Федеральное министерство продовольствия и сельского хозяйства

оказывает содействие в соответствии с постановлением Германского Бундестага

Deutsch-Kasachischer Agrarpolitischer Dialog
Германо-Казахстанский аграрно-политический диалог

AFC
AGRICULTURE & FINANCE CONSULTANTS

Agriculture & Finance Consultants

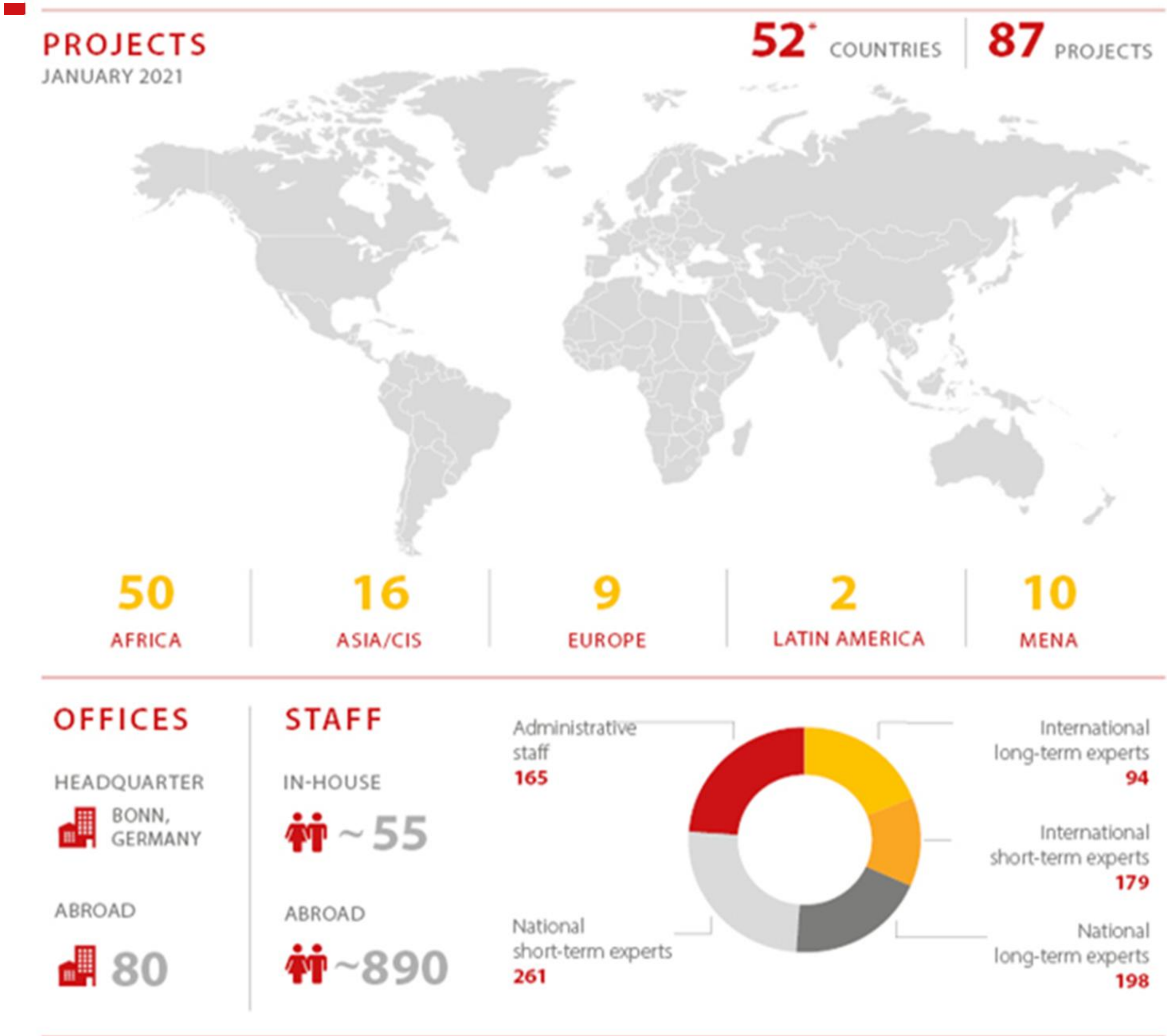
Эффективные методы для оценки кредитоспосособности клиентов на основе применения скоринговой модели

Dean Caire, CFA

29/11/2023

About AFC

AFC
AGRICULTURE & FINANCE CONSULTANTS



Our services

AGRICULTURE & FINANCE CONSULTANTS

FINANCIAL SECTOR DEVELOPMENT

- Micro and SME Finance
- Financial Institutions Development
- Agriculture & Value Chain Finance
- Green Finance
- Insurance Systems
- Financial Literacy
- Banking Regulations & Supervision
- Digital Finance
- Housing Finance

AGRICULTURE & AGRIBUSINESS

- Crop & Livestock Production
- Food Security & Nutrition
- Policy Advice
- Value Chain Approach
- Climate Smart Agriculture
- Food Safety
- Public Private Partnership
- Marketing & Trade
- ICT in Agriculture

CV – Dean Caire, CFA

- 20+ years of international experience.
- in 60+ countries on hundreds of scorecards for retail lending in the following segments:
  - consumer, credit card
  - Microfinance
  - mobile banking
  - small and micro business
  - agricultural inputs lending and equipment leasing.
- Done research in use of alternative data for credit scoring and has contributed to recent World Bank Group publications on digital financial services and data-driven business analytics.

How does credit scoring work?

Given historical data | If right now | The future

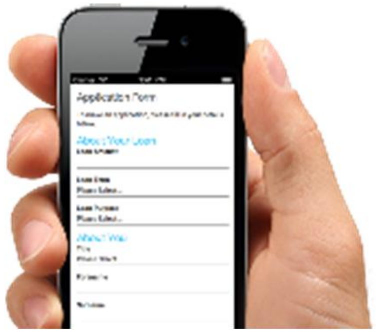
Given historical data

Borrowers with certain characteristics

Had an observed loan repayment behaviour

If right now

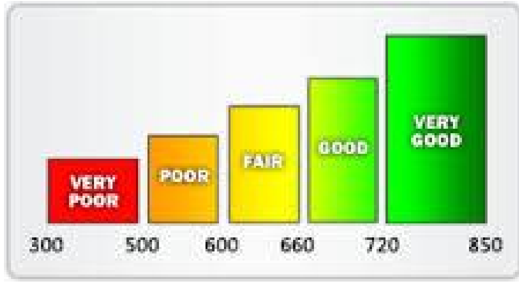
We obtain the same characteristics about a potential Borrower



We can compute a numeric indication of

The future

Possible/expected Loan repayment behaviour or ranking



Of potential borrowers now/future who have similar characteristics

Data sources

- "Borrower characteristics" (input data) and "observed loan repayment behaviour" (target data) is required to create a credit scoring model
- Once model is created, same input data can be used to compute/predict "future loan repayment behaviour"
- But where does this data come from?

INTERNAL

- Credit application form/questionnaire
- Required application documents
- Historical use of (your) financial services

EXTERNAL

- Credit Reference Bureaus
- Partners e.g. Mobile Network Operators, PSP
- Social networks
- Government agencies

Traditional Full Agri-Loan Analysis

- Кредитная история
- история полей
- нормы расхода
- Себестоимость
- Баланс зерна
- Сыбага, Кулан, жив-во
- Financial Statement information

Scoring-based Agri-Loan Analysis

- Parametarize and collect “key” data points
- Compare farm activity data with regional benchmarks
- Minimize qualitative judgment
- Find quantitative, objective measures to ‘proxy’ for opinions
- Create a “comprehensive risk profile” of the farmer

What to Measure?

1. Financial Ability to Repay
    - Cash flow from farming activity
    - Farm assets and liabilities
2. Willingness to Repay
    - Track record (years in business, years planting crop to be financed)
    - Credit history
    - Business and/or owner personal characteristics (legal form of business, number of business partners, owner's personal credit score)

Scorecard Segmentation

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Segmentation

By Value-Chain	By Legal Type	By Product
Cocoa	Small holder	Input loans
Coffee	Larger entity	Equipment leasing
Cotton		Education Loans
Vanilla		Consumption loans
Rice		

Data Sources

- Field agents and value chain [Anchor/ Buyer]
- Collected by loan officers and third parties (i.e. coops)
- Self-reported application data; bureaus, alternative data

Credit Scorecard ‘accuracy’ is a function of the data available

Answer the key questions:

- To whom do we want to lend to?
- What data is possible to obtain consistently about/from such clients?
- How will each field of data be obtained (at what cost)?
- What data is verifiable?
- Can we get this data **and past loan repayment data** for target clients?

What Data is Best for Scoring Models?

"Digital Credit Scoring in Agriculture: Best Practices of Assessing Credit Risks in Value Chains"; Sponsored by SAFIRA and Grow Asia with support of the Australian Government Department of Foreign Affairs and Trade, May 2018.
http://exchange.growasia.org/system/files/GA_Digital%20Scoring%20Guide_Double.pdf

Chart 1: Data Set Ranking Table

Data Set Ranking Table	Relevance	Availability	Cost to Lender	Reliability	Predictive Power
Credit History	HIGH	LOW	LOW	HIGH	HIGH
Transaction Records	HIGH	HIGH	LOW	HIGH	HIGH
Agronomic Surveys	HIGH	HIGH	LOW	AVERAGE	AVERAGE
Demographics	AVERAGE	HIGH	LOW	AVERAGE	AVERAGE
Mobile Phone/Wallet	AVERAGE	AVERAGE/LOW	AVERAGE/HIGH	HIGH	HIGH
Psychometrics	AVERAGE/LOW	HIGH	HIGH	LOW	AVERAGE
Social Media	LOW	AVERAGE/LOW	HIGH	LOW	LOW
Satellite	HIGH	AVERAGE/LOW	AVERAGE/HIGH	AVERAGE	LOW

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Data collection by Field Agents

- Survey the farmers (ask questions)
- Measure the farm (with GPS coordinates)
- Photograph the farmer and farm
- Record baseline data on the farm's current practices for fertilization, weeding, pruning, harvesting, rotation, etc.

Data collection external sources

- Remote sensing (Khetscore)
- Third-party data (credit bureau, mobile operators, etc.)
- Other possible sources of alternative data (from ‘data-partners’, data aggregators/vendors)

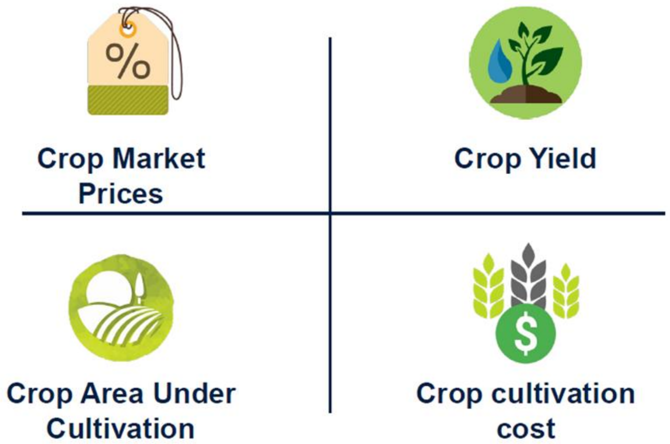
How Agri-Scorecards Work

- Score based on farm/farmer characteristics ranks farmer by risk of non-repayment or late repayment

- Benchmarks are used to calculate estimated cash-flow from agri-activity

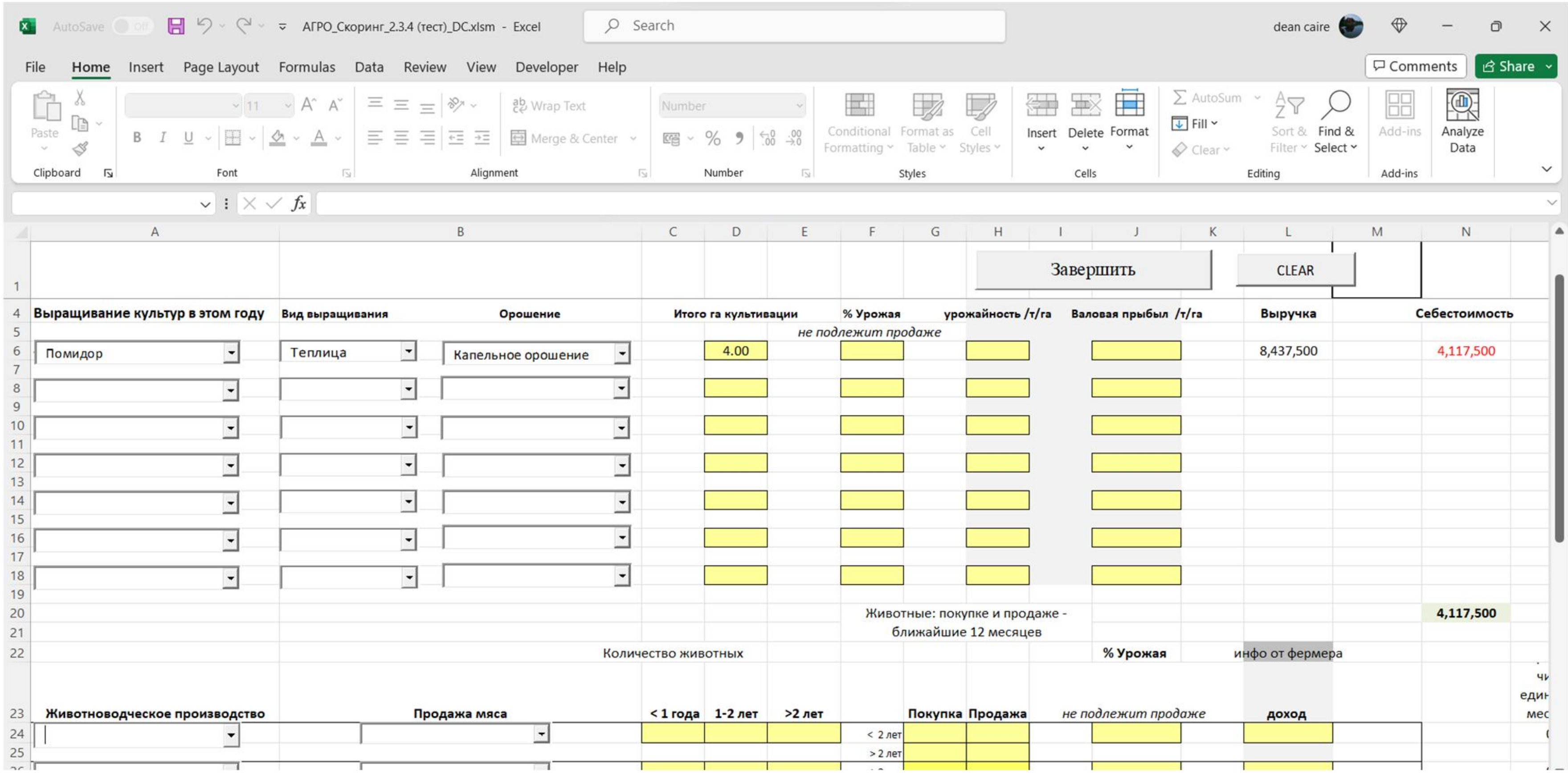
Tableau I: Classification des risques fiche de notation Expert

Groupe à Risque	Points >	Points<=	Total en %	TOTAL	Mauvais	Mauvais Taux	Par tranch
1	385	500	2%	9	1	11%	10,2%
	327	385	13%	67	7	10%	
	294	327	16%	81	8	10%	
2	265	294	17%	88	13	15%	13,7%
	235	265	14%	74	10	14%	
	215	239	13%	65	8	12%	
3	194	215	8%	39	8	21%	14,7%
	165	194	10%	50	7	14%	
	130	165	6%	29	2	7%	
	0	130	2%	11	2	18%	
TOTAL				513	66		



Agri Cash-Flow Calculators

Q: What methods of profitability analysis are used?



Agri Cash-Flow Calculators

Benchmark data are stored in look-up tables

	Av. Yield (t/ha)	Av. Price (LC/t)	Variable costs (LC/ha)	Land Type
Wheat	5	4400	7329	C
Corn	7	4000	8646	C
Rice				C
Barley	5	3400	5568	C
Rye	5	2100	5133	C
Oat	4	3200	3534	C
Potato	27	4500	37511	V
Bean				V
Pea				V
Soybean				C
Sunflower	2.3	8500	8253	C
Rape	3.2	9000	9633	C

Estimated Income (from benchmark) –
Estimated Costs
=
Estimated Cash Flow

How Scorecards Work?

- Scores built up from single characteristics relating farm characteristics to:

Expert Model: Perceived Relationship to Late Repayment Risk

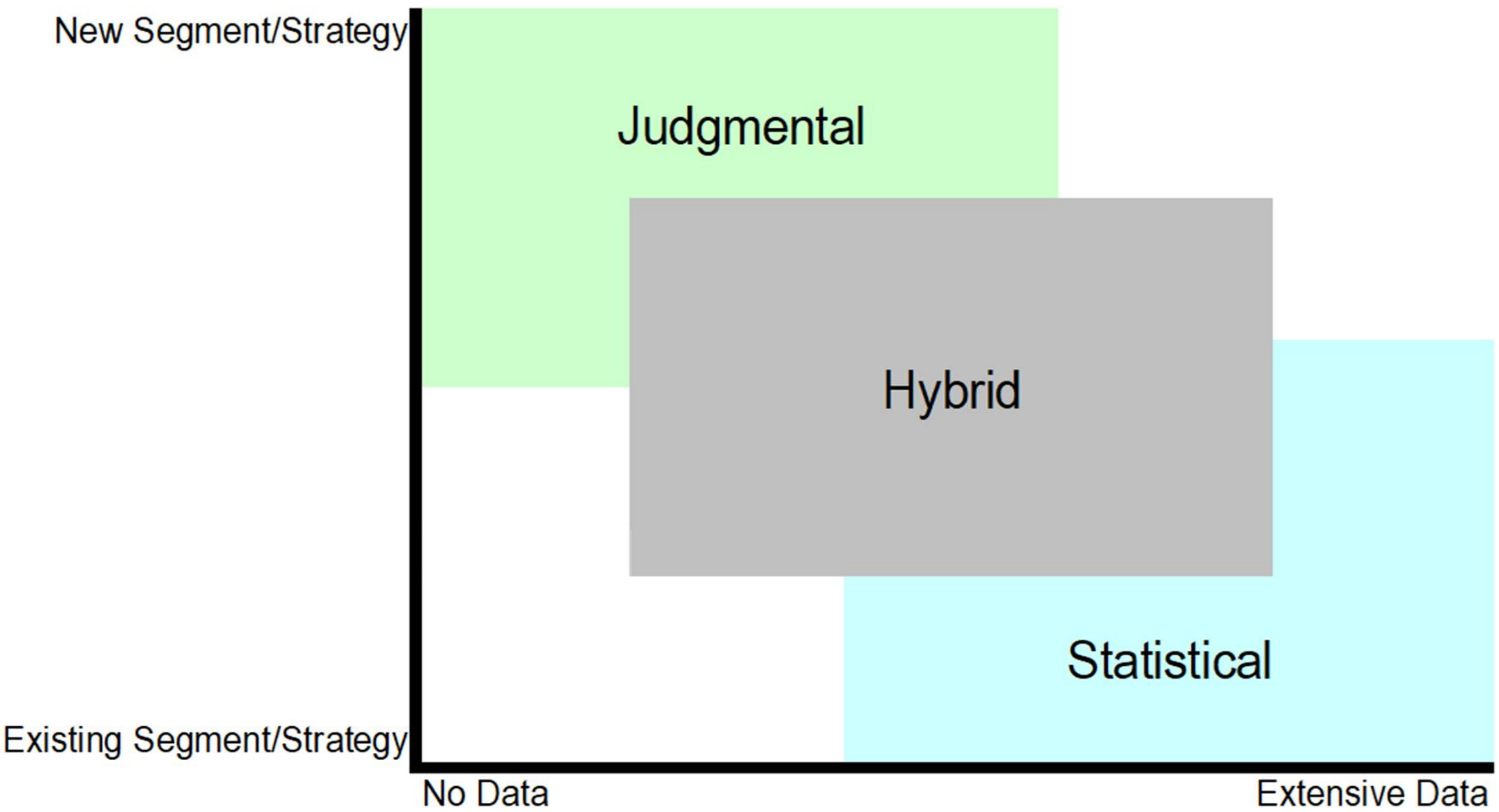
Group	Risk Level	Points
1 crop / source of income	High	0
2 crops / sources of income	Above average	5
3 crops / sources of income	Below average	10
4 crops / sources of income	Low	15

Statistical Model: Observed Relationship to Late Repayment

Group	Default Rate	Points
1 crop / source of income	9%	9-9 = 0
2 crops / sources of income	6%	9-6 = 3
3 crops / sources of income	3%	9-3 = 6
4 crops / sources of income	1%	9-1 = 8

What Type of Scorecard to Develop?

MODEL SELECTION DRIVERS



How a Scorecard Looks?

Ref	Feature	RISK GROUPS	Wgt. Points	MAX
1	Average Amount Sold to Kamapim	< 75 KIN	10	10
		>= 75 KIN & <= 150 KIN	5	
		> 150 KIN	0	
2	Number of Past Orders	1	0	20
		2	10	
		2 or more	20	
3	Quality Score	< 0.33	0	30
		>= 0.33 & <= 0.8	15	
		> 0.8	30	
4	Age	< 30	0	10
		>= 30 & <= 50	5	
		> 50	10	
5	Marital Status	married	30	30
		widowed	30	
		N/A	15	
		divorced	0	
		single	0	
6	Gender	Male	0	10
		Female	10	

Differences: Scoring vs. Rating Models

SCORING	RATING
Small ticket, high volume loans to homogenous pool of borrowers	Larger loans to smaller pool of more complex (heterogenous) borrowers
Objective inputs	Involves subject judgment
Data can be input by anyone based on instructions	Data must be input by analyst with experience and domain knowledge
Output is a score that ranks borrowers by risk	**Output is a score that ranks borrowers by risk**

Key Point Summary: What is Important

- **Whom do we lend to?** This needs to be specific.
- **What data do we have** for that target population?:
  - Historically
  - Going forward
- **Quality of models** will be a function of:
  - quality of **data**
  - how well **we understand what drives credit risk** in the target segment
- **Model management:** who will ‘own’ and manage the model to improve results over time

Uses of Scoring

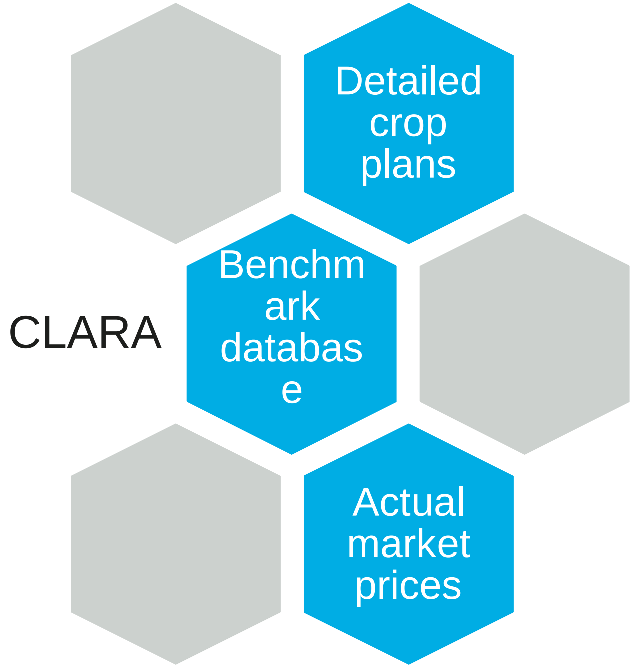
- Decisioning
- Structuring loan terms and conditions based on risk
- Input to provisioning calculations (internal-ratings based approach)
- Risk-based pricing

	SCORES							Target Margin
Risk Group	>	<=	Bad Rate	Amount Lent to Risk Bar	Fee	Interest Margin	Charge Off	Total Gross Margin
1	195	227	0.6%	8,953,748	3.0%	268,612	20,000	248,612
2	182	195	1.0%	17,233,563	3.0%	517,007	145,100	371,907
3	170	182	1.7%	27,292,047	5.0%	1,364,602	558,000	806,602
4	160	170	2.7%	37,349,464	6.0%	2,240,968	1,369,001	871,967
5	146	160	4.9%	58,988,209	7.0%	4,129,175	3,611,300	517,875
6	132	146	6.2%	57,230,890	8.0%	4,578,471	3,916,164	662,307
7	121	132	10.1%	34,807,256	13.0%	4,524,943	4,178,145	346,798
8	106	121	14.2%	30,181,411	20.0%	6,036,282	5,624,184	412,098
9	84	106	24.9%	18,461,182	37.0%	6,830,637	6,414,096	416,541
10	0	84	40.5%	4,112,882	50.0%	2,056,441	3,037,574	-981,133
			8.0%			32,547,139		3,673,575

Cost of funds	0.0%
Overhead cost	0.0%
Economic capital requirement	10.0%
Cost of capital	12.0%
Risk-free rate	1.2%
Cost of Risk	1.0%
Break-even loan price	2.2%

Example of IFC Tool CLARA

- A holistic risk assessment system for banks
- A summary of crop management steps resulting in a monthly cash flow
- Benchmark Cash Flow and Cash Flow forecast
- Provides whole farm analysis
- Limited set of understandable indicators
- Automatized data processing



Adaptation of CLARA by Country

- Adaptation affects the following components:
  - Crop growing plans
  - Norms of use of fertilizers, plant protection chemicals, and seeds
  - Typically used plant protection chemicals, seed varieties
  - Typically used equipment
  - Typical feed ratios for animals
  - Local data provider updates actual market prices on a regular basis

- Ukraine
- Azerbaijan
- Tajikistan
- Uzbekistan
- Kyrgyzstan
- Serbia
- Kosovo

Challenges Faced with CLARA

- Striking the balance between precision and simplicity;
- Finding optimal interface elements that would work best for the majority of users;
- Reflecting the dynamics and variability of agriculture in a robust algorithm and then finding and removing bugs;
- Identifying which of the client requests should and which should not be implemented, and explaining that to clients;

Successes Reported with CLARA

- Bringing NPL in ag-lending down by 2 p.p.
- Increase productivity across the credit process value chain by 30-40%

Questions

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