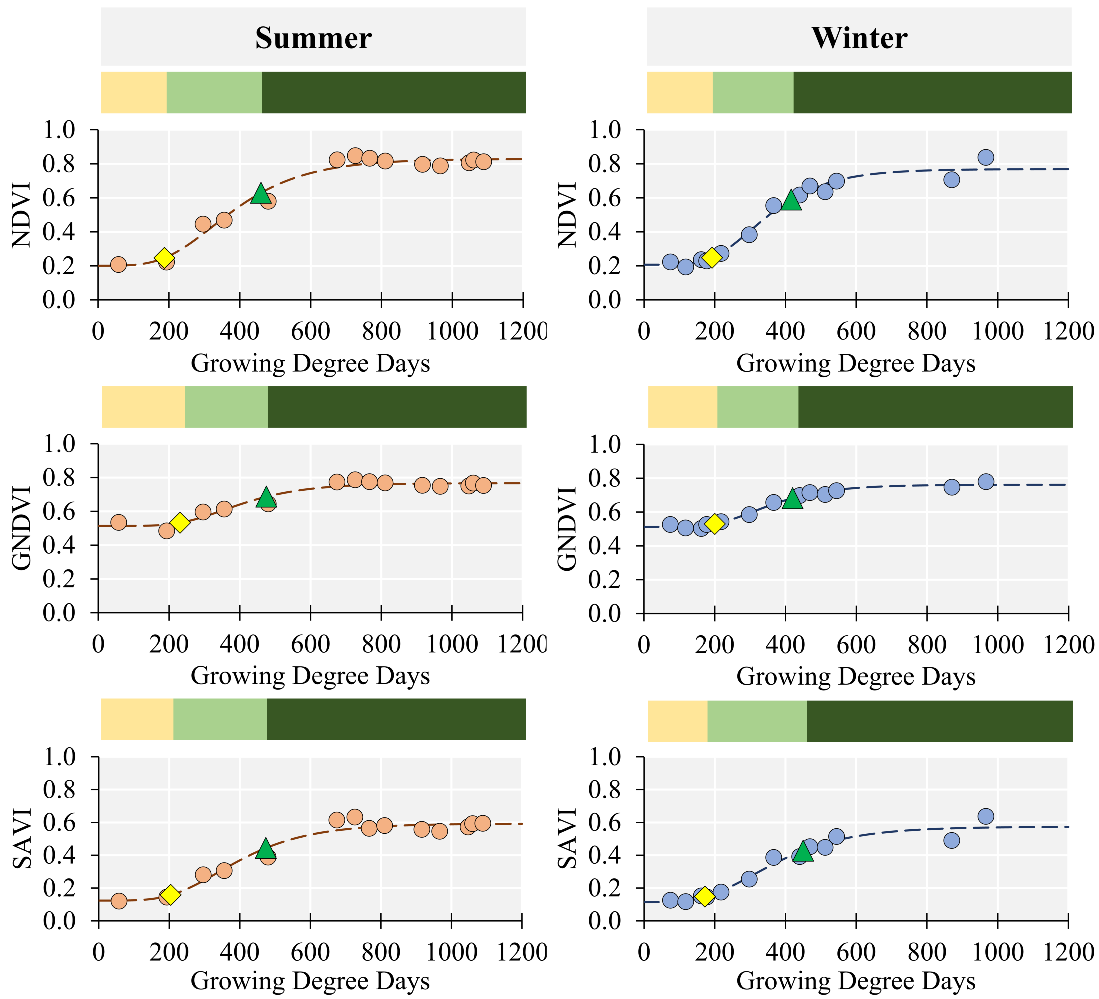
The comparative results of the Gompertz-model fit for VI growth patterns in both seasons considered the limits of variability defined by the standard error (SE) of each parameter (Table 3.2). Therefore, the model parameters for each VI are not different when the SE values overlap. Thus, when comparing the two seasons for each VI, we observed that the minimum (W_o) and maximum (W_f) parameters showed similar performance for all VIs in both growing seasons, except for GNDVI in the winter. Moreover, no differences were observed for the relative growth rates (k) and the moment when it is maximized (M) between the VIs.

Table 3.2: Comparative result of the adjustment parameters of the Gompertz model by vegetation index and growing season.

VI	Parameter	Summer			Winter		
		Mean	SE (±)	R^2	Mean	SE (±)	R^2
NDVI	W_f	0.6279	0.0494	0.97	0.5619	0.042	0.97
	k	0.007	0.0015		0.0086	0.0015	
	M	323.37	25.44		303.95	19.86	
	W_o	0.2001	0.0414		0.2064	0.0269	
GNDVI	W_f	0.2525	0.0283	0.94	0.2492	0.0144	0.98
	k	0.0079	0.0028		0.0088	0.0013	
	M	353.44	35.52		310.33	15.3	
	W_o	0.5145	0.0234		0.5119	0.0089	
SAVI	W_f	0.4691	0.046	0.96	0.4587	0.0537	0.96
	k	0.0071	0.002		0.0069	0.0017	
	M	338.92	31.85		310.69	33.19	
	W_o	0.1238	0.038		0.1143	0.0356	

W_f is the maximum reflectance, k is the relative growth rate in M, M is the GDD at which the growth rate is maximized, and W_o is the reflectance of the first GDD. SE is the standard error of the mean.

All models showed high precision (R2 $>$ 0.94). However, a functional relationship must be established with crop development throughout the production cycle to better interpret these results. Therefore, critical points were analyzed in the growth curve of each vegetation index (Figure 3.4), wherein the model fit to the observed data is represented by the dashed line, according to the parameters in Table 3.2.



VIs	Critical Points	Summer GDD	Summer ρ	Winter GDD	Winter ρ
NDVI	D_x	187	0.24	192	0.24
	D_y	460	0.62	416	0.58
GNDVI	D_x	231	0.53	200	0.52
	D_y	475	0.68	420	0.68
SAVI	D_x	204	0.15	172	0.14
	D_y	474	0.44	450	0.42

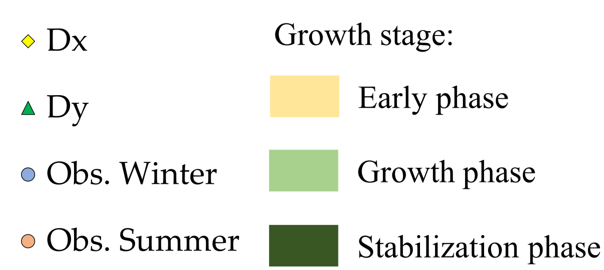


Figure 3.4: Critical points during the growth of sweet potato vegetation indices in two growing seasons. Critical points represent the moment when the accelerated growth of vegetation indices is maximized (Dx) and minimized (Dy). GDD refers to degree-day values and is the vegetation index value.

Overall, vegetation index changes are mostly influenced by vegetation development and soil exposure, given the spatial resolution of the images. For this reason, we observed few differences between the amplitudes of the GDD values that define the development phases (Figure 3.4). Therefore, the growth of VIs could be divided into three stages, as a function of the observed reflectance: (I) initial stage ($<$200 GDD), when vegetation has little influence on VIs; (II) growth stage (from 200 to 500 GDD), when vegetation has high influence on VIs due vegetative growth; and (III) stabilization stage ($>$ 500 GDD), when major changes in VIs no longer occur because vegetative growth has ceased.

In the initial stage of development, all the VIs showed *Dx* values close to 200 GDD regardless of the growing season, except for GNDVI, whose *Dx* values were of 230 GDD only in the summer. In both growing seasons, VIs showed low values, within this GDD range. This characterizes that the crop had little vegetation cover and may have been influenced by the exposed soil reflectance, mainly in the NIR band.

In both growing seasons, the expansion of area covered by vegetation provided an increase of about 60 and 65% from *Dx* to *Dy* in NDVI and SAVI, respectively (Figure 3.4). These values indicate that sweet potato plants reached their peak growth between 200 and 500 GDD, with NDVI and GNDVI values of 0.63 and 0.45, respectively. Regardless of the growing season and growth rate, *Dy* values occurred between 200 and 500 GDD. Among the VIs, GNDVI presented similar values at all critical points analyzed for the two seasons, which suggest that GNDVI, compared to the other VI's, better describes changes in sweet potato growing phases, regardless of the growing season. Regarding the stability point of the tested VIs (after *Dy*), there is no significant variation between the studied VIs. All of them showed a stability pattern above 500 GDD, regardless of the growing season.

3.4.2 Best growing season and vegetation index to estimate crop yield

Winter cultivation showed increases in average (62.40%), minimum (167.14%), and maximum (29.88%) yields compared to the summer cultivation, with lower values of error and standard deviation (Table 3.3). This increase was not expected because the winter harvest occurred at approximately 1000 GDD and the summer harvest at 1150 GDD. In other words, as the crop remained longer in the field during the summer, it should have shown a higher increase in yield.

Table 3.3: Descriptive statistics on sweet potato production (t ha^{-1}) in two growing seasons.

Season	Sample	Average	Minimum	Maximum	Standard deviation	Standard error
Summer	123	22.38	5.6	45.12	9.67	0.87
Winter	100	36.35	14.96	58.6	7.78	0.77

MAE was adopted as a criterion to interpret the results of the training stage of machine learning algorithms and ultimately determine which are the best VI and time for estimation of sweet potato yield in the summer and winter seasons. The estimation results with AutoML indicated that depending on the crop development stage, the same algorithm and vegetation index may not be optimal. For this reason, using AutoML is promising to easily obtain estimation results when a large data set is available. Going deeper into the mathematical details of each algorithm is beyond the scope of our study.

Figure 3.5 shows the results of yield estimates using the VIs in both growing seasons. In the summer season, the lowest yield estimation error occurred during the growth stage (200–500 GDD), when NDVI at 355 GDD showed errors of 2.63 and 5.61 t ha^{-1} for training and validation, respectively (Figure 3.5a). The lowest error of GNDVI occurred at 766 GDD, at the beginning of the stabilization stage (>500 GDD), with values of 3.47 and 6.78 t ha^{-1} for training and validation, respectively (Figure 3.5b). Moreover, SAVI had the lowest error at the end of the stabilization stage (1047 GDD), with values of 3.30 and 7.95 t ha^{-1} for training and validation, respectively (Figure 3.5c).

In the winter season, the lowest error of yield estimation occurred at the end of the growth stage (200–500 GDD), when GNDVI at 440 GDD had errors of 3.06 and 5.12 t ha^{-1} for training and validation, respectively (Figure 3.5e). Both SAVI and NDVI showed the lowest errors at the beginning of the stabilization stage (>500 GDD). At 512 GDD, SAVI had error values of 4.71 and 5.67 t ha^{-1} for training and validation, respectively (Figure 3.5f). At 544 GDD, NDVI showed errors of 4.60 and 5.82 t ha^{-1} for training and validation, respectively (Figure 3.5d).

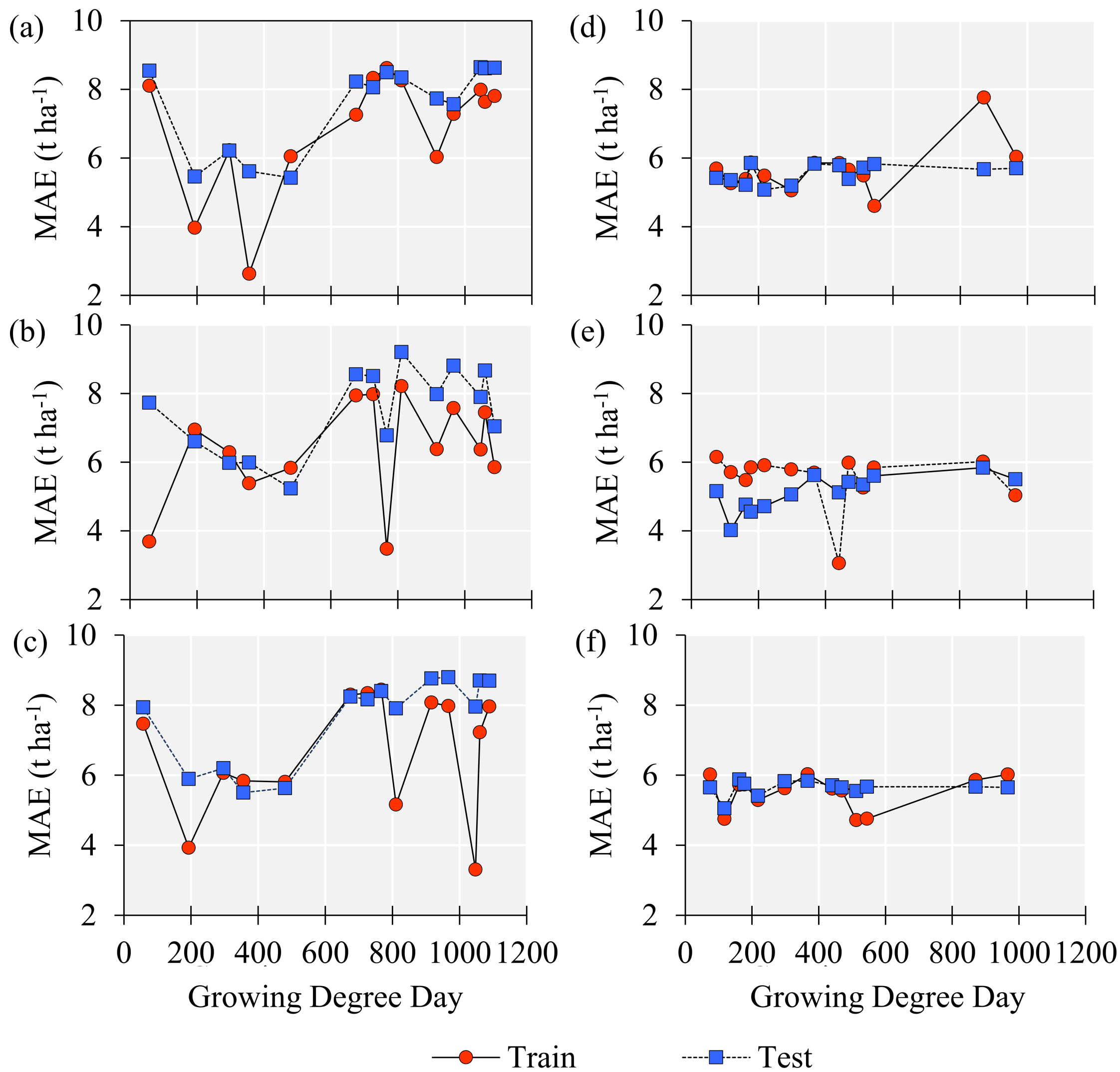


Figure 3.5: Performance of sweet potato yield estimates by vegetation indices, NDVI (a and d), GNDVI (b and e), and SAVI (c and f), as a function of image acquisition time (GDD) in two growing seasons: summer (right) and winter (left).

3.4.3 Sweet potato yield maps

The best estimates of yield in the summer season (NDVI, at 355 GDD) and winter season (GNDVI at 440 GDD) were used to build maps for comparison with Kriging estimates. The maps were classified into six yield classes (Figure 3.6) and enabled visualizing considerable variations in production in each field.

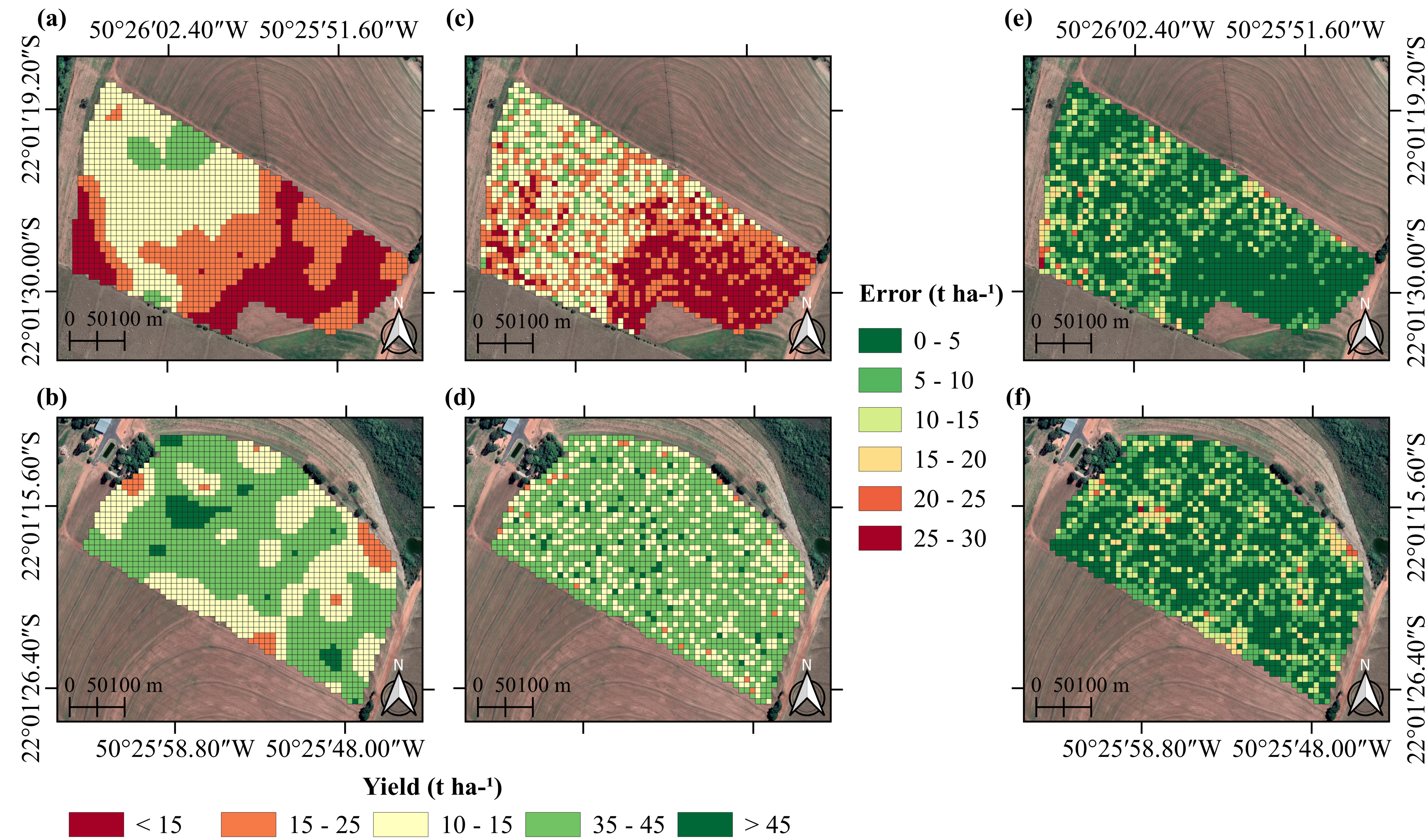


Figure 3.6: Comparisons of maps of yields observed by Kriging (a-b) and estimated (c-d) with error maps (e-f) in two growing seasons, summer (right) and winter (left).

Overall, the maps generated by the kriging method (Figure 3.6a and b) better delineate the yield variability of each study field than the yield maps estimated by VIs (Figure 3.6c and d). In summary, when the Kriging method is used, the maps are generated from data interpolation, where the information from all yield samples collected in the field are considered. Whereas, the estimated yield maps are created using only the vegetation index information. The error maps indicated that the greatest estimation errors occur mainly in borders and where the terrain is uneven (Figure 3.6e and f).

Thus, to make easier understanding and allow comparison of maps of each study field (Figure 3.7), an analysis of the percentage of area occupied by each yield class was presented in the yield maps observed in summer (Figure 3.6a) and winter (Figure 3.6b) with estimated yield using NDVI (Figure 3.6c) and GNDVI (Figure 3.6d). Overall, no major differences were observed between the percentages of the area occupied by each yield class (observed vs. estimated) within each study field (Figure 3.7). The analysis of variability between observed and estimated sweet potato yields by maps indicated that, for summer cultivation (Figure 3.7a), very-low yield class occupied 26.14% of the total area (0.87%), low-yield 31.19% (1.06%), intermediate-yield 36.56% (1.31%), and high-yield only 6.11% (1.12%). Conversely, for winter cultivation, maps (Figure 3.7b) showed that yield concentrated in the intermediate and high classes, with 33.15% (3.54%) and 65.36% (7.51%), respectively, while low and very-high yields covered only 1.49% (2.48%) and 3.54% (1.49%), respectively.

This evidence indicates that using vegetation indices, which can be generated from satellite images and machine learning algorithms to perform yield estimations, can present results as good as maps generated by Kriging methods. One of the possible reasons for this result is that satellite imagery considers the field as a whole (in our study, divided into small parts of 10x10m dimensions, where the information of vegetation indices is extracted), while the Kriging method uses information from the locations where samples were collected to estimate unsampled locations. This may have contributed to establishing the potential relationships between the above and below-ground information. In this way, it is possible to observe in detail the difference between the yield classes that occur within each production field. In the summer range, for example, yields were concentrated in the very low, low, and medium yield classes (Figure 3.7a), while in the winter range yields were concentrated in the medium and high yield classes (Figure 3.7b). These differences between yield classes can be explained by a number of factors related to soil conditions, climate, and genetics that should be monitored during the production cycle. Therefore, it is precisely by exploring these differences to investigate the reasons/problems that determine them, that producers and decision-makers can define strategies to improve the management of production fields.

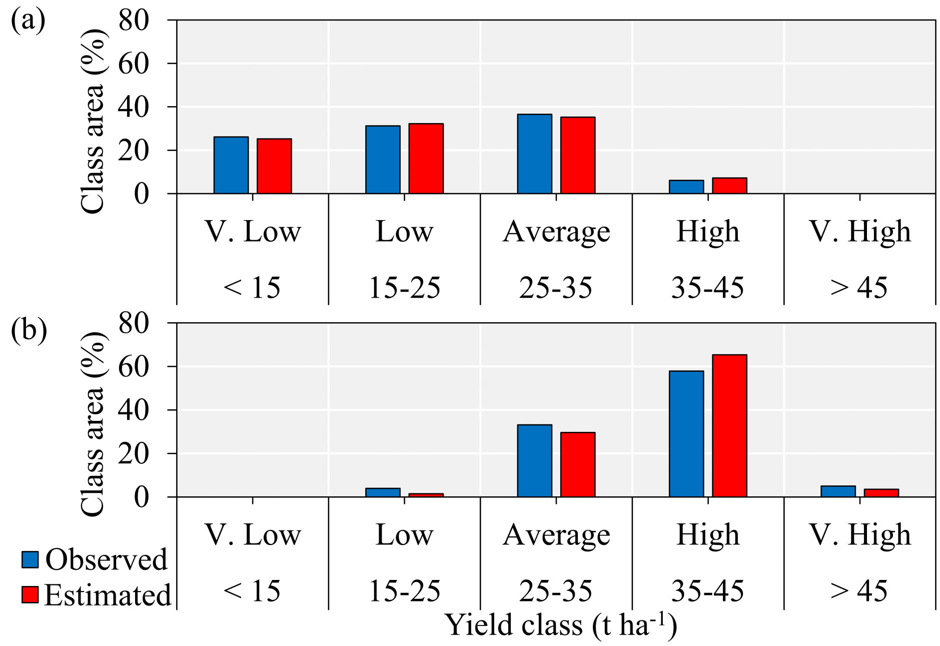


Figure 3.7: Comparison among classes of area occupied by observed and estimated yields in the summer (a) and winter (b).

Figure 3.8 shows the analysis of percentages of the area occupied by estimation errors in both growing seasons. In the summer season (Figure 3.6e), for example, estimation errors up to 5 t ha^{-1} (with a mean of 2.16 t ha^{-1} and standard deviation of 1.44 t ha^{-1}) were observed in 59.51% of the total area of the production field; errors from 5 to 10 t ha^{-1} (7.16 $\pm$ 1.41 t ha^{-1}) in 25.76% of the area; errors from 10 to 15 t ha^{-1} (12.22 $\pm$ 1.44 t ha^{-1}) in 10.36% of the area; and errors higher than 15 t ha^{-1} were observed in only 4.36% of the area. In the winter season (Figure 3.6f), estimation errors up to 5 t ha^{-1} (2.37 $\pm$ 1.45 t ha^{-1}) were observed in 50% of the area, errors from 5 to 10 t ha^{-1} (7.17 $\pm$ 1.46 t ha^{-1}) in 29.98% of the area, errors from 10 to 15 t ha^{-1} (12.06 $\pm$ 1.43 t ha^{-1}) in 13.72% of the area, and errors higher than 15 t ha^{-1} were observed in only 5.46% of the area.

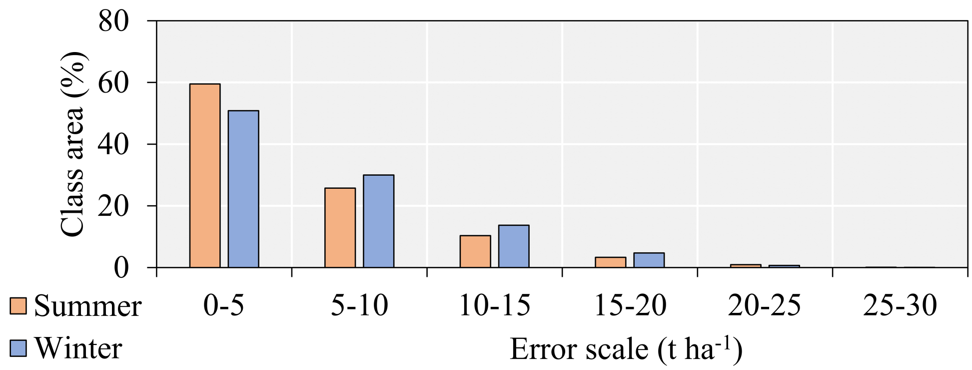


Figure 3.8: Classification of percentage of area occupied by estimation errors for sweet potato yields in both growing seasons.

3.5 Discussion

To our knowledge, this is the first study evaluating sweet potato growth using vegetation indices (VIs) throughout its cycle to establish functional relationships with its phenological stages and yield. Our results showed that the VIs derived from Sentinel-2 satellite images can provide useful information for monitoring sweet potato growth dynamics and for estimating sweet potato yield. In this sense, our findings can assist in management strategies aimed at improving crop management.

3.5.1 Vegetation indices and sweet potato phenological stages

Establishing empirical relationships between sweet potato growth and vegetation indices aligned with thermal accumulation allowed an understanding of crop growth without the need for field inspections. Also, using the critical points by the first and second derivatives of the Gompertz equation showed to be a potential tool to separate the sweet potato stages as the method fit with the growth stages established in the litetature that are initiation, induction, and development (SOLIS et al., 2014; VILLORDON; LABONTE; FIRON, 2009).

The VI values observed before the first critical point (<200 GDD) represented the initial development of the crop (establishment stage) in both growing seasons, normally characterized by adventitious roots production, which initiates 13 days after planting (VILLORDON et al., 2010). This was clearly evidenced by the VIs, mainly NDVI and SAVI to the detriment of GNDVI. In root crops (sweet potatoes and cassava), the establishment is considered the most critical stage during the production cycle (USHA; SINGH, 2013; WIJEWARDANA et al., 2018). The state of the crop at this stage determines a large part of the subsequent growth throughout its production cycle, as well as its yield (PARDALES; ESQUISEL, 1996). Importantly, it is at this stage that some of the roots will multiply and develop into economically important storage roots through the proliferation of cambial cells that form parenchymal cells that accumulate starch (BELEHU; HAMMES, 2004; RAVI et al., 2009; VILLORDON; LABONTE; FIRON, 2009). Therefore, using VIs to monitor the early development stages of the sweet potato crop will help to remotely verify areas with a higher incidence of roots that will be economically important, which consequently implies higher yields.

However, it is worth pointing out some limitations of the early stage monitoring method through remote sensing, where areas with a low incidence of vegetation cover can be misinterpreted due to the reflectance of the soil in the images, which can vary with soil texture, organic matter content, and moisture (HUETE; JACKSON; POST, 1985; QI, 2000). On the other hand, remote sensing can also assist in reducing bottlenecks in plant phenotyping and accelerating breeding programs. For example in the evaluation of genotype $\times$ environment interaction and selection for sweetpotato drought adaptation, that loss of turgor in expanded cells under drought conditions (KIRNAK et al., 2001) and reduced source strength negatively affected the amount of storage root yield under drought (ANDRADE et al., 2016).

During the growth period (200-500 GDD), intermediate stage, sweet potato starts developing tuberous roots, which is the part used in human consumption, in addition to intense growth of cuttings and significant increase in leaf area. It was noticed that the VIs had a significant increase in their values, with higher amplitude for NDVI and SAVI, and lower for GNDVI. This increase in VI values coincides with the change in the growth rate of the crop which after covering the soil changes the preferential source of drainage from the leaf to the tuberization process (CONCEIÇÃO; LOPES; FORTES, 2004) and consequently increases leaf reflectance values. These results indicate that the method proposed in this paper, associating Gompertz growth modeling and VI, is a potential tool to increase the ability to manage the growth variables of sweet potato crops, such as relative rate growth, specific leaf area and unit leaf rate (HUNT et al., 2013; SONNEWALD; FERNIE, 2018). In addition, the use of the Gompertz and IV model has been reported as a potential tool in the analysis of the temporal variability of peanut ripening, indicating the optimal moment of harvest through the inflection point (SANTOS et al., 2021).

Responses varied among the VIs, mainly due to the way they were created. It occurs because these responses are influenced by the reflection of incident radiation from vegetation. It can then be changed according to leaf properties, branches, soil, water presence, and canopy architecture (USHA; SINGH, 2013). NDVI, for example, is more sensitive when vegetation is denser, with a tendency to saturation of the values and decrease of the field variability (CARNEIRO et al., 2019), making it unfeasible for relationships with agronomic parameters. Although SAVI is composed of the same spectral bands as NDVI, it has a factor to correct the soil reflectance effect. In this period, there could still be regions in the production field with a higher proportion of exposed soil, which would explain the reduction in the upper asymptote (Table 3.2, Wf = 0.46) of this VI compared to NDVI. By contrast, GNDVI uses the green band, which is more related to chlorophyll than the other bands (GITELSON et al., 2002). This is an interesting feature because high photosynthetic activity rates and chlorophyll contents are usually observed during the growth period (DWELLE, 1990; PÉREZ-PAZOS et al., 2021; SONNEWALD; FERNIE, 2018), thus potentiating the results of this VI. Therefore, a VI sensitive to changes in chlorophyll contents may be useful to define management strategies to explore the productive potential of sweet potatoes, as this crop responds well to intensive management practices (IESE et al., 2018).

In the stabilization period ($>$ 500 GDD), which corresponds to final development, tuberization increases root mass until the end of shoot growth. Since then, substances in cuttings and leaves are transported to tuberous roots until leaf senescence (WANG et al., 2019). At the end of this period, under rainfed conditions (non-irrigated), plants usually reach senescence and their leaf area is reduced after yellowing and leaf fall, thereby decreasing canopy reflectance. However, this was not evidenced by the VIs used in our study, as there was no decrease in their values. What is common in irrigated sweet potato, where vegetative development can be extended by water availability (WATANABE, 2019).

Tuberization is strongly influenced by canopy growth (PÉREZ-PAZOS et al., 2021). This is because photosynthesis produces photoassimilates used in root development. This process, in turn, can be influenced by endogenous factors such as the hormones cytokinin and abscisic acid, and by environmental factors such as temperature and availability of water and nutrients (FIRON et al., 2009). Therefore, knowing the mass accumulation dynamics of roots during this period is important to define harvesting strategies and verify whether the roots are in accordance with the standards of the market. However, additional studies to investigate the dynamics of daily mass accumulation in sweet potato roots are needed.

The growth dynamics could also assist in determining when to start harvesting, considering the available workforce. This way, producers could prevent the roots from growing too much and being out of commercial standards. However, the low temporal resolution of satellite images makes it unfeasible to obtain the information to establish such a relationship. An alternative would be using unmanned aerial vehicles (UAVs), which can be embedded with a diverse range of sensors, enabling an increased spatiotemporal resolution (ZHANG et al., 2019).

3.5.2 Sweet potato yield estimates and maps

Our study demonstrates the feasibility of estimating sweet potato yields by remote sensing of the crop canopy. Since there is a potential relationship between aboveground and belowground crop information. Such relation was evidenced by PÉREZ-PAZOS et al. (2021), where leaf traits and plant architecture influence the root yield.

The best results in both growing seasons were observed during the growth stage (200-500 GDD), using NDVI in summer and GNDVI in winter. Estimating yield at this stage may seem premature since sweet potato harvest usually occurs around 1000–1200 GDD. However, it is promising since, as stated above, the state of the crop at the initial phase ($<$200 GDD, ie establishment) will determine their subsequent growth and yield (PARDALES; ESQUISEL, 1996). Still, the environmental conditions and soil properties in the stabilization stage must also be considered ($<$200 GDD). High temperatures, for example, can delay or prevent tuberization due to the lignification of adventitious roots (VILLORDON et al., 2010). Moreover, changes in soil characteristics, such as increased density, decreased porosity, and nutrients content are also unfavorable for the development of sweet potato roots (AGBEDE, 2010). In addition, the high efficiency of the ground cover with the canopy is involved in the adaptation to the sub-humid environment (PÉREZ-PAZOS et al., 2021), an important condition for good initial growth. All the above conditions can affect the initial development of the crop, impairing its growth and later development, ocorruing yield variability. Knowing these conditions helps to understand the reasons for the yield variability in each field of the study presented in Figure 3.6.

Regarding the best VI for estimation (NDVI and GNDVI), both use the NIR band of the invisible spectrum in their composition, which is related to the cell structure of the crop leaf and canopy (IMRAN et al., 2020; OLLINGER, 2010). Thus, the main difference in the yield estimate performances between growing seasons may be related to the amount of light reflected in the visible spectrum (green and red bands). NDVI uses the red band, which is more absorbed by chlorophylls (ROMERO-TRIGUEROS et al., 2017). Therefore, this band is less sensitive to changes in chlorophyll content, which is fundamental in biochemical processes for photoassimilate production. By contrast, GNDVI uses the green band, which is more sensitive to high chlorophyll levels for being less absorbed by chlorophyll a and b. Thus, this region of the visible spectrum is more sensitive when these changes occur (CHEN; ORLOV-LEVIN; MERON, 2019; GITELSON, 2005; GITELSON; KAUFMAN; MERZLYAK, 1996; HUNT et al., 2013; YODER; WARING, 1994). Although it is one of the main differences, factors such as climate, cultivation region, and sensor type can directly interfere with the VI performance (AL-GAADI et al., 2016; SUAREZ et al., 2020).

In the summer cultivation, the growth stage of sweet potatoes is faster due to environmental conditions (e.g., high air temperature, photoperiod, and solar radiation). Therefore, tuberization is accelerated, and plants use more water to convert photoassimilates into tuberous root biomass. In this case, the red band is less sensitive to canopy changes since leaf evapotranspiration increases due to environmental conditions. This can therefore explain why NDVI performed better in the summer. On the other hand, since environmental conditions are milder in winter cultivation, sweet potato development in the growth stage is slow. So, the contents of photosynthetic pigments in plants are higher, which, at first, may delay biomass accumulation in tuberous roots. In this sense, plants remain vigorous for longer, and the green band can capture crop canopy changes in greater detail, which also explains the best GNDVI estimates in the winter. This evidence shows that although growing seasons have different environmental conditions during the growth stage of sweet potatoes, reflectance detected by invisible spectrum (infrared) was less sensitive, that is, its relationship with leaf structure changes little when estimation performance was higher. But conversely, reflectance within the visible spectrum (green and red bands) is more sensitive and thus changes in photosynthetic pigments are more evident.

3.6 Future perspectives and applications

Our results provide directions and applications to improve sweet potato cultivation and production through better management and conduction of the crop. From a practical point of view, farmers, researchers, and government agencies could use high-resolution satellite images to monitor crop growth and generate yield maps. This may be an interesting strategy to support decision-making in harvest and post-harvest operations, such as the definition of the market for commercialization, optimal moment to start harvesting, labor required for harvesting, and product logistics and storage.

Sweet potatoes do not have a specific harvest point, but there is a minimum size or weight of roots, which should be approximately 300g. The harvest can be brought forward or delayed depending on market prices, but generally, early harvest means lower yields because smaller roots are harvested. Delaying the harvest can imply more damage by insects and the formation of overly large and often more defective roots. Thus, the grower must identify the moment close to the ideal size of roots to start harvesting. It is known that naturally there is soil variability, among other environmental components, which generates uneven development of plants. Thus, plants located in more favorable locations will potentially be able to harvest faster. Overall, our results can directly and practically help growers to identify which field is more developed and should be harvested first. However, to determine harvest strategies at the sub-field level it is necessary to estimate the root mass to determine which market will be marketable. But there are no studies for this level of detail yet.

Using satellite images to divide the growth phases in sweet potato enables growers to easily define the points where growth phase changes occur, based on meteorological information that can easily be acquired in the region of the production fields. By knowing when these changes occur, it is possible to define, for example, at what time images will be acquired to make yield estimates. Or even, investigate from the images how the sweet potato growth is for several production fields, simultaneously, without the need for field inspection, and then define in which fields seasonal inspections will be performed to collect information. Furthermore, this study indicates that it is possible to monitor the crop's hydric, nutritional, and phytosanitary status, because if these parameters are not normal, a change in the spectral behavior of the plant is expected, which could be identified by satellite images. This information is useful to correct existing deficiencies in the area or even to identify specific plots that need more attention.

Moreover, farmers can use the yield maps to set specific management strategies on a subfield scale, thus achieving their production goals. In this sense, low-yield areas can be defined to investigate soil properties for potential fertility and compaction issues. Otherwise, high-yield regions could be defined for the selection of vigorous seedlings, with good phytosanitary quality, to be further used in new plantings. Sweet potatoes are generally propagated through cuttings taken from previous harvest vines (JIANG et al., 2016) since there is no production for multiplication. Such approach would improve the quality of propagation material to be used in the next harvest. Vegetative propagation keeps characters of plants of interest, thus allowing multiplication of the best material (BISOGNIN, 2011; MEGERSA, 2017). But, to the best of our knowledge, there are no studies on implementing remote sensing for such purpose, which opens new horizons for studies. This could be used to speed up plant breeding programs focused on increasing sweet potato yields. After testing different genetic materials, an early yield estimate based on remote sensing would help to identify fields with high productive potential more easily.

3.7 Conclusions

Our study clearly demonstrates the feasibility of using VI-based remote sensing information derived from Sentinel-2 images to assess growth dynamics, phenological stage changes, and yield variation of sweet potato grown in the summer and winter. The paths are now open to define management strategies to improve cultural, harvest, and post-harvest practices and to understand root growth using crop canopy-based remote sensing. We believe that our approach, although developed in Brazil, can potentially be used in different regions of the world, not only for sweet potato but also for other crops that have roots, rhizomes, and tubers as raw materials of economic interest.

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CHAPTER 4 – Predicting on multi-target regression for the yield of sweet potato by the market class of its roots upon vegetation indices

4.1 Abstract

Single-target regression can accurately predict the crop's performance but fails to generalize problems with more than one true and cross-validatable solution. An alternative to output multiple numeric values upon the input, we think, would be multi-target regression (MTR) with either Random Forest (RF) or k-nearest neighbors (KNN). Therefore, we captured the advantages of high-resolution remote sensing and multi-target machine learning into an immersive single framework then analyzed if it could be possible for accurately predicting for the yield of sweet potato by the market class of its tuberous roots (i.e., Extra $<$0.15 kg; 015 Extra AA 0.45 kg; and Extra A $>$0.45 kg) upon imagery data on summer and winter full-scale fields. The remote sensing captured the spectral changes on both fields and enabled the MTR to accurately predict for the yield of sweet potato in total and by the market class of harvestable roots upon normalized difference vegetation index (NDVI) and its derivative version (GreenNDVI) as well as upon soil-adjusted vegetation index (SAVI). The SAVI-RF framework predicted the summer field to yield marketable roots at the proportions of 2.04 t ha^{-1} Extra, 3.86 t ha^{-1} Extra AA and 2.08 t ha^{-1} Extra A, and the spectral data from the mid-stage of cultivation at 296 growing degree days (GDD) minimized its mean absolute error (MAE) to 2.66 t ha^{-1}. The GNDVI-RF framework predicted the winter field to yield 1.64 t ha^{-1} Extra, 5.02 t ha^{-1} Extra AA and 3.65 t ha^{-1} Extra A, with an error of 3.44 t ha^{-1} upon spectral data from sampling on the late stage at 966 GDD. Our insights are timely an absolutely will open up the horizons for harvesting high-quality roots to commercialization, industrialization and propagation, and scaling up this essentially provocative yet emerging crop for food safety and energy security.

Keywords: high-resolution remote sensing; Ipomoea batatas; k-nearest neighbors; Random Forest; smart harvesting; transformative agriculture.

4.2 Abbreviations and nomenclature

CEAGESP, general warehouse company of São Paulo

GDD, growing degree days

GNDVI, green normalized difference vegetation index

GNSS, global navigation system

KNN, k-nearest neighbors

MAE, mean absolute error

MLR, multi-label regression

MTR, multi-target regression

NDVI, normalized difference vegetation index

RF, random forest

SAR, synthetic-aperture radar

SAVI, soil-adjusted vegetation index

STR, single-target regression

UAVs, unmanned aerial vehicles

USGS, United State geological survey

4.3 Introduction

Food safety undoubtedly is one of the world's biggest challenges to sustainable agriculture. Thus, cooperation is necessary for farming with more productivity yet societal and environmental responsibly (BAROUDY et al., 2020). If not, we will fail to progress and fulfill the rising global demands for health-promoting safer food items and life quality (MILERIENE et al., 2020). Sweet potato (*Ipomoea batatas* [L.] Lam.) ranks sixth for the world's production of carbohydrate-rich food, absolutely, one of the most commercially valuable starchy horticultural crops, especially for scoping agricultural systems (ALAM, 2021). Sweet potato's ability to produce starch-rich tubers can assist with tackling societal impacts of malnutrition. Its role in minimizing food unsafety is more likely for emerging tropical and subtropical countries, where deficiencies or imbalances in people's dietary intake of daily energy and/or nutrients threat the healthily lifestyle and regrettably take millions of lives away, annually (MOLLINARI et al., 2020). Also, it is an excellent source of sugars for making future-proof biofuels via fermentation (e.g., bioethanol) and anaerobic digestion (e.g., biogas), thus potentially contributing to energy security (TRUONG et al., 2018). In order for sweet potato to grow healthily and accumulate an appreciable amount of starch in its harvestable tuberous roots, suitable practices are necessary for managing fields.

The nutritional composition of sweet potato's roots varies drastically with the genotype and its dynamic relationships with the environment (TRUONG et al., 2018). If the rainfall is not regular, the soil is poorly fertile, the solar radiation is not physically enough to effective photosynthesis or the management is unreasonable, the agroecosystem usually limits the roots to grow and develop vigorously and productively, as vital resources are not sufficiently available for the nutrition of the plant (SANTOS et al., 2006). If, however, climatic conditions and systematic agricultural operations are reasonable, sweet potato is able to structure up tubers harvestable and acceptable at the market, and its vegetative propagation into new fields is appropriate (SANTOS et al., 2006). In Brazil, CEAGESP classifies and values the sweet potato by the mass of its roots. If they are up to 0.15 kg, they are class Extra. If, however, they are between 0.15 and 0.45 kg or more than 0.45 kg, they are class Extra AA and class Extra A, so about 55% and 30% more profitable than class Extra, respectively. Since market class defines size of production and profitability, its on-field prediction can do support more precisely harvesting high-quality material for commercialization and propagation (TEDESCO et al., 2021), and reducing generation of unsuitable roots as agro-food residues post-harvest.

Conventional methodologies for measuring the mass of roots are simple to set up but labor-intensive, time-consuming and destructive (ERPEN et al., 2013). Also, an expert is necessary for accuracy and reliability. If not, sampling is not adequate and makes it difficult for capturing the spatial-temporal variability of the field, leading to bias and misinformation (ERPEN et al., 2013). Monitoring becomes more complex for sweet potato or any other geocarpic crop. Because of habit of growth, it sets its fruits underground, and thus digging is necessary for removing them out of the soil to sample (TEDESCO et al., 2021). This adds costs to the process, which further emphasizes the necessity for alternatives. An option to replace manual sampling, we think, would be an emerging technology of precision agriculture, the remote sensing. Orbital (e.g., satellites), suborbital (e.g., UAVs) and ground-level sensors can monitor spectral changes on the canopy without touching about the object (MICHAEL et al., 2021). Therefore, they are non-destructive, acquire precise survey-grade data in real-time and export reflectance into useful VIs. NDVI, GNDVI and SAVI are highly capable of deriving functional relationships between features of morphophysiology and components of production, so can accurately monitor the on-field variability and do support making decisions on planting and harvesting aboveground (ASHAPURE et al., 2019) and underground (TEDESCO et al., 2021) crops. The assistance of machine-learning algorithms can compensate for the complexity of using VIs as inputs to output the yield for sweet potato, preventing computational unfeasibility (TEDESCO et al., 2021).

Machine learning is powerful to analyze high-dimensionality database and can optimize predicting crop's performance from structurally complex arrays (ASHAPURE et al., 2020). Diversity of algorithms with particular statistical and computational properties does support robustly processing pixel-wise information at the level of experimental plots or commercial scale into interpretable and assignable linear and non-linear patterns (MASTELINI et al., 2018). However, if the task of ML is multi-objective, they become rather complex and fail to generalize problems with more than one true and cross-validatable solution. Quality is one factor determining value and acceptance of an agricultural product at the market. It can vary drastically with the weather and management, as in the particular cases of coffee's grains (KAZAMA et al., 2020), cotton's fibers (CONSTABLE et al., 2014) and sweet potato's roots (TEDESCO et al., 2021). A completely mature material is more commercially valuable, and thus the on-field monitoring to precisely harvest it at the optimum stage is of great relevance to maximize yield and minimize losses and costs. However, food-producing areas often are spatially and temporally heterogenous and make it extremely difficult for predicting on single-target algorithms for the yield of an agricultural product by its quality. As sweet potato matures, it transports photoassimilates to the roots until the stage of tuberization levels off. These reproductive structures compete interspecifically for physical space and nutrients, so they are completely distinctive in size, shape and composition. An alternative to output multiple numeric values for the specific yield of its market classes, we think, would be MTR.

The MTR is an exceptional multi-output learning approach and can predict more than one value up the input merely as a result of processing numeric variables (MELKI et al., 2017). If, however, the independent variable is categorical, it reads better as MLR instead. Advantages of MTR, relative to STR, potentially include less probable overfit and greater predictive performance and inductive transfer by learning from an empirical situation with several tasks (BORCHANI et al., 2015). Additionally, its ability to optimally combine linear functions with descriptive attributes into an intuitive framework makes it one of the most expressive and readable algorithms to learn from complex problems, especially in association with random forest by creating rules to export the output of multiple decision trees into a single result (BORCHANI et al., 2015). As it handles both classification and regression, it is applicable to many fields of research. The literature focuses most on ecological modeling (KOCEV et al., 2009), signal processing (TUIA et al., 2011) and healthcare operating logistics (SIMSEKLER et al., 2021), and thus further in-depth investigations are necessary for its capability of resolving agricultural datasets. Therefore, our exploratory study profits from the gaps and opportunities from the progressing academic literature on predicting crop's performance to set out the possibility of advantageously integrating high-resolution remote sensing and multi-target learning into an immersive single framework to accurately predict for the yield of sweet potato by the market class of its tuberous roots upon imagery data on summer and winter full-scale fields.

4.4 Methodology

Empirically, we remotely sensed commercial fields of sweet potato to realistically monitor and capture spectral changes on the canopy in time and space then analyzed if it could it be possible for the multi-target regression to accurately predict the yield by the market class of its tuberous roots.

4.4.1 Site description

The subject of study was the sweet potato cultivar Canadense. To roll out full-scale fields ($\sim$16 ha) in the region of Tupã at coordinates $W\ 50°43'31''$ and $S\ 22°02'39''$ healthily seedlings were harvested from earlier cultivations then vegetatively propagated on February and July 2018 to refer the summer and winter, respectively. Local climate was Aw, with rainy summer and dry winter. The soil was Oxisol, with predominantly clayey texture. A central pivot was set and programmed to irrigation on the plantations to prevent any drought, which might interfere with the reflectance. More detailed information on crop management can be found in TEDESCO et al. (2021). These authors empirically analyzed the potential of remote sensing to characterize the phenological development of sweet potato, and emphasized the usefulness of GDD to establish relationships between spectral changes on the canopy and components of production and thus compare the results of contrasting growing seasons.

4.4.2 In-situ measurements

To quantitatively analyzed the yield of sweet potato, regular grids of one-hundred twenty-three points at 35 m apart and one-hundred points at 40 m apart were programmatically generated and projected on the respective fields of summer and winter to optimize sampling roots (Figure 4.1). The plots effectively were 3-m^2 in area and were georeferenced by a GNSS receiver, an electronic device able to receive and process signals from one or more satellite constellations into position, velocity and precise time of an object. To measure the roots in quantity and mass, they were removed out of the plots by manually digging, cleaned up then visually counted and weighted on an analytical scale approximately 120 and 110 days after planting on the fields of summer and winter, respectively. Afterwards, the material was classified by the market class, as per the standards of CEAGESP, and its yield was calculated in tons per hectare (t ha^{-1}) as the usual unit among growers in Brazil and abroad.

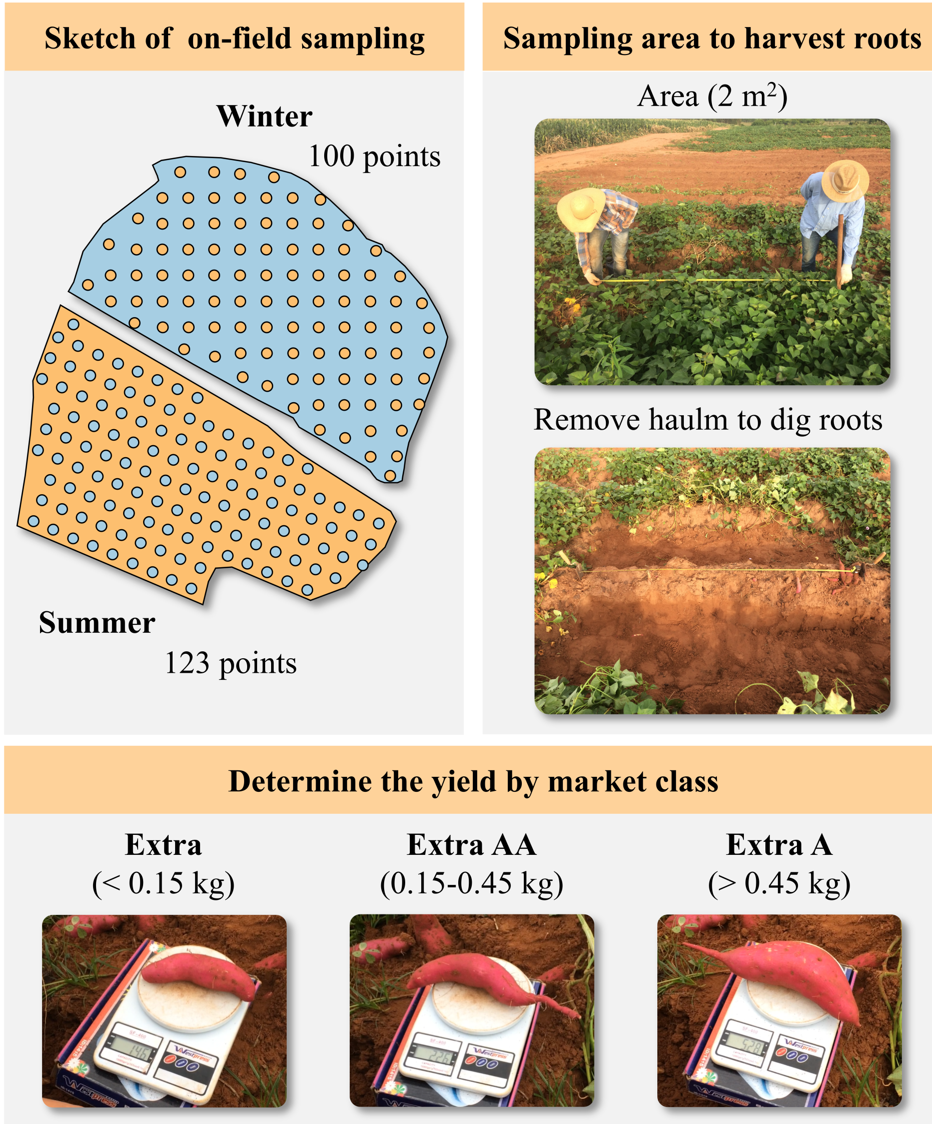
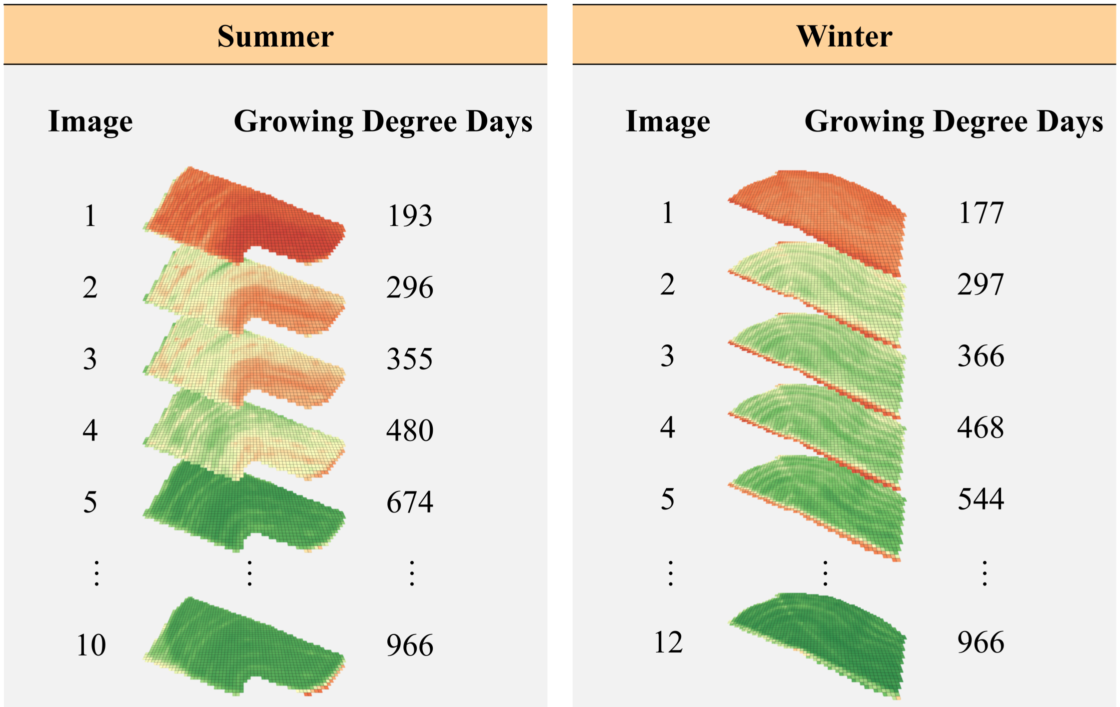


Figure 4.1: Sketch of on-field sampling.

4.4.3 Satellite data collection

To establish functional relationships between yield of sweet potato by the market class of its roots and spectral changes on the canopy over time, Sentinel-2 imagery data available from Earth Explorer of the USGS were downloaded to extract VIs (Figure 4.2). All images from planting to harvesting were critically analyzed to quality (e.g., cloudiness) then radiometrically corrected by converting radiance into surface reflectance of the bands of green (0.540-0.575 um), red (0.650-0.680 um) and near-infrared (0.785-0.900 um) in the environment of Semi-Automatic Classification Plugin for photogrammetry (CONGEDO, 2021).

The VIs to reflectance on the canopy over time included NDVI, GNDVI and SAVI, which are useful to analyze biophysical features.



Vegetation index	Equation	Reference
NDVI	$\left(\frac{\rho_{NIR} - \rho_{RED}}{\rho_{NIR} + \rho_{RED}}\right)$	Rouse et al. (1974)
GNDVI	$\left(\frac{\rho_{NIR} - \rho_{GREEN}}{\rho_{NIR} + \rho_{GREEN}}\right)$	Gitelson et al. (1996)
SAVI	$\left(\frac{\rho_{NIR} - \rho_{RED}}{\rho_{NIR} + \rho_{RED} + 0.5}\right)(1 + 0.5)$	Huete et al. (1992)

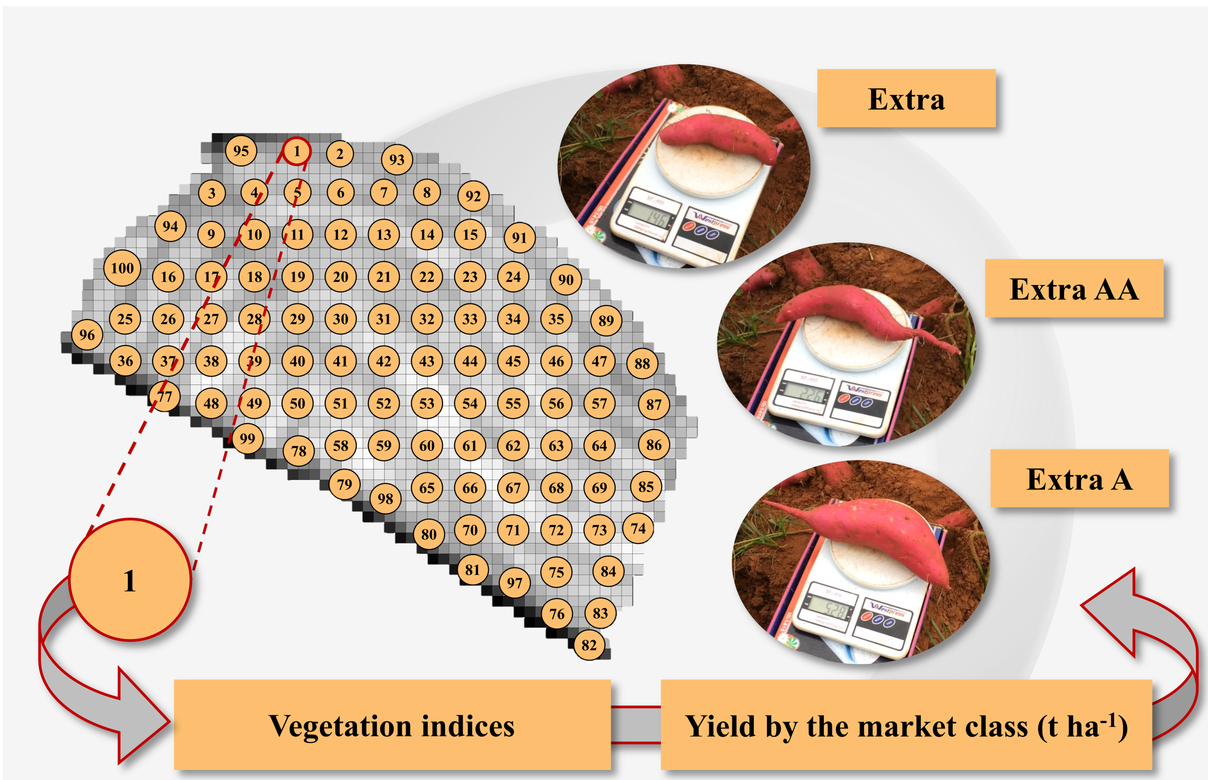
Figure 4.2: An illustrative example imaging on the fields to extract vegetation indices.

4.4.4 Prediction on MTR

This section, firstly, introduces the creation and curation of dataset then describes the prediction on MTR for the yield in the environment of Google Collaboratory. This platform provides the user cloud-computing service on Jupyter Notebook.

4.4.4.1 Data curation

A representative dataset was generated to each field (Figure 4.3). Afterwards, vegetation indices were computationally extracted individually from the samples on the snapshoots then associated with the values of yield by the market class. A z-score method to measure central tendency and deviation (UROLAGIN; SHARMA; DATTA, 2021) was carried out to detect and remove outliers out of the datasets then they were divided into subsets with 80% and 20% of original information for training and cross-validation of algorithms.



Sample	NDVI	GNDVI	SAVI	Extra	Extra AA	Extra A
1	0.4997	0.6349	0.3473	6.41	23.64	12.08
2	0.4939	0.6322	0.3424	4.78	29.85	6.25
3	0.5081	0.6490	0.3556	5.84	25.70	9.62
⋮	⋮	⋮	⋮	⋮	⋮	⋮
100	0.5881	0.6791	0.4067	2.56	20.88	6.67

Figure 4.3: An illustrative example creating dataset to predict on MTR for the yield of sweet potato by the market class of its tuberous roots.

4.4.4.2 Multi-target regression

Since sweet potato can produce roots with distinctive size, shape and mass, MTR was implemented to predict the yield by the market class (i.e., Extra $<$ 0.15 kg; 0.15 kg Extra AA 0.45 kg; and Extra A $>$ 0.45 kg), not only in total as the corresponding collection of STR algorithms do. The algorithms to output multiple numeric values for the independent variable upon the VIs included RF (BELGIU; DRĂGUŢ, 2016) and KNN (ALI; NEAGU; TRUNDLE, 2019). These approaches are highly capable of resolving empirical problems with several tasks, without bias or computational unfeasibility (CHLINGARYAN; SUKKARIEH; WHELAN, 2018). Training and validation of algorithms were conducted on toolkits available from the package Scikit-learn (PEDREGOSA et al., 2011), which is a Python module for machine learning built on top of SciPy. For training, datasets were scaled between 0 and 1 (StanderScaler) and hyper-parameters were optimized upon the inputs (GridSearchCV). As for the cross-validation, ten epochs were iteratively carried out as the minimum number of passes to prevent overfitting (DUAN et al., 2014).

4.4.5 Data analysis

To describe the data of crop's yield for position and dispersion measurements, the minimum, maximum, mean and standard deviation were calculated. The metric to analyze the adequacy of MTR algorithms was the MAE. The lower the value of MAE is, the closer from the original observation the estimate is, and thus the predictability of an algorithm increases. To adequately visualize the most accurate combinations for predict the sweet potato's yield by the market class of its tuberous roots, a Sankey diagram was designed from data on predictive error. The graphical components or layers of flow chart included phenological development (early, middle and late) according to TEDESCO et al. (2021), vegetation index (NDVI, GNDVI and SAVI), growing degree day and MTR algorithm (RF and KNN).

4.5 Results

4.5.1 Crop's yield by the season

The yield of roots, regardless of the market class, widely varied in both seasons (Figure 4.4). In the summer, the crop produced 5.60-45.10 t ha^{-1}, and the range for the winter was 14.95-58.60 t ha^{-1}. Therefore, the cooler period outperformed the warmer period in the amount of mass and also was more homogeneous, 36.35 $\pm$ 7.80 t ha^{-1} and 22.40 $\pm$ 9.65 t ha^{-1}, respectively. The fields were quantitatively distinguishable and assisted with adequately mapping the site-specific yield by the market class, supporting the innovative nature of our study. The summer field yielded more Extra AA (11.85 $\pm$ 6.80 t ha^{-1}) than Extra (8.45 $\pm$ 3.30 t ha^{-1}) and Extra A (3.30 $\pm$ 2.25 t ha^{-1}), an evidence of production with intermediate quality. The prevalence of Extra AA (23.10 $\pm$ 6.20 t ha^{-1}) over Extra A (8.65 $\pm$ 5.80 t ha^{-1}) and Extra (4.60 $\pm$ 2.05 t ha^{-1}) also existed for the winter field. Clearly, the growing season determined the quality, and the winter tended to go on larger quantities of Extra A, relative to the summer, which produced most the Extra, with approximately 48.80% of total harvested. An inferior class usually is less commercially valuable, and thus the profitability decreases as well as the acceptance by the consumer. This inference can further support the importance of our study to areas, whereby heterogeneity makes it difficult for growing sweet potato with high cost-effectiveness.

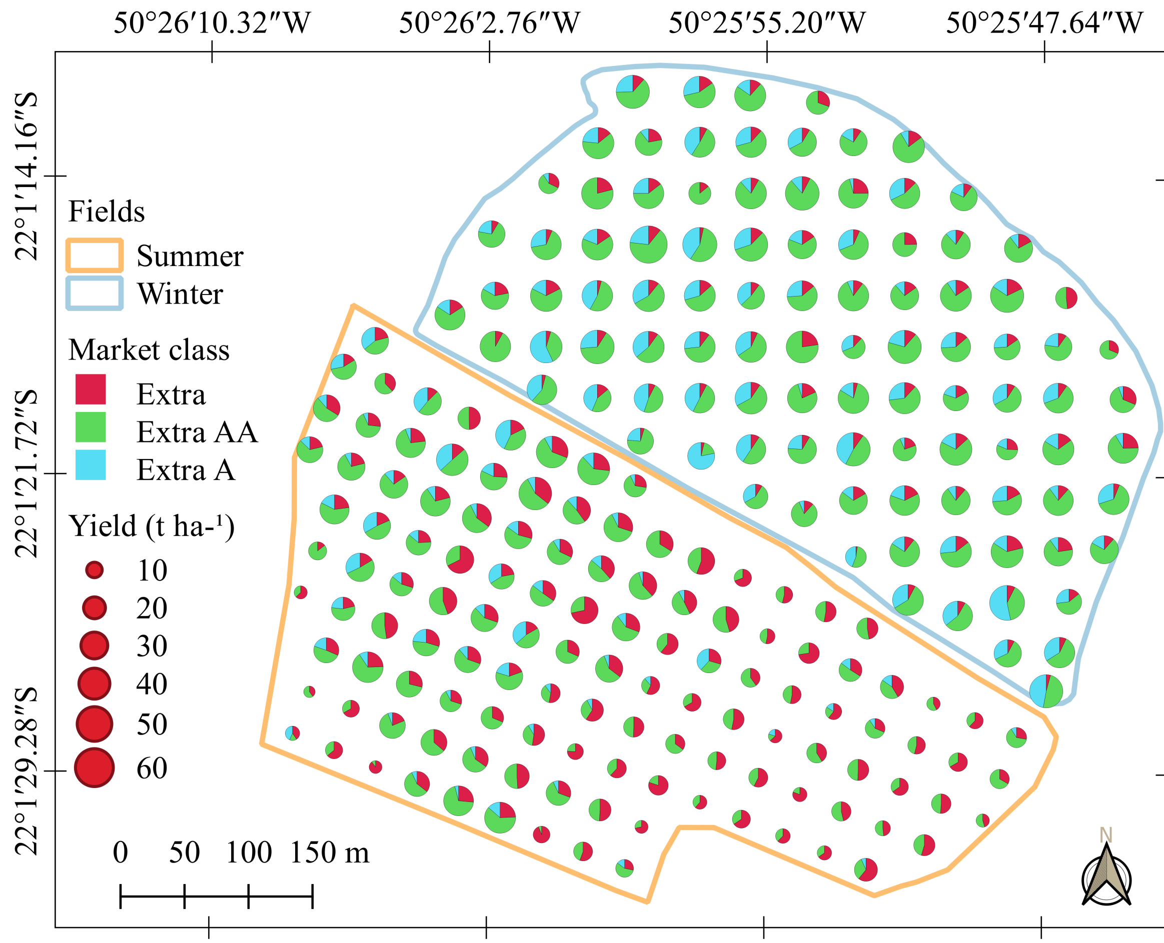


Figure 4.4: Spatial variability of yield of sweet potato by the class of valorization in two growing seasons.

4.5.2 Prediction on MTR

The RF and KNN robustly outputted multiple numeric values for the independent variable upon the VIs, supporting our hypothesis to the ability of MTR for easily and flexibly coping with an empirical situation with several tasks, even for spectral data. The Sankey diagram (Figure 4.5) adequately illustrated the most accurate combinations to export the reflectance into the estimate yield by the market class, not only in total as the corresponding collection of STR does. The RF outperformed the KNN in the prediction of yield upon the SAVI from imaging on the canopy at the early stage of cultivation at 175-195 GDD, irrespective of the field. As for the mid-stage at 215-295 GDD, RF enabled the most accurate learning examples upon SAVI and GNDVI, thus further supporting its greater predictability. Likewise, GNDVI outperformed the other VIs in the prediction of yield at the late stage of cultivation at 915-965 GDD, regardless of growing season and algorithm.

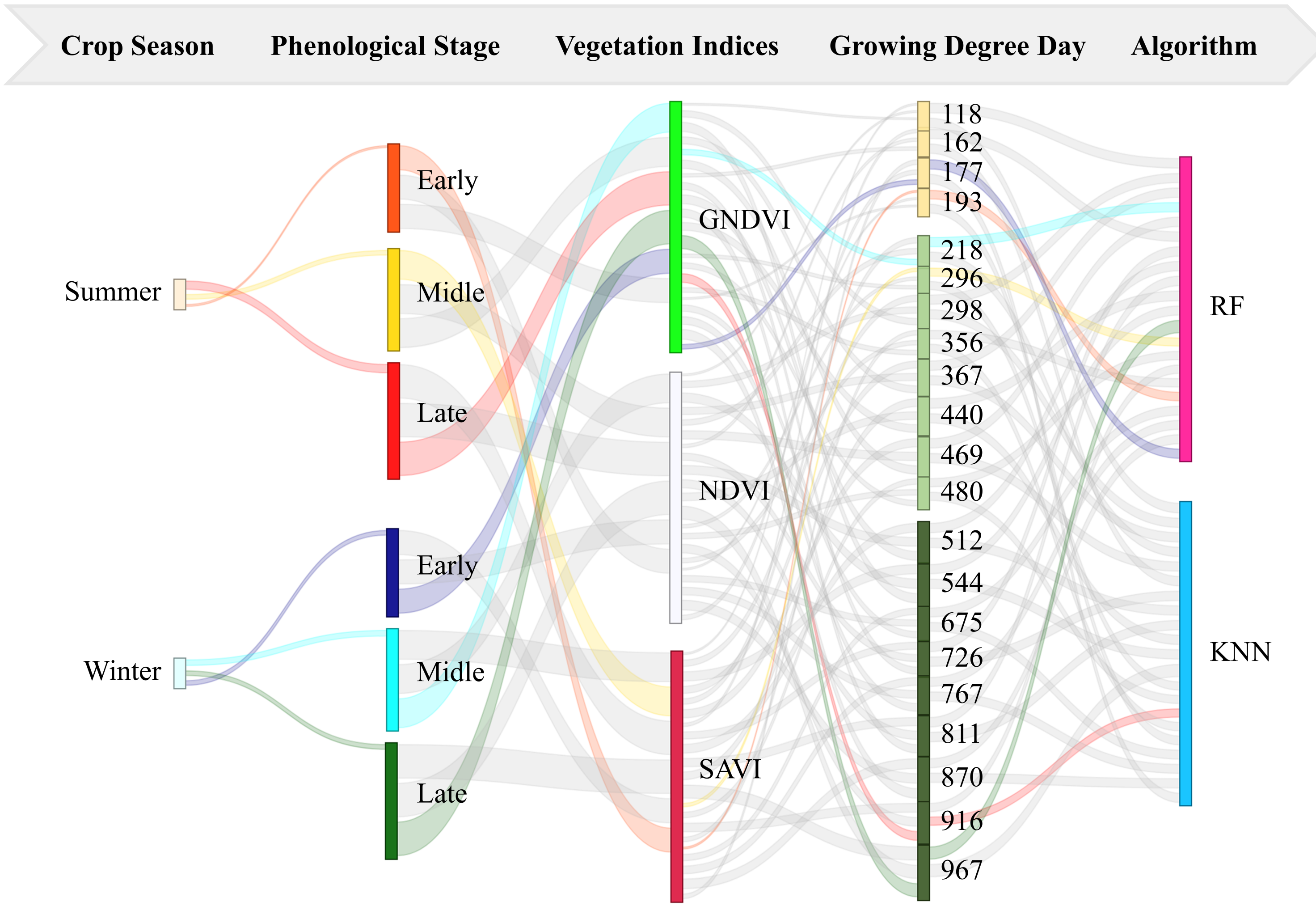


Figure 4.5: Sankey diagram for the most accurate combinations of MTR algorithms and vegetation indices to predict for the yield of sweet potato by the market class of its tuberous roots. The flow chart intuitively displays bars and paths drawn in proportion to predictive error. Colorful paths visually assign to the best solutions possible to MTR, with the opposite true for the greyscale paths. The finer they are, the lower the MAE is, and thus an accurate prediction is more likely. As an illustrative example, imaging on the canopy at the early stage of cultivation in the summer at 193 GDD can allow for extracting SAVI as the most reliable VI to predict on random forest for the yield upon the reflectance, as it minimizes the MAE.

The inputting of imagery data from remotely sensing on the crop at the beginning of cycle produced predictive errors of 2.50-2.90 t ha^{-1}, regardless of the growing season. Adequacy of both algorithms considerably increased with computationally extracting and processing VIs from imaging on the canopy at the subsequent phenological stages. Sampling on the winter tended to produce larger values of MAE of 3.55 t ha^{-1} at 215-480 GGD (mid-stage) and 3.45 t ha^{-1} at 510-970 GDD (late stage), with the opposite true for sampling on the summer at the same intervals. As for the market class, random residuals ranged from 1.65 t ha^{-1} to 2.05 t ha^{-1} for the Extra. In contrast, Extra AA associated to the largest values of MAE of 3.90-5.05 t ha^{-1} (Table 4.1). Therefore, the quality of sweet potato influenced on the predictability of MTR, with straightforward evidence of computational outperformance for roots as massively as 0.45 kg, consistent with their higher homogeneity in the winter than the other classes in the summer or even in the same climatic situation. Presumably, spatial-temporal variability naturally existing in the fields determined the robustness of predicting on MTR for the yield, but not critically enough to an unacceptable/intolerable adoption, so it is scalable.

Table 4.1: Most accurate combinations of MTR algorithms and VIs to predict the yield of sweet potato by the class of valorization.

Season	Stage	Most accurate combinations			Yield error (t ha^{-1})			
		VI	GDD	Algorithm	Extra	Extra AA	Extra A	General
Summer	Early	SAVI	193	RF	1.76	5.17	1.76	2.90
	Middle	SAVI	296	RF	2.04	3.86	2.08	2.66
	Late	GNDVI	916	KNN	1.44	5.07	1.70	2.74
Winter	Early	GNDVI	177	RF	1.79	4.33	4.40	3.51
	Middle	GNDVI	217	RF	1.84	4.98	3.84	3.55
	Late	GNDVI	966	RF	1.64	5.02	3.65	3.44

4.6 Discussion

Our study is the first mentioning the use of MTR in the prediction for the yield of sweet potato by the market class of its tuberous roots upon spectral data. The RF and KNN can successfully learn from the VIs, and thus adequately output multiple numeric values for the independent variable. The amount of production per area unit can vary spatially with harvesting roots Extra, Extra AA and Extra A as well as temporally with planting on the summer and winter to analyze the climatic influence on the acquisition, quality and processing of survey-grade images, which are readily predictable by MTR. The RF can predict the yield more accurately than the KNN, except for the spectral data from imaging on the canopy at the late stage of cultivation in the summer. The outperformance of RF is attributable to its particularity of correcting for decision's habit of overfitting to the training subset. Its disadvantages are few, but this method of determining variable importance eventually can fail to process data with collinearity or permutation, thus favoring features with more levels and smaller groups over larger groups. The lack-of-fit for its learning from spectral data from remotely sensing on the sweet potato at the mid-to-late stage in the winter can support this weakness. As its predictability greatly depends on the characteristics of dataset, the choose of an appropriate VI as an input is extremely important to prevent computational unfeasibility. SAVI and GNDVI can be the best options possible to maximize predicting on RF for the yield, while the NDVI cannot apply to any of the algorithms. A peculiarity of KNN refers to its sensitivity to site-specific structure of the data (ABBAS et al., 2020), and its lower predictability in most of the samples in this study can support this trend from the existing literature. In regression by KNN, the input consists of closest training examples in the dataset, and the output is the property value for the object, or equivalently, the average of the values of k-nearest neighbors. Evidently, distance is the key to its successfully adoption, and the structuration of training data can improve its accuracy in representing vectors or multidimensional features. An option of VI to make its use in the prediction for the yield of sweet potato feasible is GNDVI, as it can minimize its predictive error at on-field samples at the late stage of cultivation in the summer.

The most adequate VI to accurately predict the yield from remotely sensing on the canopy at the beginning and middle of the cultivation is SAVI, as it more effectively captures the reflectance and minimizes the function of MAE. The primary assumption for the outperformance of SAVI is its property of equalizing the effect of soil exposure on the quality of image. At the beginning of cycle, the plant of sweet potato is not able to entirely cover the soil, and thus the exposure damages some regions on microarray data. The temperature can delay the growth and development, limiting the vegetation (VILLORDON et al., 2010), in accordance with the trends in this study for the higher predictability of MTR upon the SAVI to reflectance in the warmer period at 115-195 GDD. The most accurate predictor to mid-stage is GNDVI. This VI often catches the dynamics of growth and development at 215-480 GDD more precisely than the others (ROMERO-TRIGUEROS et al., 2017). Vegetative indices within red-phase of visible spectrum, as NDVI and SAVI in this study, often fail to adequately capture the spectral changes in actively growing vegetation. At the mid-stage, the plant grows and develops vigorously until production and transportation of photoassimilates level off (KARUP-PANAGOUNDER, 2008). As GNDVI meets the green, it is more sensitive to chlorophylls a and b (GITELSON; KAUFMAN; MERZLYAK, 1996), and thus its usage as an input for predicting the yield at the late stage of cultivation at 510-970 GDD becomes unfeasible, especially for on-field samples within the winter. At the end of winter, radiation increases and, consequently, the production of leaves and massive tubers. In contrast, temperature and radiation decrease at the end of this summer, and thus the photosynthetically active parts of the plant are not able to effectively capture physical energy, store it then convert it into photoassimilates and other sources of metabolizable energy for the tuberization (CONCEIÇÃO; LOPES; FORTES, 2004). This reference can support the lower yield in the summer, as well as the great relevance of GDD to model the growth and development as well as identify specific periods to extract VIs for prediction upon reflectance.

4.7 Concluding remarks and outlooks

Our study clearly demonstrates the possibility of advantageously integrating high-resolution remote sensing and multi-output machine learning into an immersive single framework to accurately predict for the yield of sweet potato by the market class of its tuberous roots upon imagery data on full-scale fields. Straightforward preliminary evidence exists for the exceptional ability of both random forest and k-nearest neighbors to learn from the on-field reflectance at GNDVI and SAVI then output multiple numeric values to the independent variable, without any bias or computational unfeasibility. Our insights are timely and absolutely will open up the horizons for more precisely harvesting high-quality material to fulfill the rigors of commercialization and industrialization. Also, they will do support selecting healthily seedlings to vegetative propagation into new fields in croplands, where heterogeneity makes it difficult for planning and leveling up cost-effectiveness. Thereby, the grower who wishes to use our approach can expect, for the ideal scenario, suitable on-field management to produce sweet potato with more profitability and societal and environmental responsibility. These are key-aspects to food safety, especially in regions where this starch-rich crop structures up the basis of scoping agriculture and human nutrition. Finally, our approach will assist with scaling up this rural food towards an essentially provocative yet emerging transformative agriculture for its supply chain. Future directions are basically to (i) predict daily tuberization for progressively harvesting; and (ii) test if it could be possible for an integrative UAV-SAR imaging system to improve acquiring data with higher spatial-temporal resolution and without any damaging factor.

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CHAPTER 5 – Final considerations

Our thesis is the first to be concerned with the sweet potato crop in the context of e-farming agriculture. Currently, digital tools that assist farmers and decision-makers in assessing the development characteristics of this type of crop, whose raw material of economic interest grows below ground, do not exist. Therefore, here we generate knowledge that enables the introduction of sweet potatoes in the concept of digital agriculture.

In summary here are some of our main contributions:

1. We provide insights for the sustainable management of sweet potato and profile it from every conceivable angle to promote it as a food that can ensure food and energy security.

2. We proposed and validated a methodology capable of monitoring the growth dynamics of crop and differentiating between its phenological phases. Likewise, we predicted its pattern of production and quality. We found that inside each phenological phase of development is a key moment to obtain data for predicting production traits.

3. We found that regardless of vegetation indices and machine learning algorithms, the accumulation of growth of degree-days (GDD) for the temporal assessment of developmental traits is the key to detecting changes in phenological phases or predicting yield traits.

Considering these contributions, several directions for future work still exist, and we outline a few that are particularly promising:

1 . We use Sentinel-2 imagery, so a cloud over our study fields, for example, would jeopardize our data analysis. Hence, it would be interesting to test other sources of remotely sensed images (e.g., micro-satellites, drones, and radars). Such an approach would allow amplifying the spatial, temporal, and spectral resolution of the data acquisition.

2. Remote monitoring of daily tuberization is not yet possible. Developing an agroclimatic (soil-plant-atmosphere) system of data assimilation by multi-source data remote sensing will allow the understanding of the dynamics of daily root mass accumulation. In this way, maps can be created to delimit regions of interest, and strategically optimize the harvest operation, so that it only occurs when the roots meet the standard of market acceptance. Such practice can add value to the harvested product and reduce discarding of non-standard foods.

3. No information is available on the location of sweet potato plantation areas and the varieties that are being cultivated. Therefore, mapping them by satellite images at the regional or territorial scale would assist in the more responsible policy formulation for sustainable management and for ensuring availability of food.

4. Finally, the prediction of nutritive value of sweet potato would help in the selection of higher quality materials, both for breeding and for establishing new seasons.