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Empowering and Assessing the Utility of Large Language Models in Crop Science

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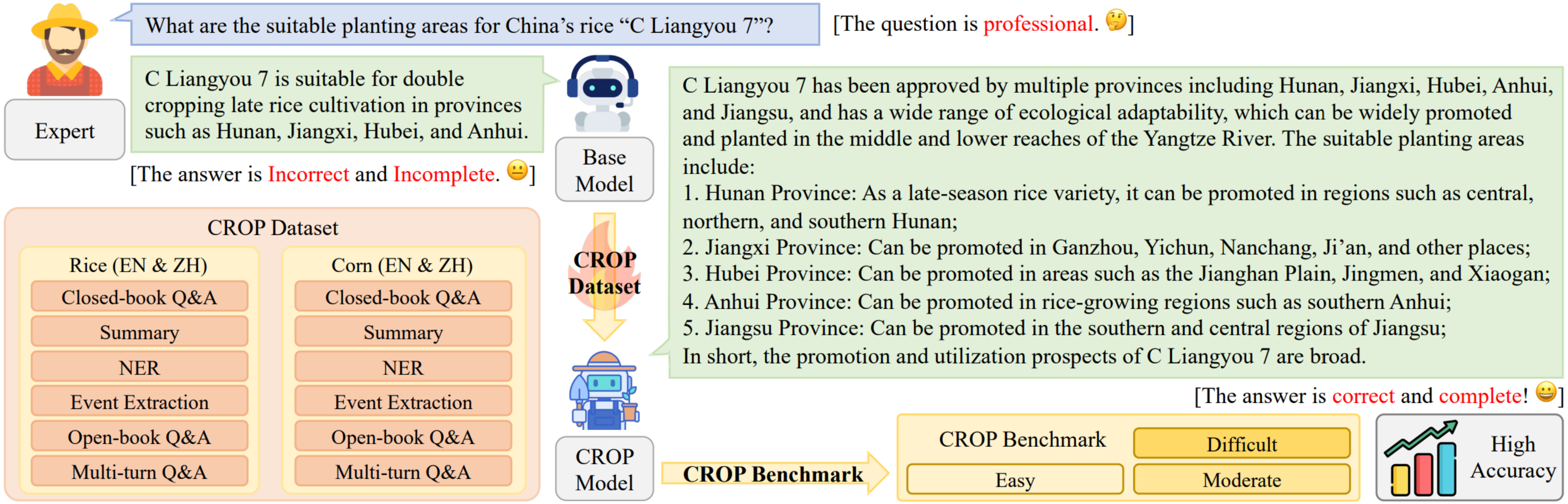
Motivation for the CROP

- Crop cultivation has historically been a significant challenge, with uncertainties in harvest yields due to factors like weather and pest diseases. These issues can lead to reduced agricultural output and food shortages.

- Large language models (LLMs) can generate professional knowledge and context in response to user inquiries, finding applications in various fields such as legal consulting and clinical management.

- However, LLMs currently face limitations in specific areas, such as pest management, and the existing datasets for agricultural evaluation are insufficient in quantity and locality.



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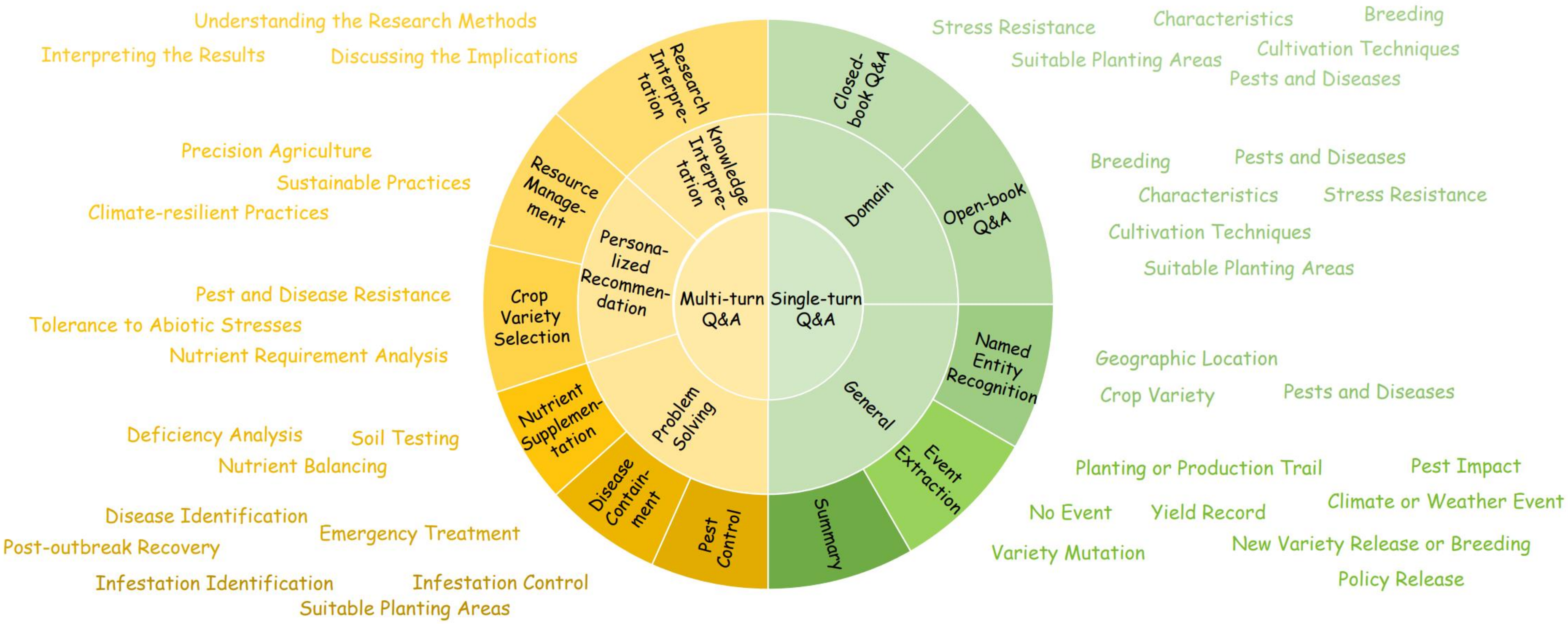
Overview of the CROP

To harness the full potential of LLMs for crop science, we propose a suite called CROP, which encompasses

- an extensive instruction tuning dataset, designed to enhance the domain-specific proficiency of LLMs in crop science.
- a meticulously constructed benchmark, aimed at assessing the performance of LLMs across a variety of domain-related tasks.



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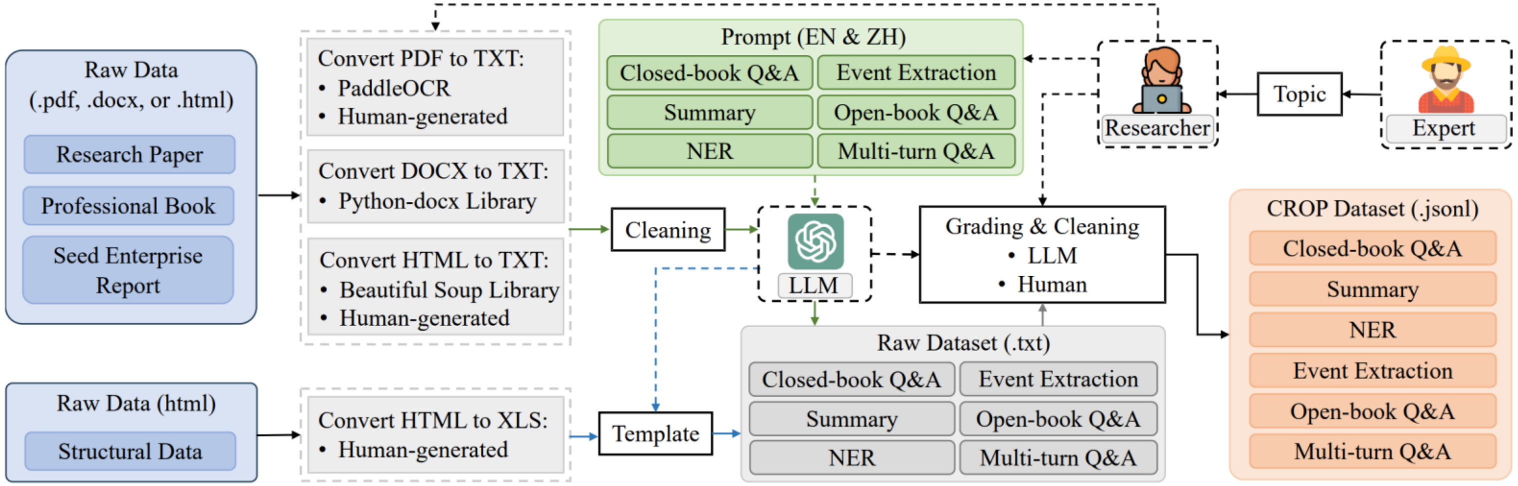
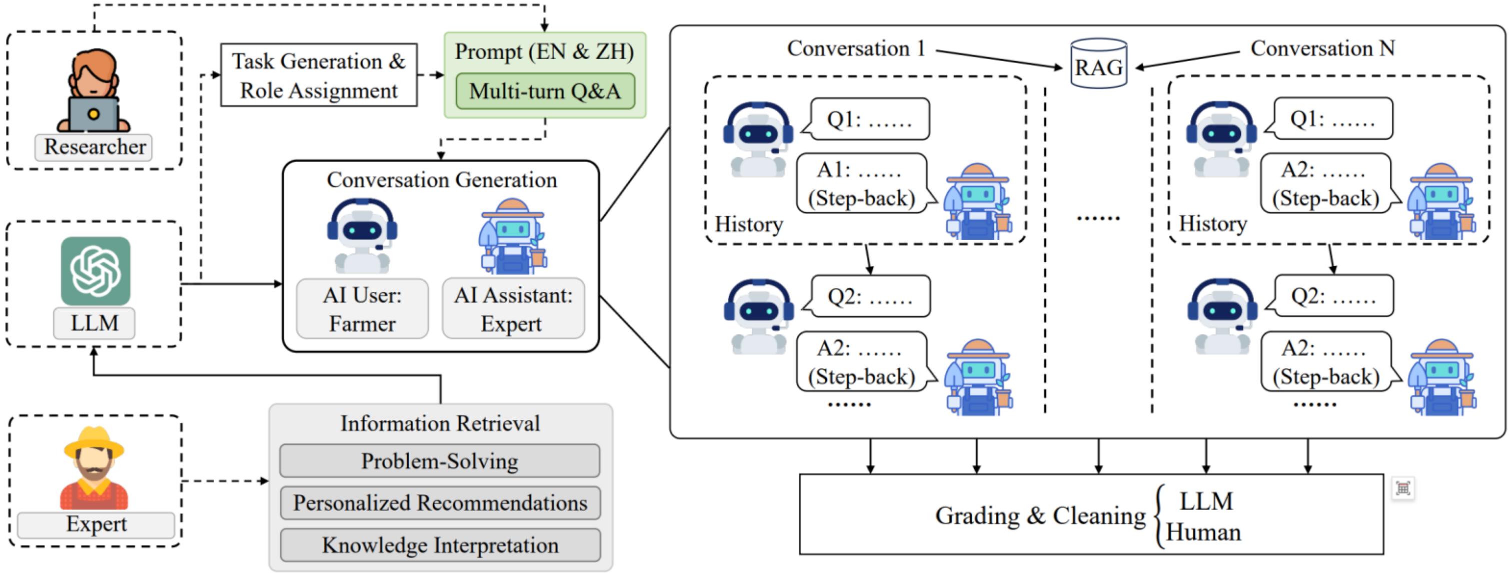
CROP Dataset Collection

- Raw data is first converted to TXT or XLS format using text extraction tools.
- Prompt an LLM to either generate Q&As from unstructured data or design templates that transform structured data into dialogue format.
- Filtering steps with both human and LLM involved.



Schematic overview of the dialogue collection procedure

- An LLM creates tasks under the guidance of domain experts and assigns roles to two agents.
- Using task-dependent prompts from researchers, the LLM generates dialogues with RAG.
- Filtering steps.



Schematic overview of the multi-turn dialogue dataset collection procedure

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CROP Dataset Analysis

- The single-turn dialogues comprise 210,038 high-quality samples.
- It contains 140,056 dialogue samples for rice and 69,482 for corn.

Cereal	Type	Task	Abbr.	English Q&A	Chinese Q&A	Total
Rice	Domain	Closed-book Q&A	CQA	42,951	83,396	126,347
		Open-book Q&A	OQA	2,430	2,037	4,467
	General	Event Extraction	EE	1,891	1,030	9,742
		Named Entity Recognition	NER	2,003	1,604	
		Summary	Summary	1,586	1,628	
Corn	Domain	Closed-book Q&A	CQA	25,259	27,667	52,926
		Open-book Q&A	OQA	3,202	3,047	6,249
	General	Event Extraction	EE	2,245	1,322	10,307
		Named Entity Recognition	NER	2,008	1,316	
		Summary	Summary	1,559	1,857	
Others*			—			<1000
Overall		—		85,134	124,904	**210,038**

Composition of single-turn dialogues

- The multi-turn dialogues include 1,871 high-quality samples.
- Each task within the multi-turn dialogues possesses a minimum of 80 samples.

Cereal	Scenario	Task	English Q&A	Chinese Q&A	Total
Rice	Problem Solving	Pest Control	14+71	8+37	130
		Nutrient Supplementation	19+93	2+ 90+ 1	205
		Disease Containment	19+ 60	4+ 39	122
	Personalized Recommendation	Crop Variety Selection	12+ 53	9+ 9	83
		Resource Management	4+ 110+ 1	5+ 50	170
	Knowledge Interpretation	Research Interpretation	3+ 125+ 1	8+ 85	222
Corn	Problem Solving	Pest Control	20+ 84	7+ 77	188
		Nutrient Supplementation	24+ 56	8+ 30	118
		Disease Containment	21+ 64	2+ 19+ 1	107
	Personalized Recommendation	Crop Variety Selection	19+ 75	46+ 47	187
		Resource Management	8+ 94	1+ 69	172
	Knowledge Interpretation	Research Interpretation	5+ 94+1	6+ 61	167
Overall	—		1,150	721	**1,871**

Composition of multi-turn dialogues

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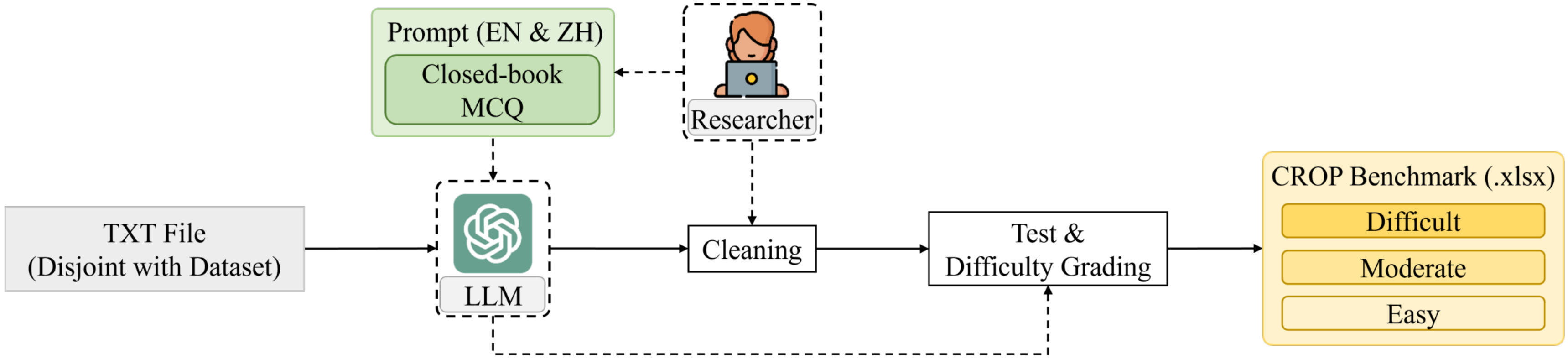
CROP Benchmark Collection

- We prompt an LLM to generate MCQs from TXT files. After additional filtering steps with both human and LLM involved, we get the CROP benchmark, comprising three difficulty levels.



- We classify the 5,045 questions in the benchmark into three difficulty levels: easy, moderate, and difficult.

Level	Count	Proportion
Easy	1,613	31.97%
Moderate	2,754	53.72%
Difficult	722	14.31%

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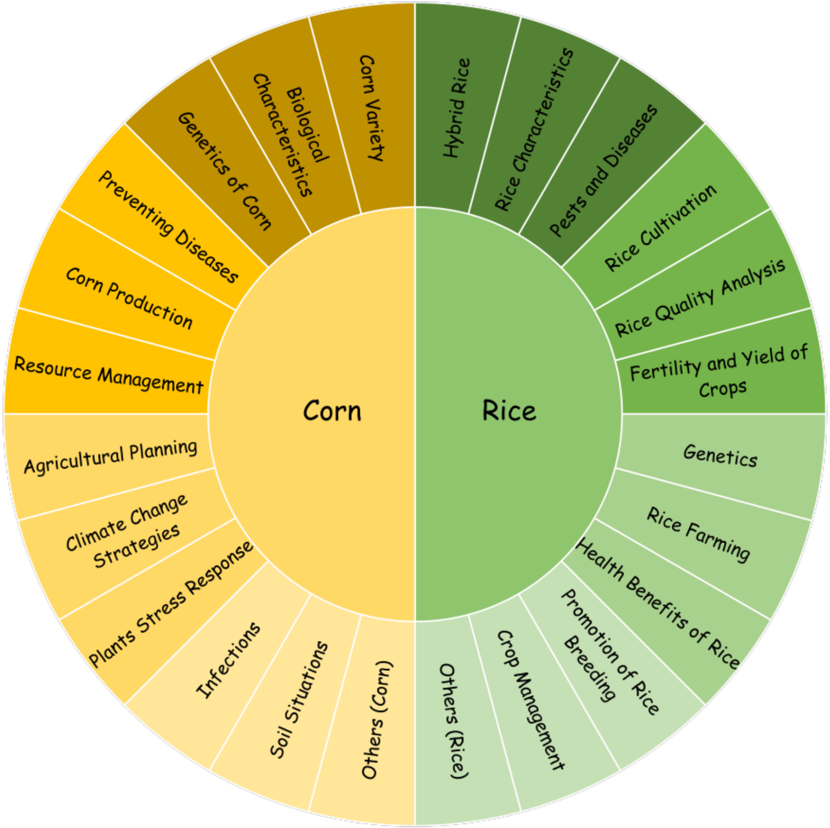
CROP Benchmark Analysis



- For corn-related MCQs, the most frequently occurring topics are corn variety, biological characteristics, and genetics of corn.
- For rice-related MCQs, the most frequently occurring topics are hybrid rice, rice characteristics, pests, and diseases.

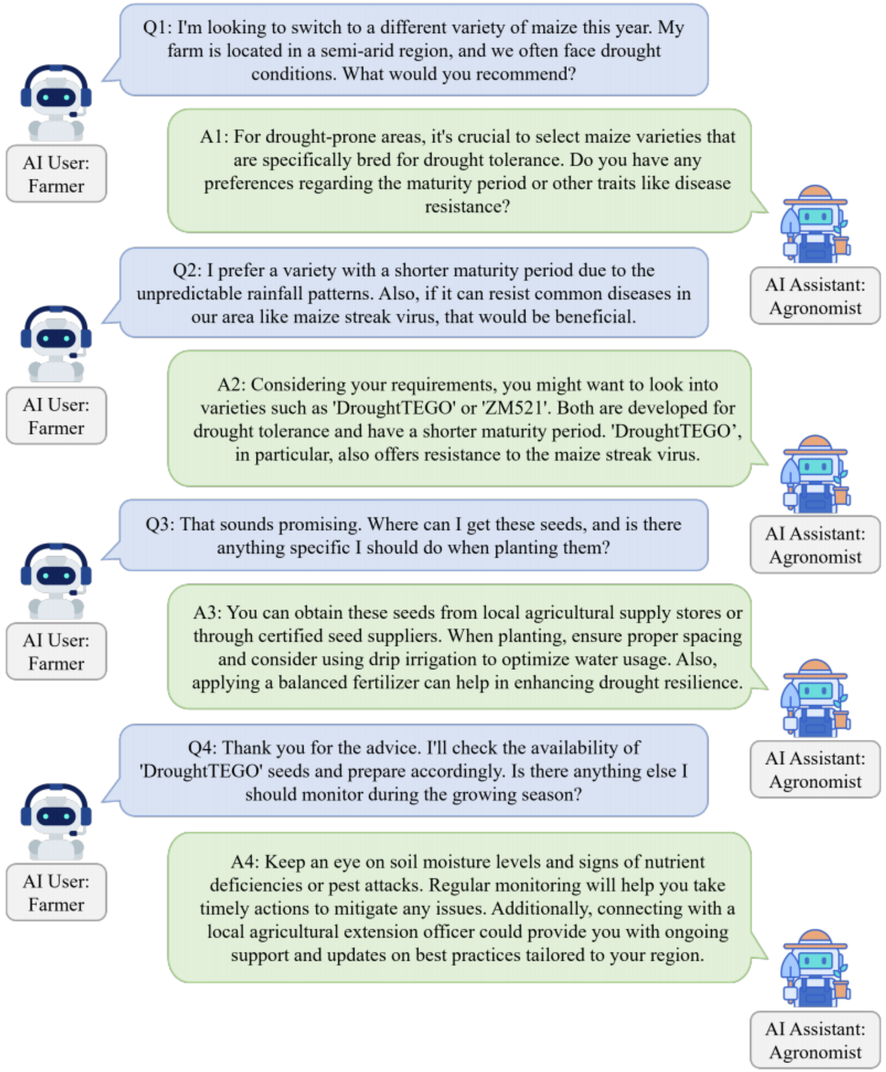
- CROP benchmark consists of 5045 Chinese and English MCQs and covers 22 countries across six continents.

Dataset	Language	Format	Size	Region
Certified Crop Advisor (CCA) Exam[1]	English	MCQs	312	United States
EMBRAPA[2]	Portuguese	Test-based Inquires	1,000	Brazil
AgriExams[3]	English	MCQs	1,723	India
CROP (Ours)	English & Chinese	MCQs	5,045	22 Countries

Examples in CROP

Problem-solving Scenario

Personalized Recommendation Scenario



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Experiments

- The performance of selected LLMs on the CROP benchmark.
- GPT-4, Claude-3, and Qwen struggle with difficult tasks, demonstrating the rationality of difficulty level division and the efficacy of the CROP benchmark.
- The findings indicate that when further fine-tuned with the CROP dataset, there is an average improvement of 9.2%.

Model	Access	Size	Overall ↑	Difficulty		
				Easy ↑	Moderate ↑	Difficult ↑
Commercial LLMs						
GPT-4[1]	API	N/A	0.856	1.000[2]	1.000[2]	0.000[2]
GPT-3.5[1]	API	N/A	0.328	1.000[2]	0.000[2]	0.061
Claude-3[1]	API	N/A	0.900	0.982	0.968	0.458
Qwen[1]	API	N/A	0.866	0.987	0.945	0.301
Open-source LLMs						
LLaMA3-Base	Weights	8B	0.348	0.443	0.341	0.161
+CQIA	Weights	8B	0.643 (+0.295)	0.791 (+0.348)	0.651 (+0.310)	0.281 (+0.120)
+CROP	Weights	8B	0.752 (+0.404)	0.866 (+0.432)	0.772 (+0.431	0.378 (+0.217)
+CQIA+CROP	Weights	8B	0.754 (+0.406)	0.918 (+0.475)	0.779 (+0.438)	0.295 (+0.134)
Qwen1.5-Base	Weights	7B	0.646	0.799	0.646	0.302
+CQIA	Weights	7B	0.688 (+0.042)	0.880 (+0.081)	0.689 (+0.043)	0.258 (-0.044)
+CROP	Weights	7B	0.676 (+0.030)	0.849 (+0.050)	0.688 (+0.042)	0.202 (-0.100)
+CQIA+CROP	Weights	7B	0.709 (+0.063)	0.910 (+0.111)	0.704 (+0.058)	0.227 (-0.075)
InternLM2-Base	Weights	7B	0.368	0.445	0.381	0.148
+CQIA	Weights	7B	0.723 (+0.355)	0.861 (+0.416)	0.750 (+0.369)	0.317 (+0.169)
+CROP	Weights	7B	0.748 (+0.380)	0.945 (+0.500)	0.761 (+0.380)	0.212 (+0.064)
+CQIA+CROP	Weights	7B	0.768 (+0.400)	0.939 (+0.494)	0.794 (+0.413)	0.285 (+0.137)

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Experiments

- The performance of fine-tuned LLMs under different training epochs and languages.
- Different open-source LLMs show distinct convergence tendencies.
- After four epochs of training, models did not exhibit a remarkable language bias. Results underscore the robustness of the model in multilingual contexts, ensuring its applicability in diverse linguistic scenarios.

Model	Epoch	Size	Overall ↑	Difficulty			Language		
				Easy ↑	Moderate ↑	Difficult ↑	Chinese ↑	English ↑	Variation ↓
LLaMA3-Base	N/A	8B	0.348	0.443	0.341	0.161	0.327	0.369	4.2%
+CQIA+CROP	1	8B	0.738	0.903	0.758	0.292	0.719	0.757	3.8%
+CQIA+CROP	2	8B	0.742	0.902	0.772	0.271	0.729	0.755	**2.6%**
+CQIA+CROP	4	8B	**0.754**	**0.918**	**0.779**	**0.295**	**0.738**	**0.770**	3.2%
Qwen1.5-Base	N/A	7B	0.646	0.799	0.646	**0.302**	0.667	0.624	4.3%
+CQIA+CROP	1	7B	0.702	**0.910**	**0.717**	0.183	**0.725**	0.680	4.5%
+CQIA+CROP	2	7B	0.670	0.875	0.677	0.181	0.690	0.649	4.1%
+CQIA+CROP	4	7B	**0.709**	**0.910**	0.704	0.227	0.717	**0.686**	**3.1%**
InternLM2-Base	N/A	7B	0.368	0.445	0.381	0.148	0.409	0.327	8.2%
+CQIA+CROP	1	7B	0.764	**0.942**	0.787	0.276	0.770	0.757	3.3%
+CQIA+CROP	2	7B	**0.809**	0.909	**0.855**	**0.414**	**0.811**	**0.807**	**0.4%**
+CQIA+CROP	4	7B	0.768	0.939	0.794	0.285	0.770	0.766	**0.4%**

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Conclusions

- We propose the CROP dataset to improve the professional capabilities of LLMs in the crop science domain.
- We introduce the CROP benchmark to compensate for the absence of an open-source benchmark for evaluating models' expertise in this domain, which comprises MCQs for objective assessment.
- We hope that the proposed dataset and benchmark can foster AI research in crop science, facilitate knowledge transfer for agricultural practitioners, enhance crop yields, and contribute to solving hunger issues.