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Decision analysis and hyperspectral imaging to support farmers in ornamental heather production

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Contents

Summary

Ornamental Heather (*Calluna vulgaris*) is an important crop for the farmers of Germany's Lower Rhine region. These farmers produce more than 78% of the ornamental heather in Germany. Successful production of this crop requires management of a variety of fungal pathogens, including *Botrytis cinerea*, *Glomerella cingulata*, and *Phytophthora* spp., which threaten the economic success of the farms. Fungal pathogens can lead to sudden mass disease outbreak and reduce the attractive and healthy look of ornamental plants, which is critical at the market. It is nearly impossible to make a profit with heather plants that have disease symptoms. To prevent the occurrence of disease symptoms, farmers often apply frequent and intensive prophylactic fungicide applications. However, the future of heather cultivation will likely require new cultivation techniques without prophylactic spraying. This is partly because intensive pesticide applications can favor the development of pathogen resistance and because some of the existing plant protection product approvals are set to expire. Moreover, consumers favor products with environmentally friendly cultivation strategies and farmers do too. Therefore, farmers are looking for more sustainable and less pesticide-intensive crop management options. In this thesis I outline a successful approach to working together with farmers, stakeholders, and experts to understand and make forecasts about changes to these cultivation systems. Following holistic research techniques, I gathered the many uncertainties and risks and made scientifically supported recommendations for more sustainable production techniques. The chapters of this thesis will outline my process of understanding the complexity of ornamental heather production, generating probabilistic impact pathway models in direct collaboration with experts and farmers, developing methods to analyze the vitality of heathers using hyperspectral sensors, and generating forecasts to support decision-making and assessment of farmers' individual risk preferences:

1. In chapter 2, I report the results of a model-based simulation of management options in heather production. A general reduction in prophylactic fungicide applications does not currently appear to be beneficial to farmers. In contrast, implementing a monitoring plan to monitor disease symptoms is likely to result in a positive net benefit. We conclude that more intensive visual monitoring of disease symptoms has the potential to optimize crop management in heather production.

2. In chapter 3, I present a method for hyperspectral analysis of ornamental plants and the potential of sensor-based monitoring of heather plants. We applied a trained Partial Least Squares Regression model on the spectral reflectance data collected from measured heather plants. The model classified plants into healthy and stressed with an accuracy of 98.1% and identified the most important wavelengths for the classification process. The method is promising for high-resolution measurements of ornamental plants and particularly well suited for small plant samples.

3. In chapter 4, I report the projected impact of different monitoring approaches on the profitability and on the expected utility of heather farmers. The results show that heather production is inherently risky. Financial benefits appear to be better with the intensive visual monitoring strategy, which is more preferred by risk-taking farmers who want to maximize profits and optimize their system. Risk-averse farmers, on the other hand, would rather stay with currently applied management. Sensor-based monitoring incurs a risk of financial losses that currently seems to be too high for application in the heather production system.

The collaborative research approaches outlined in the thesis could be widely applied for research into risks and uncertainties of decision-making in agricultural production systems. These processes could also be used by decision-makers and policy-makers working in the agricultural sector. The specific results of the model building processes and the resulting forecasts generated in this work have helped farmers and producers of ornamental plants who seek to implement changes to optimize their horticultural crop management, to assess applicability of new technologies, and to improve disease control strategies while considering individual risk preferences.

Zusammenfassung

Die Callune (*Calluna vulgaris*) gehört zu den wichtigsten Zierpflanzen am Niederrhein. Die Produzent*innen erzeugen dort mehr als 78% der in Deutschland produzierten Callunen. Die erfolgreiche Produktion erfordert die Kontrolle einer Vielzahl pilzlicher Pathogene, einschließlich *Botrytis cinerea*, *Glomerella cingulata* und *Phytophthora* spp., die den wirtschaftlichen Erfolg der Betriebe bedrohen. Pilzliche Pathogene können zu einem plötzlichen massenhaften Krankheitsausbruch führen und das Aussehen der Pflanzen beeinträchtigen. Es ist fast unmöglich Gewinn durch den Pflanzenverkauf zu erzielen, wenn Callunen Krankheitssymptome aufweisen. Um das Auftreten von Krankheitssymptomen zu verhindern, führen Produzent*innen häufige und intensive prophylaktische Fungizidapplikationen durch. Die zukünftige Calluna-Produktion könnte eine Kulturführung ohne intensive Fungizidapplikationen erfordern, da Pflanzenschutzmittelanwendungen die Pathogen-Resistenzbildung begünstigen können und einige der bestehenden Zulassungen für Pflanzenschutzmittel bald auslaufen. Außerdem bevorzugen Verbraucher*innen wie Produzent*innen umweltfreundlichere Anbaustrategien. Daher suchen Calluna-Produzent*innen nach neuen und nachhaltigeren Anbaumethoden. In dieser Arbeit präsentiere ich einen erfolgreichen Ansatz, der durch direkte Zusammenarbeit mit Produzent*innen und weiteren Expert*innen erlaubt, Veränderungen aufgrund von neuen Entscheidungen im Produktionssystem zu prognostizieren. Ich habe mittels ganzheitlicher Forschungstechniken die vielen Unsicherheiten und Risiken in der Calluna-Produktion erfasst, um wissenschaftlich gestützte Empfehlungen für eine nachhaltigere Kulturführung zu erstellen. Die Kapitel dieser Arbeit behandeln den Prozess, die Calluna-Produktion zu erfassen, von der partizipativen Erstellung probabilistischer Modelle, über die Entwicklung eines Verfahrens zur Detektion der Vitalität von Callunen mittels Hyperspektralsensoren, bis hin zur Unterstützung der Entscheidungsfindung und Bewertung der Risikopräferenzen der Produzent*innen:

1. In Kapitel 2 berichte ich über die Ergebnisse einer modellbasierten Simulation von Managementoptionen in der Calluna-Produktion. Eine generelle Reduzierung der prophylaktischen Fungizidanwendungen scheint derzeit keinen Nutzen für die Produzent*innen zu haben. Im Gegensatz dazu führt die Implementierung eines Monitoringplans zur Überwachung von Krankheitssymptomen eher zu einem positiven Nettonutzen. Eine intensivere visuelle Überwachung der Krankheitssymptome scheint das Potential zu haben, die Calluna-Produktion zu optimieren.

2. In Kapitel 3 stelle ich ein Verfahren zur hyperspektralen Analyse von Zierpflanzen vor und erörtere das Potential von sensor-basiertem Monitoring an Callunen. Wir wendeten ein trainiertes Partial Least Squares Regression Modell auf die gemessene spektrale Reflektanz von Callunen an. Das Modell klassifizierte die Pflanzen mit einer Genauigkeit von 98,1 % in „gesund“ und „gestresst“ und identifizierte die wichtigsten Wellenlängen für den Klassifizierungsprozess. Die Methode ist vielversprechend für hochauflösende Sensormessungen von Zierpflanzen und besonders gut für kleine Pflanzenproben geeignet.

3. In Kapitel 4 berichte ich über die prognostizierten Auswirkungen verschiedener Monitoringansätze auf die Wirtschaftlichkeit und den erwarteten Nutzen der Calluna-Produzent*innen. Die Ergebnisse zeigen, dass die Calluna-Produktion generell risikoreich ist. Der finanzielle Nutzen scheint bei der intensiven visuellen Überwachung höher zu sein, die eher von risikofreudigen Produzent*innen bevorzugt wird, die ihren Gewinn maximieren und ihr System optimieren wollen. Risikoscheue Produzent*innen hingegen würden das aktuell angewandte Management weiterhin bevorzugen. Die sensorbasierte Überwachung birgt ein Risiko für finanzielle Verluste, das für die Calluna-Produktion aktuell zu hoch zu sein scheint.

Die in dieser Arbeit dargestellten kollaborativen Forschungsansätze können in großem Umfang für die Erforschung von Risiken und Unsicherheiten bei der Entscheidungsfindung in landwirtschaftlichen Produktionssystemen eingesetzt werden. Die Methoden können von politischen Entscheidungsträger*innen, die im landwirtschaftlichen Sektor tätig sind, genutzt werden. Die Ergebnisse der Modellbildungsprozesse und die daraus resultierenden Prognosen, die in meiner Arbeit generiert wurden, haben Produzent*innen von Zierpflanzen geholfen, nachhaltigere Anbaumethoden in ihrer gartenbaulichen Kulturführung zu implementieren, die Anwendbarkeit neuer Technologien einzuschätzen und Strategien zur Kontrolle von Krankheiten unter Berücksichtigung der individuellen Risikopräferenzen zu bewerten.

Abbreviations, acronyms, and units

#	number
%	percentage
€	Euro
®	Registered Trade Mark
°	degree
°C	degree celsius
Baseline	Current regime of visual monitoring with occasional observations of plant health
Caret	Classification and Regression Training
CE_k	Certainty Equivalent of monitoring strategy k
cf.	*confer*
cm	centimeter
COVID-19	Coronavirus Disease 2019
DA	Decision Analysis
DAP	Days after Planting
DIVA	Data Interpolating Variational Analysis
DLR	Dienstleistungszentrum Ländlicher Raum
DN	Digital Number
doi	digital object identifier
DoMoreVisual	*Improved* vs. *Baseline*: The decision to switch from the current visual monitoring regime to intensified visual monitoring
$E(NPV)_k$	Expected value of the probabilistic NPV distribution of monitoring strategy k
e.g.	*exempli gratia*
e.V.	eingetragener Verein
EC	Electrical Conductivity
et al.	*et alii*
etc.	*et cetera*
EVPI	Expected Value of Perfect Information
Fig.	Figure
GmbH	Gesellschaft mit beschränkter Haftung
ha	hectare
HS	hyperspectral
i.e.	*id est*

IBG-2	Institut für Bio- und Geowissenschaften – Pflanzenwissenschaften
Improved	Intensified visual monitoring with frequent observations
INRES	Institut für Nutzpflanzenwissenschaften und Ressourcenschutz
INRUGA	Innovationen für NRW zur Steigerung der Ressourceneffizienz und Umweltverträglichkeit im Gartenbau „Entscheidungshilfen im Zierpflanzenbau"
k	a predefined monitoring strategy for calculation of expected utility
K	kelvin
L.	*Linné*
log	*logarithmus naturalis*
Max	maximum
Min	minimum
ML	Machine Learning
mm	millimeter
ms	millisecond
mS	millisiemens
NIR	Near Infrared Radiation
nm	nanometer
NN	Neural Network
Normal	Standard practice in a system without improved monitoring
NPV	Net Present Value
NRW	North Rhine-Westphalia
pH	*pondus Hydrogenii*
PLSR	Partial Least Squares Regression
QGIS	Quantum Geographic Information System
r_a	farmers' risk aversion
Reduce	Reduced prophylactic pesticide application
RGB	Red, Green, Blue
ROI	Region of Interest
RP_k	Risk premium of monitoring strategy k
Sensor	Sensor-based plant health monitoring using hyperspectral imaging
SERF	Stochastic Efficiency with Respect to a Function
spp.	*species pluralis*
SprayLess	*Reduce* vs. *Normal*: Reduced prophylactic pesticide application compared to standard practice, in a system without improved monitoring

SV_k	Semi-Variance of Monitoring Strategy k
SVM	Support Vector Machine
UAV	Unmanned Aerial Vehicle
UseSensor	*Sensor* vs. *Baseline*: The decision to switch from the current visual monitoring regime to sensor-based monitoring
VIP	Variable Importance in the Projection
VIS	visible
vs.	versus
W	watt
Watch	Improved monitoring combined with normal prophylactic application
WatchMore	*Watch* vs. *Normal*: Improved monitoring combined with normal prophylactic application compared to current standard practices
WatchMoreSprayLess	*WatchReduce* vs. *Normal*: Improved monitoring combined with reduced pesticide application compared to standard practices
WatchReduce	Monitoring combined with reduced pesticide application
ZEF	Zentrum für Entwicklungsforschung

Chapter 1
Introduction

The relevance of heather production for the Lower Rhine region in North Rhine-Westphalia, Germany

Production of ornamental heather (*Calluna vulgaris* L.) in the Lower Rhine region in North Rhine-Westphalia (NRW), Germany (Fig. 1-1), represents an important source of income for local farmers. The livelihoods of farm employees, foreign workers, and their respective family members are also dependent on heather production. In 2017, farmers from the Lower Rhine region produced about 78% of Germany's heather production (around 90 million plants) (Statistisches Bundesamt, 2017). This contribution makes the Lower Rhine region the main heather production area in Germany representing a unique place for the concentrated knowledge and specific expertise of heather cultivation.

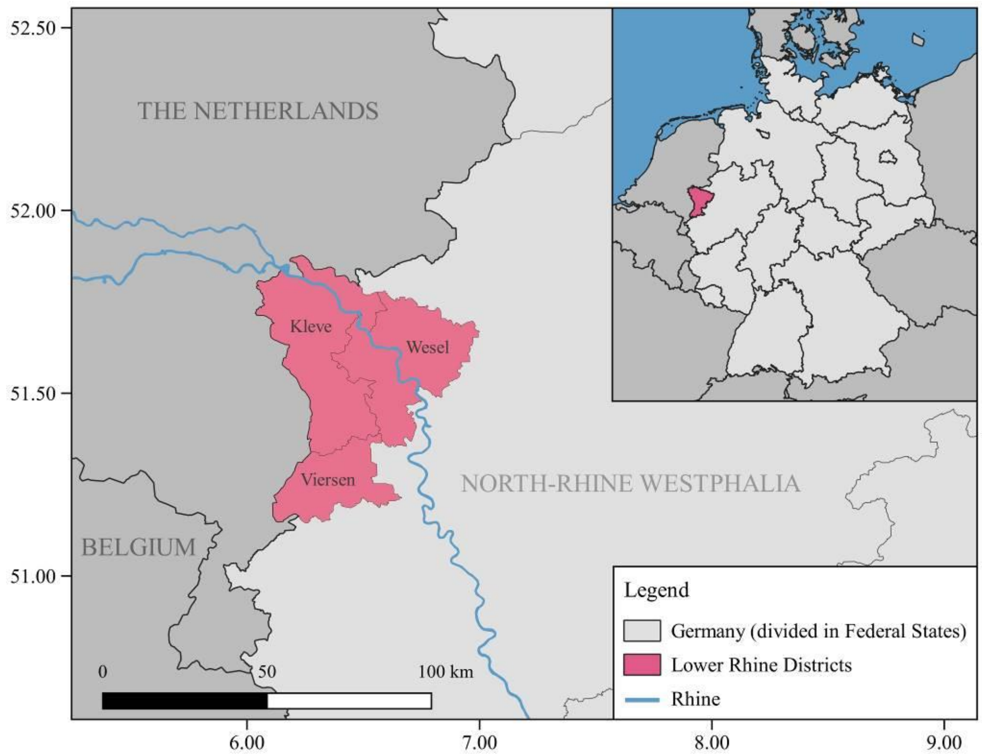

Figure 1-1. Map of Germany showing the location of the Lower Rhine region (pink area) within North Rhine-Westphalia. Figure generated with open-source data from DIVA-GIS (2021) using a geographic information system software (QGIS Development Team, 2021)

The relevance of bud-flowering heather varieties

In the 1980s, the so called ‘bud-flowering’ or ‘bud-blooming’ mutation was discovered. This mutation causes the buds of the heathers to stop opening, preventing them from flowering (Gardengirls Heidezüchtung GmbH, 2021). As a result, plants show the respective color of the cultivar brightly for a considerably long period (up to 4 months) as buds no longer fall in autumn and winter (Fig. 1-2). Farmers growing heather plants in Germany made use of this advantage by incorporating these varieties in their production systems. Today a large proportion (about 80% - 90%) of heathers produced in Germany exhibit the mutation, most of which belong to the two brands Beautyladies® (Eden’s Creations B.V., 2021; Europlant Canders GmbH, 2021) and Gardengirls® (Gardengirls Heidezüchtung GmbH, 2021).

Figure 1-2. Close-up of closed buds of a bud-flowering heather variety in autumn

Varieties of heather with the bud-flowering mutation have contributed to the great success and high demand of heather as an ornamental plant since the 1990s (Europlant Canders GmbH, 2021). This success may be explained by the wide multi-purpose markets for the varieties. From cemetery plant to lifestyle product, bud-flowering heathers have a variety of uses due to their long-lasting colored buds but also thanks to professional strategic marketing and promoting these plants among customers. Breeding programs are now focused on developing new varieties of bud-flowering heathers with different shapes, large foliage, various bud colors and resistance to fungal pathogens (Eden’s Creations B.V., 2021). In this regard, heather production is likely to continue to play an important role in ornamental plant production with customers having access to a growing portfolio of bud-flowering heather cultivars in the upcoming years. The studies that make up this thesis are all focused on the bud-flowering heather variety.

Risks associated to heather production

Heather production is characterized by many uncertainties. The outbreak of diseases caused by fungal pathogens is one of the main risks in heather production (Ruett et al., 2020). Fungal pathogens, which can spread rapidly and uncontrollably through the whole production system, can cause moderate to severe disease symptoms (Fig. 1-3). The symptoms of damage can occur at any time during the growing cycle and therefore represent a constant risk for farmers. The symptoms of infection can result in unmarketable plants, a situation that might cause high economic losses for farmers. Planning and implementing crop protection measures therefore is essential for farmers growing heather plants.

Figure 1-3. Symptomatic heather with an infection by *Botrytis cinerea*, also known as gray mold rot. This disease mostly occurs in the lower part of heathers that often remain moist due to lack of ventilation

To some extent, farmers can prevent infection of plants by fungal pathogens through management practices such as the selection of strong heather varieties, and adequate fertilization and irrigation strategies. These practices help farmers promote overall plant resistance in advance as well as during the entire cultivation period. Since heathers are vegetatively propagated, farmers could, for instance, select only suitable high-quality plants as source of parental material, which is likely to produce vigorous and healthy cuttings. According to farmers, differences in susceptibility to fungal symptoms vary among heather varieties but are not dependent on the bud-flowering mutation. There are many factors that cannot be controlled by farmers. Among these, high air humidity and warm weather conditions create higher risks of infection. Under these conditions even high-quality plants can get infected by fungal pathogens shortly before sale, after farm resources have already been invested in the plants.

Due to the high risk of losses, prophylactic fungicide application is currently farmers' primary choice for preventing fungal diseases. However, these fungicide applications may not be effective when mixed infections from different pathogens occur. Other factors related to poor management practices can also lead to some pathogen-like symptoms. For example, poorly timed or excessive irrigation on hot summer days can cause large amounts of water to evaporate from the substrate and may cause the cells in the shoot tips of heathers to burst.

Thus, the typical symptoms associated to infection by *Glomerella cingulata* (i.e. shoot tip dying) can appear even when the pathogen is not present (Fig. 1-4).

Figure 1-4. Shoot tip dying (highlighted using red cycles), which may be a typical indication of infection by *Glomerella cingulata*, can also be observed after inadequate management practices such as over-irrigating on hot days

In general, current fungicide management in heather production seems to be unsustainable. Inadequate plant health-status monitoring might lead to ineffective management decisions, such as unnecessary fungicide applications when heather plants show symptoms of misleading non-fungal disease. Unnecessary or inappropriate fungicide spraying represents a waste of resources as well as a considerable burden to the environment (Bika et al., 2020). Ornamental farm employees can be exposed to unnecessary health risks if they are in regular contact with pesticides (Nassar and Ribeiro, 2020). Additionally, intensive fungicide application can increase the risk of fungal pathogens developing multi-resistance to active ingredients. Alternative management strategies are needed to effectively control fungal diseases without promoting multi-resistances (Hahn, 2014). Currently approved plant protection products may lose efficacy due to misused plant protection management strategies. Evidence suggests that fungicides currently used in German ornamental plant production to control infections by *Botrytis cinerea* are losing effectiveness due to the development of fungal resistance (Rupp et al., 2017). In addition, due to gradual expiration of plant protection product approvals and possible future restrictions on the fungicides currently available, farmers' options may become further restricted. Therefore, farmers are looking for more sustainable management strategies in heather production to cope with disease risks. Other than discussions with peers, farmers usually remain unsupported when making decisions about crop protection options. Although farmers may aspire to implement more sustainable crop protection strategies, large uncertainties and risks prevent them from making major changes.

Decision analysis approaches to support sustainable farm management

Farmers often need to make risky decisions when deciding how to optimize their management strategies to meet current and future challenges. Controlled experiments alone may not account for all risks and uncertainties associated with available interventions. In addition, long-term trials may be expensive and require a lot of time before recommendations can be retrieved from results. Farmers, however, may need quick and practical decision support to predict the likely outcomes of prospective management adjustments. Decision analysis approaches can support decision-making by applying participatory methods to consider important facets and interactions in complex decisions (Shepherd et al., 2015). They can generate forecasts and provide guidance when assessing interventions in systems characterized by large uncertainties (Luedeling et al., 2015). Decision analysis approaches can overcome data scarcity through participatory group work processes that integrate expert knowledge into decision models. In Tigray, Ethiopia, for example, the decision to build a dam for irrigation was successfully evaluated without quantitative data sets, but merely by developing a decision model with local experts through participatory approaches (Yigzaw et al., 2019).

Participatory group work processes can be used in various ways when collecting expert knowledge. To generate comprehensive understanding of a complex system it is important that selected participatory approaches are able to integrate the diverse knowledge of the actors involved (Villamor et al., 2014). Decision analysis approaches seek to integrate all available expert knowledge (Whitney et al., 2018c). Collaborative workshops can be used to collect people's knowledge by gathering a large variety of experts concerned with the system under investigation. These expert groups are made up of decision makers and other, often quite diverse, stakeholders. For instance, a group of experts evaluated the importance of homegardens for human nutrition in Uganda and included farmers, staff members, consultants, policy-makers, members of non-governmental organizations as well as scientists (Whitney et al., 2018b).

After appropriate decisions are defined, experts can share their knowledge to develop initial conceptual models (also known as graphical impact pathways) individually or jointly in small groups. Experts use nodes and edges to develop graphical impact models to illustrate how variables and factors interact with each other within a system. These graphical impact models represent the most likely relationship between sub-system components from the experts' point of view (Whitney et al., 2018a). For example, in Burkina Faso analysts and experts came up with an impact model illustrating different sedimentation options to detect the best option increasing efficiency of a reservoir (Lanzanova et al., 2019). Using expert knowledge can help identify important parts of a system that might otherwise be ignored (MacMillan and Marshall, 2006). Decision-making based on data sets only can be error-prone, whereas available data sets combined with expert knowledge can improve decision-making (Fenton and Neil, 2018). All generated graphical impact models can be summarized and adjusted using feedback and further group work processes until all participants agree on a model structure. This can then be translated into a mathematical code representing the final decision model (Whitney et al., 2018c).

After the general structure of the decision model is approved by all experts, further meetings with these stakeholders can help quantify and measure model variables. In this stage of the process it is important to clarify what is meant by measurement. According to Hubbard (2014), the definition of a measurement is a “quantitatively expressed reduction of uncertainty based on one or more observations”. Since measurements can be performed by calibrated technical instruments, humans, as the ‘ultimate measurement instrument’, can also be calibrated for estimating variable values (Hubbard, 2014). Here, a so-called ‘calibration training’ procedure is helpful to train estimating skills in order to help providing better estimates for model variables (Hubbard, 2014). A calibration training consists of two stages. In the first stage, participants estimate the most likely numeric interval for a number of questions (e.g. how many Christmas trees were sold in Germany in 2019?), so that the correct answer is contained within their interval (i.e. a good interval would have included the correct answer, which is 29.8 million trees (Statista, 2020)). In a second stage, participants answer true or false questions and indicate their percentage of confidence. In contrast to a real game, the aim of a calibration training lesson is not to obtain the most correct answers, but to assess the uncertainty individual experts (Hubbard, 2014). The calibration training procedure is usually repeated several times, with rounds of feedback for stakeholders between the calibration stages. Optimization possibilities (e.g. if participants are too under- or overconfident) are communicated in the feedback rounds to continuously make participants aware of possible biases (cognitive errors) that might influence the way value intervals and true-false questions were estimated (Hubbard, 2014).

The calibration training procedure guides participants in raising awareness for vulnerability to cognitive errors. Debiasing techniques can help to recognize and partly overcome the cognitive biases that can occur when participants are asked to provide estimates (Montibeller and von Winterfeldt, 2018). There are many biases that can negatively affect the performance and accuracy of making estimates. Among the most relevant biases negatively affecting expert estimations are ‘overlooking of important variables’ (Bond et al., 2010), ‘overconfidence’ (Moore and Healy, 2008), and ‘certainty effect’ (Kahneman and Tversky, 1979). Overlooking of important variables can happen when participants e.g. focus too much on one variable so that they overlook other variables (Bond et al., 2010). Participants who believe they are correct in their assessment, e.g., because of their reputation in a particular field, but are actually wrong, may be described as overconfident (Moore and Healy, 2008). A ‘certainty effect’ arises when participants tend to consider e.g. the minimal reduction of a risk from 5% to 0% as more important than the reduction of a risk from 50% to 10% (Kahneman and Tversky, 1979). After a successful calibration training procedure, model variables can be estimated more accurately since participants become able to generate intervals that incorporate likely values for model variables.

Heather farmers are highly specialized experts in their field, as successful crop management in heather production requires a lot of special knowledge and experience. Nonetheless, there are almost no scientific case studies, hardly any statistics and only a few experiments, dealing with professional ornamental heather production. Using participatory group work processes to develop decisions together with farmers might allow development of decision models overcoming data scarcity to eventually support decisions and therefore a successful heather production. A calibration training might be promising for elicitation of calibrated estimates from experts to use as input data for a programmed decision model, allowing to take into account existing uncertainties of heather production.

Model outputs to derive decision recommendations for farmers

A decision model fed with calibrated stakeholder estimates for model variables can be used to perform probabilistic simulations of the decision and assess likely outcomes. A Monte Carlo simulation allows to generate model outputs in form of a probabilistic distribution by several model runs. For each model run, a random number is drawn from the range of values, for each input variable to calculate the output. By using a high number of model runs (e.g. 10,000), this procedure generates the distribution of what might happen in a system if the decision is made. Probability distributions thus allow a forecast of possible scenarios for decisions based on calibrated input variables. Based on these probability distributions, the percentage of simulated outcomes in the positive and negative region can be identified to determine how likely it is to obtain gains and losses or respectively benefits and costs from the generated forecasts. However, probability distributions alone might not reveal the importance and uncertainty of individual model variables. Post-hoc analysis allows calculation of Variable Importance in the Projection (VIP) scores, a sensitivity analysis using Partial Least Squares Regression (PLSR) (Luedeling and Gassner, 2012). The VIP calculation reveals the relative importance and correlation that a certain model variable has on the output of the decision model (Wold et al., 2001). VIP estimates allow researchers understand the importance of each estimated range for a model variable on the computed outcome and, most importantly, to identify the critical factors in the system to pay special attention to when making new decisions (Do et al., 2020). Instead of optimizing variables that are less relevant to a particular decision, decision-makers can then focus their actions and narrow the uncertainty of range estimates for model variables having only a major impact on the outputs (Whitney et al., 2017). In addition, calculation of Expected Value of Perfect Information (EVPI) values, as a measure of decision sensitivity, can be used to explain the average improvement that a decision-maker would achieve if perfect information had been available before the actual decision was made (Felli and Hazen, 1998). The results of the EVPI analysis are illustrated as monetary values (also known as 'value of information') to represent how much money decision-makers would have to be willing to pay to fully reduce the uncertainty in the respective variable (Hubbard, 2014). The EVPI analysis can be extremely helpful to locate the greatest uncertainties and, as a consequence, where additional information might change decision recommendations (Wafula et al., 2018). In addition, quantifying uncertainty in terms of monetary values allows to show where and how much effort should be invested in future research (Tamba et al., 2021).

The successful application of decision analysis approaches to support agricultural decisions under uncertainty has already been demonstrated. For instance, Liman Harou et al. (2020) developed a procedure to use expert knowledge in combination with spectral indices to map flood-based agricultural systems to support farmers in Kenya and Ethiopia. Tamba et al. (2021) forecasted potential outcomes of a number of interventions regarding forest and landscape restoration in Ethiopia. For the modeled restoration decisions, the VIP scores showed the importance of the variables on the Net Present Value (NPV), with the EVPI values showing the greatest uncertainties. For example, for restoring a forest with enrichment plantings, the cost per ton of carbon was identified as both the most important variable for NPV calculation and the variable displaying the greatest uncertainty within the simulation (Tamba et al., 2021). A similar approach was used by Do et al. (2020) who simulated different agroforestry cropping options in Vietnam for ex-ante evaluation of possible profits for local farmers. The model outputs showed the variable importance and value of the information for the respective variables, e.g. crop yields, crop prices and the discount rate, ordered according to their importance for each cropping option (Do et al., 2020). Rojas et al. (2021) supported farmers by assessing the economic benefits of implementing crop covers for Chilean sweet cherry production. For Northern-central Chile, they identified yield losses due to low fruit firmness as both the variable with the highest VIP scores and the highest EVPI values. For Southern-central Chile, the market price per kilogram sweet cherries showed the highest VIP scores while the yield losses due to low fruit firmness displayed the highest EVPI values (Rojas et al., 2021). The results therefore allowed formulating region specific decision recommendations (Rojas et al., 2021).

Although decision analysis approaches and their corresponding outputs have proven useful in various research contexts globally, they have not yet been applied in heather production so far. Application of decision analysis approaches in heather production as a case study might allow the calculation of probability distributions, VIP scores, and EVPI values to evaluate promising but risky farm management decisions in the Lower Rhine region in Germany. By revealing the most important uncertainties in their production system, the outputs can then contribute to the formulation of detailed management recommendations to support farmers implement more sustainable production strategies.

Assessing farmers' risk preferences

The outputs of collaborative decision analysis approaches help scientists provide decision support for farmers under uncertain scenarios. The resulting probability distributions reveal potential profits and losses, taking into account existing uncertainties. Value of information assessment can help indicate where further research efforts should best be invested (Luedeling et al., 2015; Wafula et al., 2018; Yigzaw et al., 2019). Extending decision analysis approaches with analyses of expected utility is the natural next step. The analysis of expected utility allows for the mapping of farmers' optimal decision along a gradient of different risk preferences (risk-taking, risk-averse or risk-neutral). Taking into account the individual risk preferences of farmers, i.e. how farmers individually weight the riskiness against the return of investment prospects can show how a given distribution of potential revenues is assessed by farmers (Dalhaus et al., 2018). In their valuation of risk vs. average return, risk-taking farmers tend to weight risks, which also include upside opportunities, higher than average returns. In contrast, risk-averse farmers try to avoid higher risks and are willing to give up average returns to obtain lower risk (Vollmer et al., 2017). Risk-neutral farmers are indifferent about risks and tend to make decisions only based on average outcomes (Hardaker et al., 2015). The approach offers a powerful tool to map the risk behavior of farmers regarding their current management strategies as well as new alternatives to identify options that would be actually implemented in farms. Applying this approach to heather production might provide new insights into farmers' risk behavior when applying new management options.

Hyperspectral imaging to support farmers' decisions

The application of hyperspectral imaging using optical sensors to analyze plant health shows great potential to support horticultural production (Yang and Xu, 2021). In particular, hyperspectral imaging in combination with appropriate evaluation methods is able to detect diseases on plant tissues (Mahlein et al., 2017) and fruits (Fazari et al., 2021), automatically and non-invasively. A large number of studies shows that the analysis of hyperspectral images has a high potential for early detection of diseases and/or stress symptoms (Bauriegel et al., 2011; Behmann et al., 2014; Chen et al., 2020; Fazari et al., 2021; Kuska and Mahlein, 2018; Lowe et al., 2017; Rumpf et al., 2010; Thomas et al., 2018). The results of these studies indicate that farm management strategies might be supported by collection of hyperspectral data for effectively monitoring of plant quality and certain physiological parameters of plants. Spectral ranges and indices based on reflectance at specific wavelengths can reveal detailed information about plant physiological parameters (Gitelson et al., 2002; Mahlein et al., 2013). For example, hyperspectral signatures of 48 heathers defined by experts either as healthy or stressed, supplemented with information about plant compounds, show where wavelengths from 430 nm - 900 nm can indicate the respective plant physiological parameters (Fig. 1-5).

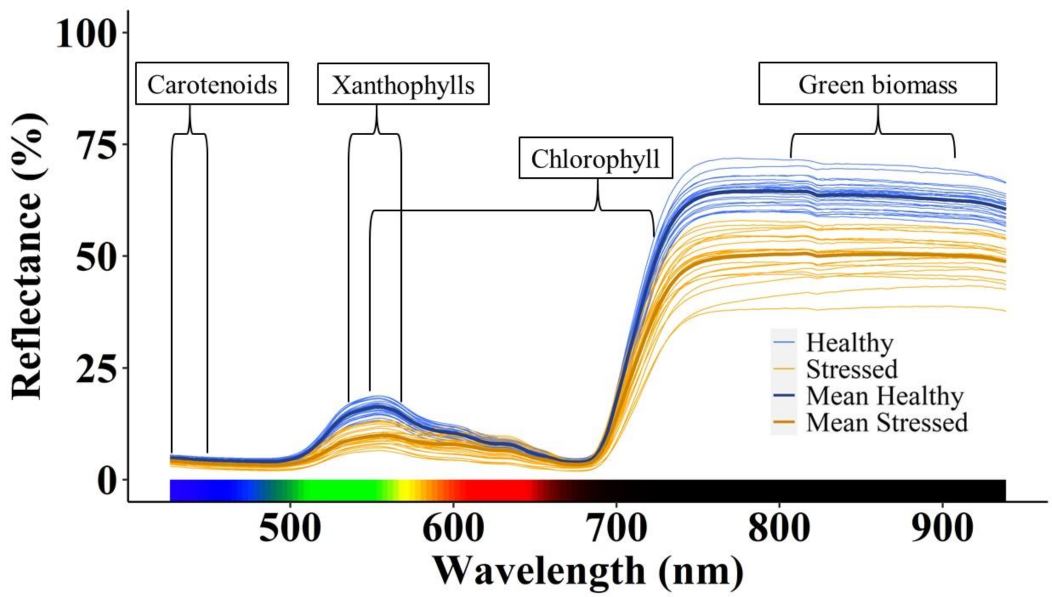

Figure 1-5. Hyperspectral signatures of 24 healthy heathers (thin blue lines) and 24 stressed heathers (thin orange line) from 430 nm to 900 nm. Mean values are indicated by a bold dark blue line for healthy heathers and a bold dark orange line for stressed heathers, respectively. Description for wavelengths indicating plant physiological parameters of healthy leaves adapted from Peñuelas and Filella (1998)

In general, plant stress can be detected within the visible light spectrum at wavelengths ranging from 540 nm to 700 nm (Carter, 1993). When using wavelengths in the visible range as indicators of specific plant compounds, slight differences and overlaps may occur when comparing Figure 1-5 to the available literature. These differences may be due to the intensity of absorption of plant tissues, which varies depending on plant species, leaf age, and water content (Horler et al., 1983). Spectral measurements of the chlorophyll content can also vary due to illumination and structure of the measured plant material (Gitelson et al., 1996). Spectral signatures from 400 nm to 700 nm are mainly influenced by foliar pigments (Blackburn and Steele, 1999). Anthocyanin as a red pigment can be detected at 550 nm and 700 nm in plant tissues (Gitelson et al., 2007), whereby the wavelengths overlap with those of chlorophyll detection since chlorophyll also absorbs in these spectral regions (Merzlyak et al., 2003). Low spectral reflectance at the red-edge region around 700 nm indicates a high chlorophyll concentration in the respective plant tissues (Curran, 1989; Filella and Penuelas, 1994; Gitelson et al., 1996). In particular, the chlorophyll content in plant tissues is higher when the red-edge inflection point is shifted to wavelength with lower frequency (Gates et al., 1965). Appropriate methods capable of dealing with the high-dimensional information density of hyperspectral signatures are required to allow meaningful analyses of collected datasets (Kuska and Mahlein, 2018; Thomas et al., 2018). Application of Support Vector Machines (SVMs) on hyperspectral datasets enable detection of plant disease with high accuracy (Rumpf et al., 2010). By means of suitable classification approaches, it might be important to find out to what extent the respective wavelengths and thus their relation to plant physiological parameters contribute to the differentiation of various health classes. Wahabzada et al. (2016) were able to assign disease symptoms to specific wavelengths that were most important for disease detection. Partial Least Squares Regression (PLSR) models are suitable to classify plants with high accuracy and allow identification of the relative importance of wavelengths for assessment of environmental stress in maize (Yendrek et al., 2017) and foliar diseases in cucumber (Zhao et al., 2016). Suitable evaluation approaches have to be found which are applicable for reasonable interpretation of complex hyperspectral datasets (Mahlein et al., 2018).

Most studies on hyperspectral analysis of *Calluna vulgaris* focused on heather ecosystems (Mac Arthur and Malthus, 2012; Nichol and Grace, 2010) rather than commercial ornamental heather production and their corresponding risk factors. To my knowledge, no studies have been documented or published so far for application of optical sensors performing hyperspectral imaging in heather production. Optical sensors can increase objectivity due to data-based disease detection, increase precision in plant protection, and thus can reduce the workload for farmers (Kuska and Mahlein, 2018). Application of optical sensors performing hyperspectral imaging of disease and stress symptoms in heather production thus might support disease management decisions of farmers. Some benefits for farmers might be that the high risk of fungal pathogens and the large uncertainties in defining disease symptoms could be greatly reduced by the use of optical sensors. In addition, farmers appear to have a strong interest in more detailed monitoring of disease and stress symptoms on heathers in order to define plant quality more accurately. Future farming goals, such as reduced dependence on fungicide applications, might be realized with optical sensors if symptomatic heathers would be sorted out earlier, preventing infections from spreading. In current practice, farmers sort out symptomatic heathers without sensor support. For a sensor-based decision-support application in heather production, first an appropriate measurement setup is needed to conduct hyperspectral measurements. Subsequently, methods would need to be identified from the multitude of possible classification approaches to explore the potential of certain approaches for heather production. Detection of specific wavelengths for health status classification might then provide information for further research in optical sensor development specialized for heather production.

Research objectives

A major challenge in agricultural research is to provide accurate decision support for farmers while considering existing risks of their production systems. These systems are continuously influenced by both internal and external factors that cannot be fully controlled. Potential outcomes when making decisions in complex systems are often unclear due to many uncertainties, leading to a range of possible results. Heather production represents a complex production system where farmers search for more sustainable management strategies to cope with risks. Farmers are hindered to test new strategies directly in their production system due to high risk of economic losses. Heather farmers might greatly benefit from predictions of promising management decisions that currently appear risky. Application of participatory decision analysis approaches allows new management decisions to be evaluated in advance and the risks in the system to be quantified. This might facilitate practice-oriented decision support for heather farmers and the heather production system to be understood holistically. In addition, these approaches might improve knowledge about which decisions are able to lead to environmentally and economically more sustainable heather production and aid to indicate the uncertainties that should be addressed by future research.

My first objective presented in this thesis was to explore the overall complexity of heather production systems and assess the economic outcome of new management options, aiming to improve system's sustainability (chapter 2). In chapter 2, my co-authors and I build up a network of heather experts, which helped to holistically describe heather production systems in North Rhine-Westphalia. Together with all experts, my co-authors and I defined management decision options like performing 'less prophylactic fungicide applications' and implementing 'more intensive visual monitoring' for disease detection. Using participatory modeling procedures, we designed conceptual models to show what really happens within the heather production system if the decision is made. All generated model drafts were merged into one final conceptual model that was used as a template to program a decision model whose results were calculated performing probabilistic simulations. The collaborative decision analysis approaches allowed me to identify the risks and uncertainties in heather production while supporting farmers' decision-making process regarding management options.

Throughout my studies, heather farmers demonstrated a considerable interest in using sensors to identify heather plants, showing disease symptoms or failing to grow adequately for other reasons. Normally, substantial long-term experience is needed by farmers to adequately monitor plant health status in heather production. Farmers suggested that sensor measurements could potentially support their work in heather production if these instruments were able to detect the visual parameters that indicate disease or other stresses. For instance, a difficult task for farmers can be to assess whether a heather will recover from a disease or whether the infected plant is dangerous for adjacent plants. The use of a sensor to discriminate between plants that can remain in the system and plants that need to be removed immediately would be a widely appreciated tool for heather farmers. Since hyperspectral sensors have shown great potential in terms of detecting plant health status in general, my co-authors and I developed a hyperspectral set-up to monitor heathers. The second objective of this thesis was to test sensor-based monitoring by performing hyperspectral measurements of heathers and applying a machine learning approach for plant classification (chapter 3). I proposed a hyperspectral sensor as a potentially promising approach for heather farmers to collect high resolution data from small heather plant samples. In addition, I suggested a Partial Least Squares Regression (PLSR) to classify heathers according to their health status while identifying the most important wavelength for the classification process.

Plant monitoring can be conducted in many different ways, with more intensive visual monitoring and sensor-based monitoring appearing to be promising approaches for heather production. However, before adopting new strategies, uncertainties regarding the emerging costs and benefits need to be analyzed. For instance, a monitoring strategy or a sensor tool must add the necessary monetary value to farm-use to make the investment worthwhile for farmers. In this context, a cost-benefit simulation performed considering the existing uncertainties regarding costs and benefits over ten years might provide the necessary information to generate the most adequate recommendations for farmers. Although the decision analysis approaches used in earlier chapters allow for detailed management recommendations, they alone are not able to consider the individual risk preferences of farmers, which may strongly vary from one individual to another. My third objective in this thesis was to develop a cost-benefit simulation of different monitoring strategies based on the knowledge collected from our heather expert network. In addition, my co-authors and I extended the decision analysis approaches by using its simulation results for conducting an analysis of expected utility to assess the individual risk preferences of heather farmers in the context of new monitoring strategies (chapter 4). This advanced approach allowed for the formulation of detailed monitoring recommendations according to personal risk preferences of heather farmers.

Overall, the research objectives I set for this thesis helped to understand and explore the complexity of heather production systems by generating practice-oriented decision support for heather farmers as well as establishing a powerful network for scientific collaboration in ornamental plant production systems.

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Chapter 2

Model-based evaluation of management options in ornamental plant nurseries

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Abstract

Agricultural management decisions are usually made without perfect knowledge. Decision Analysis (DA) approaches translate available uncertain information on costs, benefits and risks involved in decisions into actionable management recommendations. We illustrate the use of DA procedures to inform decisions on disease management strategies in ornamental plant production. We worked with heather growers and other stakeholders in North Rhine-Westphalia, Germany, to model the impacts of changing disease management practices and to generate comprehensive forecasts of net returns. Through sensitivity analysis and Value of Information assessment we identified critical uncertainties regarding the feasibility of improved practices. Partial Farm Budgets for decision options ranged from a loss of more than 200,000 € to a gain of nearly 70,000 € per hectare and year. Findings suggest that reducing pesticide applications without additional monitoring may substantially increase production risks (chance of loss of 76%) and that intensified plant monitoring is likely to increase net benefits (chance of gain of 68%) by allowing earlier detection and more focused fungicide application. Our Decision Analysis approach facilitated ex-ante evaluation of innovative management strategies in heather production, and it holds promise for similar evaluations in other agricultural production systems.

Introduction

Decision Analysis approaches can be applied to support the often risky decisions that agricultural producers face, even in the absence of perfect knowledge on how these decisions will affect production systems (Luedeling and Shepherd, 2016). Such approaches can allow for detailed systems understanding (Ingrao et al., 2015) and facilitate decision making (Lopes et al., 2018). In agriculture, the outcomes of management decisions usually cannot be predicted with high precision. Decision Analysis addresses this limitation by providing probabilistic forecasts that translate risk and knowledge limitations into possible outcomes of various decision options (Luedeling and Shepherd, 2016). The use of probabilistic simulations relaxes the need for high-precision data (Hubbard, 2014), which is not always available or easy to gather in a time frame that is relevant for decision-makers (Shepherd et al., 2015).

Decision Analysis allows for sound management recommendations based on the current state of knowledge (Whitney et al., 2017). It requires holistic assessment to identify all the relevant variables that are likely affected by a stated decision. The approach seeks to accurately appraise the current state of knowledge on all uncertain parameters (Shepherd et al., 2015) to fully capture real-life systems, while retaining all the important interactions that affect decision outcomes. Rather than omitting decision aspects that are difficult to quantify precisely, it fully considers them and estimates the full range of effects they can plausibly have (Whitney et al., 2017). The approach makes use of all available sources of information, including elaborate participatory procedures to elicit inputs from experts and stakeholders, in order to produce accurate models that capture relevant decision aspects (Luedeling and Shepherd, 2016).

Decision Analysis has proven useful for generating guidance in a number of agricultural and development contexts, including plans to construct a water pipeline in northern Kenya (Luedeling et al., 2015), impacts of an agricultural development plan on food security in Uganda (Whitney et al., 2017), restoration of an irrigation reservoir in Burkina Faso (Lanzanova et al., 2019) and assessing agroforestry options in Vietnam (Do et al., 2020). Here, we explore use of this approach to support horticultural growers, using the case of an ex-ante evaluation of innovative disease management strategies in the production of heather (*Calluna vulgaris* (L.) Hull).

Decision Analysis to support horticultural production

Increasing global demand for horticultural products has led to substantial efficiency gains in the production of fruits, vegetables and ornamental plants (Dorais and Cull, 2017). In many contexts, such intensification has relied on protected cultivation, fertilization, irrigation and agrochemical use (Ingrao et al., 2015). These trends and rising annual temperatures have led to considerable increases in the ecological footprint of horticultural production (Cerutti et al., 2010). Few modern industrial horticultural enterprises can be considered environmentally, socially or economically sustainable, and it is often difficult for growers to adjust, given the economic pressures exerted by an increasingly competitive marketplace for horticultural products (De Silva and Forbes, 2016).

Current research on the implementation of sustainable ornamental plant production mainly focuses on the reaction of plants to individual parameters such as salinity (Plaza et al., 2019) or fertilization (Freidenreich et al., 2019). Farmers are generally concerned with increasing their profit margins (Wilson, 2014) and tend to shy away from the risks involved in changing established practices (Harwood et al., 1999). However, they also care about both the ecological and social implications of their production practices (De Silva and Forbes, 2016).

Consumers also have sustainability concerns (Lu Hsu et al., 2009) and demand products that meet environmental and social dimensions of sustainability (Yue et al., 2011). Such sustainability-oriented consumption already plays a strong role in fruit and vegetable value chains (Moser et al., 2011), with customers increasingly requesting products that meet sustainability criteria (Pullman et al., 2009). This trend has not yet risen to similar prominence in the production of ornamental plants (Dennis et al., 2010). However, given consumer interest in sustainable products, this could certainly change in the near future.

Various management challenges need to be overcome in order to reap the potential benefits of cleaner production approaches (Matos et al., 2018). The main obstacle is the increased risk of large, or even complete income losses if certain risk events occur (Hall et al., 2009). Many pests and diseases can inflict major damage on horticultural produce. Even if these are only cosmetic in nature, they can still lead to drastic reductions in market value (Gullino and Garibaldi, 2007). We explore an innovative research methodology that allows evaluating the merits of alternative production practices regarding their feasibility from the farmer's perspective, as well as their environmental impacts.

Disease management in ornamental plant production

Disease outbreaks can quickly spiral out of control in horticultural systems, reaching severity levels that can be economically devastating (Gullino and Garibaldi, 2007). Disease risk mitigation is thus a central objective of farm management, affecting both day-to-day and strategic decisions. For many crops, diseases are controlled through frequent preventive chemical applications to ensure product quality. However, such strategies can have detrimental implications for surrounding ecosystems, occupational health and safety, and groundwater quality.

Research has uncovered some scope for horticultural producers to reduce the environmental footprint of disease management without sacrificing economic viability (van Lersel et al., 2016). Possible strategies to achieve environmental objectives include disinfection techniques, early-detection systems and improved strategies to prevent the spread of infections and diseases. Besides reducing environmental hazards, improved management strategies should also aim to prevent the development of resistant pathogen strains (Daughtrey and Benson, 2005). Intensified disease monitoring (McQuilken and Hopkins, 2001), disinfection approaches (McQuilken and Hopkins, 2004) and optimized chemical applications (McQuilken and Thomson, 2008) have proven to be promising approaches for controlling the propagation of pathogens.

Here, we report on the outcomes of a collaborative analysis process between scientists and practitioners, which aimed to explore options for raising the sustainability of heather production. Together, we analyzed and compared the advantages and risks of optimized management strategies for fungal infections in large-scale ornamental heather production. Decision Analysis approaches allowed us to capture local expert (farmers, agricultural advisors, and researchers) understanding of costs, benefits, risk factors and uncertainties and use this information to generate performance forecasts for novel practices in horticultural production. The procedures expose critical knowledge gaps that hinder confident decision-making and identify uncertainties that should be addressed in order to reduce uncertainty about the best decision option. Based on our results, we provide recommendations on the feasibility of innovative fungal control strategies for heather producers, considering possible production risks, economic prospects and environmental impacts.

Materials and Methods

Heather production in North Rhine-Westphalia

More than 75% of Germany's commercial heather production takes place in the state of North Rhine-Westphalia (Statistisches Bundesamt, 2017). Heather is in high demand as an ornamental plant, mainly because of its ability to maintain bud color into the winter (Borchert et al., 2012, 2009). Since relatively little formal research has been done on heather production, growers rely heavily on their own experience and skills.

Heather plants that are grown outside frequently experience weather conditions that facilitate fungal infections, which are difficult to prevent completely. If not adequately controlled, initially isolated infections can spread to the entire plant population, causing potentially devastating losses to producers. Production success therefore directly depends on controlling diseases before their symptoms appear. This is usually achieved by prophylactic pesticide applications. The risk of fungal infections is particularly severe under warm and humid weather conditions. Temperatures above 20°C, wet shoots and high air humidity greatly raise the probability of fungal infection. Prophylactic treatments are considered necessary during the high-risk months between May and August, and after certain management measures such as plant cutting. Nursery-grown heather needs 'pot to pot contact' at least until the middle of June to maintain a stable microclimate, and shoot contact for optimal growing conditions. In late May to June pots are separated by 12 – 15 cm to reduce the spread of grey mold (*Botrytis cinerea*) and to ensure sufficient growing space.

Appearance of fungal infection is highly dynamic, and complete control of fungal pathogens is not yet possible (McQuilken and Hopkins, 2004). Many pathogens evoke similar symptoms, making it difficult to precisely identify which pathogen is responsible for a particular infection (Orlikowski et al., 2004). Since fungal infections can quickly spread within dense stands of genetically uniform plants, failure to adequately control for this production risk can lead to a strong increase in the number of non-marketable plants.

Decision framing

We convened 16 local experts (i.e. industry stakeholders, agricultural advisors and researchers) in a set of workshops and meetings between June and November of 2018 to evaluate various disease management strategies in heather production. We selected experts that represented the full range of relevant stakeholder groups (Whitney et al., 2018a) and understood the complexity of the target system well enough to logically describe the impact pathways of interventions (Anastasiadis and Chukova, 2019). To identify relevant stakeholders, we enlisted the help of heather producers and agricultural advisors (see acknowledgements). The expert group included six agricultural and decision scientists, three heather farmers, two plant protection advisors, two experimental trial managers, two experts on fungal infections and pesticide applications, and one user of heather products. Together we sought to develop a holistic decision model to describe possible outcomes of innovative disease management strategies with a view to economic and environmental impacts.
First we convened experts in a workshop to specify and analyze decisions, to outline current management strategies and to devise alternative strategies for heather production. The model-building workshops consisted

of five stages: (1) detection of risks and uncertainties in the production system, (2) decision framing, (3) generation of a decision impact pathway, (4) calibration training, and (5) estimation of input variables for model quantification (adapted from Lanzanova et al., 2019).

We used plenary discussions to explore the main challenges and risks in heather production. Growers were particularly concerned about damages caused by a host of fungal pathogens, including *Glomerella cingulata* (asexual stage usually referred to as *Colletotrichum gloeosporioides*), *Phytophthora* spp., *Rhizoctonia solani*, *Botrytis cinerea*, *Cylindrocladium scoparium*, *Cryptosporiopsis* spp., *Fusarium* spp. and *Pestalotiopsis* spp. Many of the perceived production risks were associated with control of these diseases, with farmers listing poor pesticide application management and poor monitoring as major risks.

Generating graphical models

During a second workshop, held in October of 2018, we applied group work techniques (Whitney et al., 2018b) to generate impact pathways of alternative management strategies. Impact pathways can be effective for integrating knowledge held by researchers and practitioners (Silva and Guenther, 2018). They should include all relevant variables that are considered important for the decision at hand (Hubbard, 2014), whether or not they are considered easily measurable (Luedeling and Shepherd, 2016). To achieve realistic impact pathways, and to reduce the cognitive biases that can affect individual participants (Kahneman, 2011) and groups (Montibeller and von Winterfeldt, 2018), we implemented a step-by-step approach to knowledge elicitation (Fig. 2-1). Decision options were defined and clarified in plenary sessions and key aspects of these decisions were addressed separately by subsets of workshop participants. In these subgroups, experts were asked to describe their personal understanding, share it with their peers and develop an influence diagram describing their collective understanding. Experts followed this procedure for each major aspect of the decision. Ultimately, all diagrams were consolidated into a single diagram describing the impact pathway of the overall decision (Whitney et al., 2018b).

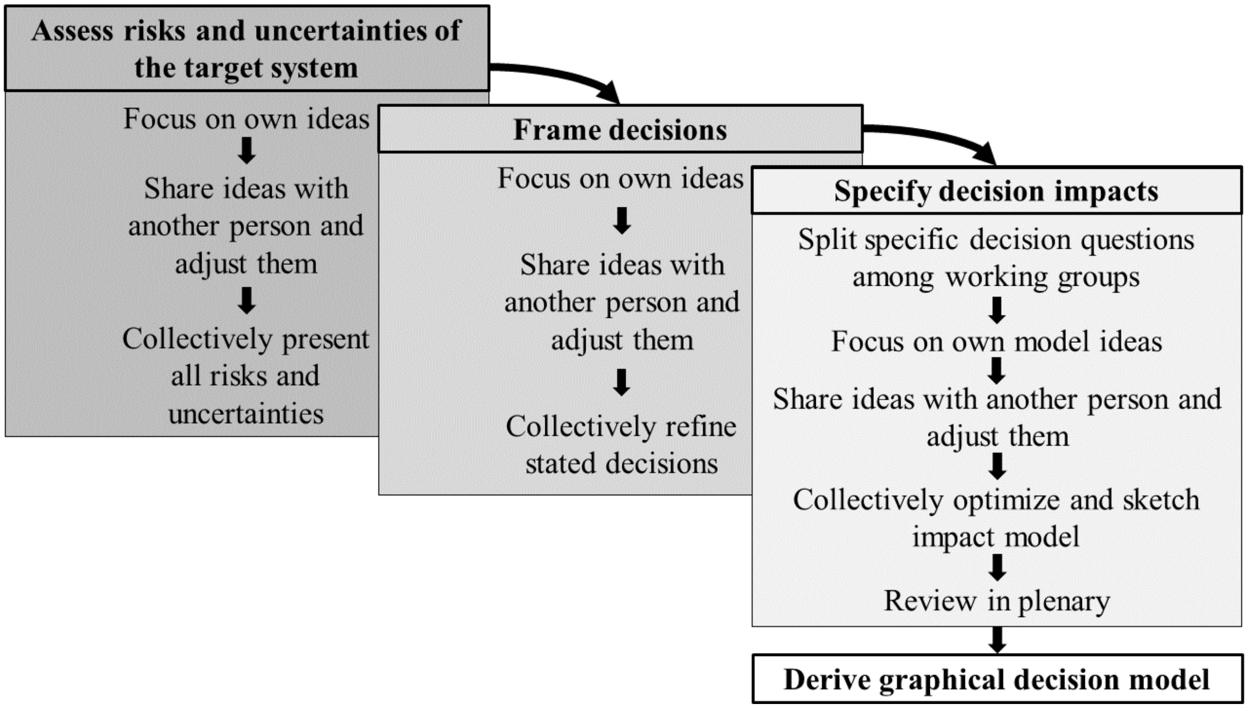

Figure 2-1. Workflow of collaborative group work approaches for developing a graphical impact pathway model (adapted from Whitney et al., 2018a)

We generated one impact pathway model for each decision option. Versions of models were shared with experts and analysts to confirm that all the important aspects of the decisions were covered. Experts were allowed to optimize and update the models as they felt necessary throughout the process.

Calibration Training

For decision models to produce accurate information, they must be parameterized with information that reflects the state of knowledge of the decision-makers (MacMillan and Marshall, 2006), or, if possible, the objective uncertainty about input parameters (Sebok et al., 2016). Such uncertainties can be defined by probability distributions for model parameter values (Yigzaw et al., 2019). These distributions can be developed using expert elicitation approaches (Bolger and Wright, 2017) for generating inputs for probabilistic simulations (Lanzanova et al., 2019), either alone or in combination with available data (Jochmann et al., 2010). Expert judgment has been shown to be highly useful for emulating decision situations (Wafula et al., 2018). Expert knowledge has been used as a data source in a diverse range of studies, such as risk assessment of supply chains (Giannakis and Papadopoulos, 2016), sustainability risk analysis (Valinejad and Rahmani, 2018) and life cycle assessment (Florindo et al., 2020). Expert knowledge elicitation can also provide insights that expand the scope of information that is considered in the assessment of decisions (Mach et al., 2017).

Expert knowledge elicitation requires participatory processes to support experts in providing estimates of parameters of interest (Andrade and Gosling, 2018). The challenge in eliciting such inputs is that most people start off with fairly poor ability to make such estimates. Research has shown, however, that estimation skills can be greatly improved through a process known as calibration training (Hubbard, 2014). Calibration training begins by establishing baseline data on estimation skills, which exposes experts to their initial ability to estimate uncertainty (usually people start off overconfident, i.e. they are correct less often than they expect). Experts are trained by going through a series of tests based on trivia questions, for which they provide quantitative estimates for both Boolean (true or false, including a self-assessment of their confidence) and range estimation (upper and lower bounds of 90% confidence intervals) questions. They are given opportunities to compare the number of expected correct answers with actually correct answers, allowing a self-evaluation of their ability to make predictions. Feedback on this process exposes experts to (some of) their biases and allows them to either narrow or widen their intuitive range estimates (Hubbard, 2014). The accuracy of their estimates improves after instruction in various techniques that have proven effective in enhancing such estimations, such as the 'equivalent bet' approach (Hubbard, 2014) and Klein's premortem (Klein, 2008). These practical instructions are accompanied by examples of cognitive biases such as the risk of becoming 'anchored' on particular numbers (Tversky and Kahneman, 1974). After our experts completed this calibration training, they were asked to provide ranges for all variables in the decision models. All range estimates for variables in the model are listed in the Supplementary materials.

Decision evaluation

Model comparisons were based solely on economic outcomes for farmers to see if the innovative practices we analyzed could be economically competitive with current practices, or even preferable. We used Partial Farm Budgets to quantify the net benefits of new practices. Partial Farm Budgets can be used to compare relevant benefits and costs of an innovative technology or practice to current management procedures (Soha, 2014). They can also be used for sustainability assessment of new management practices at farm scale (Clark 2014) and provide detailed analysis of how changing production methods can affect a farm's economic outcomes (Roth and Hyde, 2002).

Probabilistic simulation and sensitivity analysis

The final graphical impact pathway model was coded in the R programming language (R Development Core Team, 2019) and parameterized with inputs elicited from experts (listed in the Supplementary materials). We used functions from the decisionSupport package (Luedeling et al., 2019) to run a Monte Carlo simulation with 10,000 model runs. The simulation tools allow for random selection of values from the distribution defined for each variable (Rosenstock et al., 2014) and generate outcome distributions for different decision options (Luedeling et al., 2015). Risk factors were considered by including their impacts on plant health status over the production period. All such risks were taken into account by estimating probabilities of occurrence for each risk event. These probabilities were then used to program the likelihood of respective risk events in each model run. Decision options were evaluated with regard to their potential to reduce plant losses associated with the risk factors.

We implemented sensitivity analysis using the Variable Importance in the Projection (VIP) metric of a Partial Least Squares (PLS) regression model as a criterion for quantifying the strength of each variable's influence on projected outcomes (Luedeling and Gassner, 2012).

In many decision situations, model outputs based on the initial state of uncertainty are sufficient for deciding which of a set of decision options should be preferred. Sometimes, however, projected outcome distributions for decision options overlap, so that no clear preference emerges. In such cases, 'Value of Information' analysis can be used to identify critical uncertainties that are responsible for the lack of clear guidance for the decision at hand. Unlike a classic sensitivity analysis, Value of Information analysis relates variation in input variables not to the projected numeric outcome of the decision, but to the emerging recommendation. The information value (Expected Value of Perfect Information; EVPI) can help identify decision-critical uncertainties, whose reduction would lower the likelihood of making a poor choice. The EVPI is expressed as the maximum monetary value that a rational decision-maker should be willing to invest to obtain perfect information about a particular variable (Hubbard, 2014). The EVPI thus indicates variables for which further research would be helpful for supporting the respective decision (Strong et al., 2014). We used an empirical procedure from the decisionSupport package (Luedeling et al., 2019) to compute the EVPI.

Results

We integrated all the models that resulted from our collaborative group work into one comprehensive impact pathway, which served as a template for the development of a mathematical model and simulation of decision outcomes (Fig. 2-2).

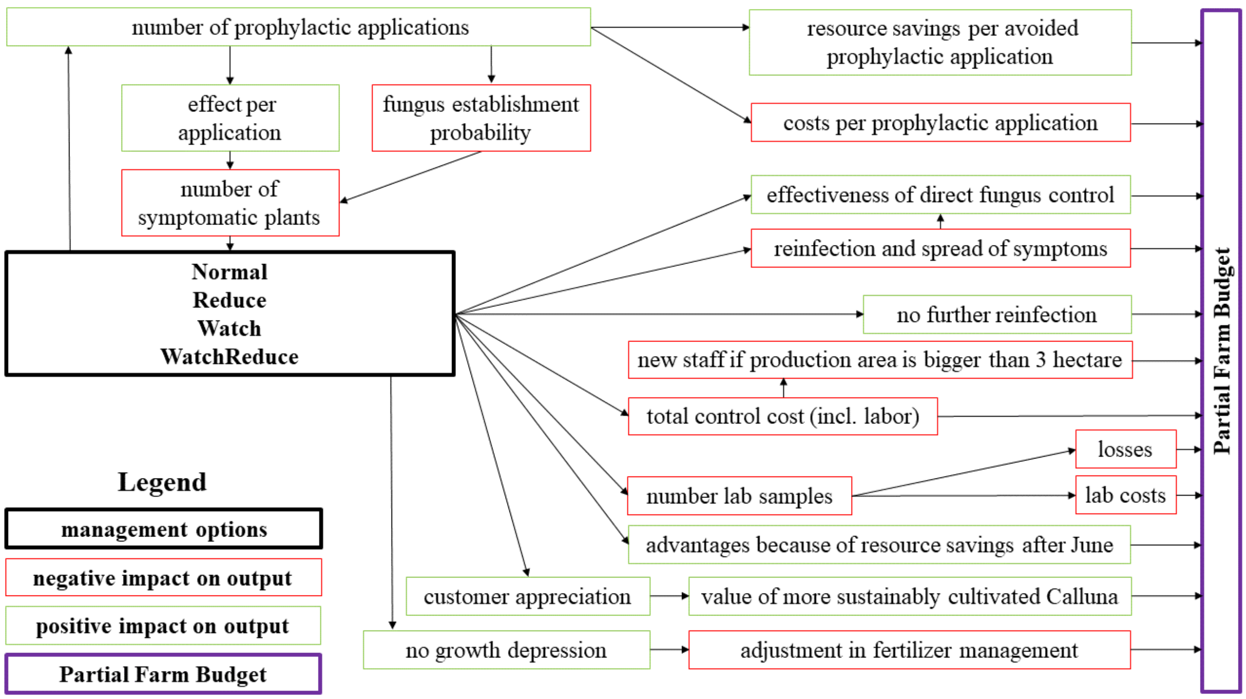

Figure 2-2. Conceptual model of fungal management options in heather production. The production process starts with the management options (black). The model output is defined as Partial Farm Budget (purple). Important variables expected to have a positive impact on the output (green) or negative impact on the output (red) are also shown

Management options

Experts defined their established heather production strategy as the baseline scenario. Current disease management practices include routine monitoring of plants whenever weather conditions are considered risky (high humidity and temperatures above 20°C). Producers spend relatively little time on sampling and detection of fungal infections, because labor costs are high and monitoring often requires extensive sampling schemes. Prophylactic fungicide applications, on the other hand, are considered cheap and effective. Such prophylactic applications are the disease control strategy of choice. This scenario was compared to innovative management practices that experts considered promising for reducing the ecological impact of heather production.

Experts considered a reduction of prophylactic fungicide applications during the most intensive application period as an alternative management strategy. This would occur between May and August, when weather conditions are associated with a high risk of fungal infections. Reducing the number of fungicide applications is expected to lower direct pest management costs and reduce environmental impacts. It would also require intensified disease monitoring (incurring additional labor costs). Reduced pesticide applications may thus have multiple effects: they may lead to higher disease detection rates (due to more monitoring), or to increased fungal infections and disease spread (due to less effective control). Both possible impacts were considered in the model according to occurrence probabilities indicated by experts. Reducing pesticide applications is also expected to require adjustments in fertilizer management, since they would increase growth rates of heather. Possible positive implications of reduced pesticide application include increased market prices and new product development opportunities for more sustainably produced heather. To account for potential benefits of reduced fungicide applications, we considered a scenario where heather plants grown under such reduced-input conditions fetched a higher selling price (price premium of 0.01 - 0.10€ per plant).

Experts also considered the possibility of increasing the frequency of manual monitoring for potential fungal infections and symptomatic plants (e.g. producers walking through fields and checking plants). This would require more intensive sampling and laboratory tests of plants by experts on fungal infections, which would need to happen before separating container-grown plants in June. Intensified monitoring is thus expected to decrease fertilizer use, water consumption and pesticide losses, and to reduce the number of symptomatic plants after June. These impacts were reflected in lower expected production costs, as well as a reduced number of consequential fungal infections. As a result of intensified laboratory analyses and monitoring, however, we expect fewer plants to be sold, because a considerable number of plants are either sent to laboratories for analysis or discarded because of detected fungal infections.

These scenarios were formally modelled as four management options: 1) **Watch**: Improved monitoring combined with normal prophylactic application, 2) **WatchReduce**: Monitoring combined with reduced pesticide application, 3) **Reduce**: Reduced prophylactic pesticide application, 4) **Normal**: Standard practice, in a system without improved monitoring (Fig. 2-3). Experts agreed that alternative management strategies had the potential to improve the sustainability of production processes over the baseline scenario but that they also included risks, such as financial losses due to suboptimal disease suppression.

Expected outcomes for all management options were largely similar, as reflected by similar distribution ranges and shapes of the projected Partial Farm Budgets for all strategies (Fig. 2-3).

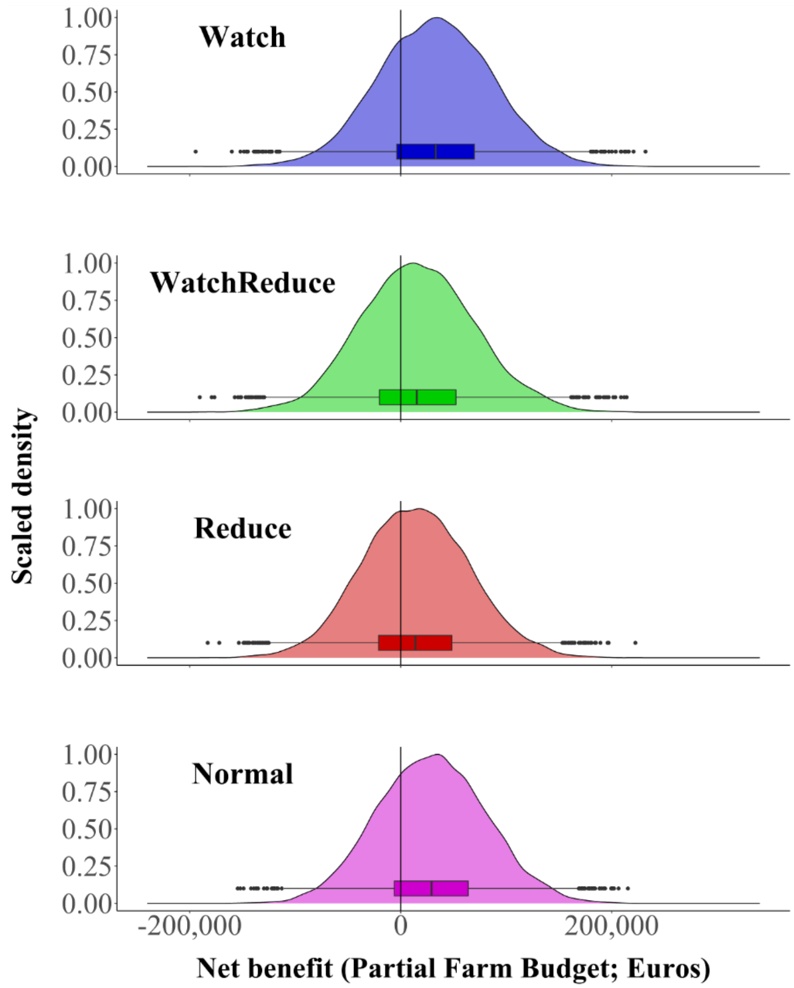

Figure 2-3. Probability density distributions (scaled density among 10,000 runs of a Monte Carlo simulation) of Partial Farm Budgets (Euros) per hectare for four heather production management strategies. Watch = Monitoring Plan and normal prophylactic pesticide application. WatchReduce = Monitoring Plan and reduced prophylactic pesticide application. Reduce = Reduced prophylactic pesticide application. Normal = Normal prophylactic pesticide application

Modeled decisions

In order to analyze whether the defined management options could provide net benefits to producers, we modeled them in comparison to the baseline scenario. We formally expressed the management decisions producers face as choices between options, focusing on three combinations:

1) Reduce vs. Normal: Reduced prophylactic pesticide application compared to standard practice, in a system without improved monitoring (SprayLess)
2) Watch vs. Normal: Improved monitoring combined with normal prophylactic application compared to current standard practices (WatchMore) and

3) WatchReduce vs. Normal: Improved monitoring combined with reduced pesticide application compared to standard practices (WatchMoreSprayLess)

To explore the relative merits of adopting the innovative disease management strategies, we computed the difference between their performance and the baseline scenario. Within each model run all random factors that were not directly related to the management practice (e.g. weather, heather price) were kept constant to allow for a fair comparison of practices. The projected Partial Farm Budgets of adopting the WatchMoreSprayLess and SprayLess strategies showed high likelihoods of negative outcomes (Fig. 2-4).

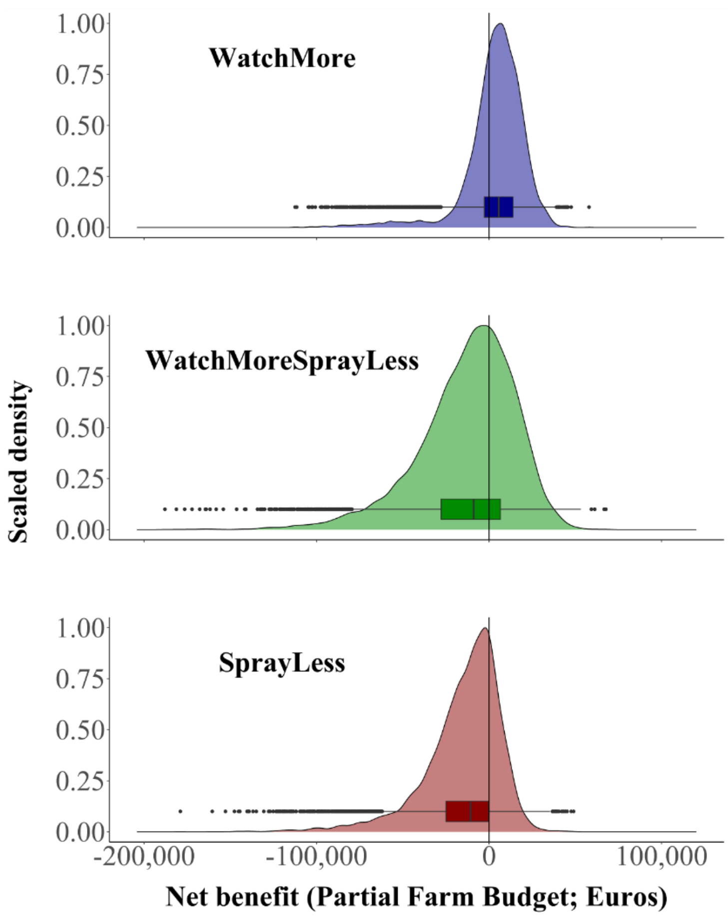

Figure 2-4. Probability density distributions (scaled density among 10,000 runs of a Monte Carlo simulation) of Partial Farm Budgets (Euros) per hectare of heather production area for three decision options for heather production. WatchMore = Improved monitoring combined with normal prophylactic application compared to current standard practices. WatchMoreSprayLess = Monitoring combined with reduced pesticide application compared to standard practices. SprayLess = Reduced prophylactic pesticide application compared to standard practices, in a system without improved monitoring

Projected probability density distributions ranged from a loss of more than 200,000 € to a gain of nearly 70,000 €. According to the outputs of our Monte Carlo simulations, the chance of loss amounted to 76% for adoption of SprayLess and 64% for WatchMoreSprayLess. WatchMore is the only option with an outcome distribution indicating a greater chance of net gains than losses. For this option, our simulation indicated a chance of gain of 68%, implying that additional monitoring efforts are likely to lead to positive outcomes in terms of the Partial Farm Budget of heather production.

Important variables for WatchMore adoption

Uncertainty about several input variables led to variation in the projected outcomes of the WatchMore option, with some variables potentially affecting the emerging adoption recommendation. Such potential, which was indicated by high (and non-zero) EVPI values, was indicated for two variables: 1) the production area threshold when more staff is needed, and 2) the savings resulting from intensified monitoring (Fig. 2-5). The threshold when costs for additional staff are incurred presented the greatest uncertainty regarding the economic viability of increasing the monitoring frequency. The magnitude of cost savings due to early detection of symptomatic plants had the second highest information value. These findings imply that additional information on these variables could provide clarity on the optimal management strategy.

Savings due to intensive heather monitoring had a high information value. It was also identified as the most relevant variable according to the VIP scores returned by PLS analysis (Fig. 2-5), underscoring its potential to influence the economic viability of the WatchMore strategy.

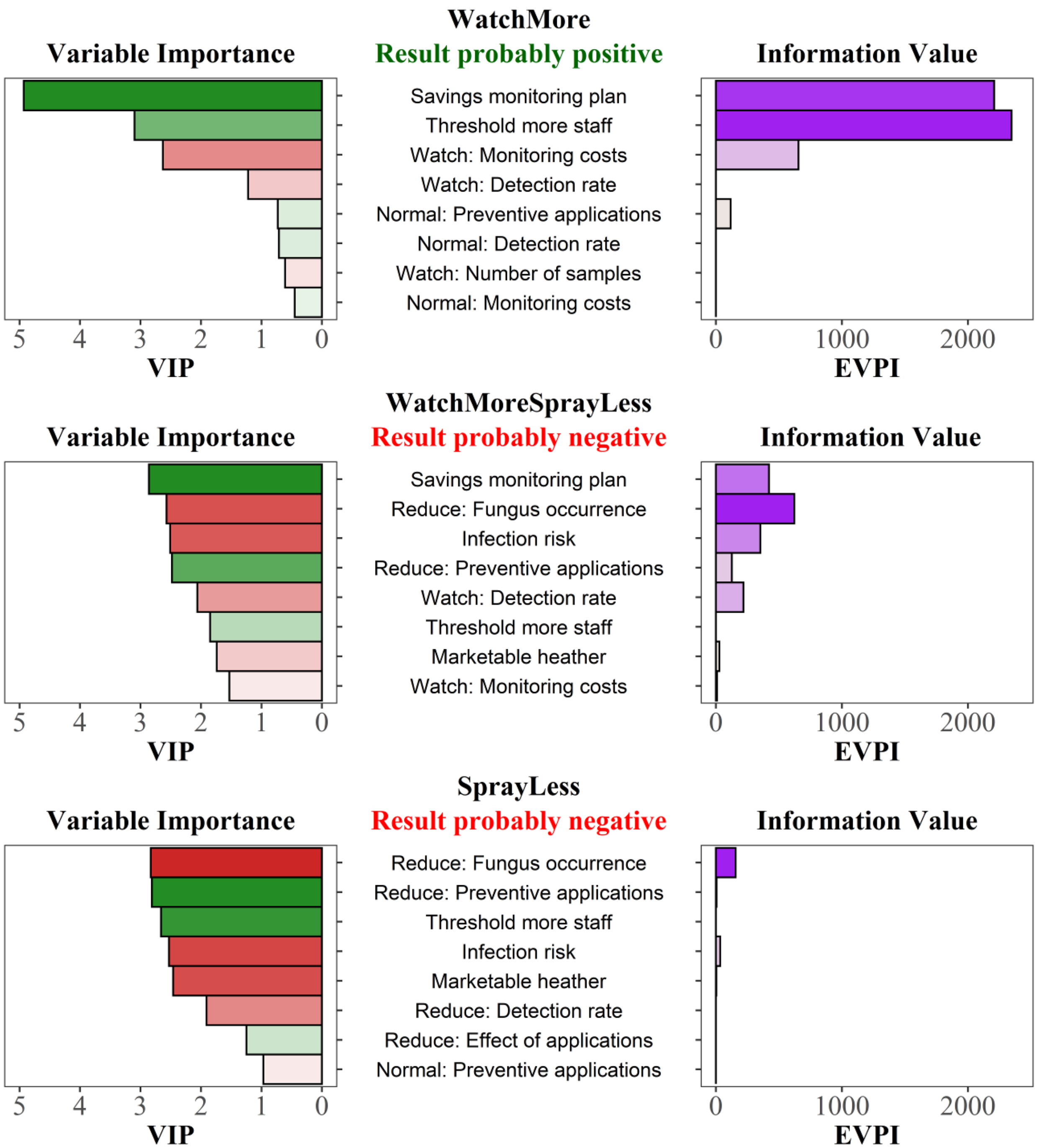

Figure 2-5. Variable Importance in the Projection (VIP) and Information Value (Expected Value of Perfect Information; EVPI) for the implementation of WatchMore, WatchMoreSprayLess and SprayLess in comparison to established heather production. VIP and EVPI specify the influence of each variable on the projected economic value of adopting each strategy (Variable Importance) as well as on whether the simulation makes adoption or non-adoption appear economically preferable. For Variable Importance, we show the top eight variables with the respective EVPI. In the Variable Importance plot, variables that positively affect projected Partial Farm Budget are shown in green, those with negative effects in red

Important variables for WatchMoreSprayLess adoption

EVPI results of WatchMoreSprayLess depict the highest information values for the probability of fungus occurrence, the savings due to intensive monitoring and the infection risk. Reduction of uncertainties for these variables would facilitate the adoption decision (Fig. 2-5). Additional information on the probability of fungus occurrence had the greatest information value by far, implicating this variable as a key entry point for decision-supporting research. The most important variables emerging from the VIP analysis were the savings resulting from intensified monitoring, the probability of fungus occurrence, the infection risk and the number of preventive fungicide applications, all of which had largely similar levels of importance.

Important variables for SprayLess adoption

Value of Information analysis indicated the highest value by far for the probability of fungus occurrence (Fig. 2-5). Hence, decision-makers considering adoption of SprayLess would benefit most from additional (ideally perfect) information on the probability of fungus occurrence.

Discussion

Projected Partial Farm Budgets for the four management strategies showed broad overlap between the expected outcomes (Fig. 2-3). Projections for all options included substantial chances of negative returns (>25%; Fig. 2-3), highlighting the risky nature of heather production.

Prospects of increased monitoring efforts (WatchMore)

Our simulations of the option to implement a monitoring plan (WatchMore) indicated a 68% chance of Partial Farm Budget gains in comparison to current practices (Fig. 2-4). This is a weak indication that implementing a monitoring plan could be a beneficial strategy. By implementing WatchMore, growers would obtain a better overview of plant health and growth performance, leading to better-informed management decisions. Past studies also suggest favorable outcomes of increased monitoring in heather nurseries, with monitoring acting as an important component of comprehensive hygiene approaches (McQuilken and Hopkins, 2004) and contributing to optimized management of chemical applications (McQuilken and Thomson, 2008).

Implementing the WatchMore option includes increased costs for additional and possibly better-trained staff to ensure that monitoring is effective. Value of information and variable importance were relatively high for the production size threshold when additional staff is needed (EVPI 2347€ and VIP = 3.1). The benefits of monitoring and resource savings (EVPI = 2208€ and VIP = 4.9) and the increased monitoring costs were also important (EVPI = 655€ and VIP = 2.6) (Fig. 2-5). Measurements of these could lead to better understanding of the difference between baseline and WatchMore, and help decision makers decide if more monitoring is worth the additional investment.

Prospects for increased monitoring, coupled with reduced fungicide application (WatchMoreSprayLess)

Simulations of preventive fungicide applications in combination with monitoring (WatchMoreSprayLess) indicated that intensified monitoring is unlikely to strongly reduce the spread of diseases (Fig. 2-4). These findings illustrate the high uncertainty of fungus occurrence and its impact on heather production. Controlling fungal occurrence by increased monitoring seems unlikely, since higher plant losses to fungi would not be compensated by monitoring benefits. Past studies have also shown that disease prevention mainly relies on frequent chemical applications (Whipps, 1992). Measures to control disease, in the form of chemical applications, reduce plant losses and therefore offer economic advantages for plant producers (Oerke, 2006). For WatchMoreSprayLess these advantages do not seem to materialize. Instead, the risk of losses due to fungus occurrence was increased when the number of preventive fungicide applications was reduced. Reducing preventive fungicide applications entails substantial risks for growers and should be accompanied by reliable disease detection and control strategies (Litterick and Mcquilken, 1998).

Further measurements of relevant variables concerning fungus occurrence and infection risks are needed to reduce uncertainty related to the WatchMoreSprayLess decision. Value of information and variable importance were relatively high for the probability of fungus occurrence for reduced preventive fungicide application (EVPI = 623€; VIP = 2.6), savings by applying a monitoring plan (EVPI = 421€; VIP = 2.9) and the risk of fungal infections (EVPI of 353€; VIP = 2.5) (Fig. 2-5). Measurements of these variables could lead to better understanding of the difference between WatchMoreSprayLess and the baseline and scenario and provide decision support on whether this option is worth the additional investment.

Prospect of reduced fungicide application without more monitoring (SprayLess)

Simulations of the intervention to reduce fungicide applications without additional monitoring (SprayLess) indicate a likely reduction in Partial Farm Budget (Fig. 2-4). During our workshop, farm managers said that reducing preventive fungicide applications could lead to a spread of fungal infections that could quickly get out of control. Additional knowledge about fungus occurrence and indications on how to administer targeted fungicide applications in their production systems could help to reduce uncertainty about SprayLess. This was the most hazardous decision in our comparison of stated decisions, with a high risk (76%) of negative outcomes (Fig. 2-4).

However, experts agreed on the possibility of a small price premium for heather produced with reduced fungicide applications. Simulation results indicated that this small increase in selling price has little influence on Partial Farm Budget or on the relative merits of this management option. Understanding the specific behavior of fungus occurrence in heather production is crucial. Two variables emerged as influential for the decision recommendation: 1) the probability of fungus occurrence (EVPI: 157€, VIP: 2.8) and 2) the infection risk (EVPI: 354€, VIP: 2.5; Fig. 2-5). Further measurements of these could reduce uncertainty about SprayLess and help decision makers decide if this option is worth the additional investment.

Our simulations of the price premiums for plants with reduced fungicide application indicated that this small increase in selling price is unlikely to influence the Partial Farm Budget or the relative merits of the SprayLess option. Many consumers prefer environmentally benign (Behe et al., 2013) and locally grown horticultural products (Krug et al., 2008), but this would likely require marketing strategies, certification and awareness-raising about the added value arising from sustainable cultivation practices.

Overall decision recommendation

Models suggest that in comparison to current heather production practices, WatchMore may be a promising innovation for heather growers. For all the management options that we evaluated, a few variables emerged as important for the decision recommendation: For the WatchMore scenario, these were related to the size of the operation that would require additional staff for monitoring, and the actual benefits arising from the monitoring plan. For WatchMoreSprayLess and SprayLess, the greatest decision-relevant uncertainties were the probability of fungus occurrence following fewer preventive fungicide applications and the general fungal infection risk. It is worth noting that farming decisions cannot exclusively focus on one aspect of farm management, even one as central to heather production as fungal control. Growers involved in our modeling exercise mentioned additional challenges such as fertilizer management and adapting to the possible impacts of climate change, which also shape their decision-making on adopting innovative practices.

All interventions in production systems are characterized by risks (Wu et al., 2013). Recent studies in ornamental plant production have often narrowly focused on particular risks, e.g. on salinity (Plaza et al., 2019), or on particular management practices such as fertilization (Freidenreich et al., 2019), while the interactions of all factors that influence such production systems are rarely considered. In our view, it is difficult to produce comprehensive risk assessments that do justice to the complexity of agricultural decisions when adopting such a narrow perspective. Heather production systems are complex and include many processes and mechanisms that are not precisely understood. Recent studies in heather production have not taken into account the management effort and risks that affect growers' economic outcomes. According to De Silva and Forbes (2016), the main factors hindering sustainability-oriented management in horticulture are the time and expense involved in implementing such options. Our results illustrate the importance of monetary savings and the impacts of individual benefit and cost items on overall outcomes. Besides the economic dimension, environmentally oriented strategies can only be applied by producers if they are also accepted by society (Gruda et al., 2019). We took farmers' and customers' attitudes into account by involving stakeholders, which allowed us to capture real-world benefits and ensure applicability of innovation options. Similarly to our study, Ingrao et al. (2015) were able to demonstrate an instance of stakeholder-based decision support that enabled farmers to improve system understanding, allowing them to evaluate environmental impacts of peach production.

Stakeholder-based modelling methods produce models that are well suited for practice-oriented decision support, as has been demonstrated in our study, as well as in an earlier evaluation of agricultural water policy in Malta (D'Agostino et al., 2020) and studies on stakeholder-based decision support for energy planning in local neighborhoods (Hettinga et al., 2018). By incorporating stakeholder knowledge, researchers can capture information that might be ignored by studies using classical empirical methods (MacMillan and Marshall, 2006). These methods should be applied more widely in model development.

We have demonstrated the use of alternative research approaches that do not rely on precise information. We have shown how these can be used for identifying risks and challenges related to innovative management strategies. The model development approaches we applied in this study allowed us to produce actionable information regarding the risks involved in adopting new management strategies and to identify critical knowledge gaps that should be addressed before changing practices.

Conclusion

Option comparisons based on deterministic approaches that use precise numbers and do not consider uncertainties may produce clear recommendations but convey a false sense of certainty that is not justified given the actual limitations in knowledge about the target system. Decision Analysis approaches are ideally suited for this purpose, and urgently needed due to the high uncertainties in complex horticultural systems. They can provide decision support and guidance for farm managers aiming to reduce the negative environmental impacts of their operations. Although our study involved various calibrated experts from important areas of heather production, misjudgments and biases of experts may still have led to inaccuracies. Our analysis is also limited by the dearth of current studies on the commercial cultivation of heather plants. Nevertheless, based on the current state of knowledge, it appears that additional efforts to monitor for disease occurrence are likely to generate positive net benefits. For management options involving a reduction in preventive fungicide applications, prospects currently appear less favorable, but research into some of the critical areas of uncertainty may change this assessment.

Our work can serve as a guide for further holistic research in the area of decision support in horticultural systems management. The approaches we have demonstrated can be useful for improving production systems in horticulture and elsewhere, and they are suitable for integrating sustainability-oriented thinking into feasibility studies. With wider application of such decision-focused systems-analysis tools, many horticultural operations can be supported in evaluating and adopting cleaner production techniques.

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Supplementary Materials

All data generated in this study is available in the following open access repository: https://github.com/marruett/Supplementary_Ruett_2020 and can be cited using the following doi: https://doi.org/10.5281/zenodo.4637259

Conflicts of interest

The authors declare that this research was conducted in the absence of any commercial or financial relationships that could be constructed as a potential conflict of interest.

Author contributions

Marius Ruett: Methodology, Software, Validation, Formal analysis, Investigation, Data Curation, Writing-Original Draft, Writing - Review & Editing, Visualization. **Cory Whitney:** Resources, Data Curation, Writing - Review & Editing. **Eike Luedeling:** Conceptualization, Software, Writing - Review & Editing, Supervision, Funding acquisition.

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Chapter 3

Hyperspectral imaging for high-throughput vitality monitoring in ornamental plant production

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Abstract

Ornamental heather (*Calluna vulgaris*) production is characterized by high risks such as occurrence of fungal diseases and plant losses. Given the general absence of formal research on this economically important production system, farmers depend on their own approaches to assess plant vitality. We provide a reproducible, affordable and transparent workflow for assessing ornamental plant vitality with spectroscopy data. We use hyperspectral imaging as a non-invasive alternative for monitoring plant performance by combining the long-term experience of experts with hyperspectral images taken with a portable hyperspectral camera. We tested a custom-made setup deployed in a horticultural production facility and screened thousands of heather plants over a period of 14 weeks during their development from cuttings to young plants under production conditions. The vitality of shoots and roots was classified by experts for comparison with spectral signatures of shoot tips of healthy and stressed plants. To identify wavelengths that allow distinguishing between healthy and stressed heather plants, we evaluated the datasets using Partial Least Squares regression. Reflectance in the green (519 nm – 575 nm) and red-edge (712 nm – 718 nm) region of the spectrum was identified as most important for classifying plants as healthy or stressed. We transferred the trained Partial Least Squares regression model to independent test data obtained on a different date, correctly classifying 98.1% of the heather plants. The setup we describe here is adjustable and can be used to measure different plant species. We identify challenges in data evaluation, point out promising evaluation approaches, and make our dataset available to facilitate further studies on plant vitality in horticultural production systems.

Introduction

Producers and retailers of ornamental plants have to produce plants of high quality, in order to be competitive in the marketplace (Gullino and Garibaldi, 2007). Fungal pathogens are a major risk factor in the quality of ornamental plants (Ruett et al., 2020b; Srivastava et al., 2018). Optimized disease management and pathogen detection approaches could reduce this risk and increase the stability of production (Daughtrey and Benson, 2005). Bud-flowering heathers (*Calluna vulgaris* L.) are ornamental plants of considerable economic importance (Borchert et al., 2012, 2009) that face a high risk of fungal infection. The market value of heather plants is thus strongly influenced by farmers' decisions on management measures that affect infections and product quality (Ruett et al., 2020b). Heather plants must be diligently monitored to ensure early detection of abiotic and biotic stresses. Although it can be time-consuming and require highly skilled employees, intensified monitoring has been identified as a promising optimization strategy in commercial heather production (Ruett et al., 2020b).

Non-invasive sensor technology has been proposed for early detection of abiotic (Lowe et al., 2017) and biotic stress symptoms on plants (Bauriegel et al., 2011). One of the greatest advantages of these sensor-based monitoring approaches is their capacity to allow non-destructive real-time measurements (Rascher et al., 2011) and their potential for the detection of plant-pathogen interactions (Mahlein et al., 2019). In ornamental plant production, non-invasive monitoring technologies are not yet established, but have the potential to contribute to or even replace time-consuming and costly manual assessments by experts.

Sensors can collect accurate information about current plant performance (Bohnenkamp et al., 2019), which allows improved assessment of plant vitality (Knauer et al., 2017). For instance, multispectral cameras have been shown to detect tulip virus diseases with a level of accuracy that was comparable to that of human experts (Polder et al., 2014). Red, green, blue (RGB) image analysis enabled successful rust detection on Canadian goldenrod (Wijekoon et al., 2008). Thermal sensors proved applicable for the early detection of downy mildew on roses, via detection of increased leaf temperature (Gomez, 2014). Optical sensors commonly applied in plant science cover the spectral range from the visible (VIS) to near infrared radiation (NIR) (400 nm – 1000 nm) (Lowe et al., 2017). Hyperspectral imaging in the VIS/NIR region using hyperspectral sensors has been shown to be a suitable method for detecting plant stress earlier than the naked eye of experts (Behmann et al., 2014). Hyperspectral sensors are particularly promising tools for optimized monitoring, since they allow detailed assessment of plant health status and monitoring of changes in plant physiology (Mahlein, 2016). Hyperspectral sensors have also been shown to detect the water status and chlorophyll content of sunflower leaves (Neto et al., 2017), powdery mildew on barley canopy (Behmann et al., 2018) and bacterial contamination of spinach leaves (Teena et al., 2013).

Due to these capabilities, hyperspectral sensors have high potential for early detection of stress and thus improved timing of plant protection procedures (Kuska and Mahlein, 2018). In commercial heather production, such sensor tools have not yet been applied.

Hyperspectral imaging of detached heather shoots under controlled illumination conditions have been shown to allow for a precise assessment of their photosynthetic pigment and anthocyanin content (Mac Arthur and Malthus, 2012). Similarly, canopy-level spectral reflectance measurements of heather moorlands enabled the non-invasive determination of leaf pigments (Nichol and Grace, 2010), and RGB-images taken by unmanned aerial vehicles (UAVs) have been used to map flowering phenology of heathland ecosystems (Neumann et al., 2020). However, the potential of hyperspectral approaches to monitor risk factors in commercial heather production has not yet been evaluated.

Here, we explore the potential of non-invasive hyperspectral sensor technology for continuous evaluation of plant vitality over time. The aim of our study was to provide a reproducible high-throughput measurement design, accompanied by a detailed description of all data processing steps, including a Partial Least Squares regression (PLSR) based sensitivity analysis to identify the most suitable wavelengths for stress detection in heathers. We developed a novel setup with a hyperspectral sensor, which was used for weekly imaging of 3,276 heather plants. In addition, we used a high-resolution camera to take photographs of the heather plants. These datasets were used to test whether spectral measurements of heather plants contain useful information about the plants' vitality status. All related models and data are published open–access for further attempts at classification (Ruett et al., 2020a). The novel approach of hyperspectral monitoring in commercial heather production outlined here may be adapted for other plant production lines and thus contribute to the development of efficient sensor-based vitality monitoring approaches that facilitate plant health management by farmers.

Materials and Methods

In order to produce vigorous plants, heather producers use stock plants, from which vegetative clones are cut and planted into specialized trays. Farmers try to compensate for likely plant losses by planting ~10% more cuttings than the number of plants that are needed to fulfill their production targets. Depending on the variety, plant losses vary greatly, with losses up to 30% or more that can threaten the operation and contractual obligations of a farm. Because of the high risk of plant losses during the initial cultivation phase, we focused our analysis on this stage.

Plant material and growing conditions

The experiment was carried out in a commercial production system for ornamental heather plants (Europlant Canders GmbH, Straelen, Germany). All analyses were applied to heather plants of the variety 'Sanne' (Beautyladies®, Edens Creations, Oldenbroek, Netherlands). A total of 3,276 cuttings were planted into 12 trays (273 cuttings each) in Baltic peat with a pH of 4 and an electrical conductivity (EC) of 0.1 mS cm^{-1}. Plants were cultivated in greenhouses (mean temperature of 15.8°C, with a standard deviation of 6.4°C; mean relative humidity: 82.5%, with a standard deviation of 16.9%) from 19 March 2019 until 25 June 2019 under commercial growing conditions following the farm's standard crop management practices.

Experimental layout and weekly measurement protocol

Hyperspectral and RGB images were taken nearly simultaneously to gather a dataset combining expert assessment of heather performance and hyperspectral images of the respective plants. Hyperspectral data were acquired with a hyperspectral imaging sensor device, and plant status was documented photographically with a digital single-lens reflex camera (Fig. 3-1).

The measurements were taken once a week over a period of 14 weeks from 26 March to 18 June 2019, covering plant development between the time the cuttings were planted and the young plant stage. Plant positions were recorded as tray (1-12), column (A-U) and rows (1-13).

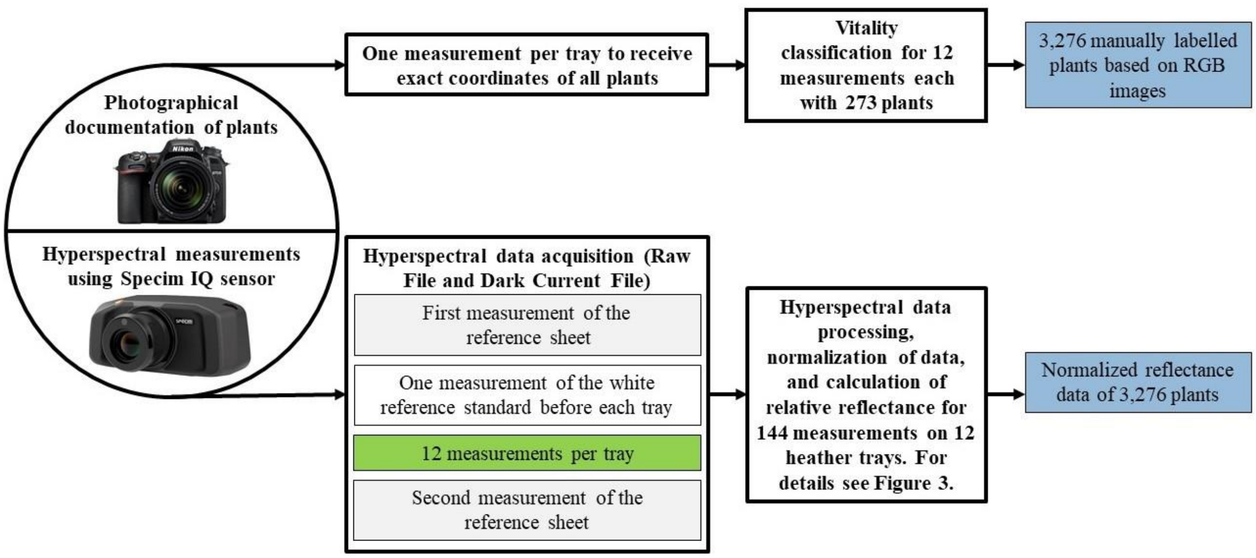

Figure 3-1. Experimental layout and protocol for weekly measurements. Twelve trays with 273 plants each were photographed using a Nikon D7500 camera and imaged using the 'Specim IQ' hyperspectral imaging push-broom sensor. Output data from the vitality classification and from processed hyperspectral images are available as open access data (Ruett et al., 2020a)

RGB imaging and expert assessment

We took the RGB images immediately after the hyperspectral imaging. For acquiring RGB image data with high spatial resolution, a Nikon D7500 camera (Nikon GmbH, Düsseldorf, Germany; Fig. 3-1) equipped with a 35 mm standard lens (Nikon GmbH, Düsseldorf, Germany) was mounted on a tripod (Manfrotto Vitec Imaging Solutions, Cassola, Italy) with a height of 101 cm above the plant samples. The setting allowed a resolution of 230 x 230 pixels per plant plot (2 cm x 2 cm) and a total of 273 plant plots per RGB image. A halogen lamp with 220 W and 5600/3200 K (ARRI AG, Munich, Germany) was used for homogeneous illumination of the experimental RGB imaging setup. The angle of the halogen lamp was set to 30° with a distance of 162 cm to the tray surface.

RGB images of all trays on all sampling dates were evaluated by two heather experts, who classified all shoots according to their perceived vitality. The heather experts focused their visual assessment on vitality traits such as shoot color, leaf structure, canopy density, and plant size. Expert #1 was a specialist in ornamental plant cultivation, and Expert #2 was an extension officer for local heather farmers. Both experts had more than 20 years of experience in heather cultivation. Experts were asked to pay particular attention to fungal disease symptoms, which often occur in heather cultivation, but which were unfortunately not detected in our study. Experts compared their classifications, adjusting and harmonizing their judgments to classify each plant. For each measurement day, experts identified ‘Healthy’, ‘Dead’, and ‘Shoot Stress’ plants (Table 3-1). On the pricking (transplanting) day (25 June 2019), experts identified 17 plants that were excluded from further cultivation due to insufficient rooting. Although the experts showed great expertise, we cannot take the experts' classification as absolute truth, since visual assessment of images can also lead to errors. Nevertheless, this approach was the most promising to incorporate long-term experiences from the practice of heather production into our study.

Table 3-1. Expert assessment of health status of initially 3,276 heather plants from one week after planting cuttings to pricking (transplanting) of young plants. One plant disappeared on day 14 and another plant on day 28 after planting, reducing the final plant number to 3,274

Days after planting	Healthy	Dead	Shoot Stress
7	3,265	0	10
14*	3,274	0	1
21	3,267	0	8
28*	3,250	0	24
35	3,226	0	48
42	3,173	1	100
49	3,191	3	80
56	3,247	5	22
63	3,259	5	10
84	3,257	5	12

* The two plants that disappeared may have been removed from the greenhouse by birds that sometimes snatch young heather plants for building nests.

Hyperspectral imaging setup

The portable hyperspectral camera ‘Specim IQ’ (Specim Spectral Imaging Ltd., Oulu, Finland) was used to capture hyperspectral images (HS images). The HS sensor captures 204 spectral bands at wavelengths ranging from 397.32 nm to 1003.58 nm.

We designed an experimental hyperspectral imaging setup that allowed us to record image data from plants under controlled conditions. Our custom-made setup was constructed using aluminum tubes to mount the sensor above a standard particle board, on which sample trays could be placed. During measurements, the room was kept dark, with all incident light blocked. Two halogen lamps (500 W and 3200 K, Bresser GmbH, Rhede, Germany) with aluminum reflectors were installed on top of the setup to illuminate the samples in the VIS/NIR wavelength range. The halogen lamps were equipped with light diffusers to ensure homogeneous lighting of the whole sample tray (the full set-up is described in Table 3-S1). We optimized conditions for data acquisition by adjusting the positions of sensor, tray surface and light source (Fig. 3-2). Each image covered an area of 512 x 512 pixels containing 36 cuttings on 17 cm x 17 cm. The hyperspectral imaging setup is adjustable to accommodate larger plants.

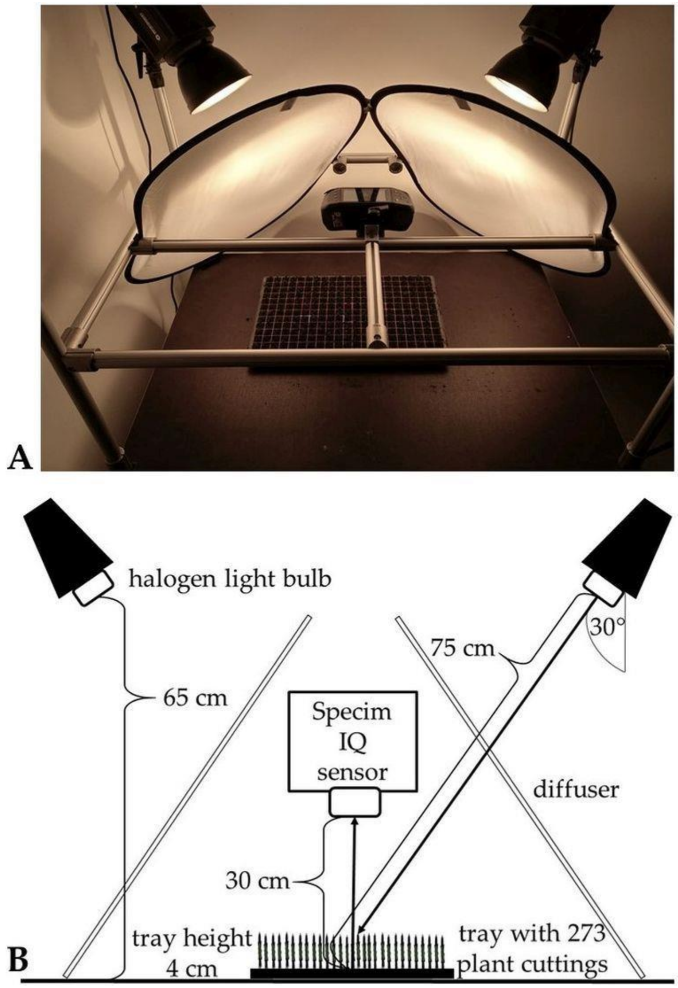

Figure 3-2. Overview of the hyperspectral imaging setup using the Specim IQ sensor, two halogen lamps and two diffusors mounted on an aluminum frame (A), and conceptual drawing of the measurement setup (B)

Each hyperspectral imaging session was initiated by setting the integration time of the HS sensor to 30 ms. An uncalibrated 10 cm x 10 cm Restan white reference standard (Image Engineering, Frechen, Germany) was used to calibrate the HS sensor at the beginning of each measurement day. The Restan white reference standard was used for spectral calibration. As the Restan standard was too small to fill the entire sensor image and thus not suitable for the spatial correction of heterogeneities, we additionally measured a white photo cardboard (folia paper Max Bringmann KG, Wendelstein, Germany) (70 cm x 50 cm) at the beginning and at the end of each measuring day in the same position where we had positioned the tray with plant cuttings before (see Fig. 3-2). The white photo cardboard is hereafter referred to as reference sheet and the uncalibrated Restan white reference standard as white reference standard. Capturing the reflectance of such a reference sheet allows for the correction of spectral, spatial, and temporal variation in illumination conditions during the measurement.

Establishing a reference sheet to correct for spatial variation in illumination

A white reference covering the complete image area is essential for the HS image processing to correct for spatial variability in illumination conditions. We established a method to correct for spatial variation in illumination conditions using a white photo cardboard as reference sheet, after confirming that it had homogeneous spectral reflectance properties. Spectral reflectance was measured at six different positions with an 'ASD FieldSpec 4' point spectroradiometer (Analytical Spectral Devices, PANalytical B.V., Boulder, CO, USA) to test for spatial homogeneity of reflectance. At each position, ten measurements were recorded and averaged to reduce noise. The spectral reflectance of the reference sheet was very homogeneous with a mean of 87.3% and a standard deviation of 2.1%. For the uncalibrated Restan white reference standard the reflection was slightly lower (mean of 82.5%) and even showed greater variation (standard deviation of 2.8%) than the reference sheet.

We then compared both measurements with the spectral properties of a calibrated 95% Zenith Polymer white reference standard (SphereOptics GmbH, Herrsching, Germany) to precisely determine the spectral properties of the reference sheet and the white reference standard. The reflectance of the white reference standard varied between 80% and 87% in the spectral range of interest (450 nm – 900 nm). The reflectance of the reference sheet was, at 80% to 100%, consistently higher than that of the white reference standard. The spatial homogeneity and generally high reflectance of the reference sheet indicated that it was well suited to compute wavelength-specific correction factors for each spatial pixel in the HS images with the additional benefit of being more applicable under commercial conditions compared to a calibrated or uncalibrated white reference standard. Computed wavelength-specific correction factors were applied to the images of the reference sheet in the data processing procedure, which were then used for the processing of raw heather images. We were thus able to correct for spatial heterogeneity in illumination conditions and to apply spectral correction when calculating the spectral reflectance of heather plants.

Hyperspectral image processing

Hyperspectral data were processed in the R programming language (R Development Core Team, 2021). The package caTools (Tuszynski, 2020) was used to load spectral raw data into the R environment. To correct for spatial heterogeneity in illumination, raw data of the first hyperspectral reference sheet measurements were multiplied with the correction factors determined from the spectral measurements of the photo cardboard in the laboratory (cf. Establishing a reference sheet to correct for spatial variation in illumination). Then we applied a Gaussian filter from the package EBImage (Pau et al., 2010) with a kernel size of 3 pixels to reduce the pixel-to-pixel variability (noise) in the first hyperspectral reference sheet measurement. Due to the homogeneous surface of the reference sheet we detected little noise, all of which was removed by the filter. The same procedure was applied for the second hyperspectral imaging of the reference sheet after each measurement. We determined the relative differences between the recorded data from the first and second hyperspectral imaging in the wavelength region of 450 nm to 900 nm (mean relative difference: 7%, with standard deviation of 2.4%). The similarity of both measurements was used as an indicator for stable illumination conditions over the measurement period of 5 - 6 hours during each measurement day. We then calculated the mean of the two reference sheet measurements to generate a white reference measurement (averaged reference sheet image), which was used in the further processing of the hyperspectral imaging of heather cuttings. This procedure was applied to the data of each measurement to correct for the spatial variation in illumination. As a next step, we subtracted the Dark Frame file, which is an image that the camera takes with the shutter closed to determine the Dark Current of the camera. The result was divided by the difference of the averaged reference sheet image and the averaged Dark Current of the reference sheet image to obtain reflectance. Figure 3-3 illustrates the process of transferring data from raw digital numbers (DNs) to spectral reflectance (see the R script in Script 3-S1).

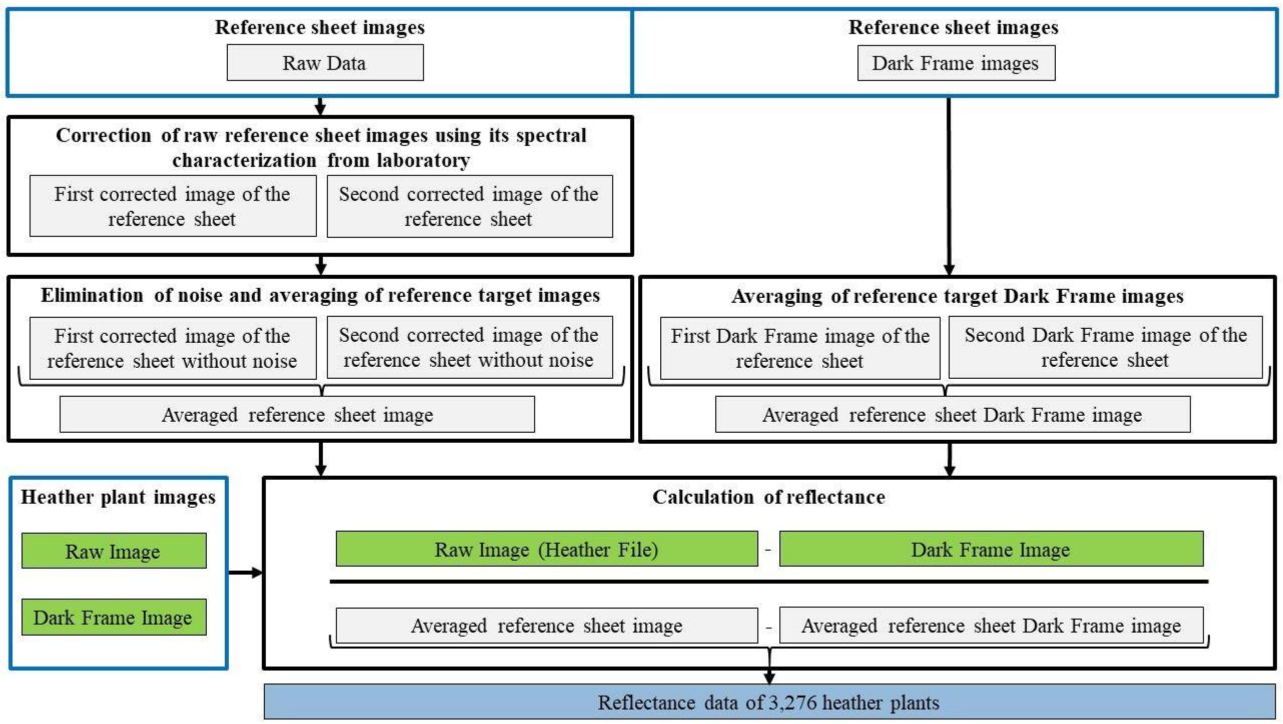

Figure 3-3. Illustration of the data processing procedure to compensate for spatial heterogeneity in illumination conditions using a reference sheet. For each measurement day, the raw images of the reference sheets taken by the HS sensor were used to correct for spatial variation in illumination conditions of the hyperspectral images of trays with heather cuttings. Reflectance data is used for further analyses to detect variation between plants. Data processing started with raw images of the reference sheets obtained by the HS sensor. Reference sheet images and heather images were then passed through different processing steps. The final outputs of the processing procedure were a set of spatially and spectrally corrected reflectance data

To illustrate spectral signatures of the final processed data files, we manually defined pixels of sample plants as the regions of interest (ROI) within the HS image using the image processing software ENVI 4.7 (Exelis VIS, Boulder, CO, USA). We selected three to six central pixels on the shoot tips of each plant. Then we used the 'Grow' function in ENVI to automatically include shoot tip pixels with similar reflectance. Pixel numbers were increased until a minimum of 100 pixels per ROI was marked, excluding background and border pixels (mixed pixels) from the evaluation (Fig. 3-4). Spectral reflectance of the ROI was averaged and used for data analysis.

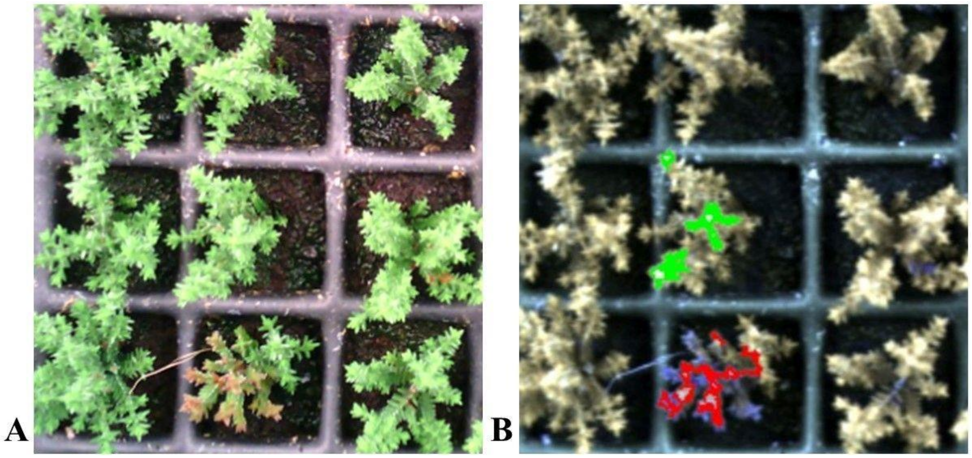

Figure 3-4. RGB image of heather plants (A) and their counterpart HS images (B). The selected ROI shows green pixels for the plant classified as healthy and red pixels for the plant classified as stressed on day 63 after planting. For illustration of HS images, we selected the following spectral bands to set the RGB color space: R = 539.75 nm, G = 525.10 nm, B = 616.34 nm

Identification of relevant wavelengths for classification

Partial Least Squares regression (PLSR) was applied to classify plants as healthy or stressed based on their average spectral signatures of the total ROI. We used hyperspectral images from 100 healthy and 100 stressed plants on day 42 after planting to train the algorithm. A sensitivity analysis revealed the relative importance of spectral reflectance at each wavelength for classification (Variable Importance in the Projection, VIP). A five-fold cross validation helped us to overcome potential inaccuracies related to training ML algorithms on a rather small training dataset (Hastie et al., 2009). We tested the trained algorithm on a second dataset containing 80 stressed plants and 80 randomly selected healthy neighboring plants that were measured 49 days after planting, resulting in a total of 160 observations for testing. The analysis was carried out using the 'caret' (Classification And Regression Training) (Kuhn, 2020) package for R and a comprehensive guide for code development (Pierobon, 2018). The PLSR code, the training dataset and the test dataset are accessible online (Ruett et al., 2020a).

Results

We screened the performance of 3,276 heather plants over 14 weeks from cutting to young plant stage. During this time, 187 plants showed shoot stress symptoms, 5 died, and 17 plants showed insufficient rooting, with only 5 of them also showing shoot stress symptoms. In total, 5.7% of the plants showed stress symptoms.

Hyperspectral reflectance data annotated with vitality scores

To compare the spectral reflectance of ornamental heather plants with different stress symptoms, we chose five plants from one of the sample trays that differed in vitality based on the expert assessment (Fig. 3-5).

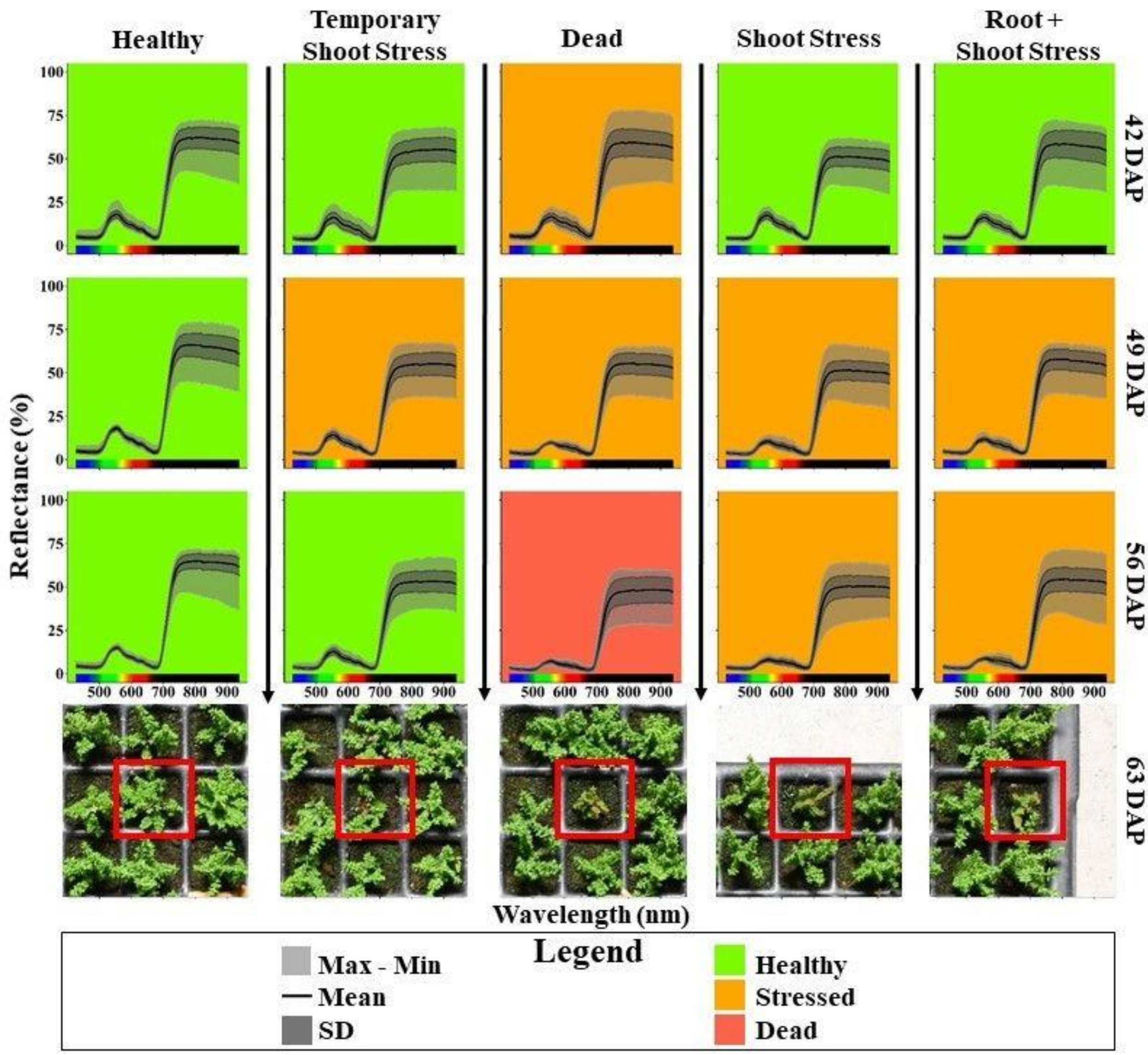

Figure 3-5. Reflectance at wavelengths between 450 nm and 900 nm of groups of heather plants assessed by experts, which we annotated with vitality scores as 'Healthy', 'Temporary Shoot Stress', 'Dead', 'Shoot Stress', and 'Root + Shoot Stress' over three points in time from day 42 after planting (42 DAP) to day 56 after planting (56 DAP). Vitality, as assessed by experts, is indicated by the background color of each plot (Healthy = Green, Stressed = Orange and Dead = Red). Plants with insufficient root development in the 'Root + Shoot Stress' group were identified by root assessment on the pricking (transplant) date and discarded. The graphs illustrate the mean (black lines), a confidence interval (mean ± 1 standard deviation; dark grey area) and the range between maximum (Max) and minimum (Min) (light grey area) of the spectral reflectance for each wavelength. Photographic images (bottom row) were taken on day 63 after planting. Red frames indicate the heather plants that were classified

All plants were initially classified as healthy on day 35 after planting, but four plants showed signs of shoot or root stress classified as 'Temporary Shoot Stress', 'Dead', 'Shoot Stress', and 'Root + Shoot Stress' (Fig. 3-5). 'Healthy' plants showed a typical spectrum with a green peak around 550 nm and high reflectance in the NIR region from 750 nm to 900 nm. 'Temporary Shoot Stress' was associated with a minor reduction of reflectance in the NIR region. The spectral reflectance of the 'Dead' plant did not show the typical green peak and featured a broader range of spectral reflectance values in the NIR region compared to 'Healthy' plants. 'Shoot Stress' and 'Root + Shoot Stress' produced a similar spectral curve over the same time period, with a lower green peak compared to 'Healthy' plants at the end of the experiment. 'Root + Shoot Stress' led to a slightly higher green peak compared to 'Shoot Stress'. Stress also affected plant development, with 'Healthy' plants being larger and without signs of the reddish leaf color that was associated with 'Dead' plants, based on photographs taken on day 63 after planting.

Classification and most important spectral regions

We applied PLSR to classify healthy and stressed heather plants. We identified the most important wavelengths contributing to classification using variable importance in the projection (VIP) (Fig. 3-6).

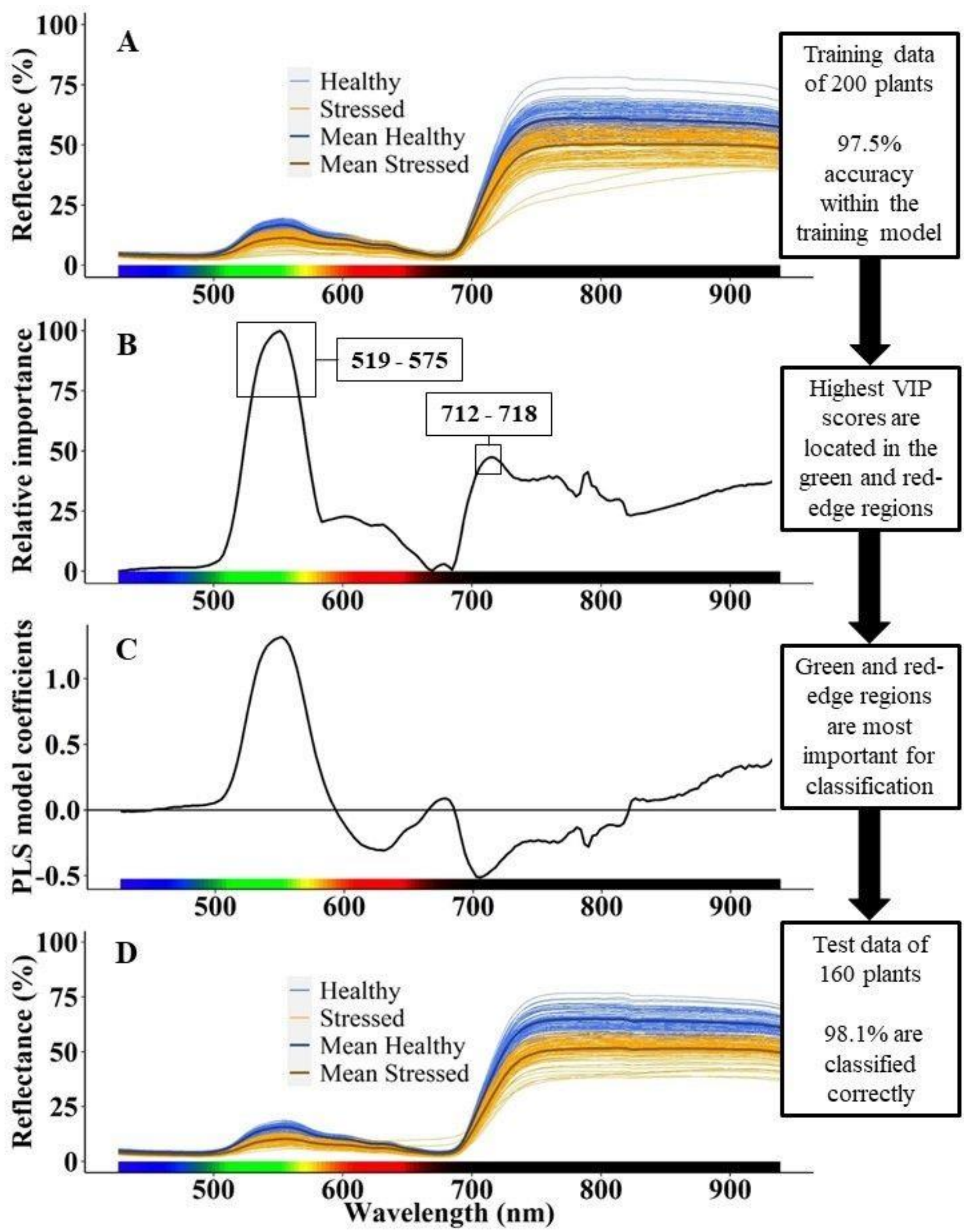

Figure 3-6. Hyperspectral dataset used for deriving the PLSR model to classify healthy (thin blue lines) and stressed (thin orange lines) heather plants in the spectral range from 450 nm to 900 nm. Bold dark blue and dark orange lines show the mean reflectance of healthy and stressed plants, respectively. A) Reflectance data of 100 healthy and 100 stressed plants from 42 days after planting were used to train the PLSR model. B) The variable importance in the projection (VIP score = black line) illustrates the relative importance of spectral reflectance at a given wavelength for the classification as healthy or stressed, scaled to 100. C) Model coefficients (black line) indicate correlation of reflectance at the respective wavelength with model outcome of healthy. D) Reflectance data of 80 healthy and 80 stressed plants from 49 days after planting was used to test the PLSR model

Normalized reflectance of training data reveals higher spectral reflectance of healthy plants in the green and NIR regions of the spectrum, while only minor differences in reflection occur in the blue and red to red-edge region (Fig. 3-6, A). The pattern of VIP scores is mostly in line with visual assessment of the spectra: the most important parts of the spectra for discriminating between healthy and stressed plants are located in the green region from 519 nm to 575 nm of the spectrum. VIP scores also show high importance in the red-edge region between 712 nm and 718 nm. Red light has a minor contribution to health classification while the contribution of blue light is negligible (Fig. 3-6, B). When applying the model to the training data, we achieved an accuracy of 97.5% in discriminating between healthy and stressed heathers. Model coefficients reveal that relatively high reflectance of green light from 519 nm to 575 nm and low reflection in the red-edge region from 712 nm to 718 nm are characteristic of healthy heather plants and most important for classification (Fig. 3-6, C). Validating the model on test data, we achieved even slightly higher accuracy of 98.1%, with only three out of 80 plants labeled as healthy by experts being incorrectly classified as stressed based on their reflectance, while all 80 stressed plants were correctly classified as stressed (Fig. 3-6, D).

Discussion

Automated screening of ornamental plants is of rising interest (Polder et al., 2014), as monitoring plant quality can support operational decisions (Parsons et al., 2009). Highly reliable and precise methods are needed to establish automated screening processes focusing on stress and disease detection (Mahlein et al., 2018). In heather production, plants are frequently assessed visually by experts to detect stress and diseases. However, manual classification and interpretation by humans is a complex task (Laskin and McDermid, 2016), with assessments being strongly dependent on experience (Giuffrida et al., 2018). More importantly, expert assessments are time-consuming and costly and thus limited in the number of plants that can be covered (Kuska et al., 2015). Optical sensors have been shown to allow estimating the nitrogen and chlorophyll content of the ornamental plants *Chrysanthemum* (Bracke et al., 2019) and *Justicia brandegeana* (Freidenreich et al., 2019) at the leaf and canopy level. We used a hyperspectral sensor to image plants in commercial heather production and tested its suitability to identify plants that were classified as stressed by human experts. Automated quality evaluation of ornamental plants using suitable sensors and data processing pipelines might have the potential to complement existing monitoring strategies.

Interpretation of hyperspectral reflectance data annotated with vitality scores

The quality of ornamental plants strongly depends on shoot vitality, root number, and root function (Druege, 2020). The spectral signatures of 'Dead', 'Shoot Stress' and 'Root + Shoot Stress' show a minor reduction in the green peak compared to 'Healthy' and 'Temporary Shoot Stress' that can be related to the slightly browner shoot color observed for stressed shoots by naked-eye observation compared to the bright green shoot color for healthy shoots (e.g. RGB images from day 63 after planting in Fig. 3-5). Such changes in leaf color and spectral reflectance of stressed plants can be related to a lower chlorophyll content, as observed for heather plants by Mac Arthur and Malthus (2012). Wang et al. (2020) also demonstrated that hyperspectral imaging can be used to assess the foliar chlorophyll content of control and formaldehyde-treated plants with reduced chlorophyll content in 15 ornamental plant species.

Classification of heather plants using PLSR

Lohr et al. (2016, 2017) used NIR techniques to develop a model assessing the quality of *Pelargonium* and *Chrysanthemum* plants. In our study, application of a PLSR model on a spectrum from 450 nm to 900 nm facilitated identification of the most important wavelengths for classifying healthy and stressed heathers (Fig. 3-6, C), achieving correct classification of 98.1% of test data (Fig. 3-6, D). We detected important wavelengths in the red-edge region (Fig. 3-6, C) with high VIP scores from 712 nm to 718 nm (Fig. 3-6, B). The observed low reflectance (= a high absorption) of radiation in the red-edge range is a well-known sign of high chlorophyll concentrations in plant tissues (Filella and Penuelas, 1994; Gitelson et al., 1996; Ju et al., 2010). Radiation with wavelengths greater than 718 nm did not carry as much information relevant for discrimination of healthy and stressed plants as radiation around 550 and 715 nm. Studies have shown that PLSR application on hyperspectral data sets is a suitable method for identifying wavelengths that are correlated with certain biological indicators (Luedeling et al., 2009). For example, PLSR has been used successfully to detect important wavelengths related to the canopy chlorophyll content in temperate forests in Germany (Hoeppner et al., 2020). The VIP score indicated the greatest potential for discriminating between healthy and stressed plants for spectral reflectance in the green spectral domain from 519 nm to 575 nm (Fig. 3-6, B), with model coefficients specifying the most important wavelengths in this domain (Fig. 3-6, C). Low reflectance of radiation in the green region at 550 nm, as observed for stressed heather plants (Fig. 3-6, A and D), is a typical sign of enhanced anthocyanin assimilation, a stress response in higher plants (Chalker-Scott, 1999; Merzlyak et al., 2008). Similar results were obtained by Cotrozzi and Couture (2020), who analyzed spectral measurements of stressed lettuce plants using PLSR and also identified the green spectral domain as closely related to chlorophyll content, confirming the importance of these spectral bands for stress detection. A similar trend was detected by Wilson et al. (2004), who identified reduced reflectance in the green spectral domain for stressed corn leaves that were exposed to heavy metals in comparison to healthy corn leaves. Although the overall accuracy of our classification was high (> 98%), we took a closer look at the three plants that were classified incorrectly. All three were classified as stressed based on their reflectance patterns, while experts labeled them as healthy, not only on the day of hyperspectral data acquisition, but throughout the entire production cycle. From a farmers' point of view, erroneous classification of a healthy plant as stressed is less dangerous than the reverse case, as stressed plants that remain in the stand may serve as entry point for pathogens, potentially threatening the entire plant population. We assume that machine learning workflows should be designed to classify plants with unclear signatures rather as stressed, to avoid missing mildly stressed plants. Such conservative approaches are in line with farmers' cultivation approaches and becomes even more evident when considering that farmers are often risk-averse (Iyer et al., 2020) and may prefer models that rather err on the side of caution than miss potential sources of infection. Our results indicate that multispectral cameras capturing the reflectance in the green and red-region of the spectrum would be just as suited to classify plant vitality. Multispectral cameras are preferred for applied approaches compared to hyperspectral cameras because of their lower price and lower requirements for data analysis (Grieve et al., 2015; Mahlein et al., 2018).

Alternative approaches to assess plant vitality in ornamental plant production

Classical approaches like vegetation indices do not consider the full spectrum, but usually focus on just a few pre-defined wavelengths (Wahabzada et al., 2016). Advanced classifiers use all spectral information and are able to deal with the high dimensionality of hyperspectral data to detect the most important wavelengths (Paulus and Mahlein, 2020). Advanced approaches like PLSR allowed classification of healthy and stressed heather plants with the advantage to identify the most important spectral regions for classification. Based on the analysis of all spectral information of heather plants, it appears that certain classifiers may classify stress symptoms more precisely than others. Non-linear classifiers such as Support Vector Machines (SVMs) have been successful in detecting abiotic stress in plants (Zhang et al., 2018), and they have shown better performance for water-, nitrogen-, and weed- stress detection in sugarbeet than other machine learning methods such as decision trees (Khanna et al., 2019). Such SVM approaches have shown promise in early detection of stress and diseases (Thomas et al., 2018), but they can be highly time-consuming in terms of data pre-processing (Piiroinen et al., 2017). Neural Networks (NNs) may overcome such limitations by directly using data without requiring much pre-processing (Singh et al., 2018). Golhani et al. (2018) describe NNs as the approach with the highest potential for precise plant diagnosis due to its speed and high accuracy. NNs could be more efficient compared to SVM approaches when applied to our heather data, if higher speed and classification accuracy are actually achieved. Like the PLSR we applied here, these tools have shown their potential to classify plants based on hyperspectral data by incorporating the totality of measured spectra.

In recent years, Machine Learning (ML) approaches have emerged as powerful tools to solve classification problems using hyperspectral data, but there are also challenges in ML that need to be considered. Many ML methods can be described as black box models, because computational steps that detect patterns in datasets are often not well understood by users of such methods (Lipton, 2018). Another challenge is the collinearity of adjacent spectral bands in hyperspectral data (Coburn et al., 2018). Plants' spectral bands carry similar information that can overlap (as shown in Fig. 3-6, A and D). The possibility that ML approaches may detect correlations in data that have no biological significance presents a major risk (Azodi et al., 2020). However, since the changes in reflectance patterns identified for heather plants by our approach are typical stress responses and physiologically well described and explained in the literature, we are confident that we did not find artificial correlations, but actual explainable changes that are caused by the plants' health status.

Inclusion of feature-based procedures that consider plant structure may hold promise for classifying plants according to their vitality. Object-based image analysis techniques consider shape and texture information within groups of pixels (Blaschke, 2010; Roscher et al., 2016). The substantial diversity in the appearance of plants, the highly branched shoot structure and the small leaf size of heather present challenges to hyperspectral sensing, but they may hold potential for feature-based classification procedures. Shoots of heather plants show considerable variation in size and color (images in Fig. 3-5). Low shoot biomass indicates weak growth, which can indicate low vitality. Compared to healthy shoots, stressed shoots are smaller and therefore represented by fewer pixels (images in Fig. 3-5). Combinations of spatial and spectral analyses have shown promise for plant phenotyping (Behmann et al., 2016). In this context, high spatial resolution in hyperspectral images can facilitate the analysis of shoot structures, allowing for a more detailed vitality assessment than hyperspectral data analysis alone (Behmann et al., 2016). If reduced vitality can be identified from shoot structure attributes of heather plants, object-based methods may increase the reliability of plant health assessments. The manual selection of pixels is a bottleneck that makes our method in its current state unattractive for farmers to apply. Identification of plant structure in theory allows to create a mask for hyperspectral data to automatically select pixels that are representative of a certain plant and thereby overcome that bottleneck. A combination of hyperspectral imaging with advanced evaluation methods might improve assessments of spectroscopic data (Mahlein et al., 2018). We anticipate that promising ML and feature-based methods may allow easy application of HS sensors and multispectral cameras for plant health status classification.

Outlook for the use of hyperspectral sensors in ornamental plant production

The hyperspectral imaging setup described in this study was designed for experiments at a horticultural production site. It was easy to use without intensive instructions, but required controlled illumination conditions. Hyperspectral images were repeatedly captured throughout the cultivation period to develop a hyperspectral vitality assessment classification. Such frequent measurements will not be needed for practical approaches. To establish automated plant classification by hyper- or multispectral sensors in farming routines, sensors should be integrated into farm machinery that face all plants regularly, such as pricking (transplanting) robots. Thereby, stressed plants unlikely to develop to marketable plants could be automatically discarded by robots (Polder et al., 2014). Such frequent monitoring could save resources and lower the risk of spreading fungal infections (Ruett et al., 2020b).

Before automated processes for stress detection with HS sensors can be fully applied in ornamental production practice, several challenges have to be investigated. Engineering challenges must be solved, such as how to conduct measurements under variable illumination conditions in the greenhouse. To facilitate fast data processing for simultaneous classification, the data analysis used in this study (Ruett et al., 2020a) must be further optimized and automated. From an economic perspective, the feasibility of applying sensors at production scales should be estimated by cost-benefit analyses under realistic application scenarios. In addition, biological variation between plant species, cultivars and growth stages requires to determine individual classification thresholds for the respective plant type and growth stage of interest.

Future research should thus focus on effective stress detection algorithms and low-cost sensors that are versatile enough to be applied to different plant species and perform under various environmental conditions, to facilitate the development of sensor-based technologies to the point of commercial applicability.

Conclusions

In commercial heather production, as in other intensive ornamental plant industries, plant quality and early detection of stress are critical determinants of economic success. We developed a testing procedure in which we integrated camera and sensor technologies, the setup of which was deployed in a horticultural production facility, to determine whether spectral reflectance measurements can support classification of heather plants with different health status. The hyperspectral imaging setup was specifically designed to resolve even subtle differences in reflection. Based on our experimental dataset we were able to classify healthy and stressed heather plants with an accuracy of 98.1% using PLSR. We identified reflectance in the green (519 nm – 575 nm) and red-edge (712 nm – 718 nm) regions as most important for classification. The setup and research design hold promise for experimental measurements on ornamental plants under controlled conditions, since they enable high-resolution measurements of small plant samples, clean data acquisition, and transparent data processing procedures. The resulting data set will be available for further studies on plant vitality. Future research should focus on the implementation of hyperspectral monitoring approaches in commercial plant production processes under greenhouse conditions.

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Supplementary Materials

Table 3-S1 and Script 3-S1 can be found in this thesis at Annex Supplementary material for Chapter 3.

Table 3-S1. List of materials needed to reproduce our hyperspectral setup. Dimensions can be adjusted to accommodate hyperspectral analyses of ornamental plants of different sizes. For each required item, we provide the name of the manufacturer and item number, as well as the total number of needed items.

Script 3-S1. R-script for the data processing procedure for our hyperspectral data of heather (*Calluna vulgaris*) plants. For citations of packages, please refer to our manuscript. The processing procedure is repeated for each tray on each measurement day. Therefore, we illustrate descriptions for data processing only for the first 12 measurements of tray one here. This example, as a template, reflects the calculation procedure for the entire dataset. We have used code descriptions to guide readers through our code.

Conflicts of interest

The authors declare that this research was conducted in the absence of any commercial or financial relationships that could be constructed as a potential conflict of interest.

Author contributions

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Chapter 4

Assessing expected utility and profitability to support decision-making for disease control strategies in ornamental heather production

Under review in Precision Agriculture (2022)

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Abstract

Many farmers hesitate to adopt new management strategies with actual or perceived risks and uncertainties. Especially in ornamental plant production, farmers often stick to current production strategies to avoid the risk of economically harmful plant losses, even though they may recognize the need to optimize farm management. This work focused on the economically important and little-researched production system of ornamental heather (*Calluna vulgaris*) to help farmers find appropriate measures to sustainably improve resource use, plant quality, and profitability despite existing risks. Probabilistic cost-benefit analysis was applied to simulate alternative disease monitoring strategies. The outcomes for more intensive visual monitoring, as well as sensor-based monitoring using hyperspectral imaging were simulated. Based on the results of the probabilistic cost-benefit analysis, the expected utility of the alternative strategies was assessed as a function of the farmer's level of risk aversion. The analysis of expected utility indicated that heather production is generally risky. Concerning the alternative strategies, more intensive visual monitoring provides the highest utility for farmers for almost all levels of risk aversion compared to all other strategies. Results of the probabilistic cost-benefit analysis indicated that more intensive visual monitoring increases net benefits in 68% of the simulated cases. The application of sensor-based monitoring leads to negative economic outcomes in 85% of the simulated cases. This research approach is widely applicable to predict the impacts of new management strategies in precision agriculture. The methodology can be used to provide farmers in other data-scarce production systems with concrete recommendations that account for uncertainties and risks.

Introduction

Ornamental plant production systems are of considerable economic importance in Europe. Germany features the largest market for ornamental plants, with sales of more than 8.9 billion euros at retail prices in 2019 (Zentralverband Gartenbau e.V., 2019). For producers of ornamental plants, control of plant quality is critical for economic success. Frequent prophylactic pesticide treatments are the first choice for maintaining plant quality, as such treatments currently represent the most reliable and most cost-effective strategy (Shtienberg, 2013).

Frequent fungicide treatments are standard practice in ornamental heather (*Calluna vulgaris*) cultivation, a production system that requires a high level of specialization and expertise on the part of the growers. In an effort to reduce their reliance on high rates of fungicide applications, heather farmers are currently searching for alternative ways to control plant quality while reducing fungicide use.

The outcomes of alternative farming practices can be predicted using decision support systems considering every variable that matters in complex agricultural production (Luedeling and Shepherd, 2016). In general, decision support systems aim to assist a decision-maker by providing information that is relevant for a given problem so that actionable solutions can be delineated (Burstein and Carlsson, 2008). Decision support systems can be based on different methods and use various modeling approaches. For instance, supervised learning models like support vector machines (SVM) have been able to provide decision support by enabling early detection of fungal disease symptoms on sugar beet leaves (Rumpf et al., 2010). Using an argumentation-based approach, Thomopoulos et al. (2015) developed a reverse engineering approach (by first setting the goal) to support decision-making in agricultural food chains regarding the impacts of the production and storing process on food quality. Winter chill models have been applied to predict how climate change scenarios might influence deciduous fruit production and to support farmers' adaptation decisions (Fernandez et al., 2020). Based on multiple survey data, Wang et al. (2012) forecasted yearly crop yields using a Bayesian hierarchical model as the basis of a decision support system. Bayesian networks have been used to support decision-making in agricultural development contexts, including application of expert knowledge elicitation (EKE) approaches to consider existing risks (Whitney et al., 2018; Yet et al., 2016). EKE-based decision support was also conducted by MacMillan and Marshall (2006), who applied the Delphi method to support wildlife conservation management.

Involving experts through collaborative modeling approaches is crucial for development of credible decision support systems, and it allows taking into account agricultural risks (Oliver et al., 2012). Probabilistic model simulations using collaborative workshops to generate input data based on expert estimates represent an established approach that has been applied in several studies to support stakeholders' risk management in production systems around the globe (Do et al., 2020; Rosenstock et al., 2014; Tamba et al., 2017; Wafula et al., 2018; Yigzaw et al., 2019). In horticultural production, similar approaches have been applied to predict the outcome of risk management strategies in sweet cherry production (Rojas et al., 2021). Apart from the mentioned decision support approaches, life cycle assessments combined with statistical risk assessment approaches also represent a digital tool that allows formulating recommendations for horticultural producers (Mouron et al., 2006). The literature confirms that digital risk management tools such as decision support systems are able to provide farmers with essential information to cope with risks. However, little literature is available on the evaluation of digital risk management tools in horticulture, although the potential of using such tools in combination with expert knowledge to provide decision support in horticulture has been recognized decades ago by Gary et al. (1998).

Alternative strategies to control plant quality while reducing fungicide use in heather production may incur risks of financial losses due to additional costs and unclear benefits. Heather farmers are exposed to a high risk of financial losses because plants are genetically similar or even identical, and the occurrence of fungal infections can be very dynamic, quickly leading to devastating plant losses (Ruett et al., 2020). Farmers may therefore hesitate to change their behavior, even if such a change holds a high chance of increasing their income. Distributions of likely outcomes produced by probabilistic analyses can indicate the likelihood of net benefits from adopting new strategies (Rojas et al., 2021), but they do not account for farmers' individual risk preferences. An analysis of expected utility can deliver decision recommendations for different levels of risk aversion on the part of a decision-maker by transforming probabilistic estimates of possible outcomes into an expected utility value using a utility function (Chavas, 2004; Hardaker et al., 2015). The concavity or convexity of the utility function indicates individual risk preference profiles, ranging from 'risk-taking', over 'risk-neutral', to 'risk-averse'. Analysis of expected utility can therefore deliver more detailed decision support that accounts for the decision-maker's risk preferences (Schaub et al., 2020). The expected utility of disease control strategies and the level of risk aversion of heather farmers have not yet been investigated in horticultural research. Incorporating risk perceptions and risk preferences into decision support systems is promising and might increase the utility of disease management for agricultural production systems (Gent et al., 2011).

Ornamental heather production systems are data- and research-poor working environments, where economic success mostly depends on individual experience. The overall aim of the research project INRUGA (see funding) is to support heather farmers by developing collaborative Decision Analysis tools to optimize production conditions and make systems more resilient. Additionally, the project aims to test the potential of sensor technologies to analyze the plant health status of heather plants.

From 2018 to 2019, a first decision model was developed together with heather farmers, fungicide experts, experimental trial managers, and horticultural scientists. The collaborative work aimed to incorporate all existing knowledge into a decision model to simulate the heather production process. The model allowed to explore the potential of reduced prophylactic fungicide applications and more intensive visual monitoring of plant health status in heather production (Ruett et al., 2020). Results indicated that just reducing prophylactic fungicide treatments is likely to lead to a lower Partial Farm Budget compared to standard cultivation practices. More intensive visual monitoring was likely to increase the Partial Farm Budget compared to standard cultivation practices. Expected Value of Perfect Information (EVPI) Analysis revealed that the respective costs and benefits represent the main uncertainties for implementation of more intensive visual monitoring (Ruett et al., 2020). This evaluation indicated the need for a cost-benefit analysis of more intensive visual monitoring to gain sufficient confidence in this strategy to recommend it to farmers.

Monitoring can not only be performed visually by humans but also through the use of sensors, which enable efficient phenotyping of plants and support the detection and investigation of disease patterns (Mahlein et al., 2019). Hyperspectral imaging with optical sensors is a proven tool to detect abiotic stress symptoms (Behmann et al., 2014) and to predict plant compounds such as water, nitrogen, and pigment contents in plants (Ge et al., 2016). Hyperspectral imaging can also detect biotic stress symptoms induced by fungal plant pathogens (Bohnenkamp et al., 2019). In ornamental plant production, sensor-based precision agriculture technologies have contributed to risk management by detecting fungal diseases using thermal sensors (Gomez, 2014) and digital cameras (Wijekoon et al., 2008). Virus diseases have been identified using multispectral cameras (Polder et al., 2014). Sensor-based approaches have also been applied to heathers, but mainly aiming to analyze flowering phenology (Neumann et al., 2020) and to assess plant compounds (Mac Arthur and Malthus, 2012) instead of focusing on managing risks in heather production. The heather farmers involved in the INRUGA project expressed interest in finding out how well hyperspectral sensors could monitor plant stress, since such tools might enable them to efficiently control plant quality. To assess the potential of hyperspectral sensor monitoring for farmers in ornamental heather production, hyperspectral imaging was applied in a heather production facility. Heather plants were classified according to their health status, based on their spectral signatures. Plants were successfully classified as 'healthy' or 'stressed' with an accuracy of 98.1%, using a Partial Least Squares regression (PLSR) model, which demonstrated the technical feasibility of hyperspectral sensor monitoring for heather production (Ruett et al., 2022). Since technical feasibility alone does not necessarily correlate with economic viability, Ruett et al. (2022) recommended a detailed cost-benefit analysis that considers the costs incurred in conducting hyperspectral measurements under realistic production conditions.

The present work aims to synthesize the results of model-based assessment of more intensive monitoring (Ruett et al., 2020) and the potential of hyperspectral imaging in heather production (Ruett et al., 2022) in the context of an actual farm-scale adoption decision. The study was conducted using the engineering research method (Koen, 1988), to determine the most feasible monitoring strategy in ornamental heather production by taking a systematic approach to address this challenge. The systematic approach allowed to frame, conceptualize, and develop all materials generated in this study. The work presented here consists of a joint application of decision support tools containing collaborative group work approaches for elicitation of expert estimates, probabilistic cost-benefit assessment and analysis of expected utility, considering individual risk preferences. Limitations of established decision support systems, which often do not consider farmers' individual risk preferences, should be overcome using this novel joint approach. Collaborative group work approaches are used to engage experts on the respective agricultural production system to frame a conceptual impact model illustrating the expected impacts of innovative practices. Costs, benefits and probabilities are defined as input variables. After experts have been subjected to a so-called 'calibration training', the state of knowledge on the values of input variables to the conceptual model are quantified by experts in the form of probability distributions, approximated by confidence intervals. The bounds of these confidence intervals should contain all plausible values (considering 90% confidence intervals) that can appear for an input variable, e.g. the investment costs for new hardware. The conceptual model with quantified variables is then transferred into a digital environment and coded as a decision model to perform probabilistic simulations. Simulation results are then used to conduct sensitivity analyses (Partial Least Squares regression with calculation of the 'Variable Importance in the Projection', as well as analysis of the 'Expected Value of Perfect Information'), and analysis of expected utility with a focus on farmers' individual risk preferences.

This study contributes to precision agriculture research by processing individual data from agricultural experts combined with elicited farm management experiences. The work also contributes to precision agriculture research by supporting farmers' management decisions through evaluation of disease control strategies in terms of resource use efficiency, plant quality and overall sustainability in the little-researched field of heather production.

Materials and Methods

Identification of principal stakeholders

The research approach taken in this study heavily relies on inputs from local stakeholders (Whitney et al., 2018). Stakeholder involvement and communication with subject-matter experts can greatly support the development of new promising interventions and generate comprehensive understanding of the key processes that drive the behavior of the target system (Young et al., 2013). Stakeholder involvement can also support practical implementation of research results (Mach et al., 2017).

Seven principal stakeholders (see acknowledgements) were involved in this study, who were well-versed in the implementation of new production strategies and capable of estimating implementation costs, as well as benefits for heather production. The expert team included four heather farmers, one economic consultant and two cultivation advisers with high technical understanding of heather growing strategies and broad knowledge of ornamental heather production and its risks. In the following sections, these principal stakeholders are referred to as 'experts'.

Development of the conceptual cost-benefit model

Conceptual models can be created through integrated modeling approaches that incorporate all available expert knowledge to provide a complete understanding of complex systems (Lanzanova et al., 2019). In developing such models, the choice of participatory methods needs to be aligned with the research objective and appropriate for the set of stakeholders involved (Villamor et al., 2014). Typically, collaborative group work approaches are used to create graphical impact pathways with all available experts in a series of face-to-face meetings and workshops (Whitney et al., 2018). Due to the COVID-19 pandemic, previous collaborative group work approaches needed to be extensively updated using tools like video conferences to comply with social-distancing rules. Video conferences were applied for the whole model development process between June and August of 2020.

Farmers' current monitoring regime was modeled as the baseline scenario. Experts agreed on two main scenarios to be modeled as new strategies and evaluated through cost-benefit assessment and analysis of expected utility. These scenarios included more intensive visual monitoring and sensor-based monitoring. In the following sections, these strategies are referred to as '*Baseline*', '*Improved*' and '*Sensor*', respectively.

1) Baseline: Current regime of visual monitoring with occasional observations of plant health. Severely symptomatic plants are discarded. A low number of laboratory samples are used to identify plants hosting fungal pathogens. Fungicide treatments are carried out without a particular focus on the infection risk.

2) Improved: Intensified visual monitoring with frequent observations. Even slightly symptomatic plants are discarded. A high number of laboratory samples is used to identify plants hosting fungal pathogens. Fungicide treatments are only carried out when farmers consider the infection risk to be high.

3) Sensor: Sensor-based plant health monitoring using hyperspectral imaging. Initial sensor investments and data processing are required. Similar to the *Improved* strategy, laboratory samples are used to identify plants infected with fungal pathogens, all symptomatic plants are discarded, and fungicide treatments are only carried out when farmers consider the infection risk high.

Together with experts, conceptual models were developed that contained all the costs and benefits that were considered important for each of the monitoring strategies, as well as the causal mechanisms through which costs and benefits arise. The overall merits of all strategies were quantified by calculating the Net Present Value (NPV). The NPV facilitates comparison of agricultural cultivation strategies. It accounts for the implications of initial investment needs, delayed profits and, in general, farmers' time preference by discounting future costs and benefits through use of an investor-specific discount rate (Do et al., 2020). Following Do et al. (2020), the following equation was applied to calculate the NPV in the present work:

$$NPV = -C_0 + \sum_{i=1}^{t} \frac{C_i}{(1+r)^i} \qquad (1)$$

C_0 represents the establishment cost and C_i the cash flow in year i. The discount rate is denoted by r and the time of simulation by t.

The collaboratively developed conceptual models expressed impact pathways for all candidate monitoring strategies. Experts continuously reviewed and updated the structure and content of the model sketches. As a last step, all resulting models were merged into one final graphical model and reviewed again by all experts, until everyone agreed with the final structure. This final conceptual model was then used as a framework to develop a mathematical model for cost-benefit simulation. The full mathematical model for cost-benefit simulation with detailed annotations, and all data generated in this study are available as supplementary materials in the following open-access repository: https://github.com/marruett/Supplementary_Ruett_Precision_Agriculture.

Generating expert estimates

Cost-benefit analyses based on single, precise numbers usually fail to adequately consider risks and uncertainties (Luedeling et al., 2015). In contrast to risks, uncertainties in decision-making represent situations in which possible outcomes of decisions and the probability of their occurrence are unknown (Tversky and Fox, 1995). These shortcomings can be overcome by expressing variables using distributions, often specified by lower and upper bounds of confidence intervals, that encompass all plausible values (Luedeling et al., 2015). Calculations with single, precise numbers can easily produce misleading results and give decision-makers a false sense of certainty, as uncertainties can greatly contribute to large fluctuations of particular investments. Decision Analysis approaches that work with distributions of all plausible values can overcome these limitations and facilitate decision support for stakeholders while incorporating the uncertainty of actual production conditions (Luedeling et al., 2015). This article reports on a cost-benefit analysis based on Decision Analysis approaches (Howard and Abbas, 2015). The approaches are rooted in the premise that it is usually impossible to obtain perfect information on all variables that are relevant for a given decision. It is however possible to estimate plausible ranges and distributions for such missing information based on available knowledge and expert judgement. Using such estimates can help overcome data availability constraints and allow for the assessment of the net benefits of management decisions, even in the absence of perfect data. The ability of experts to provide useful estimates that actually express the state of knowledge on particular variables can be enhanced through a process known as 'calibration training'. From range estimates for all model input variables, the net benefits of particular intervention options can then be computed through probabilistic simulations (Tamba et al., 2021).

Calibration training

To enhance the experts' ability to estimate their uncertainty and to make them aware of cognitive biases, the whole expert team was subjected to calibration training. Depending on expertise and level of self-awareness, a person may over- or underestimate her ability to estimate variables. For the calibration training, sets of estimation questions were used, asking experts to specify their 90% confidence intervals for the answers in the form of a lower and an upper bound. After each round of estimation exercises, the participants compared their estimates with the correct solutions, indicated how they arrived at their intervals and reflected on how errors may have occurred. Through this reflection process, experts were confronted with their cognitive biases and potential biases in risk perception, motivating them to question the rigor of their quantitative assessment. We showed experts how cognitive biases affect people's judgment and explained the 'Dunning-Kruger effect' (Kruger and Dunning, 1999) and 'anchoring effects' (Tversky and Kahneman, 1974) to reduce estimation biases. Experts were taught multiple techniques enabling them to provide accurate estimates of their own uncertainty through reasonable assumptions by using 'Fermi questions' (Tetlock and Gardner, 2015), imagining a project 'PreMortem' (Klein, 2008), and applying the 'equivalent bet' method (Hubbard, 2014).

After calibrating all experts, 90% confidence intervals were elicited from them as estimates for all the input variables of the model. After each variable estimation, experts again had to explain how they had arrived at their estimated intervals. All intervals were first estimated in individual meetings and then reviewed by all participants in plenary sessions to adjust intervals if necessary. The continuous updating allowed the estimates to be optimized to reflect the current state of knowledge (Table 4-1).

Table 4-1. Input variables of the model estimated by calibrated experts. Variable names, units, distribution types (posnorm = positive normal distribution, const = constant, tnorm = truncated normal distribution), lower bounds, upper bounds and short descriptions of the variables are provided

Variable	Unit	Distribution	Lower Bound	Upper Bound	Description
discount_rate	digit	posnorm	1	5	discount rate
var_CV	%	tnorm	5	15	desired coefficient of variation
n_years	years	const	10	10	years of production
production_area	ha	const	8	8	total area of the nursery field
chance_high_risk	%	tnorm	40	60	chance of a year presenting high-risk conditions
initial_investment_B	€	posnorm	100	200	initial investment costs to enable Baseline
initial_investment_I	€	posnorm	200	500	initial investment costs to enable Improved
initial_investment_S	€	posnorm	18,000	100,000	initial investment costs to enable Sensor
additional_investment_B	€	posnorm	50	100	additional costs to enable Baseline
additional_investment_I	€	posnorm	50	100	additional costs to enable Improved
additional_investment_S	€	posnorm	100	500	additional costs to enable Sensor
labor_costs_B	€	posnorm	100	1,500	monetary value reflecting the time spent by a person involved in maintaining Baseline

Variable	Unit	Distribution	Lower Bound	Upper Bound	Description
labor_costs_I	€	posnorm	500	3,500	monetary value reflecting the time spent by a person involved in maintaining Improved
labor_costs_S	€	posnorm	500	5,000	monetary value reflecting the time spent by a person involved in maintaining Sensor
post_processing_costs_B	€	const	0	0	costs of data post processing for Baseline
post_processing_costs_I	€	posnorm	0	0	costs of data post processing for Improved
post_processing_costs_S	€	posnorm	100	500	costs of data post processing for Sensor
sample_number_B	digit	posnorm	2	3	number of samples for Baseline
sample_number_I	digit	posnorm	2	15	number of samples for Improved
sample_number_S	digit	posnorm	2	6	number of samples for Sensor
lab_costs_per_sample	€	posnorm	15	70	laboratory costs per sample
plant_value_of_discarded_plant	€	posnorm	0.25	0.6	value of discarded plant
plant_value_of_A1_quality	€	posnorm	0.6	0.9	value of marketable plant with high quality

Variable	Unit	Distribution	Lower Bound	Upper Bound	Description
number_of_saved_high_quality_plants_B	digit	posnorm	500	6,000	number of high quality plants saved by Baseline
number_of_saved_high_quality_plants_I	digit	posnorm	2,000	18,000	number of high quality plants saved by Improved
number_of_saved_high_quality_plants_S	digit	posnorm	500	10,000	number of high quality plants saved by Sensor
adjustment_sample_size_B	%	tnorm	10	50	adjustment in sample size for Baseline
adjustment_sample_size_I	%	tnorm	10	30	adjustment in sample size for Improved
adjustment_sample_size_S	%	tnorm	10	30	adjustment in sample size for Sensor
resource_savings_B	€	posnorm	100	500	resource savings for Baseline
resource_savings_I	€	posnorm	500	1,000	resource savings for Improved
resource_savings_S	€	posnorm	500	1,000	resource savings for Sensor

Probabilistic simulation

The final cost-benefit model was coded in the R programming language (R Development Core Team, 2021) as a probabilistic Monte Carlo simulation. The simulation was run 10,000 times, with each model run initialized with random draws for all variables based on the distributions specified by the experts, to compute distributions of plausible NPV outcomes for all management strategies.

Partial Least Squares (PLS) regression was applied to evaluate the sensitivity of model outputs to variation in input variables (Luedeling and Gassner, 2012), using the 'Variable Importance in the Projection' (VIP) metric to estimate the influence of uncertainty about input values (Farrés et al., 2015). Regression coefficients of the

PLS model were interpreted to characterize the correlation of input variables with the NPV. Following Galindo-Prieto et al. (2014), the following PLS model was applied to calculate VIP scores:

$$VIP_{PLS} = \sqrt{K \times (\frac{[\sum_{a=1}^{A}(W_a^2 \times SSY_{comp,a})]}{SSY_{cum}})} \quad (2)$$

The VIP describes the importance of variables in a PLS model using components and therefore represents the weighted combination of overall components of the PLS weights W_a^2. $SSY_{comp,a}$ represents the sum of squares of the dependent variable Y explained by component a. A represents the total number of components and K the total number of variables (Galindo-Prieto et al., 2014).

Value of Information Analysis was used to detect critical uncertainties that limit the ability of the Monte Carlo simulation to produce clear management recommendations. The 'Expected Value of Perfect Information' (EVPI) metric estimates the monetary value of perfect information for each variable based on the potential of this information to prevent 'wrong' decisions, i.e. the selection of a decision option that proves sub-optimal after implementation. The EVPI can be interpreted as the amount of money that a farmer should be willing to pay in order to attain perfect information regarding the respective input variable (Hubbard, 2014). The following equation was used to calculate the EVPI:

$$EVPI = EV|PI - EMV \quad (3)$$

$EVPI$ is calculated as the difference between the expected value of the outcome variable EV given accurate knowledge on the value the tested input variable will take (perfect information – PI) and the expected maximum value EMV of the outcome variable given only knowledge about the probability distribution of the input variable (imperfect knowledge). All analyses were implemented in the R programming language using the decisionSupport package (Luedeling et al., 2021).

Calculation of expected utility

Based on the probabilistic simulation of possible NPV outcomes, farmers can decide to change their monitoring strategies or keep the production practices they currently use. This study assumes that this decision-making process is determined by the utility that farmers would gain from the different monitoring strategies and that farmers select the strategy that provides the highest expected utility. The expected utility can be derived from the distribution of possible NPVs using a utility function. This utility function represents farmers' individual risk preferences (from risk-taking to risk-averse) and translates each simulated outcome of the Decision Analysis into a utility value. The expected utility framework was used to simulate certainty equivalents for different levels of risk aversion and different monitoring practices. The decision rule is to identify the strategy that provides the highest certainty equivalent. The certainty equivalent is the amount of money (fixed income) farmers would need to be offered in order to switch from the risky investment to a fixed income. The certainty equivalent thus reflects an individual's taste for risk, i.e. her risk preference. Depending on the risk preferences of farmers and the riskiness of the investment, the certainty equivalent is smaller, equal or greater than the expected value of the risky investment (Chavas, 2004). Risk-averse farmers have a positive willingness to pay (risk premium) to get rid of the risk included in the investment option. Thus, their certainty equivalent is lower than the expected value of the risky investment. Risk-neutral decision-makers do not consider risk in their decision-making and thus for them the certainty equivalent equals the expected value of the risky prospect. Risk-taking farmers have a negative willingness to pay, i.e. they would need an additional external payment to switch away from their risky investment. They thus have a negative risk premium and a certainty equivalent that is greater than the expected value of the investment (Hardaker et al., 2015).

This framework allowed assessing the different monitoring strategies and their corresponding NPV distributions through the lens of farmers along a risk preference gradient. Here, the procedure proposed by Antle (1983), Chavas (2004), and Finger (2013) was used to calculate the certainty equivalent for each of the NPV distributions.

$$CE_k = E(NPV_k) - RP_k \tag{4}$$

In equation (4), CE_k denotes the certainty equivalent of monitoring strategy k. $E(NPV_k)$ is the expected value of the probabilistic NPV distribution of monitoring strategy k. RP_k is the corresponding risk premium, i.e. the willingness to pay to remove all the risk from the stochastic $\widetilde{NPV}_k$ (the tilde above the NPV symbol indicates the stochastic nature of this parameter). RP_k can then be approximated (Arrow-Pratt approximation) based on the variance $\sigma^2_{NPV,k}$ of the $\widetilde{NPV}_k$ distribution, which holds only for normally distributed NPVs (Chavas, 2004):

$$RP_k \approx \frac{1}{2} \cdot r_a \cdot \sigma^2_{NPV,k} \tag{5}$$

r_a constitutes farmers' risk aversion (constant absolute risk aversion), i.e. the aversion against variance in the stochastic $\widetilde{NPV}_k$. r_a is based on a farmer's individual utility function U and can be calculated from the first and second derivative of the utility function as $r_a = -U''/U'$. For U an exponential utility function of the form $U(NPV_k) = 1 - e^{-r_a \cdot NPV_k}$ was chosen, which is a common representation of farmers' utility (Hardaker et al., 2015). Negative values of r_a indicate risk-taking preferences, while positive values imply a risk-averse farmer. The certainty equivalent was determined for different risk preferences ranging from r_a =-0.1 to r_a=0.1.

To put a particular emphasis on downside risks and allow for non-normally distributed NPVs, equation (5) was adjusted and the variance of NPV $\sigma^2_{NPV,k}$ replaced by twice the semi-variance SV_k, which is the variance in below-average NPV realizations, as suggested by Conradt et al. (2015) for a sensitivity analysis. This leads to:

$$RP_{down,k} \approx r_a \cdot SV_k \tag{6}$$

Approximating the risk premium based on the moments of the NPV distribution, i.e. the semivariance, allowed to place a particular weight on downside risks in a comparison of the different monitoring strategies rather than deriving the utility values directly from the utility function. Since this study is interested in the certainty equivalent of the different monitoring strategies along different levels of decision-maker risk aversion, the 'stochastic efficiency with respect to a function' (SERF) approach proposed by Hardaker et al. (2004) was adopted. This allows for plotting the certainty equivalents obtained from the different monitoring strategies as a function of risk aversion. For a given level of risk aversion one can thus easily identify the one strategy that provides the highest certainty equivalent, i.e. the optimal strategy from the farmer's perspective.

The analysis of expected utility thus allowed to translate probabilistic simulation results into certainty equivalents based on different levels of risk preference. The SERF approach then allowed making clear decision recommendations for the most beneficial monitoring strategy.

Expected utility is a normative theory for decision making under risk given certain risk preferences. To avoid biased inference through subjective probability perceptions, the calibration training described above was applied to raise the objectivity of estimates. Other theories such as cumulative prospect theory (Tversky and Kahneman, 1992), rank dependent utility (Quiggin, 1991), and salience theory (Bordalo et al., 2012) might be better able to predict actual behavior, which is however outside the scope of this analysis. Risk preferences in expected utility theory are not considered irrational and methods exist to elicit preferences (Holt and Laury, 2002).

Results

Conceptual cost-benefit model

The conceptual model consisted of expert-identified costs and benefits that were expected to affect the Net Present Value (NPV) of the different monitoring strategies. Figure 4-1 illustrates the conceptual cost-benefit model for the monitoring strategies *Baseline*, *Improved*, and *Sensor*. The different monitoring strategies are shown by boxes with black outlines. The model output is quantified by the NPV (purple outline). Benefits of the monitoring strategies are framed in green, costs in red. These colors are also used for boxes within the cost and benefit categories, which stand for the various input variables. Arrows illustrate how the experts defined the impact of new monitoring strategies on associated costs and benefits, and thus on the NPV, in a commercial heather production system.

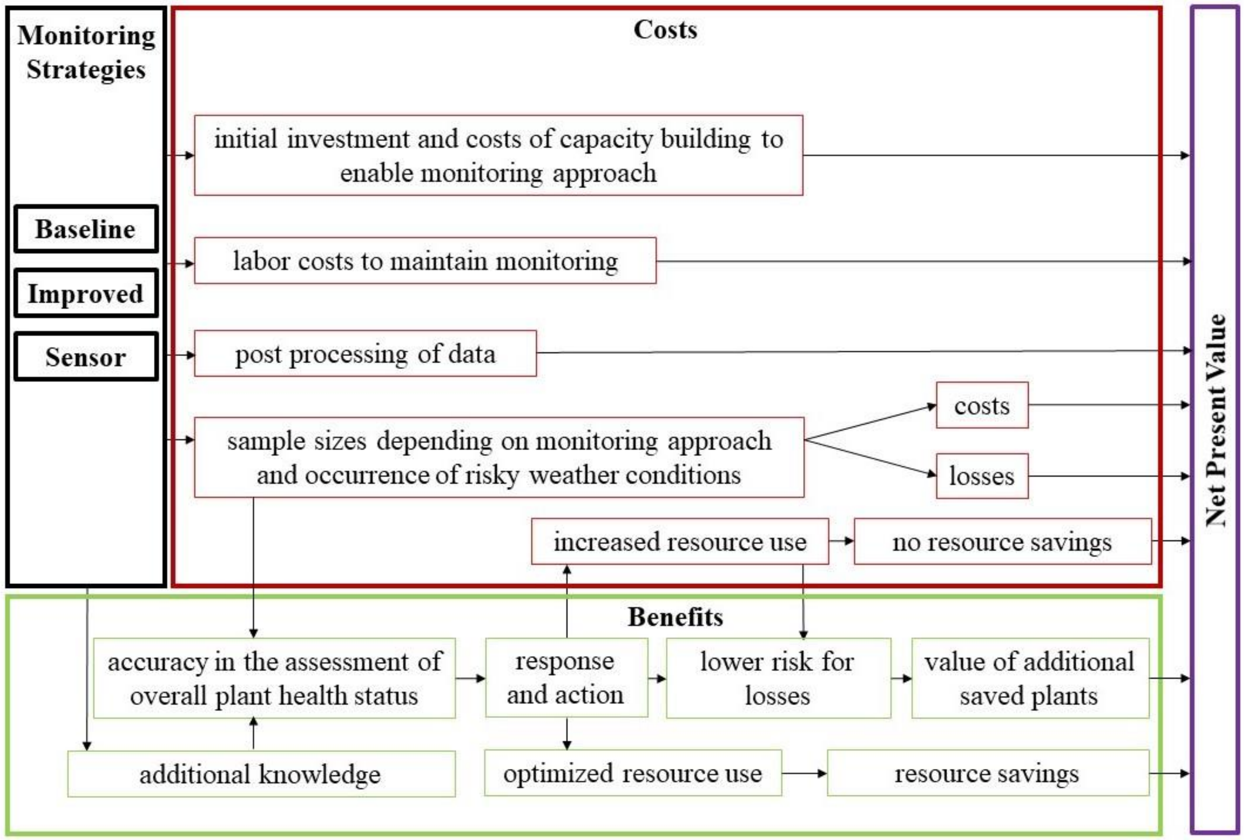

Figure 4-1. Conceptual cost-benefit model for monitoring strategies in commercial heather production. The different monitoring strategies are shown in black. The model output is quantified by the Net Present Value (purple). Benefits of the monitoring strategies are shown in green, costs in red

Code description

The conceptual model was used as a blueprint to program the mathematical model. Monitoring strategies were simulated over a ten-year time period. Initial investments during the first year, which were deemed necessary for establishing a new monitoring approach (e.g. sensors, lamps, cameras, posters for the assignment of symptoms etc.), were taken into account. Maintenance costs required for all monitoring schemes were considered over the entire simulation period. All further costs and all benefits were calculated per unit area (based on 1 ha) and then multiplied by the estimated size of an average commercial heather production system in Germany (8 ha). Labor costs and post-processing costs for recording hyperspectral data were defined for each year of the simulation. Interannual variation was introduced for all costs and benefits to make the simulations more realistic. The sample number for laboratory analyses of fungal pathogens was defined separately for normal years and for high-risk years featuring a high frequency of high-humidity weather conditions that favor fungal infections. To date, no clear trend has emerged for the occurrence of high-risk years, which have so far occurred in roughly half of all years. This uncertainty was accounted for by estimating a 90% confidence interval for the chance of high-risk years between 40% and 60%. In normal-risk years, samples are taken less frequently because infection risks are expected to be lower. In high-risk years, more samples are taken and analyzed in laboratories to identify infected plants. This strategy can convey information about the spatial distribution of symptomatic plants within the production system. The costs of sampling and the value of discarded plants are added to the costs of each monitoring strategy.

The benefits of monitoring, which allows targeted disease prevention measures, were calculated within the production system. In normal-risk years, the additional knowledge about plant health status leads to resource savings, which are achieved when disease pressure is low and plant vitality is high. In high-risk years, monitoring approaches are expected to reduce plant losses and quality deficiencies by facilitating early removal of symptomatic plants and targeted fungicide applications. Major resource savings are not achieved in high-risk years, but knowledge of the current plant conditions leads to increased reliability and predictability of production, which facilitates marketing and allows taking more high-quality plants to the point of sale.

Resource savings and a higher number of marketable, high-quality plants thus represent the potential benefits from improved monitoring strategies. The costs incurred were subtracted from the benefits in each year over the modeled time period and discounted to arrive at the NPV for each monitoring strategy. In the supplementary materials, we provide the full code with all calculations of the cost-benefit model as a R script.

Projected outcomes of monitoring strategies

The projected outcomes of monitoring strategies showed different shapes of predicted NPVs for *Baseline*, *Improved*, and *Sensor* based on an 8 ha heather production system (Fig. 4-2).

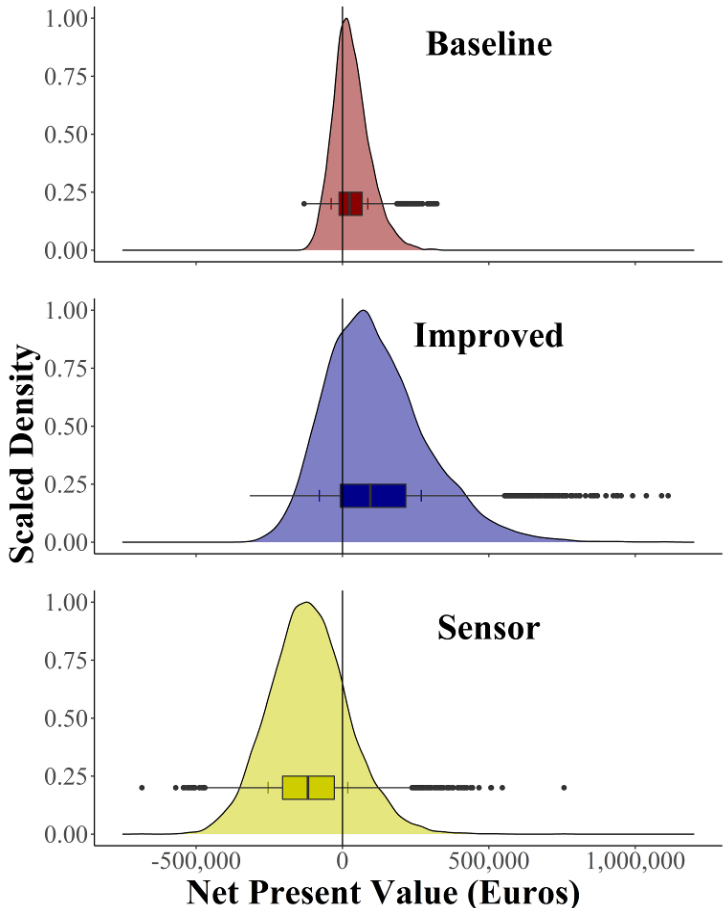

Figure 4-2. Probability density distributions (scaled density among 10,000 runs of a Monte Carlo simulation) of the Net Present Value (Euros) for three heather monitoring strategies. Baseline: Current visual monitoring regime. Improved: More intensive visual monitoring. Sensor: Sensor-based monitoring. The short vertical lines on the whiskers of the box plots indicate the standard deviation of the NPV for each strategy

The modeled NPV for *Baseline* ranged from -131,003 € to 322,594 €, with a probability of 67% of obtaining positive outcomes. For *Improved*, the NPV ranged from -316,483 € to 1,112,458 €, with a chance of 73% of obtaining positive outcomes. The NPV of *Sensor* ranged from -685,070 € to 756,778 €. The *Sensor* strategy was the only option with predominantly negative results, with 81% of the NPV distribution indicating a net loss.

Analysis of expected utility

The results of the analysis of expected utility were illustrated by plotting certainty equivalent values as functions of risk aversion for the different monitoring strategies (Fig. 4-3).

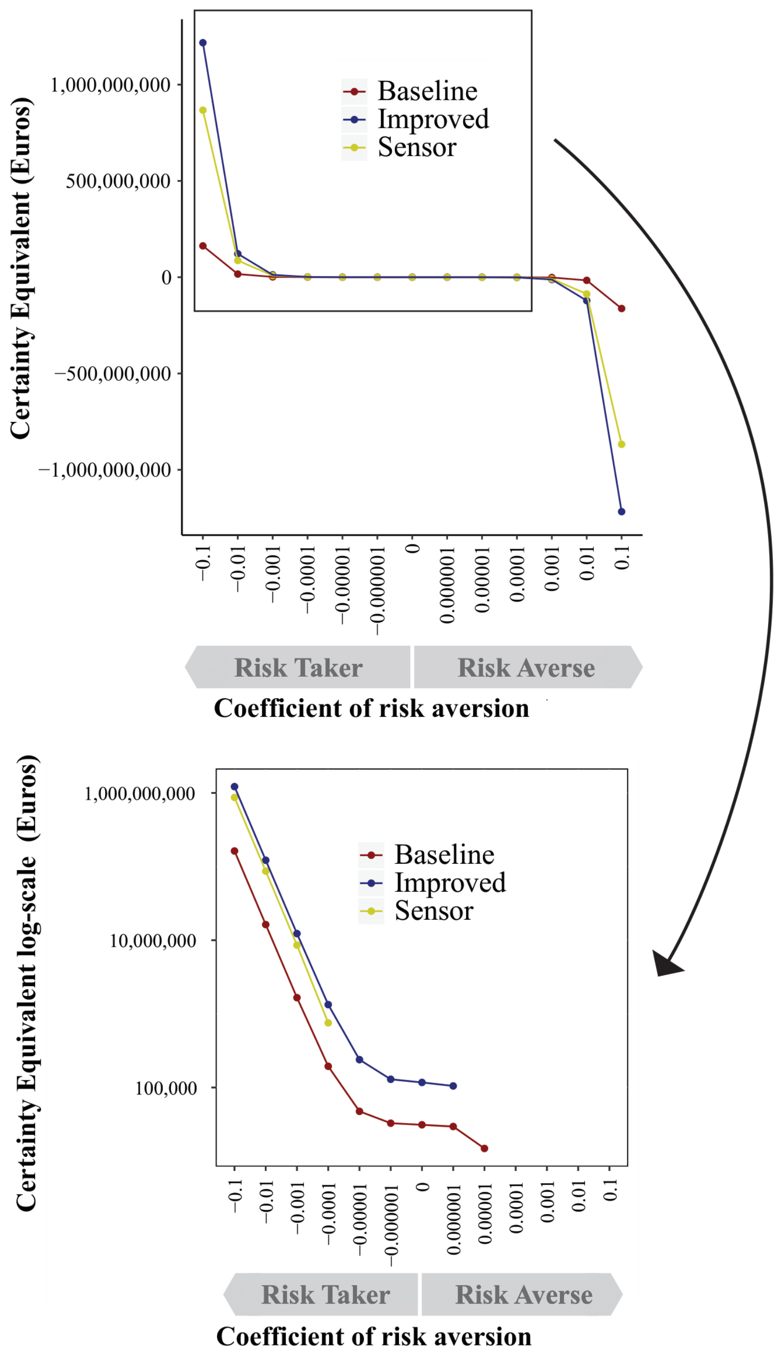

Figure 4-3. Stochastic efficiency with respect to a function (SERF) for monitoring strategies *Baseline*, *Improved*, and *Sensor*. In the upper figure the y-axis is shown on a normal scale, while the lower figure uses a log-scale to zoom into the positive parts of the SERF functions. In the latter case negative values are dropped from the illustration, because negative certainty equivalent values imply that decision-makers would not adopt an activity at all

This illustration translates the probability distributions (shown in Fig. 4-2) into certainty equivalents for different risk preferences from risk-taking (coefficient of risk aversion < 0) over risk-neutral (coefficient of risk aversion = 0) to risk-averse (coefficient of risk aversion > 0). For a coefficient of risk aversion of 0, the certainty equivalents of the monitoring strategies are equal to the expected value of the NPV. The monitoring strategy that provides the highest certainty equivalent is the recommended strategy for a given level of risk preference. Results in the upper part of Figure 4-3 show that for most of the risk-aversion preferences tested, all monitoring strategies result in negative certainty equivalents. These values imply that decision-makers would not adopt the activity at all. For risk-averse decision-makers, *Baseline* delivers low positive certainty equivalents in the risk-averse domain (for coefficients of risk aversion between 10^{-6} and 10^{-5}). This suggests that heather growers in general tend to have rather risk-taking preferences. For risk-averse decision-makers, *Improved* shows an even lower positive certainty equivalent in the risk-averse domain (10^{-6}). For application of *Sensor*, positive certainty equivalents can be observed only in the risk-taking domain (from -10^{-4} downwards). This implies that from an expected utility point of view, heather production in general and all monitoring strategies considered here are rather preferred by risk-taking decision-makers. They potentially deliver high upside outcomes, but they also involve a considerable risk of failure.

Comparing the three monitoring strategies, decision-makers with risk preferences ranging between -10^{-1} and 10^{-6} would prefer *Improved* over *Baseline* and *Sensor*. This implies that increased visual inspection of plants to reduce fungicide spraying is beneficial for a wide range of risk preferences and that farmers with such preferences would adopt improved monitoring. Only decision-makers who are strongly risk-averse (~ 10^{-5}), would prefer *Baseline* over the other monitoring strategies. The sensor technology cannot outperform the other monitoring strategies for any of the risk preferences tested here.

Projected outcomes of monitoring decisions

The stated monitoring strategies were compared with the baseline monitoring practice to determine the likelihood that adopting alternative monitoring strategies increases the net benefit for farmers. The outcome of *Improved* and *Sensor* were subtracted from *Baseline*, keeping similar risk factors (e.g. the distribution of high-risk and normal-risk years) to achieve a fair comparison of monitoring strategies. This allowed to formulate the following decisions:

1) DoMoreVisual (*Improved – Baseline*): The decision to switch from the current visual monitoring regime to intensified visual monitoring.

2) UseSensor (*Sensor – Baseline*): The decision to switch from the current visual monitoring regime to sensor-based monitoring.

The projected outcomes (Fig. 4-4) of monitoring decisions indicated a high likelihood of 68% of achieving a positive NPV, with a mean NPV of 85,965 € for *DoMoreVisual*. The decision *UseSensor* showed an 85% likelihood of a negative NPV, with a mean projected NPV of -144,875 €.

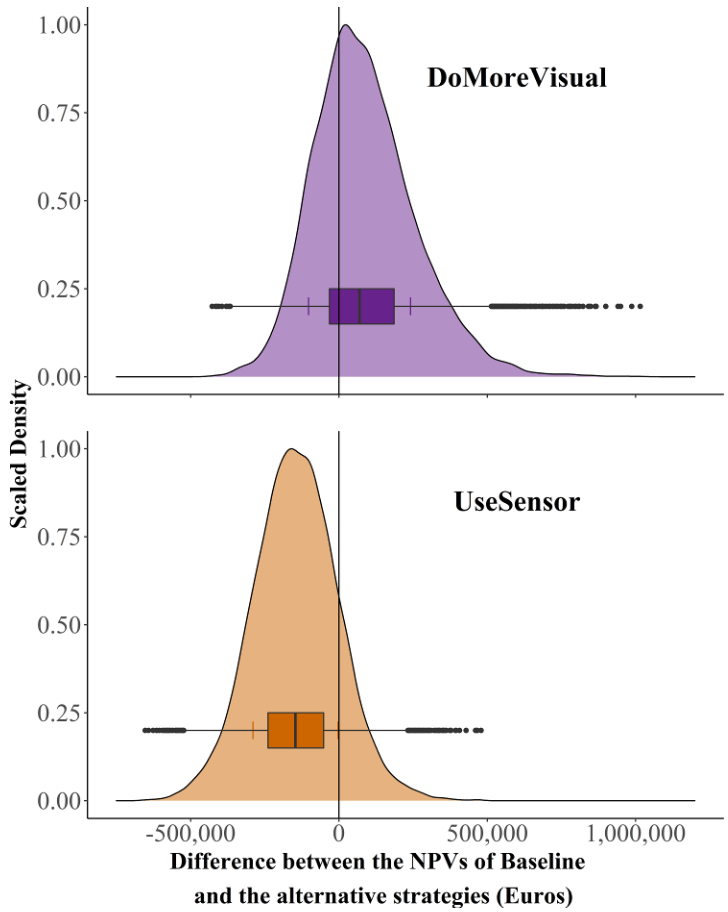

Figure 4-4. Probability density distributions (scaled density among 10,000 runs of a Monte Carlo simulation) of Net Present Values (Euros) for two heather monitoring decisions. *DoMoreVisual*: More intensive visual monitoring compared to the current monitoring regime. *UseSensor*: Sensor-based monitoring compared to the current monitoring regime. The short vertical lines on the whiskers of the box plots indicate the standard deviation of the NPV for each decision

Important variables and uncertainties for monitoring decisions

The results of the 'Variable Importance in the Projection' (VIP) and 'Expected Value of Perfect Information' (EVPI) metrics show the most important variables and the greatest uncertainties for the *DoMoreVisual* and *UseSensor* decisions (Fig. 4-5).

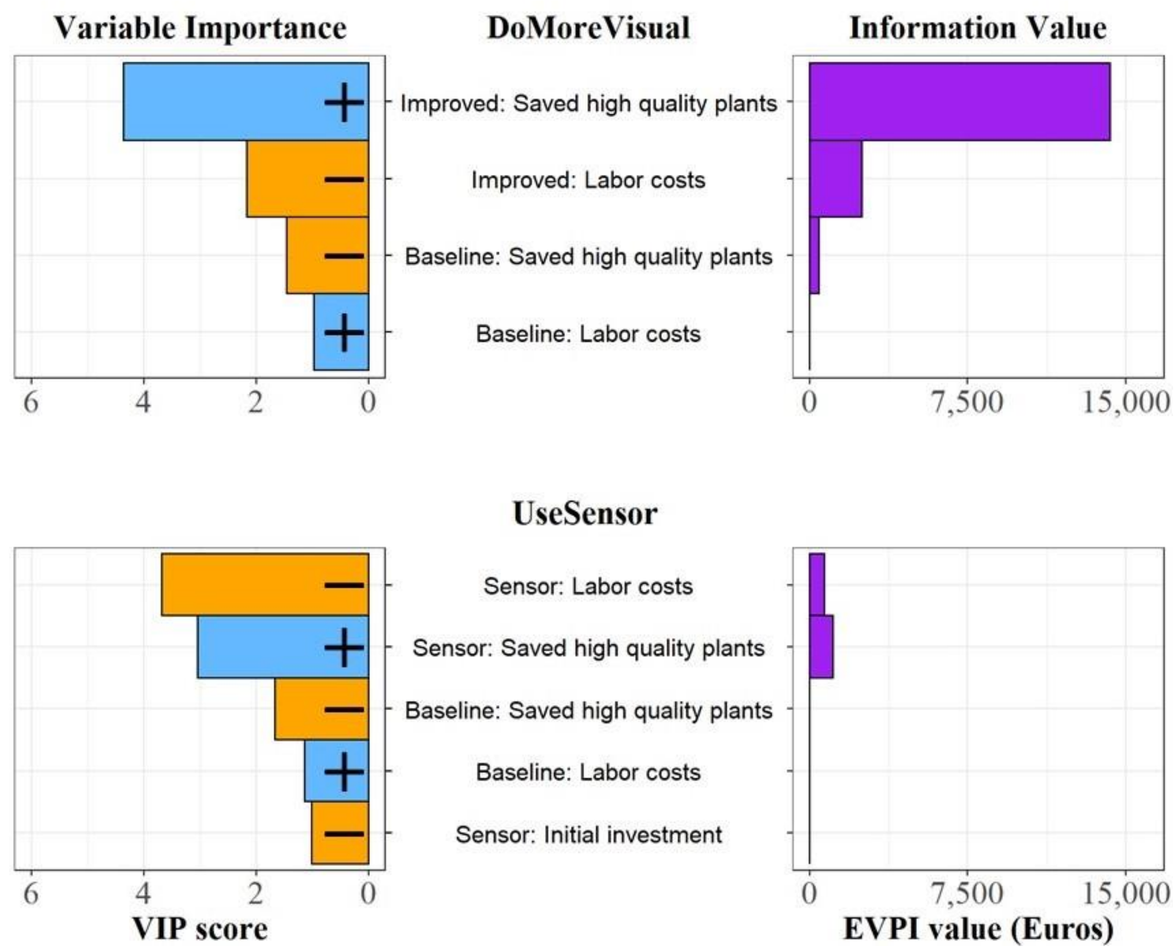

Figure 4-5. Variable Importance in the Projection (VIP scores) and Information Value (EVPI values) for the *DoMoreVisual* and *UseSensor* decisions. For the Variable Importance, only variables with VIP scores >1 are shown. Variables that have a positive impact on the projected NPVs are represented by blue bars and a positive sign '+', while those with a negative impact are represented by orange bars and a negative sign '-'

The highest-value variable in the *DoMoreVisual* decision was the number of high-quality plants saved due to *Improved* monitoring (EVPI = 14,274 €). Decision-makers would thus benefit from additional information on the number of plants that have increased quality because they use *Improved* monitoring rather than the *Baseline* strategy. This variable was also the main driver of the NPV for the *DoMoreVisual* decision, as indicated by a high VIP score.

For the *UseSensor* decision, high quality plants saved due to the sensor-based monitoring (EVPI = 1,096 €) and labor costs due to the applied sensor technology (EVPI = 695 €) represent the main uncertainties. The NPV for this decision was most sensitive to the labor costs of sensor-based monitoring (VIP = 3.68), which was negatively correlated with the NPV. The number of high-quality plants saved as a result of adopting the technology showed the second highest VIP score (VIP = 3.03).

Discussion

The novel approach applied to assess the expected utility and profitability for the most promising monitoring strategies allowed supporting decision making under uncertainty in the complex system of ornamental heather production. The outcome distributions of the strategies *Improved* and *Sensor* are wider compared to *Baseline*, highlighting the uncertainty when it comes to quantifying values for strategies that have not yet been widely applied (Fig. 4-2). Probability distributions of *DoMoreVisual* and *UseSensor* show that these decisions can lead to a wide range of possible outcomes with either negative or positive NPVs (Fig. 4-4). Given such wide outcome distributions, analyses of individual risk preferences, EVPI values and VIP scores are required for a more detailed assessment of the relative merits of the monitoring strategies. Risk-taking farmers are expected to be willing to apply more intensive visual monitoring to optimize their production system while sensor-based monitoring does not appear to be recommendable.

Risk preferences of heather farmers

Heather production is an inherently risky business. The analysis of expected utility reveals that regardless of the selected monitoring strategy, heather production is mostly attractive to risk-taking decision-makers. The outcome distribution indicated that only decision-makers in the risk-averse domain (i.e. for risk aversion coefficients between 10^{-6} and 10^{-5}) are likely to produce heather. Considering that a large share of European farmers appears to be risk-averse (Iyer et al., 2020), results might suggest that heather production is attractive to only a small share of the overall farmer population. Advancing monitoring strategies will require improved potential upside outcomes (e.g. by increasing plant quality and number of marketable plants), rather than cutting down on potential downside outcomes.

Potential of more intensive visual monitoring

DoMoreVisual showed a high likelihood of positive NPVs (Fig. 4-4), with 68% of the NPV results located in the positive area. This implies that farmers who now expend relatively little effort and money on the current monitoring regime (*Baseline)* would likely be able to increase their net benefits by adopting more intensive visual monitoring (*Improved*). *Improved* appears to facilitate safer production conditions since it can raise the number of high-quality heather plants, which is one of the main benefits of the *DoMoreVisual* decision. Farmers and the environment would benefit from safer production conditions, which could be achieved by reducing the frequency of fungicide treatments whenever fungal infection risks are low. Although farmers do not need to apply fungicides when the infection risk is low (Bika et al., 2020), many farmers might prefer to use fungicides rather than expose their production system to the risk of harmful plant losses. In this regard, *Improved* represents a monitoring strategy that may make farmers reduce unnecessary fungicide applications, since frequent visual observations provide them with reliable and up-to-date information about the current health status of their plants.

The number of high-quality plants that can be produced due to more intensive monitoring not only registered a high VIP score; it also represents the greatest uncertainty according to the EVPI analysis (Fig. 4-5). Decision-makers would therefore benefit from additional information to reduce uncertainty regarding this variable.

Based on the results, risk-taking farmers who are concerned about environmental sustainability are willing to apply *Improved* monitoring to optimize their production system. This impression is supported by the analysis of expected utility, which indicates that risk-taking heather farmers aiming to maximize upside outcomes would prefer *Improved* over the *Baseline* and *Sensor* strategies (Fig. 4-3). Risk-averse farmers will probably continue to use frequent fungicide treatments using the *Baseline* strategy. Even if some farmers stick with current production methods, external influences such as customer demand for reduced fungicide treatments may encourage them to reconsider their practices at a later date (Shtienberg, 2013).

Potential of sensor-based monitoring

For *UseSensor*, only 15% of all NPVs were located in the positive range (Fig. 4-4), indicating that the use of the technology is likely to decrease net benefits for heather farmers. To better inform the choice, decision-makers should be willing to invest in additional information on the labor costs involved in using a sensor and the effect of sensor-based monitoring on the number of marketable high-quality plants. The impact of sensor-based monitoring on the number of high-quality plants had a high EVPI within the *UseSensor* decision, followed by the labor costs of the strategy (Fig. 4-5).

Sensor-based monitoring through hyperspectral imaging has been identified as an effective approach for detecting plant diseases in greenhouses (Paulus and Mahlein, 2020) and agricultural fields (Bohnenkamp et al., 2019). The potential of hyperspectral imaging has been demonstrated for early detection of plant-related stress symptoms (Behmann et al., 2014), and for plant reactions to fungal diseases (Kuska et al., 2015). Despite this high technical potential, most studies have not considered the labor and costs required to perform regular sensor measurements in agricultural production systems. For the model of this study, the VIP scores identify an economic bottleneck in the labor needed to apply sensing technology, which had the greatest impact on the outcome (Fig. 4-5). The results suggest that the labor requirement to conduct sensor measurements is currently too high, leading to a high likelihood that a switch to sensor-based monitoring would generate net losses.

Farmers explained that the purchase of hyperspectral sensors entails relatively high costs, which is one of the reasons why buying a sensor for practical applications has not been considered so far. Practical applications are becoming increasingly feasible, however, as sensor costs have dropped considerably in recent years (Zubler and Yoon, 2020). According to Stuart et al. (2020), prices for hyperspectral sensors can range between approximately 35,000 € and 116,000 €. The experts suggested that less expensive sensors of less than 20,000 € have already proven successful in detecting fungal infections in heather plants (Ruett et al., 2022). For the simulation, a wide range of price scenarios was covered using a range between 18,000 € and 100,000 € (see supplementary materials). Nevertheless, the initial sensor investment does not seem to have a strong impact on the outcome of the *UseSensor* decision according to the VIP score results (Fig. 4-5). Contrary to initial assumptions, the initial investment to buy a sensor had the lowest VIP among variables in the *UseSensor* model, with an EVPI value of zero indicating that this was not an important uncertainty in the decision-making process.

The labor cost of performing sensor measurements represents the variable that is mainly responsible for the high chance of negative outcomes for the *UseSensor* decision. A lower workload might increase the likelihood of the *Sensor* strategy generating net benefits. Using sensor-based monitoring in ornamental heather production does not appear recommendable based on the current state of knowledge.

Conclusion and overall recommendation

Heather cultivation is an ornamental plant production system where farmers are exposed to risks and uncertainties that hamper the implementation of new strategies. Decision Analysis approaches and analysis of expected utility were used in this study to evaluate what types of farmers (risk-averse or risk-taking) are willing to implement the simulated monitoring strategies in practice, considering existing risks and uncertainties. Analysis of expected utility showed that more intensive visual monitoring is attractive to risk-taking farmers aiming to increase the chance of upside outcomes. Although our results suggest that heather farmers are risk-takers, the risk-averse group of heather farmers would be more likely to stick with the occasional-monitoring strategy that is currently practiced. The use of sensor-based monitoring with hyperspectral imaging currently appears to be inhibited by high labor costs associated with performing sensor measurements. Further research into practical application of sensors should focus on the impact of sensor-based monitoring on the number of marketable plants. In this study detailed management recommendations were formulated for farmers in heather cultivation, a production system in which little research has been conducted so far. The presented recommendations are based on current knowledge of calibrated experts and allow customized advice to be given to farmers according to their individual risk preferences. This research makes an important contribution to precision agriculture by supporting farmers' decision management, taking into account the overall variability of what might happen in the heather production system as new disease control strategies are applied. This research approach can be used for the analysis of other agricultural systems to provide farmers in data-scarce production systems with concrete recommendations, accounting for uncertainties and risks.

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Supplementary Materials

All data generated in this study is available in the following open access repository: https://github.com/marruett/Supplementary_Ruett_Precision_Agriculture and can be cited using the following doi: https://zenodo.org/record/4780875#.YKjRbqgzY2w

Conflicts of interest

The authors declare that this research was conducted in the absence of any commercial or financial relationships that could be constructed as a potential conflict of interest.

Author contributions

Marius Ruett: Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Tobias Dalhaus:** Data curation, Formal analysis, Investigation, Methodology, Supervision, Validation, Visualization, Writing – review & editing. **Cory Whitney:** Formal analysis, Investigation, Software, Validation, Writing – review & editing. **Eike Luedeling:** Conceptualization, Funding acquisition, Project administration, Software, Supervision, Writing – review & editing.

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Chapter 5
Conclusions

The main objectives for the body of work I have presented in this thesis were two-fold. I sought to analyze the complexity of ornamental heather production systems using holistic and participatory modeling procedures. I also sought to support farmers in dealing with risks and uncertainties when choosing new economically and environmentally sustainable management strategies. I showcase the work with three scientific studies based on advanced collaborative research approaches that integrate available expert knowledge from heather farmers and stakeholders into practice-oriented decision support.

Little scientific research has been conducted in heather production despite the relevant contribution of heather farmers to the German horticulture. Farmers receive little support for optimized risk management when trying to choose between options for more sustainable cultivation practices. I applied holistic analysis of heather production systems to address farmers' major concerns and challenges. I first performed an initial model-based simulation to understand the complex interactions within the system and the possible impacts of new management options on net benefits. The results of this analysis enabled me to focus further research on intensive visual monitoring, which was identified as a key strategy for farmers to optimize heather cultivation management. I gathered further knowledge from farmers and stakeholders on possible alternatives to accomplish and improve intensive monitoring in heather plants. Based on their feedback I performed subsequent experiments to test hyperspectral imaging and the creation of a procedure to analyze and classify heather plants according to their health status. The economic viability of new management alternatives must be ensured to encourage practice implementation by farmers. Therefore, I also evaluated the profitability of the most promising monitoring approaches and applied expected utility analysis to provide recommendations based on individual risk preferences of heather farmers. Throughout the research process, the ornamental heather production system served as an effective framework that enabled progress in developing new techniques for applying decision analysis approaches using iterative participatory methods.

In general, the results of my work indicate that heather farmers must cope with many risks and uncertainties when implementing new management strategies in their production systems. Evaluation of different management decisions indicated that reduced prophylactic fungicide applications is likely to cause financial losses for farmers. The risk of fungal pathogens leading to disease symptoms and low plant quality represents a crucial variable for determining economic outcomes when prophylactic spraying is reduced. Despite its environmental conflicts, prophylactic spraying of fungicides currently appears to be the most effective measure for farmers to reduce the damage by fungal pathogens. The susceptibility of heather plants to fungal diseases is another key factor for explaining the importance of prophylactic applications of fungicides. Large reductions in fungicides use might only be possible if available heather cultivars become less susceptible to fungal diseases. Plant breeding programs could then offer renewed perspectives for a less fungicide-dependent heather production. At present, a more promising approach to guide farmers towards safer heather production might be represented by intensive visual monitoring of disease symptoms. This strategy might be able to increase net benefits but may imply a number of challenges such as the need for experienced laborers detecting potential infections as early as possible. Along the same lines, laboratory analyses may also be required to properly define the pathogens before intervening with plant protection agents as well as avoid unnecessary fungicide applications when symptoms or low plant quality have a different source. Although more intensive visual monitoring appears as a promising approach, our results indicate that further research of the respective costs and benefits of this measure is still needed to improve recommendations for supporting heather farmers.

The challenges of implementing intensive monitoring in heather production systems offer an opportunity for farmers and scientists to develop new approaches based on available tools. Sensor-based hyperspectral monitoring of plants, which remains mostly untested for commercial heather production, may represent a solution to implement intensive monitoring. The results of chapter 3, demonstrated that implementing a sensor-based hyperspectral imaging system in heather production is technically feasible. We focused our analysis on the young stage of heather plants. In this stage, high economic losses might occur due to low plant vitality and fungal infections. The method I reported on in this thesis showed promising results to accurately classify heather plants according to their status ('healthy' or 'stressed'). The application of this method integrated to a pricking robot for example to continuously remove stressed plants as desired by farmers is however still a major technical challenge. Our developed setup requires measurements under controlled illumination conditions and therefore is rather applicable for experiments at present. Sensors must consider the constantly changing intensity of illumination under greenhouses as well as field conditions. This would therefore require an automatic correction by the incident light to the system. Besides necessary improvements to allow measurements within the production process, the high investment on hyperspectral sensors and use of complex data processing tools might prevent farmers from making use of this technology. In fact, our results suggest that hyperspectral monitoring of heathers may be even unnecessary since the critical wavelengths for the classification process range between the green and red-edge regions (visible at naked eye). Consequently, the implementation of this approach using high-resolution cameras (e.g. from smartphones) could offer farmers an easier and cheaper alternative compared to using hyperspectral devices while showing a comparable effectiveness. Future research and development might enable sensor measurements under production conditions and support heather farmers in the early detection of fungal symptoms and optimal monitoring of plant quality.

In the third study I reported on a probabilistic cost-benefit analysis to show heather farmers the likely distributions for the profitability and their individual risk preferences concerning sensor-based monitoring and more intensive visual monitoring. The results showed in chapter 4 highlighted that heather production in general is very risky. The intensive visual monitoring strategy is more likely to result in financial benefits for farmers but simultaneously would be rather preferred by risk-taking farmers searching for maximizing their profits. Continuous optimization of the production system is a central goal for this type of farmers. Risk-averse farmers would rather maintain their current monitoring strategy. Contrary to our first expectations, economic losses due implementing sensor-based monitoring primarily resulted from the cost of performing the measurements rather than the initial investment to acquiring the device. In general, the sensor-based option implies high risk of economic losses, which leads to conclude that hyperspectral sensors use in heather cultivation might be discouraged at the moment. Compared to sensor-based monitoring, more intensive visual monitoring is likely to be more effective suggesting that highly trained eyes are better, cheaper, and faster to capture symptomatic heather plants.

Overall, the results suggest that more intensive visual monitoring of disease symptoms by experienced laborers or farmers will be the most cost-effective measure for moving towards more sustainable heather production. This intervention will be especially relevant if existing plant protection products are banned or increasingly stringent regulations for fungicide use are implemented. More intensive visual monitoring may allow farmers to keep fungicide use relatively low by frequently checking the actual risk of fungal infections in the production system. For this approach to be effective, farmers must also continuously improve their knowledge about pathogens and obtain support from specialized consultants to take action against diseases in a timely and effective manner. Continuous optimization of monitoring is likely to lead to safer cultivation management and more precise fungicide application, contributing to more sustainable production of ornamental heathers. Despite the development of promising new sensor-based monitoring technologies, their application in heather production systems remains a major technical challenge and monitoring by experienced laborers or farmers still appears to be more effective.

The decision analysis approaches at the heart of the collection of work I presented enabled me to understand the interactions of risk and uncertainty in ornamental heather production systems. The collaborative approaches offered me the opportunity to consider the goals and perspectives of heather farmers to ensure practice-oriented research. The models that I created are mainly based on knowledge that I gathered from heather experts. This method allowed to forecast the impact of new decisions in heather production and to formulate the necessary recommendations to support and guide farmers, despite initial research scarcity. In addition, the results of this thesis allowed to provide further insights to guide future research. The research approaches used are not limited to horticultural topics but can be applied to estimate the impacts of new decisions in any system or environment. Unknown parameters and limited data access can be overcome after identification and calibration of appropriate experts, and probabilistic simulations. My co-authors and I recommend and acknowledge the broad application of decision analysis approaches in different research areas. Using this method, decisions can be constructively supported despite the inherent complexity of many systems and/or environments.

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Annex

Supplementary material for Chapter 3

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Here we provide a list of the items we used to construct our data acquisition setup, along with the analysis code, to ensure transparency and allow others to reproduce our research approach.

List of materials with corresponding item numbers

We created a table containing all the materials used to build up our hyperspectral setup and to perform the photographical measurements (Table 3-S1). This is to ensure the reproducibility of our setup and to support the application of similar setups for hyperspectral analyses of ornamental plants.

Table 3-S1. List of materials needed to reproduce our hyperspectral setup. Dimensions can be adjusted to accommodate hyperspectral analyses of ornamental plants of different sizes. For each required item, we provide the name of the manufacturer and item number, as well as the total number of needed items

Item description	Name of the manufacturer and item number	Number of items
Profil 6 D30, natur, Länge: 265mm	Item24: 0.0.616.46	1
Profil 6 D30, natur, Länge: 350mm	Item24: 0.0.616.46	2
Profil 6 D30, natur, Länge: 1000mm	Item24: 0.0.616.46	1
Profilrohr D30, natur, Länge: 600mm	Item24: 0.0.628.28	4
Profilrohr D30, natur, Länge: 645mm	Item24: 0.0.628.28	4
Profilrohr D30, natur, Länge: 800mm	Item24: 0.0.628.28	4
Profilrohr D30, natur, Länge: 1000mm	Item24: 0.0.628.28	4
Abdeckkappe Rohr D30, grau ähnlich RAL 7042	Item24: 0.0.629.78	4
Gewindeeinsatz D30 M6, grau ähnlich RAL 7042	Item24: 0.0.641.00	4
Stellfuß D30, M6x60, schwarz	Item24: 0.0.434.51	4
Automatik-Verbindungssatz 6, verzinkt	Item24: 0.0.419.71	6
Verbinder D30	Item24: 0.0.623.56	21
Winkel V 6 30 Zn	Item24: 0.0.612.78	3
Halogen lamps (ST-500 Halogen Studio Lamp)	Bresser : F000314	2
Adapter for halogen lamps (JM-60 Spigot-Adapter 95mm)	Bresser: F001161	2
Foldable diffusers (BR-TR4 Faltdiffusor 60x90cm)	Bresser: F002516	2
Hyperspectral sensor	Specim IQ: NA	1

Code for data processing in R

We used the R programming language to create our code. The R programming language and all applied R packages are cited in our manuscript. The raw data, the full code for data processing, the correction factors, the sheets of classified plants, and the processed data are accessible on figshare under the following doi: https://doi.org/10.6084/m9.figshare.13109481. Here we show a part of our code that represents our hyperspectral data processing approach (Script 3-S1).

Script 3-S1. R-script for the data processing procedure for our hyperspectral data of heather (*Calluna vulgaris*) plants. For citations of packages, please refer to our manuscript. The processing procedure is repeated for each tray on each measurement day. Therefore, we illustrate descriptions for data processing only for the first 12 measurements of tray one here. This example, as a template, reflects the calculation procedure for the entire dataset. We have used code descriptions to guide readers through our code

All hyperspectral measurements are stored in the 'E:/Catalogs' folder. We loaded the table of correction factors into the R environment. Then we created an applicable array for calculation procedures with data cubes.

```
setwd("E:/Catalogs")
x <- read.table(file = "Correction_factor.txt", header = F, stringsAsFactors = F)
x <- unlist(x)
x <- as.vector(x)
x <- array(data = (rep(x[], each = 512*512)), dim = c(512,512,204))
Correction_factor <- x
```

We loaded the raw data of the first white photo cardboard measurement into the R environment and multiplied the raw data with the correction factor per wavelength. White photo cardboard is hereafter referred to as reference sheet.

```
Raw_White_Paper=read.ENVI(filename="./03-26-2019_CM_S/2019-03-26_005/capture/2019-03-
26_005.raw",
headerfile=paste("./03-26-2019_CM_S/2019-03-26_005/capture/2019-03-26_005.raw", ".hdr", sep=""))
Raw_White_Paper <- array(Raw_White_Paper,dim=c(512,204,512))
first.Raw_White_Paper <- aperm(Raw_White_Paper, c(1,3,2))
a<-seq(512, 1)
b<-seq(512, 1)
Raw_White_Paper<-array(0,dim=c(512,512,204))
for (i in 1:512){
 for(j in 1:512){
  Raw_White_Paper[b[j],a[i],]=first.Raw_White_Paper[i,j,]}
}
first.Raw_White_Paper=Raw_White_Paper
```

```
first.Raw_White_Paper <- first.Raw_White_Paper * Correction_factor
```

We loaded the raw data of the second reference sheet measurement into the R environment and multiplied the raw data with the correction factor per wavelength.

```
Raw_White_Paper=read.ENVI(filename="./03-26-2019_CM_S/2019-03-26_179/capture/2019-03-26_179.raw",
headerfile=paste("./03-26-2019_CM_S/2019-03-26_179/capture/2019-03-26_179", ".hdr", sep=""))
Raw_White_Paper <- array(Raw_White_Paper,dim=c(512,204,512))
second.Raw_White_Paper <- aperm(Raw_White_Paper, c(1,3,2))
a<-seq(512, 1)
b<-seq(512, 1)
Raw_White_Paper<-array(0,dim=c(512,512,204))
for (i in 1:512){
  for(j in 1:512){
    Raw_White_Paper[b[j],a[i],]=second.Raw_White_Paper[i,j,]}
}
second.Raw_White_Paper=Raw_White_Paper

second.Raw_White_Paper <- second.Raw_White_Paper * Correction_factor
```

We applied a 'Gaussian' filter to reduce the noise within the data. Then we created a new image by calculating the mean out of both reference sheet data. We prepared an empty list called 'Data_List' for the next steps of data processing.

```
w = makeBrush(size = 3, shape = 'Gaussian', sigma = 5)
first.Raw_White_Paper  = filter2(first.Raw_White_Paper , w)
second.Raw_White_Paper  = filter2(second.Raw_White_Paper , w)

Mean_White_Paper_26.03 <- (first.Raw_White_Paper + second.Raw_White_Paper) /2
```

We loaded the dark current data of the first reference sheet measurement into the R environment.

```
Dark_Current_Paper =read.ENVI(filename="./03-26-2019_CM_S/2019-03-26_005/capture/DARKREF_2019-03-26_005.raw",
headerfile=paste("./03-26-2019_CM_S/2019-03-26_005/capture/DARKREF_2019-03-26_005.raw", ".hdr",
sep=""))
Dark_Current_Paper <- array(Dark_Current_Paper,dim=c(512,204,512))
first. Dark_Current_Paper <- aperm(Dark_Current_Paper, c(1,3,2))
```

```
a<-seq(512, 1)
b<-seq(512, 1)
Dark_Current_Paper <-array(0,dim=c(512,512,204))
for (i in 1:512){
  for(j in 1:512){
  Dark_Current_Paper [b[j],a[i],]=first.Dark_Current_Paper [i,j,]}
}
first.Dark_Current_Paper =Dark_Current_Paper
```

We loaded the dark current data of the second reference sheet measurement into the R environment.

```
Dark_Current_Paper =read.ENVI(filename="./03-26-2019_CM_S/2019-03-26_179/capture/DARKREF_2019-03-26_179.raw",
headerfile=paste("./03-26-2019_CM_S/2019-03-26_179/capture/DARKREF_2019-03-26_179.raw", ".hdr",
sep=""))
Dark_Current_Paper <- array(Dark_Current_Paper,dim=c(512,204,512))
second. Dark_Current_Paper <- aperm(Dark_Current_Paper, c(1,3,2))
a<-seq(512, 1)
b<-seq(512, 1)
Dark_Current_Paper <-array(0,dim=c(512,512,204))
for (i in 1:512){
  for(j in 1:512){
  Dark_Current_Paper [b[j],a[i],]=second.Dark_Current_Paper [i,j,]}
}
second.Dark_Current_Paper =Dark_Current_Paper
```

We created a mean based on the two dark current data from reference sheet measurements.

```
Mean_Dark_Current_Paper_26.03 <- (first.Dark_Current_Paper + second.Dark_Current_Paper) /2
```

We used the ‘Raw_dark’ function to load the raw data and the dark current data of heather measurements into the R environment. In the code we call the raw data ‘Calluna’ and the dark current data ‘DarkCalluna’. Then we saved them in the ‘Data_List’.

```
Raw_dark <- function(measurements, directory, end_of_file_name_raw, end_of_file_name_dark){
  Data_List <- list()
  for(i in measurements){
    setwd(paste(directory, sprintf("%03d", i), "/capture",sep=""))
    Messnummer_Calluna <- paste("Calluna", i , sep ="")
    Calluna=read.ENVI(filename=paste(end_of_file_name_raw, sprintf("%03d", i),".raw", sep=""),
```

```
                    headerfile=paste(end_of_file_name_raw, sprintf("%03d", i), ".hdr", sep=""))
    Calluna <- array(Calluna,dim=c(512,204,512))
    new.Calluna <- aperm(Calluna, c(1,3,2))
    a<-seq(512, 1)
    b<-seq(512, 1)
    Calluna<-array(0,dim=c(512,512,204))
    for (k in 1:512){
      for(j in 1:512){
        Calluna[b[j],a[k],]=new.Calluna[k,j,]}
    }

    Messnummer_Dark <- paste("DarkCalluna", i , sep ="")
    DarkCalluna=read.ENVI(filename=paste(end_of_file_name_dark, sprintf("%03d", i),".raw", sep=""),
                        headerfile=paste(end_of_file_name_dark, sprintf("%03d", i), ".hdr", sep=""))
    DarkCalluna <- array(DarkCalluna,dim=c(512,204,512))
    new.DarkCalluna <- aperm(DarkCalluna, c(1,3,2))
    a<-seq(512, 1)
    b<-seq(512, 1)
    DarkCalluna<-array(0,dim=c(512,512,204))
    for (k in 1:512){
      for(j in 1:512){
        DarkCalluna[b[j],a[k],]=new.DarkCalluna[k,j,]}
    }
    Data_List[[as.character(i)]] <- list(Calluna = Calluna, DarkCalluna = DarkCalluna)
  }
  return(Data_List)}


Data_List <- Raw_dark(measurements = c(6:17),
                      directory = "E:/Catalogs/03-26-2019_CM_S/2019-03-26_",
                      end_of_file_name_raw = "2019-03-26_",
                      end_of_file_name_dark = "DARKREF_2019-03-26_")
```

We used the ‘Normalization’ function to calculate the relative reflectance of heather data.

```
Normalization  <- function(list, MeanPaper, MeanDark){

 callunaClean <- (list[["Calluna"]] - list[["DarkCalluna"]]) / (MeanPaper - MeanDark)
```

```
 return(callunaClean)}

Normalized_Data <- lapply(Data_List, Normalization, MeanPaper = Mean_White_Paper_26.03, MeanDark =
Mean_Dark_Current_Paper_26.03)
```

The function ‘write_ENVI’ defined numbers for the processed data cubes and then saved data cubes back to disk.

```
write_ENVI <- function(list, directory, prefix, ...){
 for (i in 1:length(list)){
      write.ENVI(list [[i]][,,11:183], paste0(directory, prefix, names(list[i]), ".raw"),...)}}

write_ENVI(Normalized_Data, directory = "E:/", prefix ="Clean_Calluna_2019_03_26_", interleave ="bil")
```

Data processing of one heather tray occupies almost the complete memory of the R environment. We therefore deleted all data in the R environment with the exception of the image of the averaged reference sheets, the dark current image of the averaged reference sheets, the correction factors, the ‘Raw_dark’ function, the ‘Normalization’ function, and the ‘write_ENVI’ function. The image and the dark current image of the averaged reference sheets is needed for data processing of the next heather trays and will only be redefined at the beginning of another measurement day. The functions are used as templates for data processing of the whole data set.

```
rm(list=setdiff(ls(), c("Mean_White_Paper_26.03", "Raw_dark", "Mean_Dark_Current_Paper_26.03",
"Normalization", "write_ENVI", "Correction_factor")))
```