Modeling ecosystem management based on the integration of image analysis and human subjective evaluation - Case studies with synecological farming

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Abstract. The challenge for biodiversity restoration and augmentation is to find effective indicators for ecosystem management without discarding too much of the complexity that contributes to functionality. Many technical challenges lie ahead in setting up information measures to manage dynamically changing ecosystems in the real world. It is expected that image analysis features such as edge, texture, color distribution, etc. will provide clues, but methods to evaluate their effectiveness in the context of integrated management have not been sufficiently studied. Taking synecological farming (Synecoculture™) as a typical example of complex ecosystem management, we investigate the initial steps toward the construction of an evaluation model by incorporating image analysis and empirical knowledge acquired by human managers. As a result, we showed that it is possible to construct a model that connects the features of image analysis and human subjective evaluation with consistency according to the level of the evaluators and proposed a cycle that would refine both the evaluation model and associated human capacity. We also presented an interface for utilizing collective knowledge in ecosystem management using the proposed model and the prospect of scaling up in conjunction with robotics.

Keywords: Open complex systems, Augmented ecosystems, Inter-subjective objectivity, Image analysis, Interactive machine learning

1 Introduction

Agroecology is concerned with the management of trade-offs between environmental impacts and economic benefits in agricultural production. One of the challenges for biodiversity restoration and augmentation is to find effective indicators for the management of complex ecosystems. However, real-world ecosystems are characterized as open complex systems that are difficult to manage effectively with a few limited indicators because the diversity of elements and complexity of interactions play important functional roles [1]. Diverse ecosystem functions are supported by biodiversi-

ty, which consists of at least three levels: genes, species, and ecosystem diversity. It is difficult to measure all those interactions and to set unitary criteria of information to manage the system in the presence of environmental variability [3] [4] [5].

Image analysis such as remote sensing and in-field picture recording such as citizen science has the potential to capture diverse aspects of ecosystems at a relatively low cost, but their effectiveness depends on the method of measurement, evaluation and the database used. For example, the mainstream method for documenting species diversity is species identification based on subjective human evaluation of photographs of species [6]. In addition, research aimed at ecosystem assessment have attempted to combine remote sensing with multiple data on biodiversity and functionality through machine learning to calculate an integrated index of complexity (e.g., [7]). These are gaining credibility as a source of scientific information for conservation purposes, such as restoring natural ecosystems or assessing the impact of conventional agricultural practices. However, as in situations typical of agroecology, they are still insufficient for forecasting and managing small-scale ecosystems where humans frequently intervene with diverse objectives, and where dynamic variability and local specificity are high [3].

Synecological farming is one such example and it is an extreme form of agroecology that constructs and utilizes a high degree of biodiversity. In this method, more than 200 species of useful plants are mixed and densely grown in a small area of about 1,000 sq.m. to create a highly diverse ecosystem. This farming method is defined as an application of complex systems science to agroecology [8]. It can be interpreted as the augmentation of ecosystems by humans and has been shown to be effective in restoring and building useful and functional ecosystems beyond the natural background state, especially in the semi-arid tropics [2]. On the other hand, much of the practice is based on empirical knowledge from a farming manual [9] and direct communication.

To develop synecological farming based on scientific collective knowledge as well as human empirical knowledge, several studies have been conducted to integrate human subjective evaluation and objectively measurable indicators: A study in an urban area has successfully extracted indicators that could be significantly used to promote biodiversity, based on human assessments of biodiversity and sensor measurements of soil composition that do not depend on human evaluation [3]. At a more rudimentary level, in conjunction with image analysis, there are examples of the detection of dominant plants that hinder the growth of useful plants and reduce their diversity in a field [10], as well as the detection of vegetation cover and exposed topsoil [11]. These are only results obtained under limited conditions with a considerable narrowing of the target to be recognized and are insufficient as effective indicators for the comprehensive management of ecosystems.

Other research is underway in robotics to assist management in synecological farming [12]. The implementation of tasks such as driving, seed planting, weed pruning, and harvesting was accomplished by a mobile robotic arm. In addition, a maneuvering system is developed to minimize plant damage due to contact with the robot on the dense vegetation of a variety of plants on a synecological farm. Despite the recent innovation of automation in conventional agriculture, it is technically challenging to fully automate the system to recognize and evaluate the condition of the field with high biodiversity. The open-field management of complex vegetation with the mix-

ture of a large number of crops and naturally occurring plants still requires the robot to be operated remotely by a human operator.

Further advancing these research streams, the promotion of human ingenuity towards the integration of highly internalized empirical knowledge with scientific objectivity will lead to the development of methodologies that provide an effective foundation for managing open complex systems [13]. In this paper, we take synecological farming as an example of complex systems management in agroecology and propose a method to build an effective and reproducible management model to achieve augmentation of ecosystems by integrating subjective assessment and objective indicators based on image analysis. Since ecological situations dynamically evolve in synecological farming along with the refinement of management knowledge, it is necessary to employ an interactive framework in that human evaluation and image analysis mutually improve each other, which requires the dynamical reconfiguration of the model [14]. This article consists of an initial phase of such a workflow towards the stepwise construction of an effective management model on the basis of open systems science [1]. The inputs, outputs and function of the models developed in sections 2-5 are summarized in the supplementary material [16]. The databases are limited to case studies on a trial basis and are subject to future expansion.

2 Subjective and inter-subjective human evaluation of a synecological farm

A 4-sq.m. vegetable garden in Machida, Tokyo, Japan, was operated according to the Synecoculture™ manual [9] and 26 photographs were taken from 4 m above during the period from May 2019 to January 2021 (Fig. 1, hereafter the farm M). A subjective evaluation was conducted by 8 experienced persons with different periods of practice of synecological farming, referring only to these photos. The evaluators were divided into four levels based on the number of years they had been engaged in synecological farming and their experience: expert (1 person), advanced (1 person), intermediate (3 people, including one person who played a part in the management of farm M), and beginner (3 people, including one person with no experience at all). "Expert" was a person who had been engaged in the farming for more than 13 years and had trained and produced many practitioners of synecological farming; "advanced" was a person who had been engaged in the farming for more than 8 years; "intermediates" for 3 to 10 years; and "beginners" for less than 3 years.

The indicators of subjective evaluation were defined using the Visual Analog Scale (VAS) scores, which were defined on a scale from 1 to 10 and used to assess human subjective measures with an interval scale such as in web surveys [15]. The three evaluation indicators were defined as follows:

1. **Appraisal Score (AS):** subjective evaluation of how good the field is in terms of synecological farming. As a criterion, 1 refers to the condition of the field that he/she thinks is not at all suitable for synecological farming, and 10 refers to the condition that has achieved the highest degree of synecological farming imaginable.

2. **Harvest Prediction (HP):** subjective assessment of how much yield, including future potential, could be expected from the plots in that image. The criterion was defined as 1 being a field that was unlikely to yield any useful plants, and 10 being the highest yielding field condition imaginable.
3. **Management Grade (MG):** subjective estimation of the degree to which managers of the field in the image were proficient in synecological farming. The evaluators were asked to respond by referring to the shape of the ridges, the arrangement of plants, and whether appropriate management such as thinning and harvesting had been done, as well as changes over time. The criteria were: 1 to 2.5 is beginner, 2.5 to 5 is intermediate, 5 to 7.5 is advanced, and 7.5 to 10 is expert.

All evaluators self-evaluated their levels, and only one of them was concerned with the management of farm M. By examining the correlations between these indicators, it is possible to determine the degree to which intersubjective reproducibility is ensured between the ratings of each level. The results of the correlation analysis between the evaluation of one expert and the indicators averaged for each level from beginner to advanced are shown in Table 1.

The average of three indicators (AS, HP, and MG) showed significant correlations with an expert in the order of advanced, intermediate, and beginner averages. MG

Fig. 1. Date and the top view images of a synecological farm in Machida (farm M), 4 ㎡.

Table 1. Correlation coefficients of VAS ratings (AS, HP, MG) between an expert vs. the average at each level of practitioners in synecological farming. The p-values of all Pearson Product-Moment Correlation Coefficients of AS, HP, and MG were less than 0.01 with the test of no correlation.

	vs. Advanced(n=1)(A)	vs. Intermediates(n=3) (I)	vs. Beginners (n=3)(B)	vs. I&B(n=6)	vs. A&I&B(n=7)
Appraisal Score (AS)	**0.74**	**0.86**	**0.89**	**0.90**	**0.90**
Harvest Prediction (HP)	**0.90**	**0.93**	**0.91**	**0.95**	**0.95**
Management Grade (MG)	**0.90**	**0.71**	**0.52**	**0.74**	**0.74**
3 Indicator Average	**0.85**	**0.83**	**0.77**	**0.87**	**0.86**

alone showed the same tendency of correlations but not in AS and HP. In addition, correlation values using the averages of the three indicators for the seven non-experts showed the highest correlations for almost all indicators, suggesting the validity of group knowledge rather than individual years of experience.

As shown in the results of Table 1, the analysis of subjective indicators can be used to estimate competence compared to expert, while the internal model of the evaluator, backed by knowledge and experience, remains a black box. Since subjective indicators alone do not include objective criteria, it is impossible to determine quantitatively any mistakes or biases that may have occurred. In fact, the model uses one expert as the highest criterion for subjective evaluation and does not evaluate whether the collective knowledge of the other seven could achieve more effective management. This has been pointed out as a drift of intersubjectivity in subjective evaluation and tying it to objective indicators is essential to remove the bias prevalent in collective knowledge [13].

3 Objective classification of conventional and synecological farms based on image analyses

In the management of synecological farming, the degree of established biodiversity is an important indicator [5] [9]. On the other hand, in conventional farming methods that are typically monoculture, the level of biodiversity in the field remains low and there is dominant homogeneity in their landscapes [8]. Through image analysis of these external differences, we attempted to extract features that estimate the degree of achievement of synecological farming.

A total of 280 sq.m. of farmland in Oiso Town, Kanagawa Prefecture, Japan, was operated according to the Synecoculture™ manual, along with a total of 235 sq.m. of conventional farmland on the side. A total of 16 photographs was taken from directly above with a drone over a five-month period from May to September 2021 (Fig. Oiso, hereafter the farms O and C). The distance between farms O, C and M is about 26 km and belongs to the same temperate agroclimatic zone. Farm O is further divided into two parts: O1, 180 sq.m. managed with a diversity and quantity of seed that meets the standards of the Synecoculture™ manual; and O2, 100 sq.m. with a seed quantity of 48.5% of the standard per unit area. The adjacent conventional farm C was divided into two rectangular plots C1 (85 sq.m.) and C2 (150 sq.m.), which were photographed and analyzed in the same way. The reason for splitting C into C1 and C2 is to capture only the productive surface in a rectangle, with as little extraneous material as possible in the image. Therefore, a qualitative relationship of C1, C2<O2<O1 was established empirically as the degree of achievement of synecological farming.

Using the programming language Python version 3.9.15, 241-dimensional image features were designed from a set of basic libraries related to image analysis. The library used and the variables set are listed in the supplementary material [16], which mainly focused on the edge, texture, and color distribution of the images. The 16 photos in Fig. 2 were each divided into 100 parts, by dividing the image into 10 vertical and 10 horizontal segments, creating a total of 1600 test data. Note that there is no overlap between divided images. From this dataset, 80% of the divided images were randomly selected to train Random Forest learning methods, and the percentage of

correct responses to the remaining 20% was examined using the Random Forest classifier with RandomForestClassifier() function in the “sklearn” library “ensemble” class. We obtained a 91.2% overall accuracy as the output of the “accuracy_score” function in the “sklearn” library “metrics” class for distinguishing C1, C2 from O1, O2. Using the RandomForestRegressor() in the “sklearn” library “ensemble” class, the coefficient of determination was 0.781. The target variable is given as 0: for conventional and 1: for synecological farming plots. Hyperparameters of RandomForestClassifier() and RandomForestRegressor() are specified in the online supplementary material [16].

Next, we examined what features have gained importance with the initial learning step to assess the ecological plausibility. The five most important features with respect to the output “feature_importances_[ ]” of RandomForestRegressor() are listed as follows:

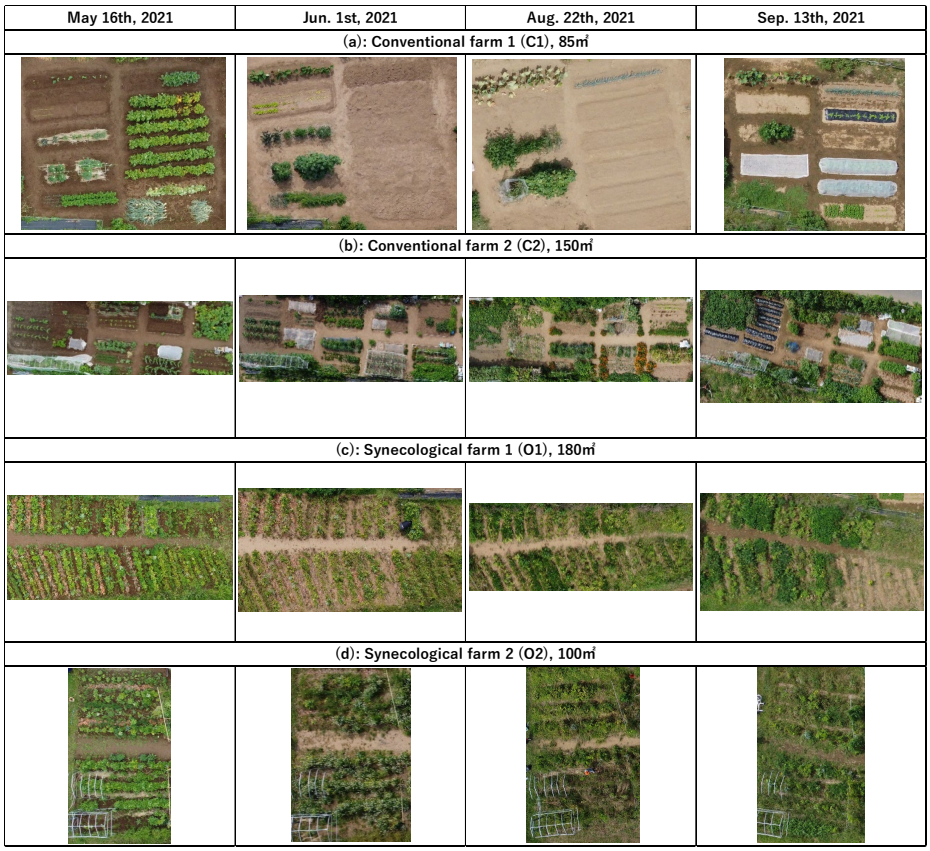

Fig. 2. Top view images of synecological (O) and conventional (C) farms in Oiso. (a): Conventional farm 1 (C1), 85 ㎡. (b): Conventional farm 2 (C2), 150 ㎡. (c): Synecological farm 1 (O1), 180 ㎡. (d): Synecological farm 2 (O2), 100 ㎡.

1. "GLCM1_0 homogeneity," which represents the homogeneity of neighboring pixels
2. "plt_seg_area bmean - rmean," which represents the difference between the mean values of red and blue components of the vegetation area
3. “edge fractal," which represents the fractal dimension of the detected boundaries of the whole image
4. "plt_seg_area hmode - smode," which represents the difference between the mode hue and mode saturation of the vegetation area
5. "plt_seg_area hue median," which represents the median value of the hue of the vegetation area

These indices are related to the complexity of the vegetation shape and the diversity of colors and can be considered as important characteristics to discriminate between conventional and synecological farming, since they may reflect differences in the level of biodiversity.

As a result, if the task is to discriminate between conventional farming and synecological farming as is the case with the certification of the farming method, the classification model is successfully trained with the small data, and the basis of discrimination can be clearly and easily shown as features in image analysis. On the other hand, the generalization capacity and tuning need to be explored to examine the performance of the model in wider and more ambiguous situations. Actually, it is more difficult to find differences that are important for actual human management of synecological farming, such as the difference between O1 and O2, from image analysis alone. It is necessary to search for features that increase the resolution of the model and to provide more teacher data.

4 Integrated modeling of ecosystem management based on inter-subjective objectivity

To construct a model that complements the features of image analysis and the subjective measures of human VAS scores (AS, HP, MG) in a consistent manner, we propose the "Integrated Inter-Subjective Objective Model (ISOM)" (Fig. 3). In this model, even if there is bias or error in a person's subjective evaluation, the image features serve as an objective anchor and can be corrected quantitatively. Furthermore, it is possible to construct an improvement process that cycles between subjective and objective to weight the effectiveness of objective indicators according to a skilled person's subjectivity and to judge the overall effectiveness of the model.

ISOM first takes the feature values obtained from vegetation images of the field and additional information such as weather as objective data, and the human VAS scores (AS, HP, MG) as subjective data, and trains a Random Forest regression model between the two, as schematized in Fig. 3 (a). By looking at the feature importance of the trained model, we can estimate what features the evaluator is potentially utilizing, but we cannot guarantee how reliable this is. Therefore, we use the evaluator's level information (beginner, intermediate, advanced, expert) and weight the reliability with such empirical knowledge by examining the correlation between the level information and feature importance (b). Note that the results can also be interpreted by the nature of the data features to see if empirical knowledge is consistently developed. The

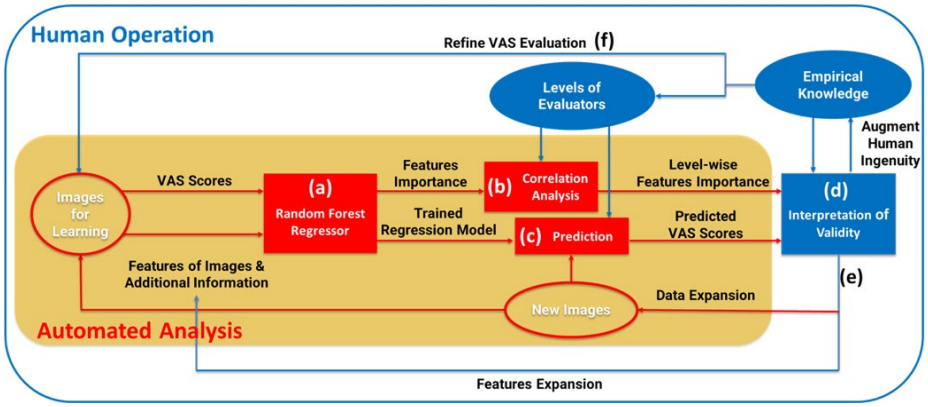

Fig. 3. Integrated Inter-Subjective Objective Model (ISOM). (a, b, c): Learning of and prediction from ISOM. (d, f): Updates of subjective empirical knowledge and VAS methods. (e): Expansion of objective measurement and analytical framework.

trained model can then estimate VAS scores (AS, HP, MG) from those features alone for new field images (and associated weather information) in a way that reflects the evaluator's level (c). The validity of the estimated results is interpreted considering the actual field operation history (d). The findings will suggest the characteristics of the database that should be expanded and new features that should be analyzed (e). It is also expected that human empirical knowledge can be improved by referring to objective indicators, leading to the refinement of the subjective indicators of the VAS method (f). Such an interactive framework between human and image analysis follows the methodology of open systems science [1] and is an attempt to encapsulate the ever-changing complexity inherent in ecosystem management, which cannot be simply addressed with a fixed set of features and/or without the distinction of human competence. At the same time, a practical application such as the certification of the farming method is supposed to assess the field starting from small initial datasets, in many cases without prior knowledge on other practices, which fits the scope of the initial cycle of ISOM. As ISOM develops through the repetition of feedback cycles (a)-(f), the model is expected to acquire more generalization capacity to novel situations.

Examples of actual analyses for farms M and O (defined in sections 2 and 3, respectively) are shown in Fig. 4 and 5, respectively. First, we trained ISOM using 8 people's subjective evaluation of farm M (Table 1) and 26 images (Fig. 1). The same 241-dimensional image features were used as in Section 3, which corresponds to the process of Fig. 3 (a). From the trained ISOM, we obtained an estimated model that approximates the internal model implicitly known by the evaluators in terms of image features (Fig. 3 (b)). By choosing the level of the evaluator we want to approximate and giving arbitrary top view images of vegetation, we can obtain estimates of the three subjective ratings (AS, HP, MG) (Fig. 3 (c)). For the estimated output, the evaluation image was divided into 3x5=15 sections, and the VAS score estimates were smoothly color-coded among the 15 sections. An example is displayed in Fig. 4.

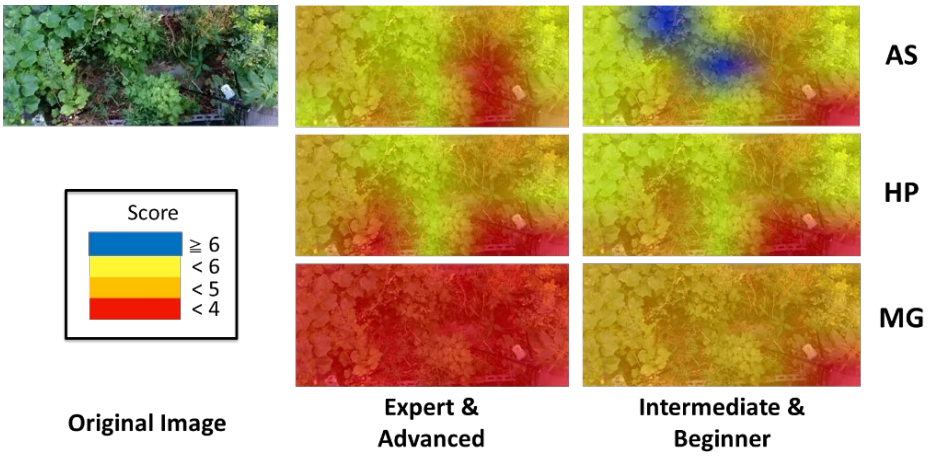

Fig. 4. ISOM outputs of VAS scores prediction (AS, HP, MG) for the evaluation of farm M. The blue-yellow-orange-red color gradient represents the ISOM outputs learned from farm M. Examples based on the picture of Aug. 30th, 2020, in Fig. 1.

The areas of attention and evaluation differ depending on the level of the evaluator. Therefore, we analyzed the importance of image features for each evaluator's regression model, focusing on the degree of topsoil coverage by vegetation ("plt_seg"), which is particularly important for synecological farming. The average importance of "plt_seg" in the regression model trained on AS was 0.036 for expert and advanced, 0.166 for intermediates, and 0.179 for beginners. In the regression model trained on HP, expert and advanced were 0.052, intermediates were 0.116, and beginners were 0.091. In the regression model trained on MGs, the importance scores were 0.002 for expert and advanced, 0.008 for intermediates, and 0.209 for beginners. Overall, the importance of topsoil coverage in the VAS evaluation tends to decrease with years of experience in farming.

Next, to examine the degree of dependence on features other than topsoil coverage, we examined the standard deviations of the top five feature importance values comprising the learned regression models. If the standard deviation is high, the evaluator relies on specific features and tends to ignore the others, while if low, the evaluation equally refers to all five features. The standard deviations for the regression model trained on AS were 0.018 for expert and advanced, 0.053 for intermediates, and 0.55 for beginners. For the regression model trained on HP, the standard deviations were 0.014 for expert and advanced, 0.027 for intermediates, and 0.027 for beginners. For the regression model trained on MG, the standard deviations were 0.025 for expert and advanced, 0.118 for intermediates, and 0.096 for beginners. Overall, the standard deviations of the five highest feature importance values tended to be higher with years of farming experience, with the five features supporting the decision more evenly.

These results suggest that beginners rely more on easily discernible indicators such as the degree of topsoil cover to make their evaluations, and that the others potentially synthesize other diverse characteristics such as temporal development of images and the forms of vegetation according to the post-survey interview, to make judgments as their years of experience progress. This is qualitatively consistent with the process of

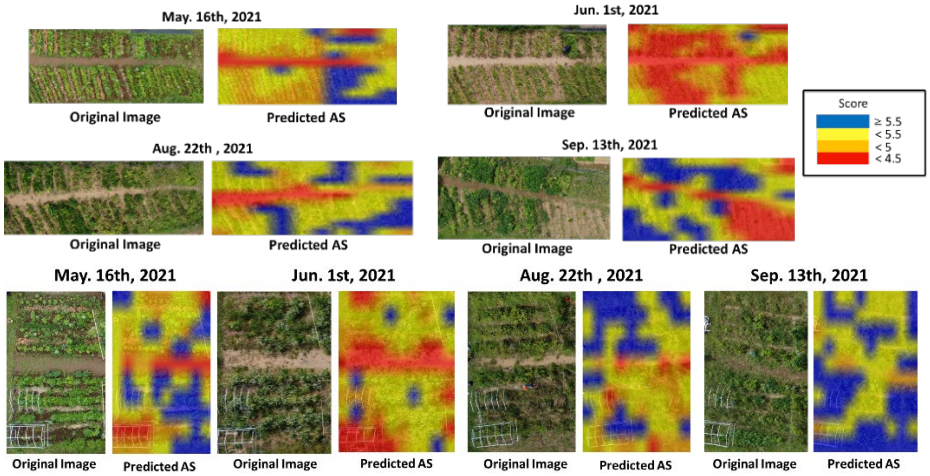

Fig. 5. ISOM outputs of VAS scores prediction (examples of AS) for the evaluation of farm O1 (Top) and O2 (Bottom). The blue-yellow-orange-red color gradient represents the ISOM outputs learned from farm M with 8 evaluators. The red-dominant VAS prediction of Jun. 1st seems to capture the effects of drought in O1. Examples based on the pictures in Fig. 2 (c, d).

deepening experiential knowledge of managing ecosystems by considering their diverse relationships in a holistic manner [9], which contributes to (d).

The ISOM learned in farm M was further applied to a larger-scale farm O (Fig. 5). VAS scores (AS, HP, MG) were estimated for each model on top view images taken by drones in two areas: O2, where there is a full-time manager and sufficient seed input and management, and O1, where the amount of seed input and management is about half that of O2. Farm O1 is about 45 times larger and O2 is 25 times larger than farm M to investigate the effectiveness of the model concerning the scale difference. As a general result, the predicted VAS scores showed general superiority in O2 compared to O1. We referred to meteorological data and management information for the field to further assess the validity of the estimation results. One meteorological feature was zero precipitation for the 5 days prior to the observation on June 1, 2021 (data not shown). As a result, fields were dry and growth was poor in O1 than O2 with low seed introduction and management frequency; ISOM predicted worse field conditions on O1 for all indicators AS, HP, and MG for the Jun 1st, 2021, image which was consistent with actual observations of managers.

As a subsequent effect of drought, useful plants declined, and weeds became dominant in O1 during the summer months of August and September. However, the ISOM output estimated higher VAS scores where weeds dominated and did not seem to be able to determine crop growth status. To improve this, it may be necessary to consider further incorporation of features related to the number of crop species and their coverage. In fact, we tentatively trained ISOM on farm M and O images with the number of crop species as additional information and were able to estimate the number of useful plant species with an estimation error of 20% and a coefficient of determination of 0.87 for the farm O input images, which were chosen differently from the training data (results not shown).

These processes are consistent with the dynamical assessment of ecosystems based on open systems science [4] [14] and the methodology for capturing significant changes in dynamically changing vegetation succession [3]. In other words, the model is open to constant updating to become more effective as the surrounding environment changes, such as climate change, and as managers' empirical knowledge evolves.

5 Interfaces for collaborative robotics

In Table 1, the group that averaged beginners and intermediate members had a higher correlation with the VAS ratings of AS and HP by an expert than an advanced member. Also, a group averaging one advanced member, intermediates, and beginners showed greater correlation with an expert on AS, HP, and averaged scores of the three VAS measures than did an advanced member alone. This suggests that the development of collective knowledge might be more effective in managing synecological farming than the deepening of individual experiential knowledge. More generally, it may be possible that supporting group consensus may be more effective than individual capacity building in overcoming the difficulties of managing complex ecosystems in agroecology. Additionally, in determining whether a field meets the criteria for certification of synecological farming, quality could be assured not only using objective data but also through a combination of inter-subjective review systems by multiple evaluators. In particular, the time scale of the referenced features extends as the level of the evaluator increases to advanced or expert, which is consistent with empirical knowledge where perceptions evolve to include the history of ecological development.

To assist in this cycle of synergistic enhancement of collective and individual experiential knowledge, we considered an interface that provides feedback of the VAS score predicted from ISOM to the individual VAS score (Fig. 6). In this way, the evaluator can recognize under what circumstances his or her VAS evaluation deviates from the VAS estimation by the ISOM that mimics collective knowledge and can learn what new features to pay attention to by examining the image features that contribute to the difference.

The formation of collective knowledge is expected to develop on a larger scale through automation using robotics. Even for complex ecosystems such as synecological farming, robotic management techniques are being developed for areas where vegetation is restricted to a certain height, such as the space under solar panels [12]. Capturing and processing images in conjunction with robotics can scale up the processes (a), (b), (c), and (e) in Fig. 3, and with humans contributing even more deeply to (d) and (f), the development of synergy between human empirical knowledge and robot performance can be expected.

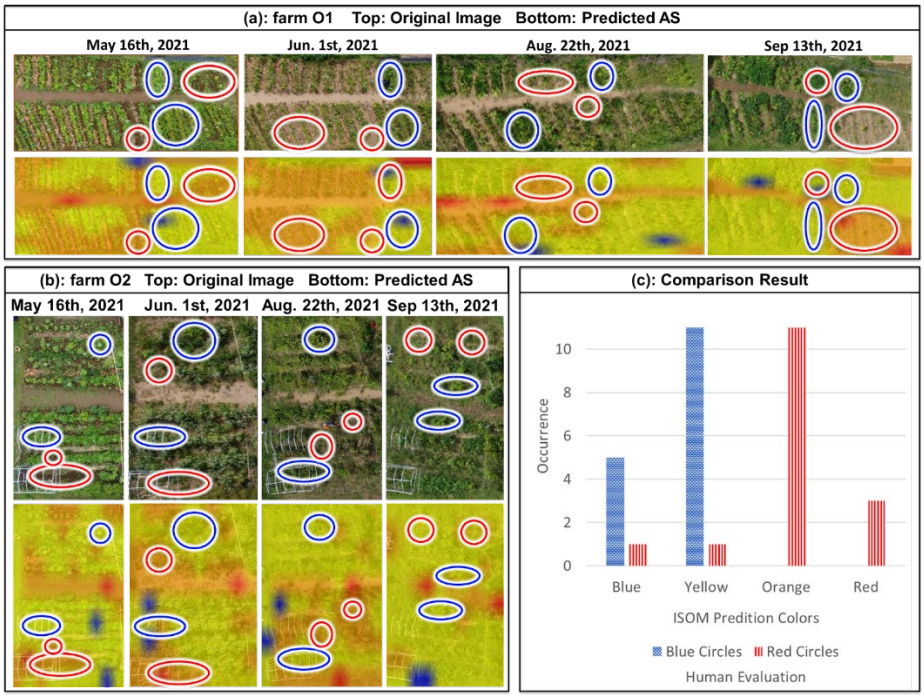

Fig. 6. Estimation of VAS scores on farm O with ISOM learned on farm M and feedback to human evaluation. Prediction of VAS scores (AS, HP, MG) with ISOM learned from the subjective evaluation of 8 evaluators on farm M (the same model as in Fig. 5) are shown with different colormaps in (a): farm O1 and (b): farm O2. The color gradient was adjusted to create two blue and two red areas in each image and is different from Fig. 5. Additionally, an evaluator of intermediate level separately evaluated these images by marking two highest and lowest areas of arbitrary size with blue and red circles, respectively. The number of agreements between the prediction with ISOM (blue, yellow, orange, and red areas) and the human evaluation (blue and red circles) is shown in (c).

6 Conclusions

In this paper, we proposed a model (ISOM) to connect features of image analysis and human evaluation in a consistent manner, using an example of ecosystem management in synecological farming to detect the information necessary for sustainable management of highly diverse ecosystems. ISOM combines subjective and objective indicators in a complementary manner, enabling the mutual evaluation between the development of empirical knowledge and its objective support. Through the analysis, the open-ended development cycles between human ecological discernment and the discovery and expansion of effective features were suggested, in which interfaces for effective sharing and utilization of collective knowledge and an automatic data expansion process using robotics would help scale-up.

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References

1. Tokoro M.: Open Systems Science: A Challenge to Open Systems Problems. in: First Complex Systems Digital Campus World E-Conference 2015, Springer Proceedings in Complexity, pp. 213–221 (2017).
2. Funabashi M.: Human augmentation of ecosystems: objectives for food production and science by 2045. npj Science of Food, vol. 2(16) (2018).
3. Ohta K., Suzuki G., Miyazawa K., Funabashi M.: Open systems navigation based on system-level difference analysis - Case studies with urban augmented ecosystems. Measurement: Sensors, vol. 23 (2022).
4. Funabashi M., Minami T.: Dynamical assessment of aboveground and underground biodiversity with supportive AI. Measurement: Sensors 18, 100167 (2021).
5. Funabashi, M.: Augmentation of Plant Genetic Diversity in Synecoculture: Theory and Practice in Temperate and Tropical Zones. in the book: D. Nandwani (Ed.) Genetic Diversity in Horticultural Plants, Sustainable Development and Biodiversity 22, Springer Nature Switzerland AG 2019 (2019).
6. iNaturalist Homepage, https://www.inaturalist.org/, last accessed 2023/3/4.
7. SEED Biocomplexity Homepage, https://seed-index.com/, last accessed 2023/3/4.
8. Funabashi M.: Synecological farming: Theoretical foundation on biodiversity responses of plant communities. Plant Biotechnology, special issue plants environmental responses, Volume 33(4), Pages 213-234 (2016).
9. Funabashi M.: (Eds) Synecoculture manual 2016 version (English Version). Research and education material of UniTwin UNESCO Complex Systems Digital Campus, e-laboratory: Open Systems Exploration for Ecosystems Leveraging, vol. 2 (2016).
10. Soya K., Aotake S., et al.: Study of a Method for Detecting Dominant Vegetation in a Field from RGB Images Using Deep Learning in Synecoculture Environment. Proceedings of the 49th Annual Meeting of the Institute of Image Electronics Engineers of Japan (2021).
11. Yoshizaki R., Aotake S., et al.: Study of a Method for Recognizing Field Covering Situation by Applying Semantic Segmentation to RGB Images in Synecoculture Environment. Proceedings of the 49th Annual Meeting of the Institute of Image Electronics Engineers of Japan (2021).
12. Otani T., Aotake S., et al.: Agricultural Robot under Solar Panels for Sowing, Pruning, and Harvesting in a Synecoculture Environment. Agriculture, 13(1), 18 (2023).
13. Funabashi M.: Citizen Science and Topology of Mind: Complexity, Computation and Criticality in Data-Driven Exploration of Open Complex Systems, Entropy 19(4), 181 (2017).

14. Funabashi M.: Open systems exploration: an example with ecosystems management. in: First Complex Systems Digital Campus World E-Conference 2015, Springer Proceedings in Complexity, pp. 223–243 (2017).
15. Reips U., Funke F. : Interval-level measurement with visual analogue scales in Internet-based research: VAS Generator. Behavior Research Methods, 40(3), pp. 699-704 (2008).
16. Online supplementary material web link: https://www2.sonycsl.co.jp/person/masa_funabashi/public/20230418_CCE23_Online%20Supplementary%20Material_v-final.xlsx