Stochastic Simulation of Restoration Outcomes of a Dry Afromontane Forest Landscape in Northern Ethiopia

Introduction

Landscapes restoration intervention planners are often faced with the challenge of prioritizing among different interventions to optimize outcomes. This is because landscape restoration outcomes are often achieved through complex mechanisms, and the success of restoration actions is rarely guaranteed, with many uncertainties preventing precise impact prediction (Luedeling et al. 2019). Success is even harder to predict when landscape restoration agencies aim to strengthen restoration efforts indirectly, e.g., by supporting livelihoods and economies of local people as an incentive for them to restore degraded landscapes (Wafula et al. 2018). However, decision support tools that allow for the expression of uncertainty and risks could help to overcome these challenges. For this case study, we used the `decisionSupport` package (Luedeling & Göhring, 2017; Luedeling & Whitney, 2018) to predict the impact of forest Landscape Restoration (FLR) efforts in Tigray, Northern Ethiopia.

1. Description of interventions

To preserve and protect the Desa'a forest, a non-profit organization with support from the Ethiopian government launched a long-term FLR program that proposes investments in a portfolio of scalable environmental and socio-economic interventions. The specific objectives of the program are to (i) restore the degraded forest's biodiversity and enhance ecological integrity (ii) contribute towards meeting the subsistence needs and hence promote economic development and (iii) build the livelihood resilience of communities living within and around the forest. To achieve these objectives, proposed interventions are to be implemented within a zoning framework in a pilot area covering 180 ha of the forest (Fig. 1). Proposed interventions include:

a) Beekeeping intervention The beekeeping intervention would mostly provide supplemental income to reduce pressure on forest resources. The possibility of profits in years when systemic risk events(drought and political unrest) are projected to occur is also used to determine economic resilience of the targeted beneficiaries. We implemented this using the `chance_event` function contained in the `decisionSupport` package. The function randomly simulates annual incidence of events and returns output values accordingly. The outputs can be single values or series of values, with the option of introducing artificial variation into the dataset. We used the code below to model outcomes for beekeeping intervention.

```
# Systemic risk events
drought_event<-rbinom(n_years,1,drought_risk)
unrest_event<-chance_event(chance_civil_unrest,value_if=1,n=n_years)

# Amount of honey produced annually for the duration of the simulation period####
  no_hives_hh<-round(n_hives_per_economic_unit)
  amount_honey_produced<-vv(honey_produced_per_hive,general_CV,n=n_years)*no_hives_hh

  ## Effects of risk events on amount of honey produced####
  honey_loss_drought<-drought_event*vv(loss_due_to_drought,general_CV,n_years)
```

```r
bee_disease_risk<-chance_event(bee_diseases,
                              value_if=loss_due_bee_diseases,
                              value_if_not=0,
                              n=n_years,
                              CV_if=general_CV,
                              CV_if_not=0,
                              one_draw=FALSE)

poor_apiary_mgnt_risk<-chance_event(poor_apiary_management,
                                   value_if=loss_due_poor_apiary_mgnt,
                                   value_if_not=0,
                                   n=n_years,
                                   CV_if=general_CV,
                                   CV_if_not=0,
                                   one_draw=FALSE)

effect_of_honey_risks<-sapply(c(bee_disease_risk+honey_loss_drought+
                               poor_apiary_mgnt_risk),function(x) min(x,1))

n_annual_honey_harvests<-round(n_annual_honey_harvests)
actual_amount_honey_produced<-amount_honey_produced*(1-effect_of_honey_risks)
honey_returns<-actual_amount_honey_produced*vv(price_honey_per_kg,general_CV,n_years)*
               n_annual_honey_harvests
beekeeping_economic_benefits<-honey_returns

## Beekeeping costs####
initial_investment<-c((apiary_establishment_cost), rep(0,n_years-1))
beekeeping_recurring_cost<-(vv(other_bee_costs,general_CV,n_years)+
                            vv(harvest_cost,general_CV,n_years)+
                            vv(transport_cost,general_CV,n_years)+
                            vv((bee_cost_labour_per_season),general_CV,n_years)+
                            vv(hive_maint_mat,general_CV,n_years))*n_annual_honey_harvests
beekeeping_cost<-initial_investment+beekeeping_recurring_cost
beekeeping_profits<-beekeeping_economic_benefits-beekeeping_cost
beekeeping_resilience<-(drought_event+unrest_event)*beekeeping_profits

# Beekeeping project implementation costs####
n_beekeepers_targeted<-round(n_beekeepers_targeted)
project_establishment_costs<-c((cost_of_beehive*no_hives_hh*n_beekeepers_targeted)+
                                (cost_honey_processing_unit*n_beekeepers_targeted/5)+
                                (cost_beekeeper_training*n_beekeepers_targeted)+
                                (cost_farmer_packages*n_beekeepers_targeted/5),
                                 rep(0,n_years-1))

beekeeping_proj_profits<-(beekeeping_profits*n_beekeepers_targeted)-
                          project_establishment_costs
```

b) Efficient cook stoves intervention The efficient cook stoves intervention would mostly reduce household energy needs, reduce health costs and reduce carbon emissions. However, the intervention would not provide direct income for the targeted households. This was modeled as shown in the code below.

```r
## Household benefits####
  reduced_fuelwood_needs_benefits<-vv(household_fuelwood_needs*decrease_fuelwood_needs/100,
                           general_CV,n=n_years)*vv(price_fuelwood_per_ton,general_CV,n_years)
  benefits_efficient_stoves<-vv(health_benefits_stoves,general_CV,n_years)+
                              reduced_fuelwood_needs_benefits

  # Household costs ####
  cooking_stoves_replacemts<-rbinom(n_years,1,chance_replacing_stoves)
  stoves_replacement_cost<-cooking_stoves_replacemts*vv(cost_cooking_stoves,
                                                        general_CV,n=n_years)
  efficient_stoves_profits<-benefits_efficient_stoves-stoves_replacement_cost

  ## Cooking stoves project costs####
  n_households_adopt_cooking_stoves<-round(n_households_cooking_stoves*
                                          cooking_stoves_disadoption/100)
  cook_stoves_project_costs<-c(((cost_cooking_stoves+cost_training_cooking_stoves)*
                                n_households_cooking_stoves),
                                rep(0,n_years-1))

  ## Cooking stoves project benefits###
  cook_stoves_project_benefits<-efficient_stoves_profits*n_households_adopt_cooking_stoves
  cook_stoves_project_profits<-cook_stoves_project_benefits-cook_stoves_project_costs
```

c) Sheep rearing intervention Sheep rearing was also expected to increase income for mixed farmers using communal grazing lands in the Desa'a forest to reduce pressure on forest resources. The code below illustrates how we modeled the sheep rearing intervention.

```r
  ## Sheep rearing cost
  n_sheep_per_household<-round(n_sheep_per_household)
  sheep_rearing_cost<-vv((sheep_labour_cost),general_CV,n_years)

  ## Sheep rearing benefits
  n_sheep_sold<-round(n_sheep_per_household*sheep_sold/100)
  sheep_rearing_benefits<-vv(revenue_sale_sheep,general_CV,n_years)*
                        vv(n_sheep_sold,general_CV,n_years)

  disease_risk<-chance_event(livestock_diseases,
                           value_if=loss_livestock_diseases,
                           value_if_not=0,
                           n=n_years,
                           CV_if=general_CV,
                           CV_if_not=0,
                           one_draw=FALSE)

  predators_parasites_risk<-chance_event(predators_and_parasites,
                                       value_if=loss_predators_parasites,
                                       value_if_not=0,
                                       n=n_years,
                                       CV_if=general_CV,
                                       CV_if_not=0,
                                       one_draw=FALSE)
  sheep_drought_risk<-drought_event*vv(sheep_loss_due_to_drought,general_CV,n_years)
```

```
  effect_risks_sheep_benefits<-sapply(disease_risk+predators_parasites_risk+sheep_drought_risk,
                                      function(x) min(x,1))
  actual_sheep_benefits<-sheep_rearing_benefits*(1-effect_risks_sheep_benefits)
  sheep_rearing_profits<-(actual_sheep_benefits-sheep_rearing_cost)
  sheep_resilience<-(drought_event+unrest_event)*sheep_rearing_profits

  ## Sheep rearing implementer cost###
  n_households_sheep_rearing<-round(n_households_sheep_rearing)
  sheep_cost<-cost_of_sheep*n_sheep_per_household*n_households_sheep_rearing
  sheep_implementer_cost<-c((sheep_cost+(cost_of_training_sheep*n_households_sheep_rearing)),
                            rep(0,n_years-1))
  sheep_proj_profits<-(sheep_rearing_profits*n_households_sheep_rearing)-sheep_implementer_cost
```

d) Poultry farming intervention The poultry farming intervention was expected to increase the resilience of impoverished female-headed households through the sale and consumption of poultry products. This would in turn reduce pressure on forest resources. We modeled this as shown in the code below.

```
## poultry farming costs###
  poultry_initial_cost<-c((labour_setting_poultry_houses),rep(0,n_years-1))
  poultry_recurring_cost<-vv(chicks_vaccination_cost,general_CV,n_years)+
                          vv(chicken_feed_cost,general_CV,n_years)+
                          vv(chicken_labour_cost,general_CV,n_years)
  poultry_cost<-poultry_recurring_cost+poultry_initial_cost

  ## poultry benefits###
  n_chicken_sold<-round(n_chicken_farmer*(1+poultry_farm_expansion_rate/100))
  revenue_sale_poultry<-vv(revenue_chicken_sale*n_chicken_sold,general_CV,n_years)
  n_layers_per_year<-round(n_layers_per_year*(1+poultry_farm_expansion_rate/100))
  revenue_sale_eggs<-vv(revenue_eggs_sale*n_layers_per_year,general_CV,n_years)
  poultry_benefits<-revenue_sale_poultry+revenue_sale_eggs

  ## poultry risks###
  poultry_disease_risk<-chance_event(chance_poultry_diseases,
                                     value_if=loss_poultry_diseases,
                                     value_if_not=0,
                                     n=n_years,
                                     CV_if=general_CV,
                                     CV_if_not=0,
                                     one_draw=FALSE)

  poultry_farm_benefits<-poultry_benefits*(1-poultry_disease_risk)
  poultry_profits<-poultry_farm_benefits-poultry_cost
  poultry_resilience<-(drought_event+unrest_event)*poultry_profits

  ## poultry project cost###
  n_households_poultry<-round(n_households_poultry)
  poultry_project_cost<-c(((cost_of_chicks+cost_training_poultry)*n_households_poultry),
                          rep(0,n_years-1))
  poultry_proj_profits<-(poultry_profits*n_households_poultry)-poultry_project_cost
```

e) High value trees intervention For the high-value trees intervention, apple trees are distributed to surrounding community members to increase incomes and household nutrition security. The code below illustrates how we modeled the high-value trees intervention. We used the `gompertz_yield` function (Waliszewski & Konarski, 2006) written into the `decisionSupport` package to predict apple fruit yield overtime.

```
## calculate benefits of high value trees###
  apple_yield<- gompertz_yield(max_harvest=max_harvest,
                               time_to_first_yield_estimate=3,
                               time_to_second_yield_estimate=7,
                               first_yield_estimate_percent=first_yield_estimate_percent*100,
                               second_yield_estimate_percent=second_yield_estimate_percent*100,
                               n_years=n_years,
                               var_CV=general_CV,
                               no_yield_before_first_estimate=TRUE)

  ## Calculate effect of risks on apple tree benefits###
  apple_pests_diseases_risk<-chance_event(chance_of_tree_pests_diseases,
                                          value_if=loss_pests_diseases_apple,
                                          value_if_not=0,
                                          n=n_years,
                                          CV_if=general_CV,
                                          CV_if_not=0,
                                          one_draw=FALSE)

  poor_tree_management_risk<-chance_event(chance_poor_tree_managent,
                                     value_if=loss_poor_tree_management,
                                     value_if_not=0,
                                     n=n_years,
                                     CV_if=general_CV,
                                     CV_if_not=0,
                                     one_draw=FALSE)

  apple_drought_risk<-drought_event*vv(loss_drought_apple,general_CV,n_years)

  effect_of_risks_apple_trees<-sapply(apple_drought_risk+apple_pests_diseases_risk+
                                      poor_tree_management_risk,function(x) min(1,x))
  high_value_trees_benefits<-apple_yield*(1-effect_of_risks_apple_trees)

  apple_yield_returns<-(high_value_trees_benefits*price_apple_fruits)*number_apple_trees

  ## Calculate costs of high value trees###
  initial_fruit_tree_cost<-c(cost_labour_apple_tree,rep(0,n_years-1))
  recurring_trees_cost<-vv(tree_management_cost,general_CV,n_years)
  high_value_trees_cost<-initial_fruit_tree_cost+recurring_trees_cost

  ## Calculate profits and resilience from high value trees###
  high_value_trees_profits<-apple_yield_returns-high_value_trees_cost
  fruit_tree_resilience<-(drought_event+unrest_event)*high_value_trees_profits

  ## Calculate project costs of high value trees###
  n_households_fruit_trees<-round(n_households_fruit_trees)
  high_value_tree_proj_cost<-c((apple_seedling_cost*n_households_fruit_trees),rep(0,n_years-1))

  high_value_tree_proj_profits<-(high_value_trees_profits*n_households_fruit_trees)-
```

```
high_value_tree_proj_cost
```

f) Exclosures establishment Exclosures establishment was expected to generate an ecosystem carbon storage of about 376 tons per ha, contributing about 30% of the total revenues from exclosures. Seventy percent of the total exclosures revenues would come from improved soil quality as a result of an increase in phosphorus and nitrogen over time. Soil quality improvement would yield additional fodder for surrounding pastoral communities, where cut and curry management practice will be implemented.

```
## Calculate amount of ecosystem carbon sequestered overtime##
b<-1:n_years
exclosure_biomass_stock<-maximum_ecosystem_stock/(1+exp(-(BCEF*(b-exclosure_maturity_age))))
increased_exclosure_biomass_stock<-exclosure_biomass_stock-vv(amount_biomass_baseline,general_CV,n_yea

## Apply risks to carbon sequestration###
wildfire_event<-rbinom(n_years,1,wildfire_risk)
exclosure_wildfire_risk<-wildfire_event*vv(biomass_loss_wildfire_exclosure,
                                           general_CV,n_years)
exclosure_drought_risk<-drought_event*vv(loss_drought_exclosure,general_CV,n_years)
effect_of_exclosure_risks<-sapply(c(exclosure_wildfire_risk+exclosure_drought_risk),
                                  function(x) min(x,1))
exclosure_carbon_benefits<-increased_exclosure_biomass_stock*(1-effect_of_exclosure_risks)
exclosure_carbon_stock_returns<-(exclosure_carbon_benefits*carbon_cost)

## Consider community fodder demand before and after intervention  i.e grazing scenario vs
## cut and carry scenario (cut and carry results in less degradation than grazing but also
## requires more labour resources).
increase_TLU_cut_and_carry<-(n_households_sheep_rearing*n_sheep_per_household*sheep_TLU)/
                            exclosure_area
annual_feed_requirement_per_TLU<-(vv(daily_feed_requirement,general_CV,n_years)*
                                    proportion_feed_fodder)*365
increase_qtty_fodder_demanded<-(increase_TLU_cut_and_carry*annual_feed_requirement_per_TLU)/
                               1000 #demand in tonnes

## Apply risks to fodder production###
loss_fodder_pests_diseases<-chance_event(p_tree_pest_diseases,value_if=
                            (vv(percentage_fodder_loss_diseases, general_CV, 1)/100),
                            value_if_not = 0, n = n_years, CV_if = general_CV,CV_if_not = 0,
                            one_draw = FALSE)
loss_fodder_drought<-drought_event*vv(percentage_fodder_loss_drought/100,
                                      general_CV, n_years)
loss_fodder_wildfire<-drought_event*vv(percentage_fodder_loss_wildfire/100,
                                       general_CV, n_years)
fodder_risks<-sapply(c(loss_fodder_drought+loss_fodder_pests_diseases+loss_fodder_wildfire),
                     function(x) min(x,1))

## Consider difference in fodder productivity between fodder harvesting and free grazing
## Additional fodder value of implementing cut and carry vs. grazing
fodder_supply_grazing<-vv(grass_yield_grazing,general_CV,n_years)*(1-fodder_risks)
fodder_supply_cut_and_carry<-vv(grass_yield_ha,general_CV,n_years)*(1-fodder_risks)
additional_fodder_value_per_ha<-(fodder_supply_cut_and_carry-fodder_supply_grazing)
additional_fodder_value<-additional_fodder_value_per_ha*exclosure_area
fodder_harvesting_benefit<-(additional_fodder_value-increase_qtty_fodder_demanded)*
```

```
                              fodder_price

  ## Cost implication of shifting from grazing to cut and carry harvesting ie effect on labour   ## cos
  increase_labour_requirement<-vv(labour_hours_cut_and_carry,general_CV,n_years)-
                              vv(labour_hours_grazing_BAU,general_CV,n_years)
  exclosure_additional_labour_costs<-increase_labour_requirement*vv(wage_per_manday,general_CV,n_years)

  ## Overall benefits from implementing exclosures with cut and carry
  community_exclosure_benefits<-((additional_fodder_value_per_ha*fodder_price)+
                                 exclosure_carbon_stock_returns)-
                                 exclosure_additional_labour_costs

  #returns to project
  exclosure_project_cost<-vv(cost_establishing_exclosures,general_CV,proj_duration)
  exclosure_project_cost[(proj_duration+1):n_years]<-0
  community_cost_exclosures<-vv(cost_administration_exclosures,general_CV,n_years)
  community_cost_exclosures[1:proj_duration]<-0
  total_cost_exclosures<-community_cost_exclosures+exclosure_project_cost
  community_exclosure_net_benefits<-community_exclosure_benefits-total_cost_exclosures
```

To estimate the impact of establishing exclosures on encroachment that causes degradation (effect on carbon loss in biomass per ha. Drivers of degradation are demand for grazing pastures and fuel energy and extractions become unsustainable whenever the demand for resources is higher than what is supplied by improved management. The impact is quantified by determining the risk of occurrence and magnitude of impact. This was implemented in the code below:

```
## Determine magnitude of impact i.e biomass losses per hectare due to degradation
  biomass_lost_grazing<-(per_ha_loss_degradation*prop_degradation_grazing)+
                       drought_event*vv(annual_loss_biomass_grazing/100, general_CV,n_years)
  biomass_lost_fuelwood<-per_ha_loss_degradation*prop_degradation_fuelwood
  exclosures_degradation<-biomass_lost_fuelwood+biomass_lost_grazing

  ## Determine the annual occurrence of degradation risk events given intervention
  fodder_deficiency<-as.numeric(fodder_harvesting_benefit<0)
  encroachment_enabled_by_governance_failure<-chance_event(chance_governance_failure,
                                                      value_if=1,n=n_years)
  degradation_events<-fodder_deficiency+encroachment_enabled_by_governance_failure

  ##determine impact of risk
  biomass_loss_due_encroachment_without_intervention<-vv(exclosures_degradation,general_CV,
                                                       n_years)
  biomass_loss_due_encroachment_with_intervention<-
  biomass_loss_due_encroachment_without_intervention*degradation_events

  degradation_without_intervention<-cumprod(
  1-biomass_loss_due_encroachment_without_intervention)
  degradation_with_intervention<-cumprod(1-biomass_loss_due_encroachment_with_intervention)
  change_in_degradation<-degradation_with_intervention-degradation_without_intervention
  risk_adjusted_exclosure_benefits<-community_exclosure_net_benefits*change_in_degradation
```

g) Soil and water conservation intervention Soil and Water conservation intervention involves the construction of a suite of harvesting structures and gully restoration to create an enabling environment for

natural regeneration of vegetation. The intervention is also expected to reduce downstream siltation, where a community dam is constructed. This was modeled in the code below:

```
## Calculate household costs in a BAU and intervention scenario
  change_volume_soil_loss<-(vv(rate_soil_loss_without_intervention,general_CV,n_years)-
                            vv(rate_soil_loss_with_intervention,general_CV,n_years))

  nutrient_loss_due_erosion_per_ha<-vv(value_soil,general_CV,n_years)*change_volume_soil_loss
  community_cost_siltation_saved<-change_volume_soil_loss*vv(cost_ton_silt,general_CV,n_years)
  reduced_water_stress_biomass_benefit<-increased_exclosure_biomass_stock*(reduced_water_stress_benefit
  soil_and_water_benefits<-nutrient_loss_due_erosion_per_ha+community_cost_siltation_saved+
                           reduced_water_stress_biomass_benefit

  gully_restoration_costs<-vv(gully_cost_materials, general_CV, n = 1)
  net_swc_benefits<-soil_and_water_benefits-gully_restoration_costs
```

h) Enrichment planting and assisted natural regeneration The enrichment planting and management intervention is expected to increase the density of forest cover. To achieve this 3,303,580 trees are targeted for enrichment planting and regeneration. The pilot project is expected to replant and manage 945,756 trees, restoring approximately 972 hectares and sequestering 77,766 tonnes of CO2 per year (over a 50-year period).

```
  ## Calculate carbon sequestration benefits of enrichment planting that improves vegetation
  ## cover from 10% to at least 40% in the buffer zone and from 40% to at least 60% in the core
  ## zone
  b<-1:n_years
  aboveground_biomass_stock<-maximum_merchantable_volume/(1+exp(-(BCEF*(b-stem_maturity_age))))
  total_biomass_stock<-aboveground_biomass_stock*(1+biomass_ratio) #tonnes dm yr^-1
  tree_population<-additional_trees_planted*seedling_survival_rate
  enrichment_total_carbon_stock<-(total_biomass_stock)*tree_population #tonnes d.m.

  ## Calculate Carbon sequestration benefit from social fencing in core and buffer zones.
  ## We estimate Mean annual increment(MAI) in woody biomass that survives due to improved
  ## governance and tree management
  MAI<-(rep(1,n_years))
  MAI[2:n_years]<-vv(biomass_mean_annual_increment,general_CV,n_years-1)
  incremental_biomass_per_ha<-vv(mean_biomass_per_ha,general_CV,n_years)*(cumsum(MAI))

 ## build restoration risk portfolio i.e natural risks,encroachment risks and market risks.
  ## Determine the risk profile that would vary tree population by natural disturbances###
  loss_due_invasive_species<- chance_event(chance_invasive_species,
                                        value_if=(percentage_trees_lost_prosopis/100),
                                        value_if_not= 0,n_years,general_CV,
                                        CV_if_not = 0,
                                        one_draw = FALSE)

  tree_loss_due_disease<-chance_event(chance_diseases_outbreak,
                                   value_if=(percentage_tree_loss_diebark/100),
                                   value_if_not = 0,n_years,general_CV,CV_if_not = 0,
                                   one_draw = FALSE)

  tree_loss_due_fire<-wildfire_event*vv(percentage_trees_lost_fire/100,general_CV,n_years)
```

```
effect_natural_risks<-sapply(c(tree_loss_due_disease+loss_due_invasive_species+
                               tree_loss_due_fire),function(x) min(x,1))
annual_effect_natural_risks<-cumprod(1-effect_natural_risks)


## Introduce the risk of anthropogenic disturbances and their impact on trends of
## deforestation and degradation. Occurrence of encroachment risk is determined  by a vector of
## resilience indicators
unrest_event<-chance_event(chance_civil_unrest,value_if=1,n=n_years)
beekeeping_resilience<-(drought_event+unrest_event)*beekeeping_profits
sheep_resilience<-(drought_event+unrest_event)*sheep_rearing_profits
poultry_resilience<-(drought_event+unrest_event)*poultry_profits
fruit_tree_resilience<-(drought_event+unrest_event)*high_value_trees_profits
lack_of_resilience_with_intervention<-as.numeric(beekeeping_resilience<0)*as.numeric(sheep_resilience
                                      as.numeric(poultry_resilience<0)*as.numeric(fruit_tree_resilien

## Use resilience as a determinant of deforestation i.e resilient household leads to no deforestation
## lack of resilience causes deforestation through agriculture and commercial logging.
annual_cover_lost_logging<-(annual_rate_deforestation/100)*prop_deforestation_logging
annual_cover_lost_agriculture<-(annual_rate_deforestation/100)*(prop_deforestation_agriculture)
rate_deforestation_without_intervention<-annual_cover_lost_logging+annual_cover_lost_agriculture
deforestation_without_intervention<-c(rep(rate_deforestation_without_intervention,n_years))
extraction_risk_with_intervention<-chance_event(chance_extracts_resources,value_if=1,n=n_years)
deforestation_with_intervention<-(extraction_risk_with_intervention+lack_of_resilience_with_interventi
  deforestation_without_intervention
remaining_forest_area_without_intervention<-cumprod(1-deforestation_without_intervention)
remaining_forest_area_with_intervention<-cumprod(1-deforestation_with_intervention)
change_in_deforestation<-remaining_forest_area_with_intervention-remaining_forest_area_without_interve

#Consider the risk that carbon markets don't materialize
carbon_market_failure<-chance_event(carbon_market_risk,value_if=1,n=n_years)
carbon_cost<-vv(carbon_cost,general_CV,n_years)*carbon_market_failure

#Apply risks to initial estimates of biomass produced with intervention
ANR_risk_adjusted_biomass_per_ha<-incremental_biomass_per_ha*
                                  annual_effect_natural_risks*
                                  change_in_deforestation

ANR_carbon_value_per_ha<-ANR_risk_adjusted_biomass_per_ha*biomass_conversion_factor
ANR_carbon_revenue<-ANR_carbon_value_per_ha*carbon_cost

enrichment_risk_adjusted_biomass_per_ha<-enrichment_biomass_per_ha*
                                         annual_effect_natural_risks*
                                         change_in_deforestation*
                                         change_in_degradation
enrichment_carbon_value_per_ha<-enrichment_risk_adjusted_biomass_per_ha*biomass_conversion_factor
enrichment_carbon_revenue<-enrichment_carbon_value_per_ha*carbon_cost


#To determine net benefits,generate costs of each restoration intervention
cost_enrichment_planting<-rep((per_ha_cost_planting*(1-enrichment_cost_labour_proportion)),
                              proj_duration)
cost_enrichment_planting[(proj_duration+1):n_years]<-0 #replanting_cost_maintenance
```

```r
## Cost of ANR
cost_social_fencing<-vv(annual_cost_community_engagement,general_CV,proj_duration)+
  vv(annual_cost_salaried_guards,general_CV,n_years)
cost_social_fencing[(proj_duration+1):n_years]<-0
cost_social_fencing_per_ha<-cost_social_fencing/(core_zone_area+buffer_zone_area)


## Determine microclimate benefits of increased moisture availability and cooling temperatures
effect_improved_microclimate<-chance_event(p_heat_wave,
                                           value_if=(p_yield_loss_heat_wave/100),
                                           value_if_not = 1,n_years,general_CV,CV_if_not = 0,
                                           one_draw = FALSE)
agricultural_savings<-prod_USD_ha*effect_improved_microclimate
microclimate_benefit<-agricultural_savings
ANR_net_benefits<-(ANR_carbon_revenue+microclimate_benefit)-cost_social_fencing_per_ha
```

Intervention net present value calculations

To calculate net present values for interventions, we apply the `discount` function from the `decisionSupport` package to discount the expected profits per intervention over a 25-year period.

```r
beekeeping_NPV<-discount(beekeeping_profits,discount_rate,calculate_NPV=TRUE)

cook_stoves_NPV<-discount(efficient_stoves_profits,discount_rate,calculate_NPV=TRUE)

sheep_rearing_NPV<-discount(sheep_rearing_profits,discount_rate,calculate_NPV=TRUE)

poultry_farming_NPV<-discount(poultry_profits,discount_rate,calculate_NPV=TRUE)

high_value_tree_NPV<-discount(high_value_trees_profits,discount_rate,calculate_NPV=TRUE)

exclosure_benefit_NPV<-discount(risk_adjusted_exclosure_benefits,discount_rate,calculate_NPV=TRUE)

soil_and_water_benefit_NPV<-discount(net_swc_benefits,discount_rate,calculate_NPV=TRUE)

ANR_net_benefit_NPV<-discount(ANR_net_benefits,discount_rate,calculate_NPV=TRUE)

return(list(cashflow_beekeeping_NPV=beekeeping_profits,
            beekeeping_NPV=beekeeping_NPV,
            cashflow_cook_stoves_NPV=efficient_stoves_profits,
            cook_stoves_NPV=cook_stoves_NPV,
            cashflow_sheep_rearing_NPV=sheep_rearing_profits,
            sheep_rearing_NPV=sheep_rearing_NPV,
            cashflow_poultry_farming_NPV=poultry_profits,
            poultry_farming_NPV=poultry_farming_NPV,
            cashflow_high_value_tree_NPV=high_value_trees_profits,
            high_value_tree_NPV=high_value_tree_NPV,
            cashflow_exclosure_NPV=community_exclosure_net_benefits,
            exclosure_NPV=exclosure_benefit_NPV,
            cashflow_ANR_NPV=ANR_net_benefits,
            ANR_NPV=ANR_net_benefit_NPV,
```

```
              cashflow_soil_water_conservation_NPV=net_swc_benefits,
              soil_water_conservation_NPV=soil_and_water_benefit_NPV))
```

2. Decision support package

The `decisionSupport` function in the R package of the same name requires two inputs:

1. An `input_table` (in .csv format) specifying the names and probability distributions for all variables used in the analysis. The variable distributions are described by a 90% confidence interval, which is specified by lower (5% quantile) and upper (95% quantile) bounds, as well as the shape of the distribution. `const` describe variables that are constant throughout, `norm` describe variables with normal distribution, `tnorm_0_1` describe variables with a truncated normal distribution that can only have values between 0 and 1 (useful for probabilities) and `posnorm` describe variables with normal distribution truncated at 0 (only positive values allowed). For this analysis, the `input_table` shared with this supplementary as 'Desaa_inputs.csv' was used.
2. An `R_function` that predicts decision outcomes based on the variables named in `input_table`. This R function is customized by the user to address a particular decision problem. For this analysis, the function `Desa'a_restoration` describing the causal relationships between benefits, costs, and risk variables for investing in beekeeping, efficient cookstoves, sheep rearing, poultry farming, fruit trees, exclosures establishment, gully restoration and assisted natural regeneration was used.

To run the model, the `Desaa_restoration` function, along with the data from the `input_table`, were fed into the Monte Carlo simulation (MC) function (Luedeling and Whitney, 2018) to conduct the full analysis. Below is the code we used to perform the Monte Carlo simulation with 10,000 model runs.

```
Desaa_restoration<-function(x, varnames){}

decisionSupport(inputFilePath = input_table, #input file with estimates
                outputPath = results_folder, #output folder
                welfareFunction = Desaa_restoration, #the function created above
                numberOfModelRuns = 1e4, #10,000 model runs
                functionSyntax = "plainNames",
                write_table = TRUE,)
```

Value of information and sensitivity analysis

To identify important knowledge gaps where further measurement efforts could help clarify whether the predicted outcome would have a negative or positive impact on FLR efforts, We computed the expected value of perfect (EVPI). EVPI represents the opportunity loss that could be incurred by a decision-maker due to a lack of information on a specific variable (Hubbard, 2014). Applied in this way, the EVPI computation can help to determine where further measurements may help gain clarity on decision outcomes. We also applied Partial Least Squares (PLS) regression analysis to the MC simulation results to generate the Variable-Importance-in-the-Projection (VIP) statistic for input parameters (Luedeling & Gassner, 2012). The VIP statistic represents the direction and strength of each input variable's relationship with the output variable (Wold et al. 2001). This was implemented as shown in the code below:

3. Results

A tabulated summary of the results describing the 90% confidence interval and the chance of loss/gain was as shown.

Table 1: Monte Carlo and VOI outputs

NPV..n.10.000.	X	X.1	X.2
Intervention	Min (5%)	Median (50%)	Max(95%)
Beekeeping	1594	4517.24	10961
Cook stoves	1165	2007.71	3140
Sheep rearing	-1258	-165.13	1013
Poultry farming	624	1053.45	1569
High Value trees	1482	4291.8	8023
Exclosure	-13119	9799.65	50785
Assisted Natural Regeneration	13231	20215.08	30286
Soil water conservation	1104	4141.32	7401
Enrichment NPV	-492	3211.62	13852

Also shown is the combined graphical representation of restoration outcomes, value of information analysis, cash flows and sensitivity analysis for referenced diagrams in the paper.

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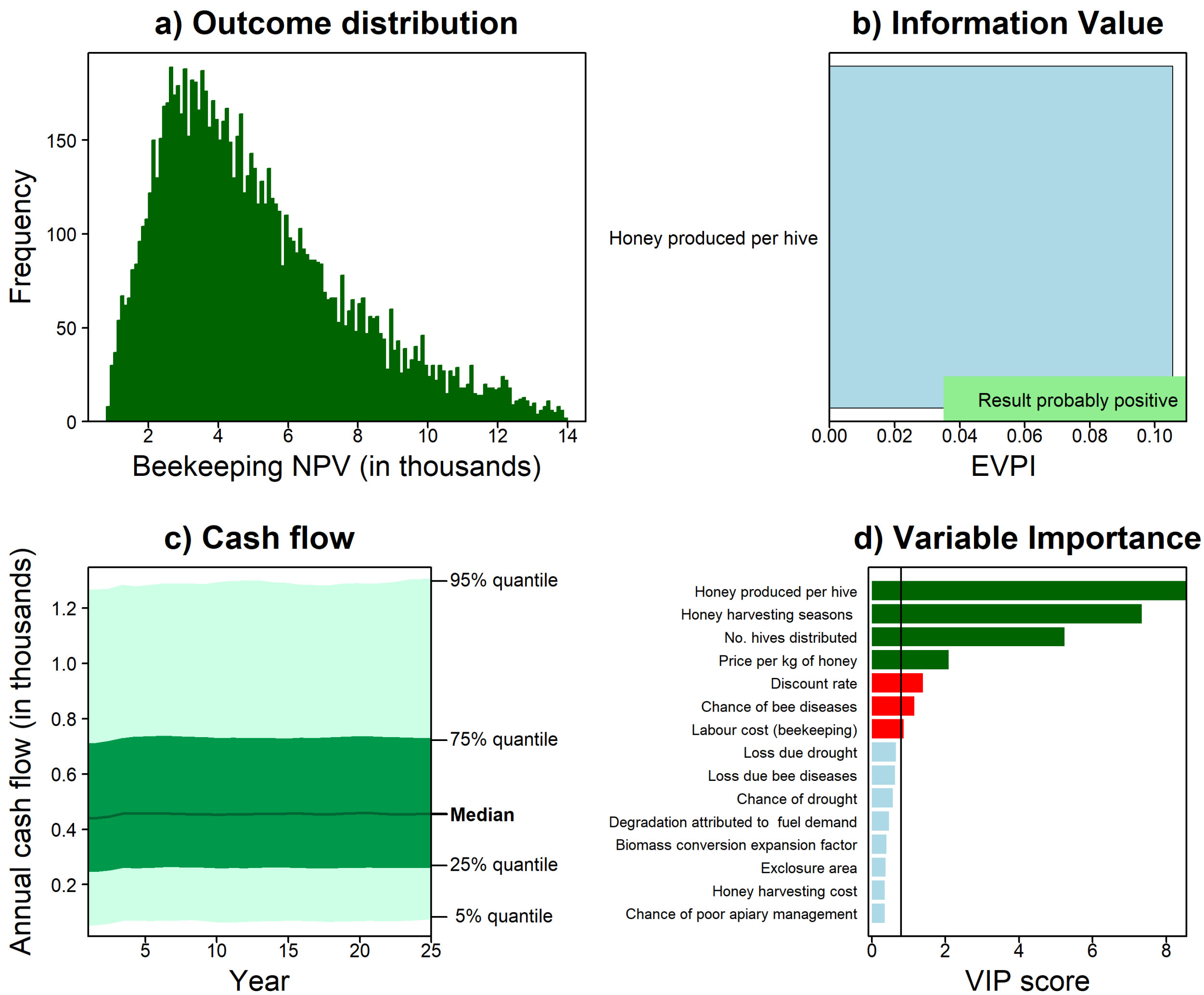

Figure 1: Projected impact of the decision to invest in beekeeping (a), high decision-value variables (b), the respective cashflows (c) and important variables (determined by VIP analysis of PLS regression models) (d). The results were produced through MC simulation (10,000 model runs) of sheep rearing intervention performance over 25 years. In the PLS plot, green bars indicate positive correlations of uncertain variables with the outcome variable, while red bars indicate negative correlations. Blue bars indicate variables that did not meet the threshold for model sensitivity analysis.

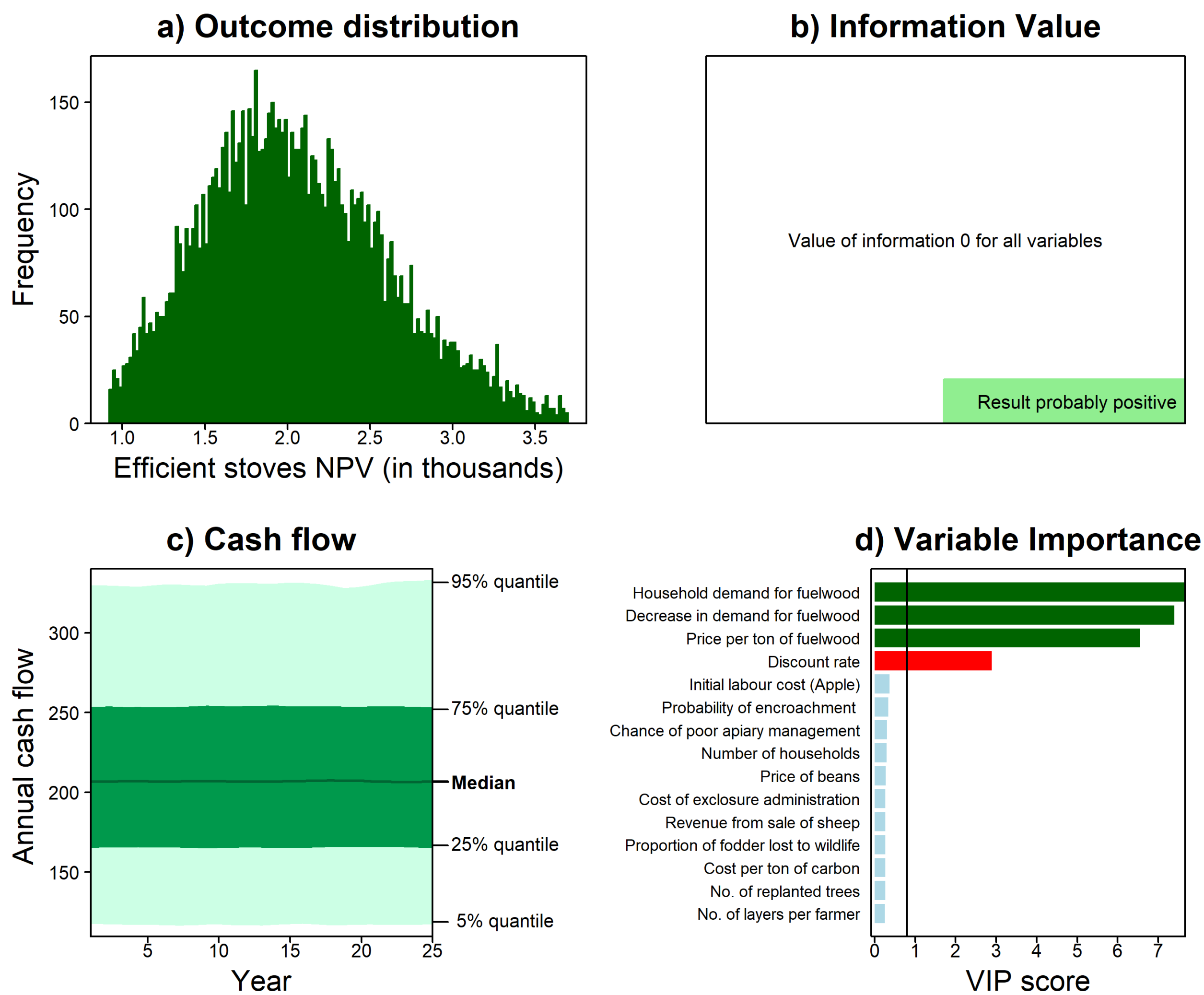

Figure 2: Projected impact of the decision to provide efficient cooking stoves to community members in Desa'a to reduce pressure on forest resources (a), high decision-value variables (b), the respective cashflows (c) and important variables (determined by VIP analysis of PLS regression models) (d). The results were produced through MC simulation (10,000 model runs) of sheep rearing intervention performance over 25 years. In the PLS plot, green bars indicate positive correlations of uncertain variables with the outcome variable, while red bars indicate negative correlations. Blue bars indicate variables that did not meet the threshold for model sensitivity analysis.

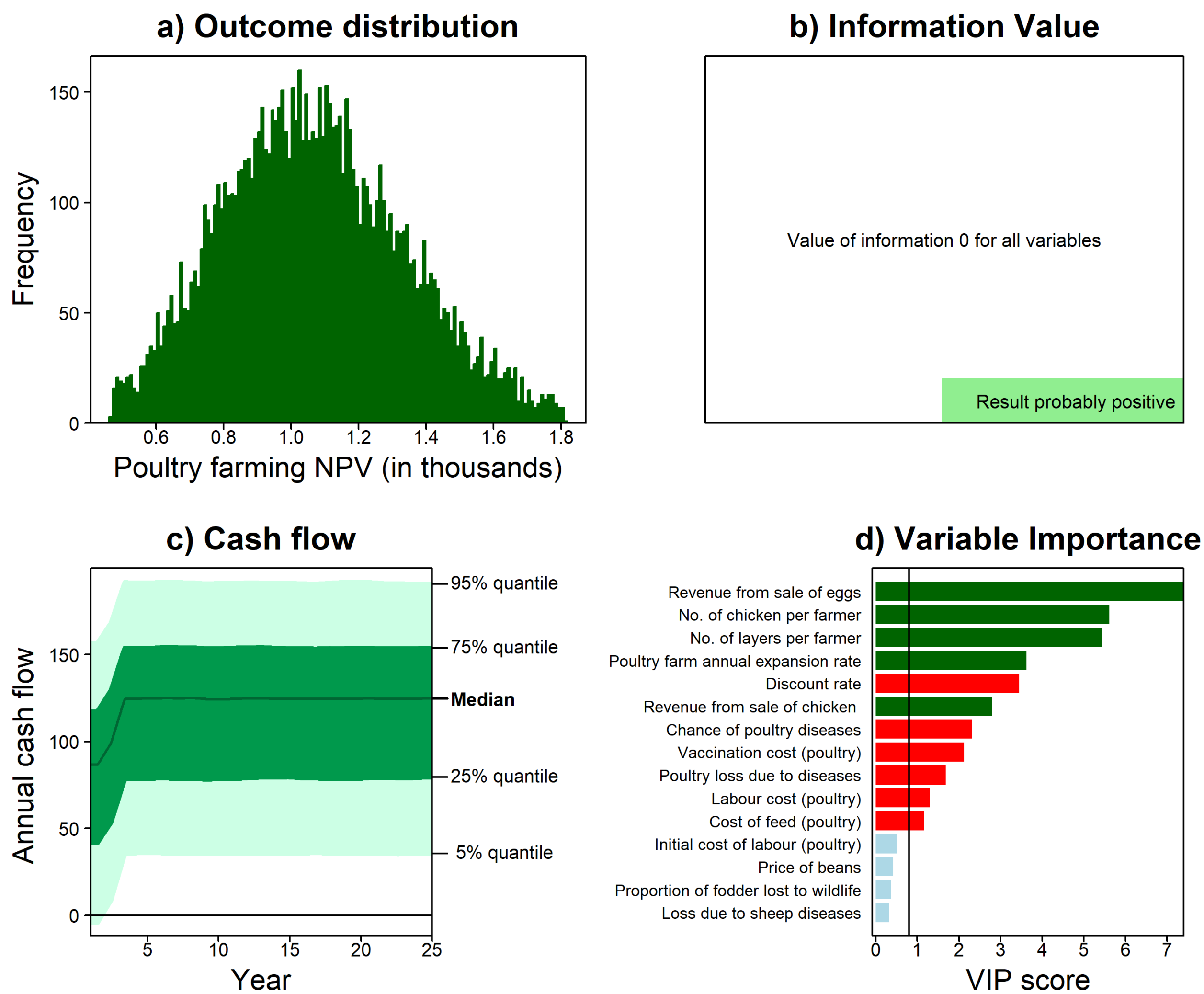

Figure 3: Projected impact of the decision to invest in poultry farming for community members in Desa'a to reduce pressure on forest resources (a), high decision-value variables (b), the respective cashflows (c) and important variables (determined by VIP analysis of PLS regression models) (d). The results were produced through MC simulation (10,000 model runs) of sheep rearing intervention performance over 25 years. In the PLS plot, green bars indicate positive correlations of uncertain variables with the outcome variable, while red bars indicate negative correlations. Blue bars indicate variables that did not meet the threshold for model sensitivity analysis.

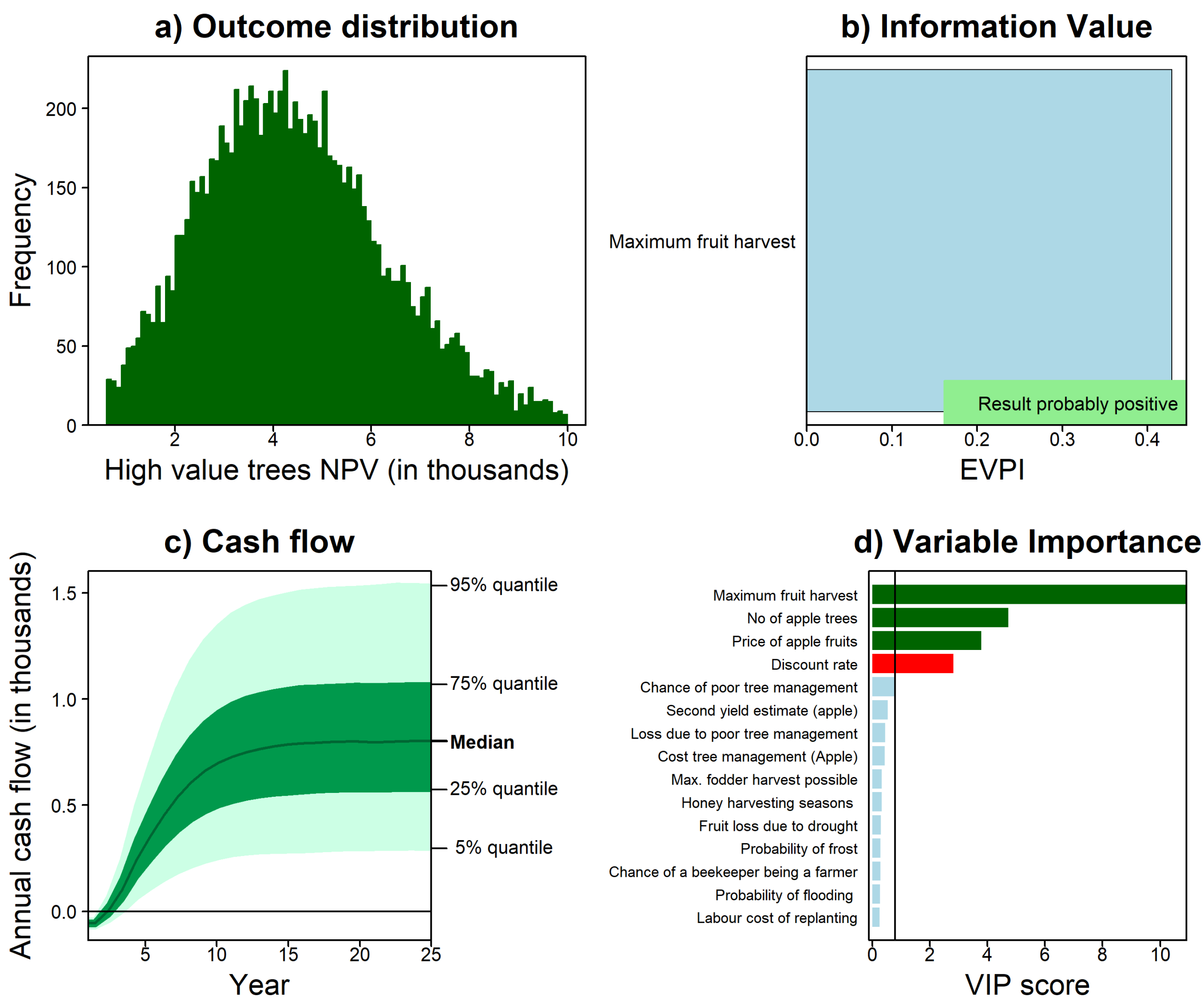

Figure 4: Projected impact of the decision to invest in Apple trees for community members in Desa'a to reduce pressure on forest resources(a), high decision-value variables (b), the respective cashflows (c) and important variables (determined by VIP analysis of PLS regression models) (d). The results were produced through MC simulation (10,000 model runs) of sheep rearing intervention performance over 25 years. In the PLS plot, green bars indicate positive correlations of uncertain variables with the outcome variable, while red bars indicate negative correlations. Blue bars indicate variables that did not meet the threshold for model sensitivity analysis.

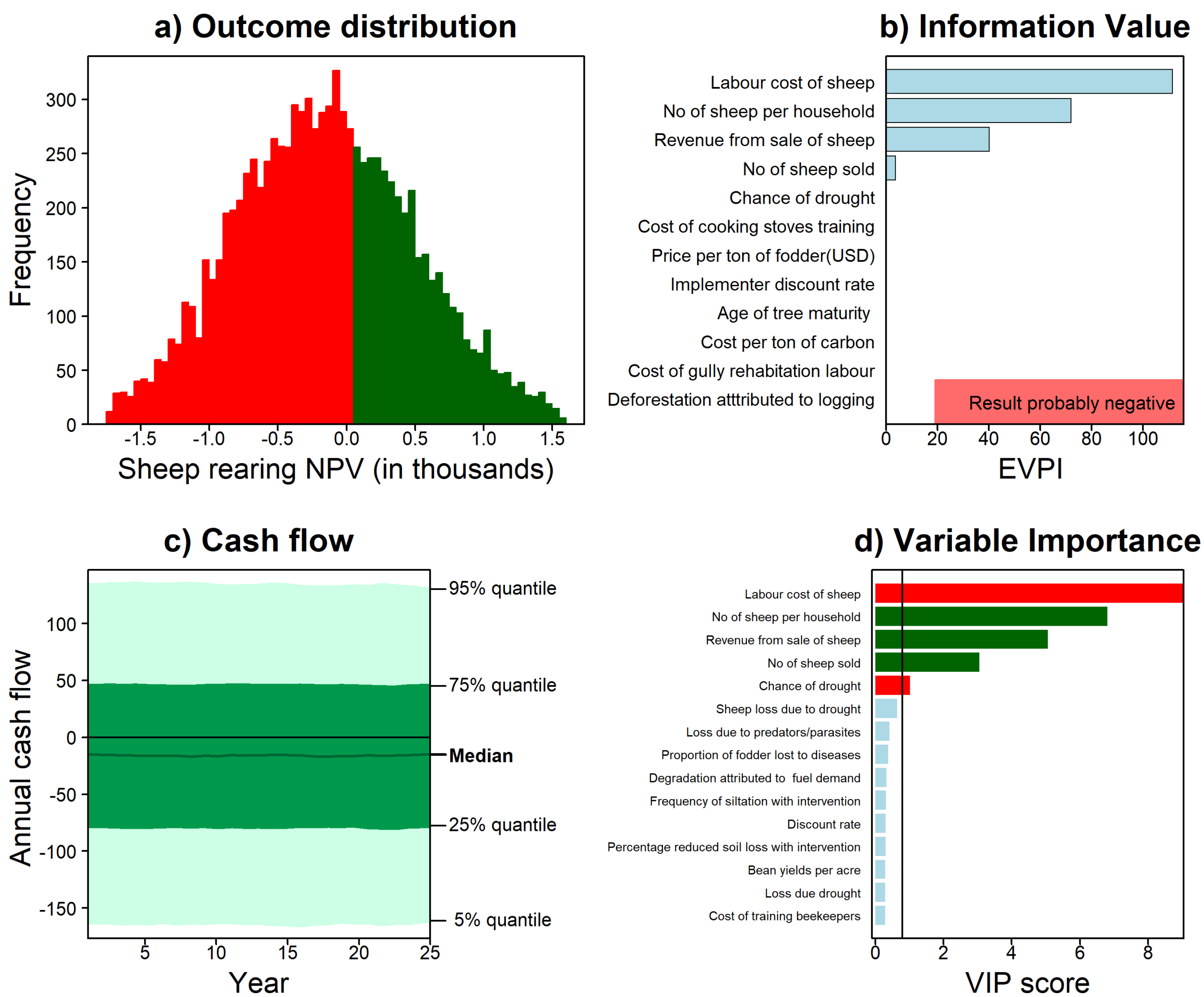

Figure 5: Projected impact of the decision to invest in sheep rearing for community members in Desa'a to reduce pressure on forest resources(a), high decision-value variables (b), the respective cashflows (c) and important variables (determined by VIP analysis of PLS regression models) (d). The results were produced through MC simulation (10,000 model runs) of sheep rearing intervention performance over 25 years. In the PLS plot, green bars indicate positive correlations of uncertain variables with the outcome variable, while red bars indicate negative correlations. Blue bars indicate variables that did not meet the threshold for model sensitivity analysis.