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Using Internet of Things (IoT), Near-Infrared Spectroscopy (NIRS), and Hyperspectral Imaging (HSI) to Enhance Monitoring and Detection of Grain Pests in Storage and Handling Operators

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Abstract: To reduce the use of insecticides, silo operators are reconsidering their practices and implementing integrated pest management (IPM) to manage insect infestations. IPM requires the early detection of insects to react before infestation spread or to isolate infested lots. Depending on their position in the storage and handling chain, operators will favor monitoring or rapid detection tools. To simplify monitoring in storage, an internet-connected trap has been designed. It includes a camera located above a tank that allows for the captured insects to be counted. A total of 89 traps were installed in elevators for a proof-of-concept phase. Compared to sample monitoring, the traps detected an average of three additional insect species in an infested batch. To improve the detection of insects in wheat, methods for detecting and quantifying live adult insects (*Sitophilus oryzae*, *Rhyzoperta dominica*, and *Tribolium confusum*) using NIRS and HSI have been developed. The used instruments, a near-infrared spectrometer and a hyperspectral camera, allow for an in-flow analysis, which reduces sampling errors. The cross-validation errors of the NIRS models ranged from 2.44 insects/kg to 2.56 insects/kg, and the prediction error of the HSI ones ranged from 0.70 insect/kg to 2.07 insect/kg, depending on the insect species.

Keywords: grain; storage; pest management; monitoring; trapping; IoT; NIRS; HSI

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Citation: Crépon, K.; Cabacos, M.; Bonduelle, F.; Ammari, F.; Faure, M.; Maudemain, S. Using Internet of Things (IoT), Near-Infrared Spectroscopy (NIRS), and Hyperspectral Imaging (HSI) to Enhance Monitoring and Detection of Grain Pests in Storage and Handling Operators. *Agriculture* **2023**, *13*, 1355. https://doi.org/10.3390/agriculture13071355

Academic Editor: Jiangbo Li

Received: 16 May 2023
Revised: 19 June 2023
Accepted: 3 July 2023
Published: 5 July 2023

1. Introduction

The presence of grain insects in a batch of cereals is likely to cause quality and economic losses that represent between 5 and 10% of the total value of the production [1]. For this reason, strategies for insect control in storage silos and detection measures during the transfer of grains have always been implemented, with all commercial contracts including a clause of absence of live insects in the grain. Even so, a significant portion of stored grain is infested with insects [2–4] at levels difficult to detect using the sampling procedures usually implemented. It has been shown that sampling according to standard sampling procedures [5] can only reliably detect infestations above five insects per kg [6]. Increasing the detection capability of a sample requires taking more incremental samples and increasing the size of each sample [7], which leads to the analysis of a large amount of grain, a difficult solution to implement daily in the grain trade when insect detection is performed using sieves.

The use of trapping methods during storage is the best way to detect infestations in cereal lots at an early stage and is therefore a key element of an integrated pest management strategy [8]. Probe traps are more effective than sampling in detecting infestations [9,10] and can detect an infestation 15 to 37 days earlier than sampling [11]. However, these traps are hardly used by silo managers in France, partly because they require regular, time-consuming readings and partly because they require regular access to the grain, which is not always possible for safety reasons.

In the contexts of the reduced use of phytosanitary products, as required by European regulations [12], and of climate change favorable for the development of insect populations in stored grains [13–15], it is particularly important to provide grain storage and handling operators tools that allow for the accurate monitoring and detection of insects in order to avoid the development and spread of a significant infestation that is likely to reduce the quality and value of traded grains. Depending on their position in the supply chain, operators will be more likely to use monitoring tools when they must store grain over time or detection tools when they have to handle large volumes of grain that are simply passing through their facilities. The challenges for improving insect management throughout the food chain are therefore to facilitate the use of traps for the early detection of infestations in country grain elevators, thus avoiding the transmission of infestations to other operators, and to facilitate the detection of insects in batches in transit, particularly in batches received at terminal elevators and intended for export.

The development of the Internet of Things (IoT) offers the opportunity to greatly facilitate storage monitoring by allowing traps to communicate with operators and with their environment. This allows one not only to follow the captures, avoiding time-consuming and dangerous human interventions, but also to interpret them considering the storage environment (temperature and hygrometry), to evaluate the risk, and to assist the silo manager in their insect management. Therefore, within the framework of a project [16] financed by the French Ministry of Agriculture, we have developed, in partnership with Javelot (a supplier of connected solutions for the monitoring of stored grains), a connected trap with the objective of providing operators with a trap that is easy to use, that is inexpensive, and that makes it possible to assess the risk with regard to storage conditions. This connected trap is an improvement on a conventional probe trap [17], but the trapping technique remains unchanged: the insects present in the grain are captured by the trap's perforated cylinder as they move and fall into a tank from which they cannot escape.

For detection, non-destructive measurement technologies have been chosen, able to quickly analyze large volumes of grain, possibly on-line on moving grain, to minimize sampling errors in the measurement of insect infestations. Near-infrared spectroscopy (NIRS) technologies have many applications in agriculture, including the detection of insects or insect damage on various food products, such as cherries [18], mung beans [19], or jujube [20]. In the area of grains, an NIRS analysis is classically used for the evaluation of seed composition [21], and its ability to detect insects, including hidden forms, has been demonstrated [22–28]. However, the analyses were conducted on small quantities of individually analyzed grains, which does not solve the problem of the sampling error. Moreover, the developed prediction models were only satisfactory for high infestations: it was observed that, although it is possible to detect infestation levels above 25% using near-infrared spectroscopy, lower levels of infestation might not be detected using this technique [26]. By combining spectroscopic and imaging techniques into one system, hyperspectral imaging (HSI) has the advantage of providing both spectral and spatial information [29]. HSI represents an advancement over spectroscopy. This technology has been used in food and agricultural areas to detect external insect infestations on jujube fruit [30] or to detect fruit fly (*Drosophila melanogaster*) eggs and larvae in intact mangoes [31,32]. Other research has investigated insect damage to plants, such as mulberry leaves [33], soybean [34], and mung bean [35]. Few studies have dealt with insect detection using HSI in cereals, but the potential of near-infrared HSI for detecting insects in wheat kernels visibly damaged by *Sitophilus oryzae*, *Rhyzoperta dominica*, *Cryptolestes ferrugineus*, and *Tribolium castaneum* has been demonstrated with a grain-by-grain analysis of small quantities [36,37]. Similarly, NIRS and HSI have been identified to detect live adults of *S. oryzae* in common wheat, even at low infestation levels (0.2 insects/kg to 15 insects/kg) and on samples ranging from 1 to 5 kg. [38,39]. These latest results suggest that this technique is promising for detecting and quantifying the insects present in grain batches.

The study presented here assesses the relevance and effectiveness of three methods developed to improve insect management throughout the cereal supply chain:

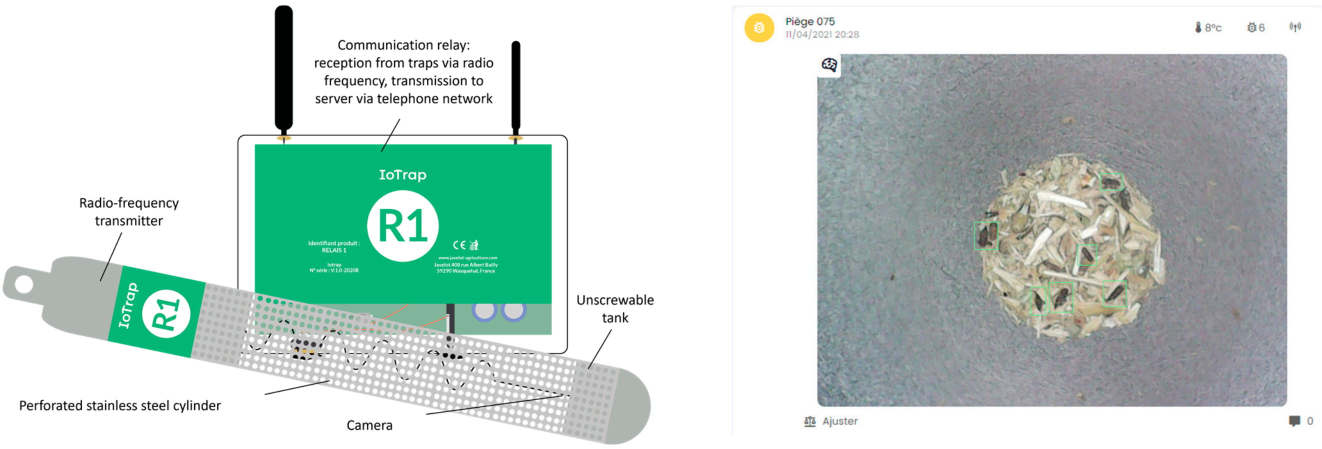
1. The early detection of insects in stored grain using internet-connected traps to facilitate monitoring and the implementation of integrated pest management.
2. The detection and quantification of insects, even at low levels of infestation, using an NIRS or HSI in-flow analysis on moving grain to limit contamination between batches and batch refusals.

2. Materials and Methods

2.1. Connected Monitoring

2.1.1. Connected Trap IoTRAP

The IoTRAP probe is made of a perforated stainless steel tube with 3.0 mm entry holes, an unscrewable tank, and a transmitter communicating with a radio frequency relay (Figure 1a). Inside the trap, a camera is inserted, which takes daily pictures of the trap tank content. The data are sent to a server and are directly accessible to users via an internet platform (Figure 1b). The insects are recognized and counted in each image.



(**a**) (**b**)

Figure 1. (**a**) Connected probe trap and its relay; (**b**) photograph of the tank with counted insects (green boxes), available on an internet platform.

2.1.2. Trapping and Sampling Campaign

A total of 89 IoTRAP probes were positioned in 19 storage bins distributed throughout France, with 3 to 10 traps per bin. The storage bins were chosen by the silo managers involved in the project. They can contain common wheat, barley, or corn. The storage capacities of the bins ranged from 600 T to 25,000 T, with one trap used for every 120 to 2500 T, depending on the situation. The management of the storage remained the responsibility of the silo manager, and the temperature of the grain was measured near each probe trap. A photograph of the tank contents was sent twice a day to a server, accessible to the operator via an interface. The photograph was accompanied by an automatic count of the insects detected using an image recognition algorithm. Every month, the contents of the trap were recovered and analyzed (manual counting and identification of species), and a sample of the grain was taken near the trap. The insects present in this sample were identified and counted after sieving. A quantification limit of 50 individuals per species was set. Beyond 50 individuals, the counting was stopped, and the number of 50 was retained. These operations were carried out during the entire storage period of the grain, for at least 1 month and for a maximum of 5 months. The number of individuals detected using the automatic counter on the last photo taken before the trap was collected was compared to the total number of adult beetles identified in the tanks.

2.2. NIRS and HSI Analysis

2.2.1. Samples Constitution

S. oryzae, *R. dominica*, and *T. castaneum* were reared in wheat grain and separated from the grain via sieving and manual sorting to obtain the required number of live adults. For each insect species, artificially infested samples were prepared from the same 400 kg batch of soft wheat, previously cleaned with a grain cleaner (NSD2, Ets Denis, Brou, France) and stored in a freezer to avoid infestations. From this batch and for each insect species, a set of 72 samples was prepared to have 24 infestation densities with 3 replications each. In total, 16 $\times$ 3 samples of 1 kg were infested with 0 to 15 live adult insects per kg, and 8 $\times$ 3 samples of 1.5 to 5 kg of grain (by steps of 500 g) were infested with 1 live adult insect each.

Additional samples were provided for hyperspectral acquisitions: three samples containing 100 live adult individuals of each species.

2.2.2. Sensors and Acquisitions

PSS (Polytec GmbH, Waldbronn, Germany) spectra were acquired from 1100 to 2100 nm with a resolution of 2 nm in a reflectance mode. Analyses were performed with the sensor head at a distance of 20 cm from the samples.

Hyperspectral images of the 72 samples, for each insect species, were acquired in the near-infrared region (from 900 to 1700 nm) using a SPECIM FX17 (SPECIM, Oulu, Finland) hyperspectral camera. This camera works in a line-scan mode and has spectral and spatial resolutions of 8 nm and 640 pixels, respectively. Two illumination rows of halogen lamps were placed on each side of the camera to ensure that the illumination covered the entire measurement area with a uniform intensity. To develop models, additional hyperspectral images were acquired: 1 image with only wheat; several images with only one insect species; and images with impurities, such as straws, foreign seeds, and husks extracted from the wheat samples.

A conveyor with a speed of 0.1 m/s was used for the acquisitions by moving the sample under the camera and the PSS (Figure 2).

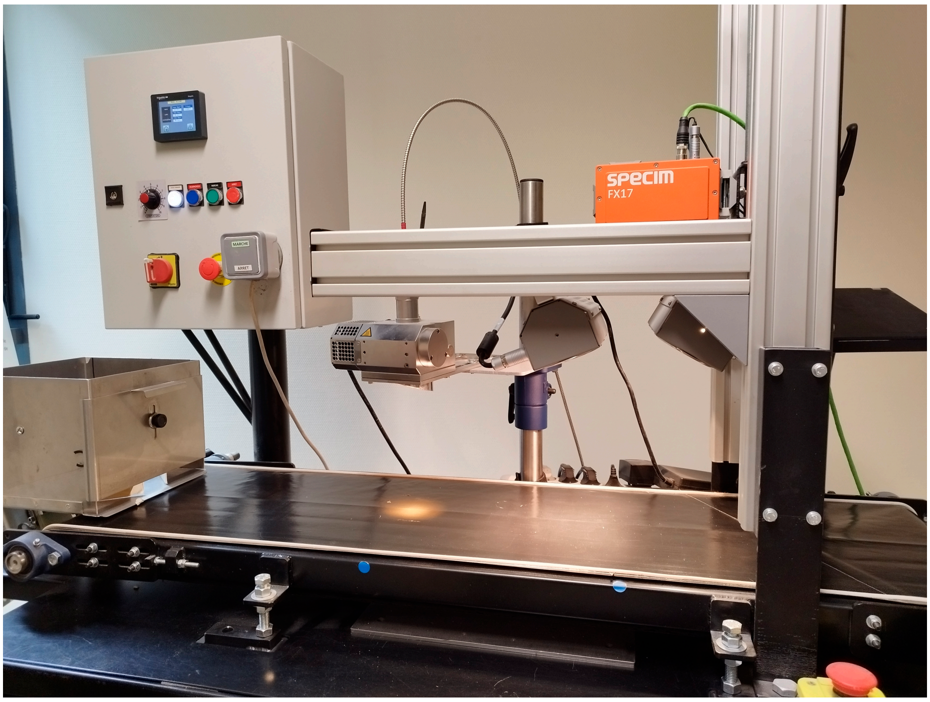


Figure 2. Optical bench with belt conveyor and two sensors (PSS and SPECIM FX17).

2.2.3. Data Treatment

- NIRS data: Calibration Wizard software (SensoLogic GmbH, Norderstedt, Germany) was used to treat the PSS data. First, the reflectance spectra were transformed to absorbance spectra. Different combinations of mathematic pretreatments, including derivatives, standard normal variate (SNV), detrending, and multiplicative scatter correction (MSC), were compared. The calibration models were carried out using partial least square regression (PLSR). PLSR is one of the most common methods in NIR spectra chemometric analysis. It aims to relate data matrices X (pretreated NIR spectra) and Y (the number of insects initially added to the wheat samples) through a linear multivariate model [40,41]. Due to the use of few samples for each insect species (72), validation using an external data set was not possible. Therefore, the cross-validation error (SECV) was used to determine the predictive ability of each calibration.
- HSI data: The background pixels of the hyperspectral images were deleted by thresholding the 75th spectral band (1193 nm). After removing the background, the spectral information was used to detect insects. To reduce multiplicative and additive effects, different combinations of the pretreatments were compared. Support vector machine recursive feature elimination (SVM-RFE) was used to select discriminative wavelengths. SVM-RFE classifies the wavelengths from the least discriminating to the most discriminating using criteria derived from the coefficients in SVM models [42]. From additional hyperspectral images with only wheat or insects, a support vector machine (SVM) classification model was built. The SVM supervised learning method consists of finding the hyperplane that best separates the data by maximizing the margin between the hyperplane and the closest data points from each group [43]. Thus, each remaining pixel was classified as wheat or an insect. As impurities are often present in wheat samples, corresponding spectra were added to the wheat class to improve classification performance.

  To quantify the detected insects, the spatial information was used. With the results of the classification model, a 2D binary image was created: 0 for pixels labeled as the background and 1 for pixels labeled as insects. The number of insects in a sample is equal to the number of contiguous regions in the corresponding 2D binary image. The images of the samples with the different infestation levels were used to test the HSI treatment. For each sample image, the number of insects detected using HSI was compared to the number of insects manually put in the sample during its preparation in order to calculate the standard error of prediction (SEP).

3. Results

3.1. Monitoring Grain with a Connected Probe Trap

In total, 275 observations from the traps and 103 observations from the samples were obtained. Despite conducting the tests during the autumn and winter, the grain temperatures remained high enough to allow captures in 88% of the 275 observations. During October, the average temperatures in the monitored grain were still frequently above 20 °C (min 17.5 °C and max 37 °C). In January or February, when grain aeration was completed, the average temperatures ranged from 6 °C to 13 °C.

The species most frequently detected in both the traps and grain samples were *S. oryzae* (53% of traps and 39% of samples collected), *O. surinamensis* (40.6% of traps and 33% of samples), and *Cryptolestes* sp. (40.3% of the traps and 21% of the samples). The species diversity in the traps was greater than that detected in the grain samples. On average, across all sites and during the entire monitoring period, the traps identified from 1 to 7 more species than the samples (Table 1), thus providing a more complete understanding of the diversity of the populations present in the stored grain.

In addition, in October 2020, in four situations, sampling did not identify any insect presence, while the traps detected infestations.

Table 1. Average number of specimens detected (automatic counting) or sorted in the traps (reference counting), and number of species identified (among *S. oryzae*, *S. granarius*, *R. dominica*, *T. castaneum*, *T. confusum*, *Latheticus oryzae*, *O. surinamensis*, *Cryptolestes* sp., *Ahasverus advena*, *Typhaea stercorea*) in grain samples (S) and in traps (T).

Elevator	Bin	Average Number of Specimens (Adult Beetles)		Number of Species Identified in Grain Samples or in Traps (Reference Counting)									
		Automatic Counting	Reference Counting	Oct-20		Nov-20		Dec-20		Jan-21		Feb-21	
				S	T	S	T	S	T	S	T	S	T
BIH	25301	0.6	9.9	1	6								
	25302	2.2	13.25			4	6	4	5	4	na		
CHA	FPO01	3.1	33.1	3	6	2	7	1	6	4	8	2	na
DES	C2G	1.2	8	0	4	1	5	1	5	2	5	na	na
	C3D	1.9	7.7	0	2	2	3	2	3	2	2	na	na
	C3G	3.8	53.3	0	6	2	6	4	na				
EPO	SD	4.1	9.5	0	4	1	7	1	3	1	2	na	na
MAI	B4	2.5	29.1							3	6	4	na
PEU	C1	3.3	92.8	5	8	3	6	3	na	4	5	2	4
	C3	17.8	91	2	9								
	C5	0	9.6									na	na
	C9	3.5	21.3			1	4	2	3	3	4		
ROU	C36	4.7	74.8	7	8	3	9						
	C37	0	229	4	8	5	10						
VER	C14	4	37.6							3	4	1	na
	C6	1.2	8.5									0	2
	C8	1.8	27.2					2	3				

na data not available (loss of sample traceability).

The automatic count provided no data (count = 0) in 155 of the 275 situations, i.e., 56%, while the reference count reported no insects in only 12% of cases (Table 2). In total, 10% of non-infested situations were predicted as infested (3 out of 33), while 52% of infested situations were predicted as non-infested (125 out of 242). However, considering for each elevator and each bin all the information collected by the traps during the whole monitoring period, and not just the information given by one photo in isolation from the others, the infestations remained ignored in only two situations (elevator PEU C5 and ROU C37), and no false infestations were found (Table 1).

Table 2. Number of observations from traps considered as infested (1) or non-infested (0) according to the automatic or reference count.

Automatic Counting Reference Counting	0	1	Total
0	30	3	33
1	125	117	242
total	155	120	275

A simple linear regression model was proposed to predict the number of insects captured in the trap tank (counted manually, considered to be the reference) from the number of insects automatically counted in the photograph (Figure 3). In general, the counter tended to underestimate the number of insects present in the tank. There is a linear relationship between the automatic count and the reference count (p-value = 0.0027), but, considering the value of the coefficient of determination (R^2 = 0.029), this relationship is not predictive.

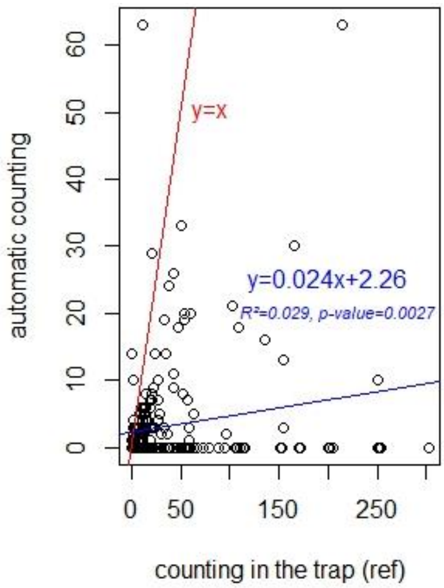


Figure 3. Linear regression between reference counting (in the trap tank) and automatic counting.

3.2. Insect Quantification Using NIRS and HSI

For the NIRS analysis, the performances of the calibration models were almost similar for the two species of insects (*S. oryzae* and *T. casteneum*). The cross-validation errors (SECV) between the actual and predicted values were quite similar (2.56 insect/kg for *S. oryzae* and 2.44 insect/kg for *T. casteneum*). For HSI, the performances were satisfactory, even if the SEP values of the *R. dominica* (1.57 insect/kg) and *T. castaneum* (1.81 insect/kg) models were higher than the *S. oryzae* one (0.7 insect/kg) (Table 3).

Table 3. Performances of PLSR models for *S. oryzae* and *T. castaneum* and HSI ones for *S. oryzae*, *R. dominica*, and *T. castaneum*.

		Insect Species		
		S. oryzae	***R. dominica***	***T. castaneum***
NIRS	SECV (insect/kg)	2.56	na	2.44
HSI	SEP (insect/kg)	0.7	1.57	1.81

na: the results of *R. dominica* are not available due to a problem with data saving.

4. Discussion

The IoTRAP probes showed their abilities to detect infestations early and to capture a greater diversity of species, which agrees with previous studies comparing trapping and sampling [10,44,45] while minimizing the constraints and risks inherent in handling traps thanks to remote reading. The automatic count, based on the transmitted photographs, proved to be unreliable and underestimated the actual number of insects present in the trap tank, which is certainly explained by the fact that only the image of the tank surface is analyzed. Moreover, we found that the tanks were frequently filled with dockage and small grains of wheat, which can also disturb the automatic analysis of the images. To overcome this problem, the design of the traps was reviewed by adapting the holes of the tube to limit the entry of dockage into the tank during the insertion of the trap in the grain. It has been shown that the diameter of the holes can affect the number of captures in the probe traps [46], but the goal is to achieve a balance between the number of captures and the amount of dockage falling into the reservoir to facilitate insect detection. The holes were reduced to 2 mm, but it remains to be seen whether this will degrade the number of captures too much, especially for larger species. In any case, the underestimation of the number of individuals in the tank is not necessarily prejudicial if detection rather than quantification is desired. Quantification could be sought to estimate the real density of insects in the grain, but several studies have shown that there are not always strong correlations between the number of captures and the density of insects [11,47], particularly in large cells and in an environment that fluctuates in time and in space (water content and temperature). Capture not only depends on insect density [48] but also on their mobility, which is itself influenced by many factors, such as temperature, water content, dockage, and gradients of these factors in the stored grain [49–51]. Recently, a linear model relating *Sitophilus zeamais* density and capture frequency for a given temperature (in the range of 18–30 °C), validated in a flat-storage warehouse holding 230 T, showed a very good predictive ability [52]. However, capture frequency is not accessible data with IoTRAP probes given the underestimation of the number of captures observed that is inherent to the chosen technology. The interpretation of the traps could instead follow a binomial approach [53], the implementation of a pest management plan depending not on the quantity of insects in each trap but on the number of traps with captured insects. Insect control action would then be required when the proportion of traps without a capture falls below 0.4 or 0.2 [49]. Therefore, it seems to us that IoTRAP probes should be used by operators to detect infestations, not to quantify them, and that IPM strategies should be implemented. The improvement opportunities identified in this study under field conditions are mainly related to the image analysis: to facilitate its reading by reducing the presence of broken grains in the tank, which disturb the interpretation of the image; to improve the image analysis to limit the number of false negatives; and later to refine classification algorithms to identify the species and thus adapt pest management.

The potential of NIRS technology has already been recognized [26], but its detection capacity has so far only been demonstrated for high infestations, above 25%, on small samples [26,36,37]. In the present work, the quantification performances of the calibration models with NIRS were satisfactory, even for low infestation densities, and they could therefore be proposed to handling operators wishing to detect infestations during the grading of a batch of grain. These results are consistent with previous ones obtained on wheat samples containing adult *S. oryzae*, with similar infestation levels [39]. Nevertheless, the error obtained in the work presented here is slightly higher than that previously measured (2.56 versus 1.62 insects/kg). This can be explained by the fact that, in our previous study, we acquired the spectra in contact with the samples, whereas here, the spectra were acquired at a distance, which may contribute to the degradation of the performance of the calibrations. Nevertheless, it seemed to us that remote acquisitions were more likely to interest the operators who could position the sensors on the conveyor belts. In any case, the performance obtained in this study with NIRS technology makes it possible to consider its use for on-line grain grading.

The HSI technology also presented very interesting performances in quantification; until now, it has been little studied for this objective. Previous works have well demonstrated its ability to detect wheat kernels visibly damaged by *S. oryzae*, *R. dominica*, *Cryptolestes ferrugineus*, and *T. castaneum* [37]. However, this technology has not been used to evaluate infestation levels in cereals. The performances obtained for wheat infested by *S. oryzae* are similar to those obtained in a previous study for identical infestation levels [38,39]. There was even a slight improvement in SECV, which can be attributed to the better spatial resolution of the SPECIM camera (640 pixels instead of 320 pixels for the previous one) and the enhancement of the data treatment procedure.

The performances obtained with the two technologies cannot be directly compared because, in the case of NIRS, cross-validation errors (SECVs) are presented, whereas in the case of HSI, standard errors of prediction (SEP) are presented. To objectively compare the two technologies, validation with an external data set (spectra and images of new samples) will be necessary.

The choice of one or the other technology will certainly have to be made based on their capacity to adapt in a real environment. For example, we can question the robustness of the on-flow analysis performances of the two technologies when they are positioned on conveyor belts whose speed is much higher than the one used for the acquisition of spectra in this study (3 m/s versus 0.1 m/s). This point should be validated later. At first sight, one could consider that the performances obtained with these two technologies are not superior to those obtained using classical methods of detection, such as sieving, microwave heating, or Berlese funnels [54]. However, the advantage of these technologies lies in their ability to be used on flow and, therefore, to analyze a very large quantity of grains. In a work on the amount of grain that should be analyzed to correctly estimate a low-density insect infestation, it was shown that the estimate was correct when sampling 100 incremental samples of 13.5 kg each [7]. This is not feasible with conventional detection methods, but it can be carried out with an on-flow analysis of grain lots. In addition, NIRS or HSI technologies have demonstrated their ability to rapidly detect the hidden forms of grain insects (*S. oryzae* and *S. granarius*) [23–27], without going through an incubation period, which is not possible with conventional detection methods. This is an additional advantage of these technologies, which will be accessible as soon as the calibrations for the detection of larval forms are available. It remains to be verified whether the detection of hidden insect forms is possible at low infestation levels.

5. Conclusions

Managing grain insects throughout the storage and handling chain requires the development of rapid and reliable monitoring and detection methods. New technologies, such as the Internet of Things, NIRS, and HSI, can facilitate and improve the monitoring and detection of insects in grain. Used in a complementary way by the different stakeholders in grain storage and handling, they contribute to a virtuous practice of insect control, limiting the risks of infestation and the use of chemical insecticide or quality losses. The presented work shows the following:

1. Connected traps allow for the early and reliable detection of species present in grain while limiting human intervention to perform measurements.
2. Calibrations developed for NIRS or HSI allow for the quantification of insects in a sample.
3. NIRS and HSI technologies allow for the rapid processing of large samples, thus potentially limiting sampling errors.

6. Patents

The IoTRAP probe has been patented in Europe and in the USA.

Author Contributions: Conceptualization, K.C. and S.M.; methodology, M.C., F.A. and M.F.; formal analysis, M.C., F.A. and M.F.; resources, F.B.; data curation, K.C., F.A. and M.F.; writing—original draft preparation, review, and editing, K.C.; project administration, K.C. and F.A. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the French Biodiversity Agency, project IoTRAP "Ecophyto 2018–2021", and by the French Ministry of Agriculture and Food, agricultural and rural development trust account, project CASDAR 21ART4027861.

Data Availability Statement: Some data presented in this study are available on request from the corresponding author at the discretion of the authors.

Acknowledgments: The authors thank the following for their technical support: Catherine Renaud (breeding, counting, and determination of insect species), Isabelle Roux, Laure Laskowiecki, and Claudia Labarrière (data acquisition).

Conflicts of Interest: The authors declare no competing interests related to this work. Javelot holds the patent for the IoTRAP connected trap (see above). The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

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