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SCHOOL *of* PUBLIC HEALTH



Modeling for Decision-Making

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Protecting Health, Saving Lives—*Millions at a Time*

The Key Question

How do we make models useful for actual decision making in the field of TB diagnostics?



The Xpert Example

Population Health Impact and Cost-Effectiveness of Tuberculosis Diagnosis with Xpert MTB/RIF: A Dynamic Simulation and Economic Evaluation

Nicolas A. Menzies^{1,2*}, Ted Cohen^{3,4}, Hsien-Ho Lin⁵, Megan Murray³, Joshua A. Salomon^{1,6}

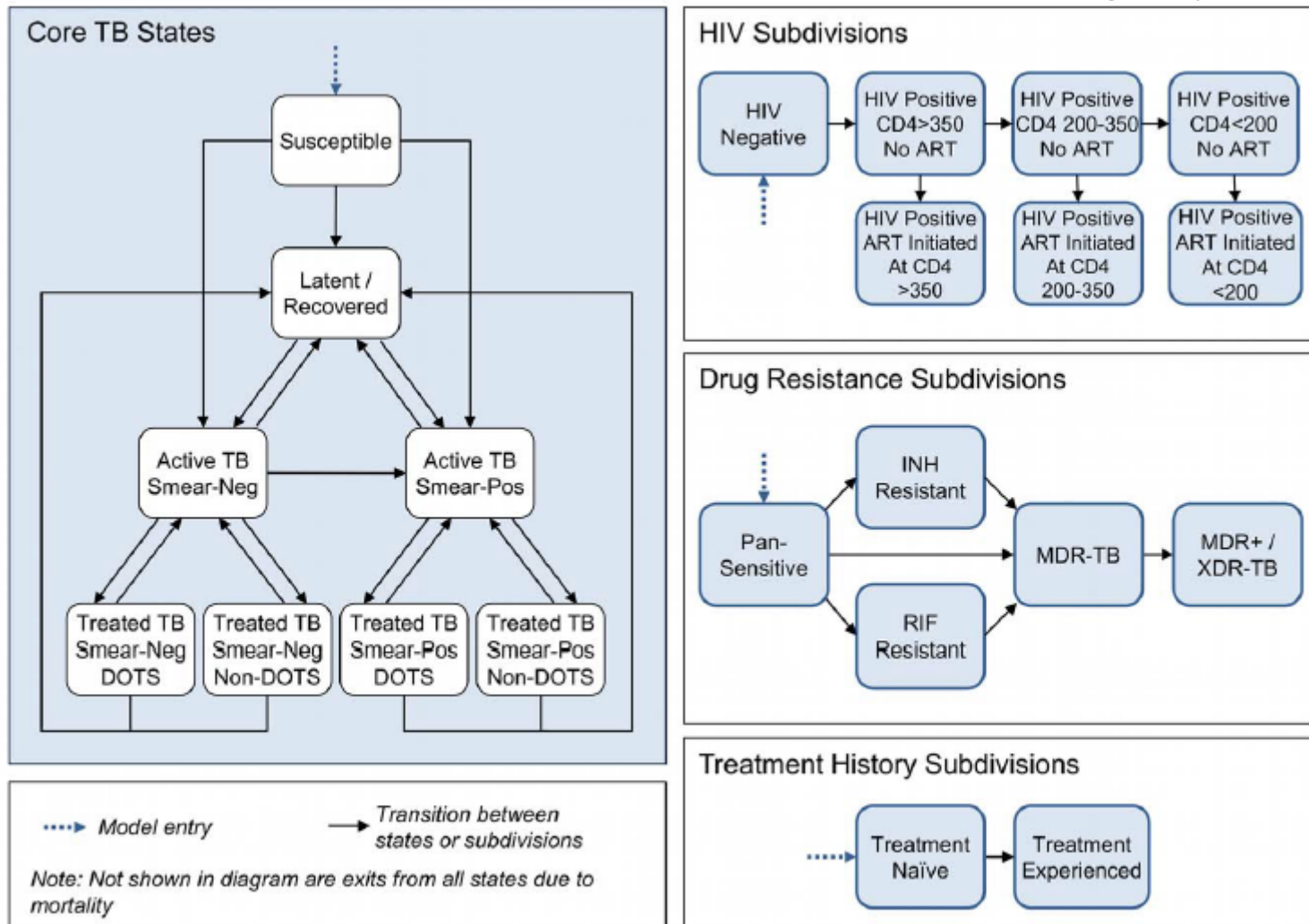
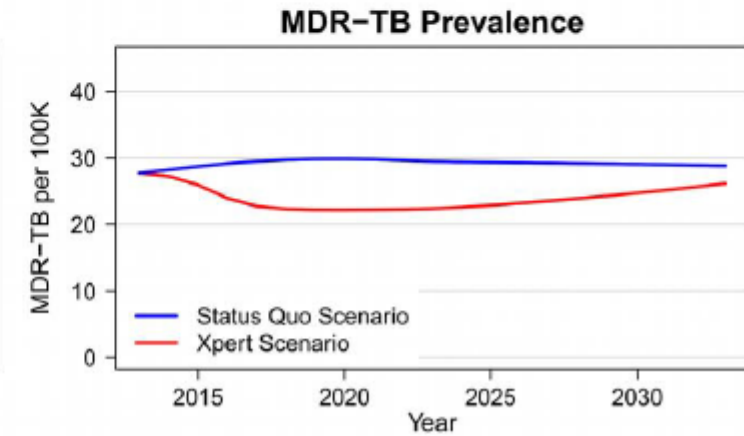
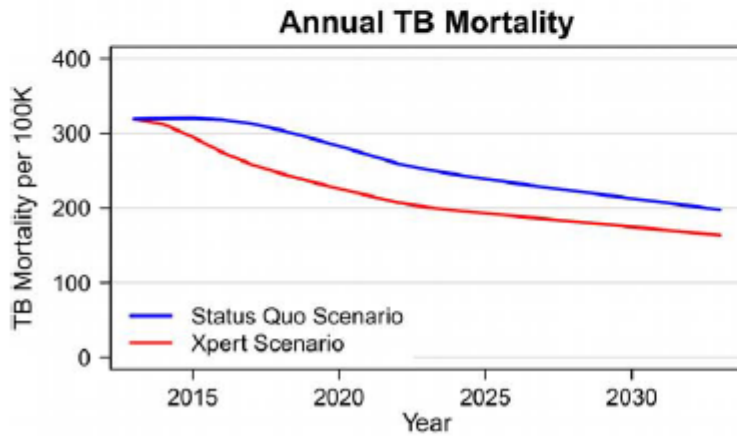
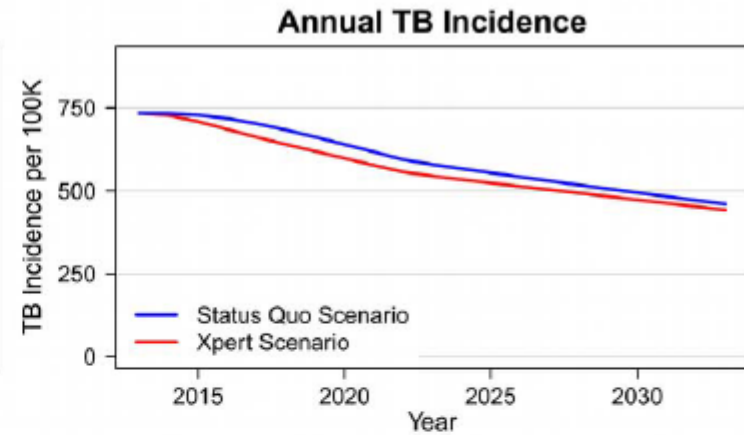
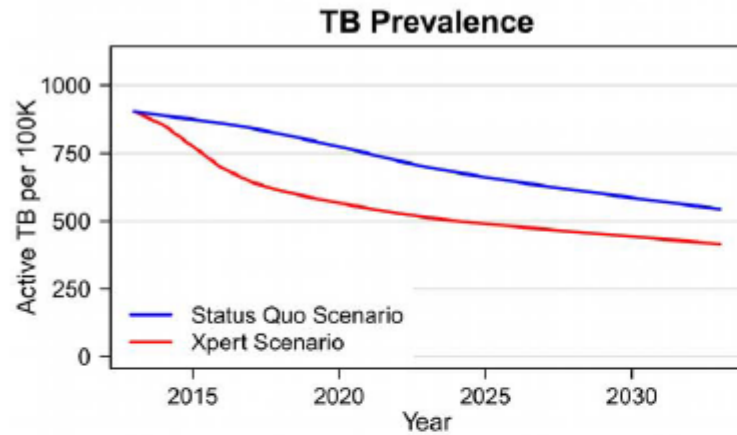


Figure 1. Model states, subdivisions, and transitions.

Main Results



How Is This Model Used?

- Conclusion: “Implementation of Xpert would avert 132,000 TB cases in southern Africa over 10 years...at a cost of \$460 million.”
 - Will the Minister of Health for “southern Africa” please stand up?
- Are we simply spinning our academic wheels and making nice publications, but with no impact on decisions?
 - Remember that the entire goal of modeling should be to better understand systems, and to help with decision-making!
- What are the barriers to using models for decision-making?



Barrier 1: Complexity

Appendix Table 2: Base-case parameter values and ranges.

Description	Base-case value	Range ¹	Source
Parameters related to η_1			
New entrants at time t	Time-varying	—	[21]

Description	Base-case value	Range ¹	Source
Parameters related to λ_1			
Transmission parameters for individuals with (pan-sensitive) an ear-positive TB in 1950 (β_{1950})	—	—	Assumed
Annual percentage decline in transmission parameter	—	—	Assumed
Infectivity of an ear-negative TB, relative to smear-positive TB (β_1)	0.984	[0.978-0.989]	[28]
Infectivity of Xpert for TB: Smear-negative TB	0.725	[0.655-0.788]	[26]
Infectivity of Xpert for TB: Smear-positive TB	0.992	—	Assumed
Fitness cost for drug-resistant TB strains (ϵ_1): Mono- <i>INH</i> resistant	0.976	—	Assumed
Mono- <i>RIF</i> resistant	0.981	—	Assumed
MDR-TB	—	—	Assumed
MDR+/IDR-TB	—	—	Assumed

Description	Base-case value	Range ¹	Source
Parameters related to γ_0 and γ_1			
Rate of attending TB testing site, for individuals with active TB	0.20	—	Assumed
Rate ratio of attending TB testing, for individuals without active TB compared to those with active TB	0.80	—	Assumed
Parameters related to $\gamma_{0,1}$ and $\gamma_{1,1}$			
Sensitivity of sputum an ear microscopy: Smear-negative TB	0.00	—	Assumed
Smear-positive TB	0.209	—	Assumed
Specificity of sputum smear microscopy	0.953	—	Assumed

Description	Base-case value	Range ¹	Source
Parameters related to η_2			
Probability of fast breakdown to active TB, for new infections	0.80	[0.472-1.272]	[14,15]
Parameters related to η_3			
Partial immunity afforded by prior infection: HIV-negative	0.65	[0.37-0.87]	[23,5,47]
HIV-positive, CD4 >350 cells/ μ L, no ART	0.45	[0.23-0.68]	—
HIV-positive, CD4 200-350 cells/ μ L, no ART	0.25	[0.14-0.39]	—
HIV-positive, CD4 <200 cells/ μ L, no ART	—	—	—

Description	Base-case value	Range ¹	Source
Parameters related to ρ			
Probability of fast breakdown to active TB, for new infections: HIV-negative	0.020	[0.012-0.032]	[81]
HIV-positive, CD4 >350 cells/ μ L, no ART	0.003	[0.002-0.005]	—
HIV-positive, CD4 200-350 cells/ μ L, no ART	0.010	[0.006-0.016]	—
HIV-positive, CD4 <200 cells/ μ L, no ART	0.020	[0.012-0.032]	—

Description	Base-case value	Range ¹	Source
Parameters related to f			
Probability of an ear-positive, for incident TB cases: HIV-negative	0.65	[0.37-0.87]	[23,5,47]
HIV-positive, CD4 >350 cells/ μ L, no ART	0.45	[0.23-0.68]	—
HIV-positive, CD4 200-350 cells/ μ L, no ART	0.25	[0.14-0.39]	—
HIV-positive, CD4 <200 cells/ μ L, no ART	—	—	—

Description	Base-case value	Range ¹	Source
Parameters related to r			
Rate of breakdown from latent/recovered to active TB (per 100,000): HIV-negative	0.020	[0.012-0.032]	[81]
HIV-positive, CD4 >350 cells/ μ L, no ART	0.003	[0.002-0.005]	—
HIV-positive, CD4 200-350 cells/ μ L, no ART	0.010	[0.006-0.016]	—
HIV-positive, CD4 <200 cells/ μ L, no ART	0.020	[0.012-0.032]	—

Description	Base-case value	Range ¹	Source
Parameters related to α			
Historical ART coverage for treatment-eligible HIV-positive individuals	0.65	[0.37-0.87]	[23,5,47]
Future ART coverage for treatment-eligible HIV-positive individuals	0.45	[0.23-0.68]	—
Effectiveness of ART in reversing effect of HIV on natural history (all TB transition parameters subdivided by HIV status, excluding mortality)	0.25	[0.14-0.39]	—
Proportion of HIV-negative individuals with prior HIV test result	—	—	—

Description	Base-case value	Range ¹	Source
Parameters related to κ			
Duration of TB treatment ($1/\kappa$): First-line	0.008	[0.007-0.009]	—
Mono- <i>INH</i> resistant	0.020	[0.019-0.021]	—
Mono- <i>RIF</i> resistant	0.008	[0.007-0.009]	—
MDR-TB	0.020	[0.019-0.021]	—
MDR+/IDR-TB	0.008	[0.007-0.009]	—
Non-DOTS (averaged)	0.050	[0.045-0.055]	—

Description	Base-case value	Range ¹	Source
Parameters related to v			
Probability that failed treatment cases are correctly identified and returned to treatment	0.008	[0.007-0.009]	—
MDR-TB	0.020	[0.019-0.021]	—
MDR+/IDR-TB	0.008	[0.007-0.009]	—
Non-DOTS (averaged)	0.050	[0.045-0.055]	—

Description	Base-case value	Range ¹	Source
Parameters related to μ			
Rate of acquisition of TB drug resistance: Pan-sensitive \rightarrow Mono- <i>INH</i> resistant, first-line regimen	0.020	[0.012-0.032]	[81]
Mono- <i>RIF</i> resistant, first-line regimen	0.003	[0.002-0.005]	—
Mono- <i>RIF</i> resistant, first-line regimen	0.010	[0.006-0.016]	—
Mono- <i>RIF</i> resistant, first-line regimen	0.020	[0.012-0.032]	—

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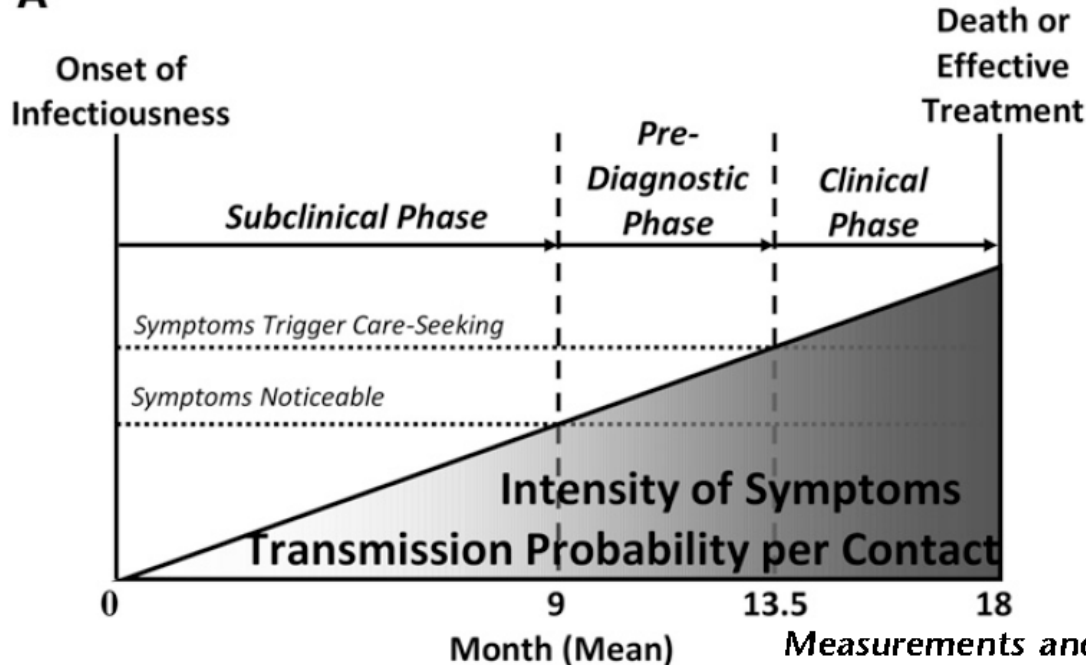
Barrier 2: Uncertainty

Is Passive Diagnosis Enough?

The Impact of Subclinical Disease on Diagnostic Strategies for Tuberculosis

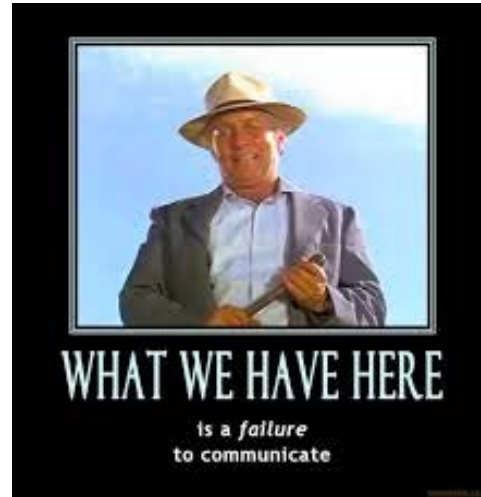
David W. Dowdy^{1,2}, Sanjay Basu^{3,4}, and Jason R. Andrews⁵

A



Measurements and Main Results: If the subclinical phase was ignored, as in most models, the passive strategy was projected to reduce TB incidence by **18%** (90% uncertainty range [UR], 11–32%) by year 10, compared with 23% (90% UR, 14–35%) for the enhanced strategy and 18% (90% UR, 11–28%) for the active strategy. After incorporating a subclinical phase into the model, consistent with population-based prevalence surveys, the active strategy still reduced 10-year TB incidence by 16% (90% UR, 11–28%), but the passive and enhanced strategies' impact was attenuated to **11%** (90% UR, 8–25%) and 6% (90% UR, 4–13%), respectively. The de-

But The Real Barrier Is...



What models are providing are good for headlines...but not what decision-makers actually need.

- *Flexibility, local relevance, interpretability, actual decisions at hand*
- *Generally can only be done through long-term partnership*

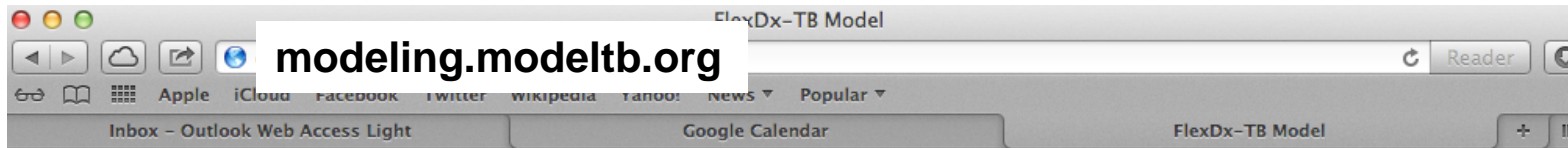


One Solution

- Go to the Web
- Input your population's TB incidence, MDR-TB incidence, HIV prevalence, costs
- Have a program create a simulated epidemic that reflects your local scenario
- Use that epidemic to evaluate the impact of control interventions from a menu of possibilities
- Change any model assumptions that don't reflect your local situation, and run the model again
- Get results within seconds



User Interface



Flex^D TB Model

A user-friendly, open-source transmission model of TB

ABOUT

MODEL INPUTS

- 1. Smear
- 2. Culture for retreatment
- 3. GeneXpert for HIV positive only
- 4. GeneXpert for smear positive only
- 5. GeneXpert for all
- 6. GeneXpert for all, culture confirmed
- 7. MODS/TLA
- 8. Same-day smear microscopy
- 9. Same-day GeneXpert
- 10. All

Target TB incidence, per 100,000 (baseline 250):

Target MDR-TB prevalence among new cases, % (baseline 3.7):

Target adult HIV prevalence, % (baseline 0.83):

Cost to treat 1 patient with first-line drugs, \$ (baseline 500):

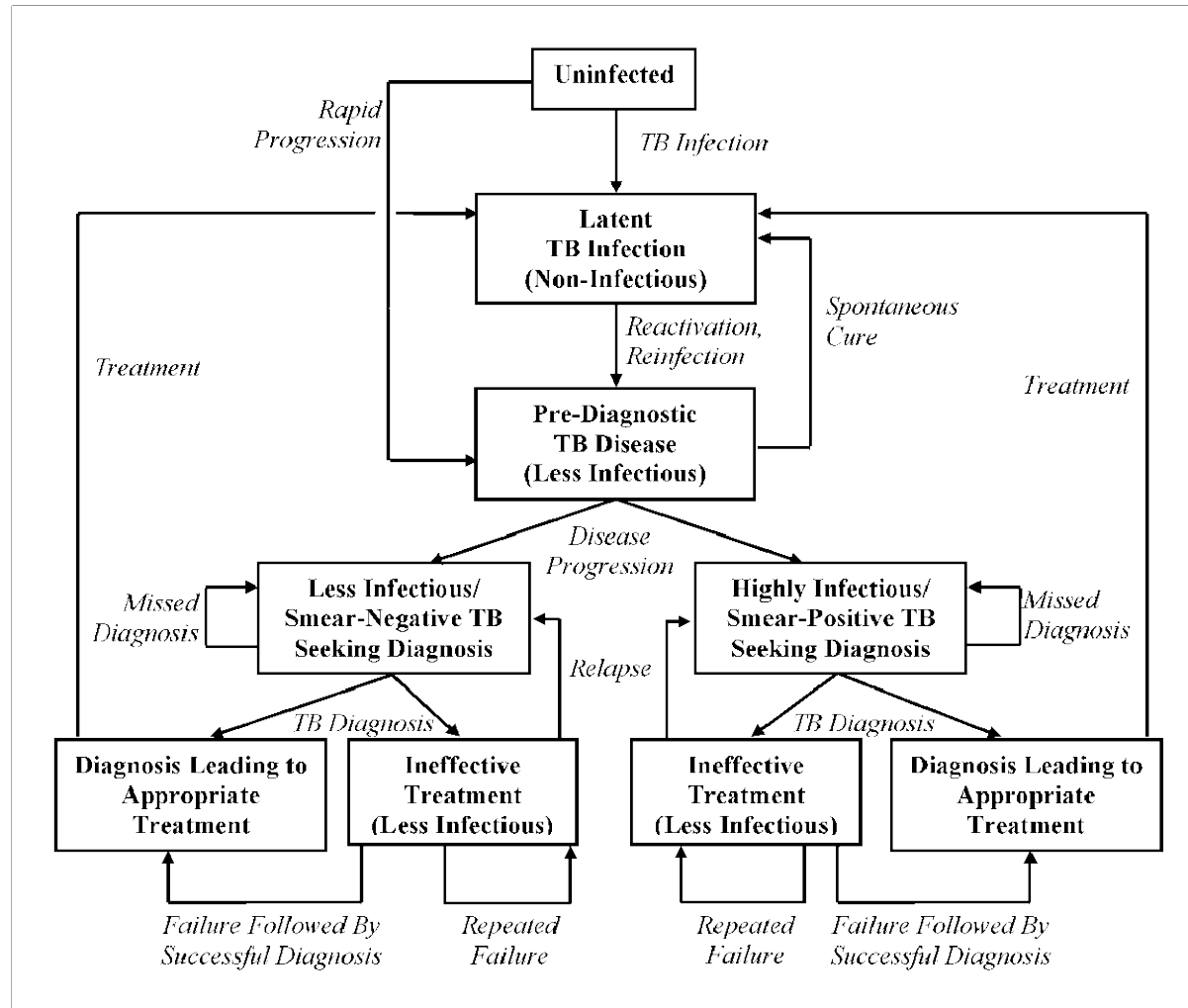
Brief Description of Diagnostic Strategies

Mouseover individual diagnostic strategies to see further details

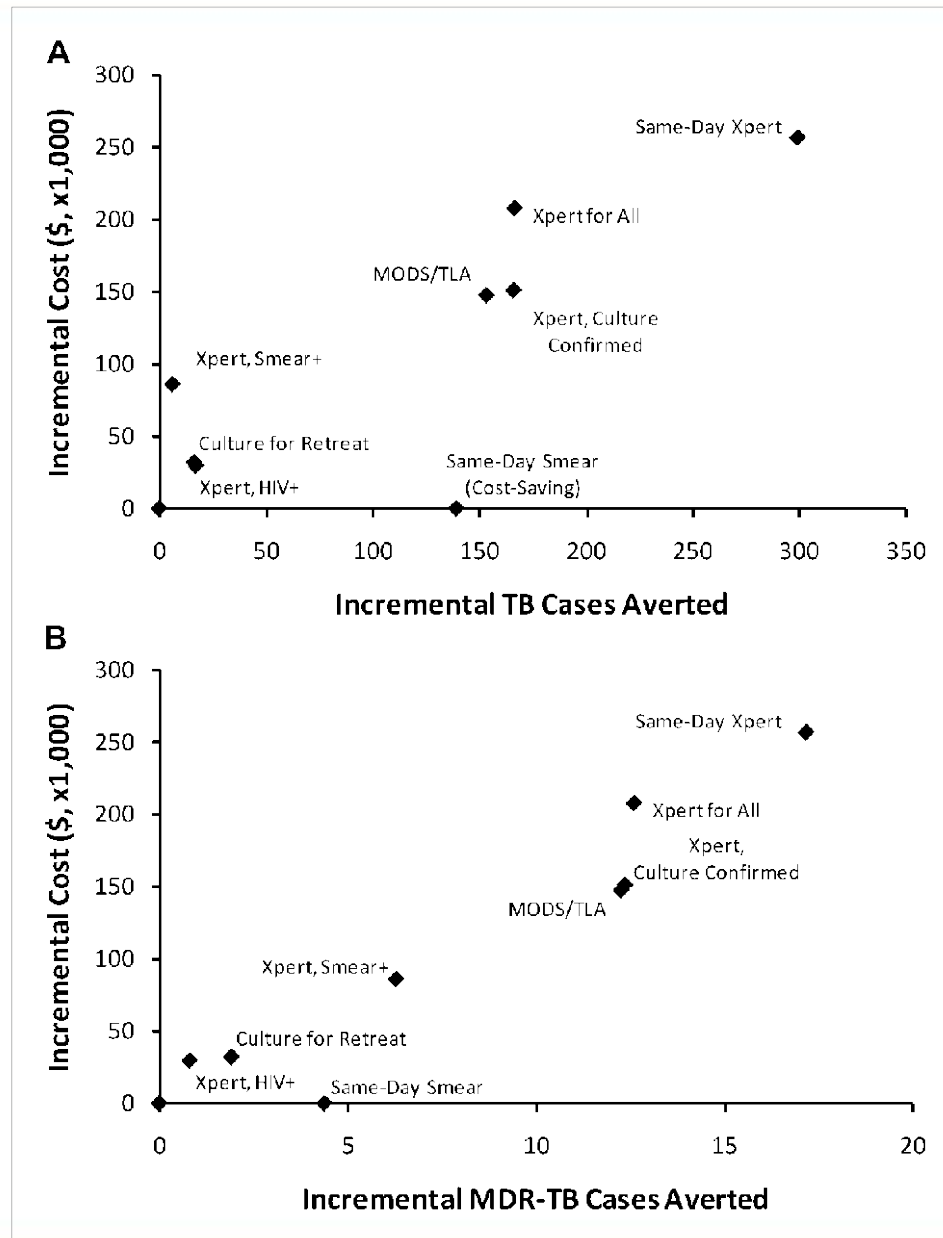




Underlying Model



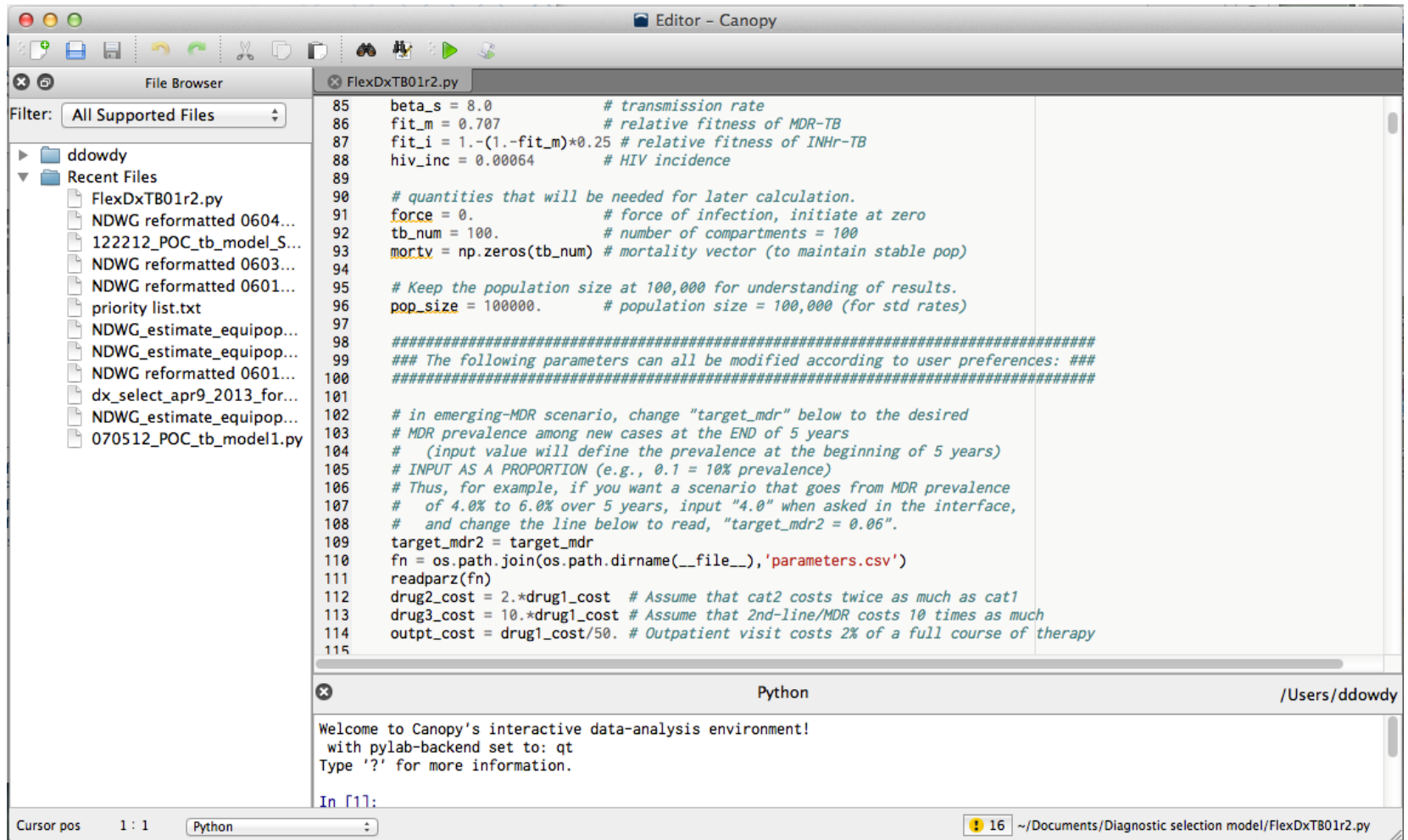
Output



Comparison



Open-Source Program Available



The screenshot displays the Canopy IDE interface. On the left, a File Browser shows a directory structure with files like 'FlexDxTB01r2.py' and 'NDWG reformatted 0604...'. The main editor window shows the code for 'FlexDxTB01r2.py', which includes parameters for transmission rate, relative fitness, and population size. The code is as follows:

```
85 beta_s = 8.0 # transmission rate
86 fit_m = 0.707 # relative fitness of MDR-TB
87 fit_i = 1.-(1.-fit_m)*0.25 # relative fitness of INHr-TB
88 hiv_inc = 0.00064 # HIV incidence
89
90 # quantities that will be needed for later calculation.
91 force = 0. # force of infection, initiate at zero
92 tb_num = 100. # number of compartments = 100
93 mortv = np.zeros(tb_num) # mortality vector (to maintain stable pop)
94
95 # Keep the population size at 100,000 for understanding of results.
96 pop_size = 100000. # population size = 100,000 (for std rates)
97
98 #####
99 ### The following parameters can all be modified according to user preferences: ###
100 #####
101
102 # in emerging-MDR scenario, change "target_mdr" below to the desired
103 # MDR prevalence among new cases at the END of 5 years
104 # (input value will define the prevalence at the beginning of 5 years)
105 # INPUT AS A PROPORTION (e.g., 0.1 = 10% prevalence)
106 # Thus, for example, if you want a scenario that goes from MDR prevalence
107 # of 4.0% to 6.0% over 5 years, input "4.0" when asked in the interface,
108 # and change the line below to read, "target_mdr2 = 0.06".
109 target_mdr2 = target_mdr
110 fn = os.path.join(os.path.dirname(__file__), 'parameters.csv')
111 readparz(fn)
112 drug2_cost = 2.*drug1_cost # Assume that cat2 costs twice as much as cat1
113 drug3_cost = 10.*drug1_cost # Assume that 2nd-line/MDR costs 10 times as much
114 outpt_cost = drug1_cost/50. # Outpatient visit costs 2% of a full course of therapy
115
```

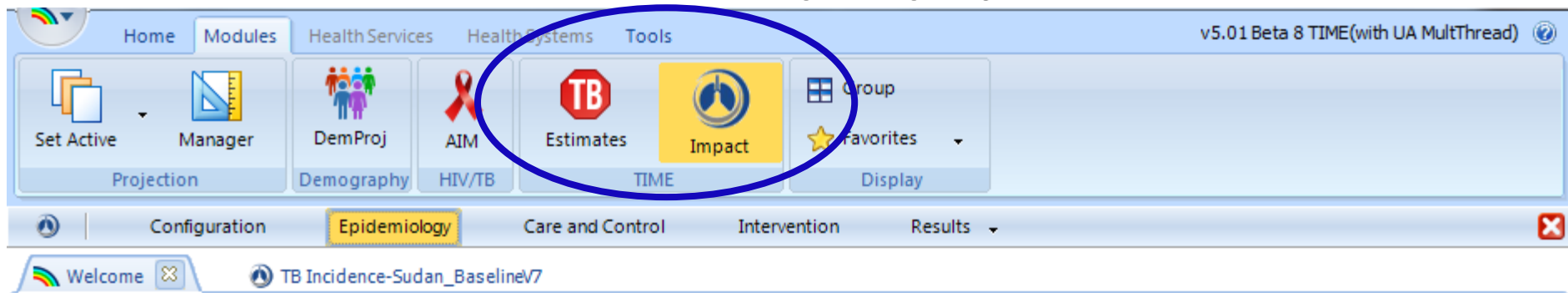
Below the code editor, the Python interactive environment is shown, displaying the welcome message: "Welcome to Canopy's interactive data-analysis environment! with pylab-backend set to: qt. Type '?' for more information." The prompt "In [1]:" is visible.





(TB Impact Model and Estimates)

A new country-level and user-friendly tool for TB-HIV
estimates and impact projections



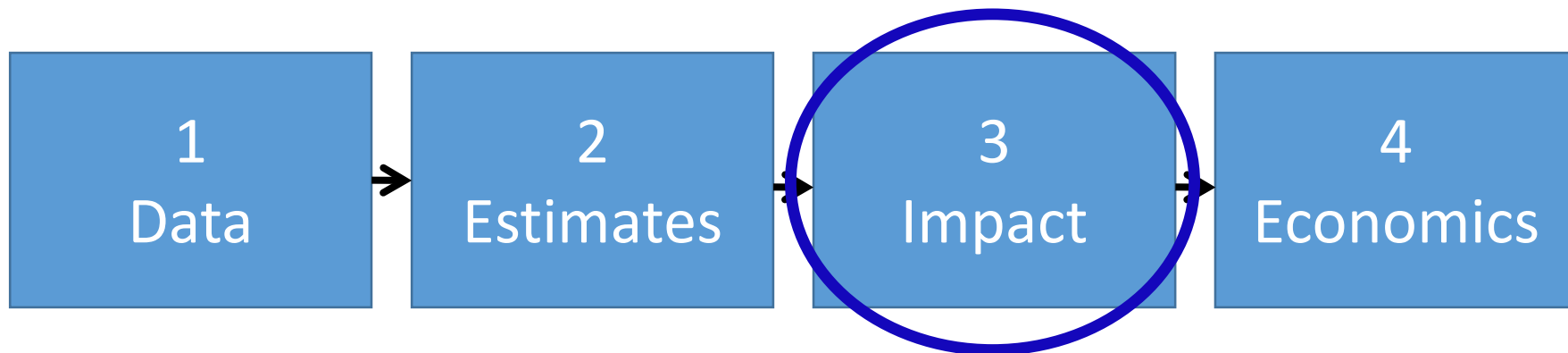
Developed in collaboration with

TB Modelling and Analysis Consortium; Futures Institute;
Global TB Programme/WHO; UNAIDS; Stop TB partnership

Contact: Rein.Houben@lshtm.ac.uk

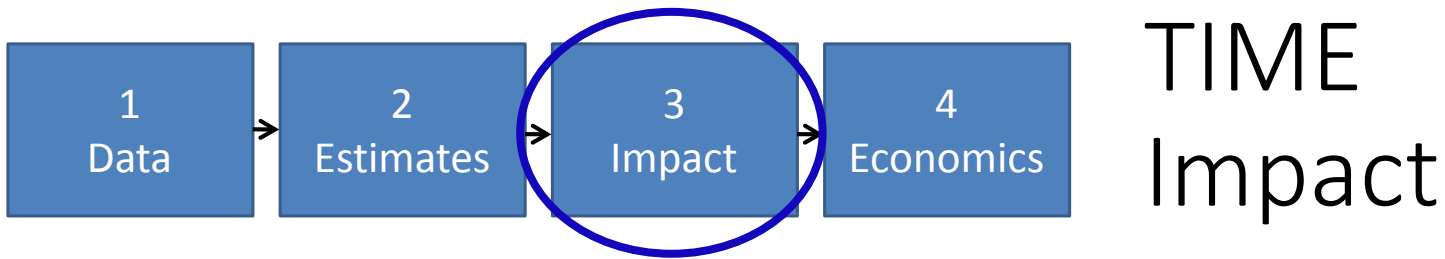
TIME

Country-level tool for TB(-HIV) estimates and projections

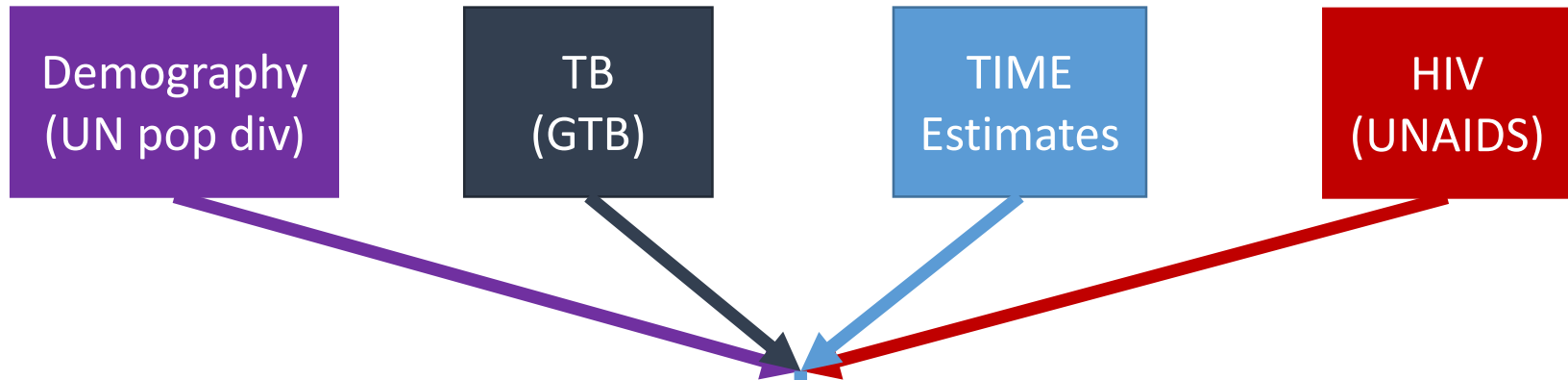


Set of modules for user

1. Data review, quality assessment and certification
2. Estimation of current burden and past trends
3. Projection and epidemiological impact
4. Cost-effectiveness and resource needs



Data pulled in automatically (sources)



TIME Impact is stratified by Treatment History, MDR, HIV/ART/CD4

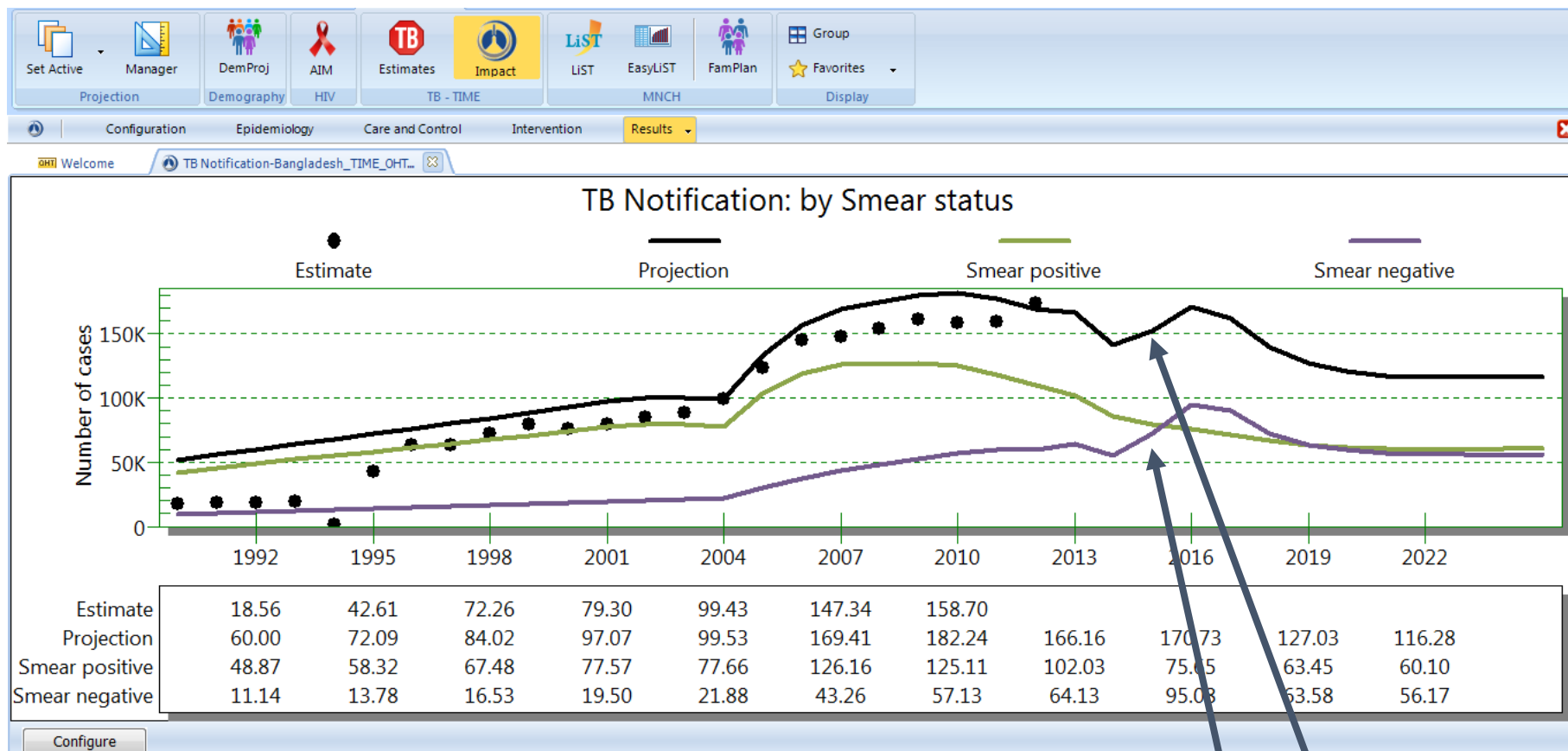


TIME Impact can handle Pre-specified or user-defined interventions

Data links automated through Spectrum software suite

Model can work on regional (multi-country) or subnational level as long as input data are available

TIME Impact: Results Bangladesh Pilot work

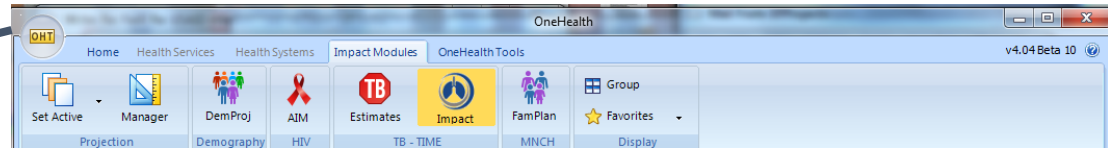
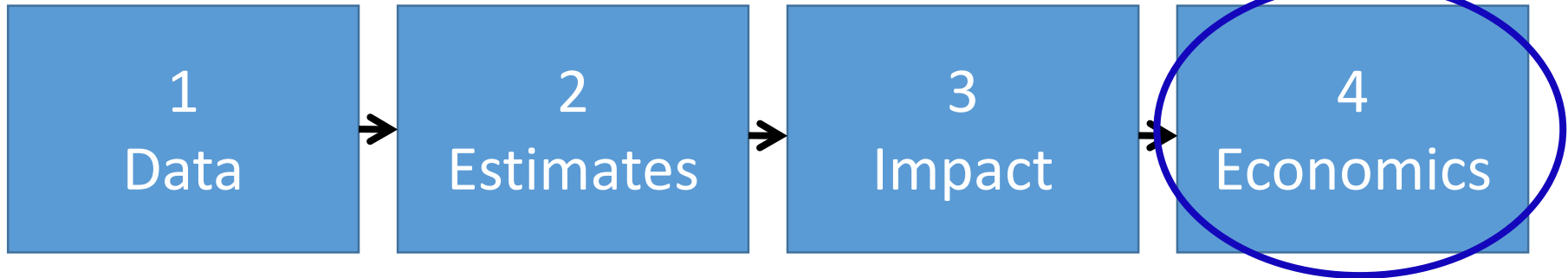


Note: Empirical treatment rates reported to be low

Xpert for smear negative TB

**TIME Impact was fit to notification, by smear status (see graph)
Captures impact of roll-out of Xpert for diagnosis of SSneg TB in 2014**

TIME Economics



Economics Tool: One Health

- Integrated costing environment for global health areas
- Supported by InterAgency Working Group on Costing
 - UNFPA, UNICEF, UNDP, UNAIDS, WHO, World Bank
- TB costing updated to reflect WHO/GTB budgeting methodology, fully linked to TIME
- Calculate costs per TB case averted, life saved, DALY/QALY, etc...

Acknowledgments

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 - Ted Cohen, David Dowdy, Anna Vassall
- **Futures Institute**
 - Carel Pretorius, Rachel Sanders
- **WHO Global TB Program (GTB)**
 - Philippe Glaziou, Babis Sismanidis, Ines Garcia-Baena
- **UNAIDS Reference Group for HIV Estimates and Projection**
 - Tim Hallet, Geoff Garnett, Simon Gregson
- **Stop TB Partnership**
 - Lucica Ditiu, Sahu Savenand
- **LSHTM TB Modelling Group**
 - Tom Sumner, Gwen Knight, Emilia Vynnycky and others.



The “Flexible” Approach is Still Limited

- Simplistic model – not enough for full decision-making
- May not speak to the precise questions in-country
 - Which generally are quite detailed and rapidly evolving
- Difficult to appropriately convey uncertainty
 - Some worry about misuse of such models
- Who would be the true user of these models, how would they use it, and can it be done without a big, well-funded team?
- *Panel discussion upcoming...*



The “Top-Down” Option: TB MAC

67th World Health Assembly 2014



Global strategy and targets for tuberculosis prevention, care and control after 2015

TB Modeling and Analysis Consortium
comparative modeling exercise



TB MAC Approach

- 11 different modeling groups
- 3 key countries (South Africa, India, China)
- Model series of pre-determined interventions:
 - Better access to care
 - Improved DOTS
 - Xpert scale-up
 - Active case-finding
 - IPT
 - Combination
- Involve WHO and health economists
- See if models agree or disagree



Challenges with the TB MAC Approach

- Different models treat interventions in different ways
 - Have to specify each intervention in a fashion that is comparable
- WHO wants different outputs than models can provide
 - Example: many models are adult models, but WHO wants all TB
- How to model the scale-up and impact of certain interventions?
 - Example: Xpert, ACF
- Crafting the take-home message
 - “2025 targets are unachievable” is not the message we want to send from this exercise.



Summary



- In theory, models are powerful tools for decision-making, but the practice of bringing model results to decisions is difficult.
- Alternative approaches exist, but none is (close to) perfect.
 - Open-source flexible model designed to be readily accessible
 - More detailed model with country technical missions to support
 - Top-down consortium engaged with global policy
- Is the process of bringing data systematically into the decision-making process impossible?
 - Meaning that we have no choice but to rely on the “mental models” of experts?
 - Time for a panel discussion...





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Modeling and Cost-Effectiveness: Synthesis



Protecting Health, Saving Lives—*Millions at a Time*

Modeling: Summary Points

- **1. The purpose of modeling is to inform decision-making, not tell the future.**
- Models serve as the link between epi data (usually individual-level) and population-level decision-making.
 - Without a quantitative structure for this, the process is subjective.
- Projections of future impact are the means, not the end.
 - Decision-makers generally can't process model results without projections.
 - But an appropriate decision-making process involves the modelers discussing strengths and weaknesses of the approach.



Modeling: Summary Points

- **2. Modeling of TB is an uncertain business.**
- Much of our data is weak, and can strongly influence results.
 - For example, we estimate natural history from pre-chemotherapy era.
- Model structure introduces as much uncertainty as the parameters.
 - Example of including a “pre-clinical infectious” stage for diagnostics
- Uncertainty is difficult to convey appropriately.
 - Do you want a confidence interval that includes every possibility?
 - Is the goal to provide precise projections in the first place?



Modeling: Summary Points

- **3. Challenges of Modeling TB Diagnostics**
- Diagnostics are part of a larger health system.
- Impact of diagnostics depends on patient behavior.
- There are many uncertainties in TB natural history.
- Heterogeneities in TB transmission are important to consider in designing smart diagnostic strategies.



Cost-Effectiveness: Summary Points

- **1. Basic Economic Concepts**
- Opportunity costs, not financial costs
- Unit costs (fixed & variable) – not straightforward
- Discounting, inflation, currency conversion
 - \$1 is not always \$1
- Perspective of the analysis
 - Costs from one perspective may not be important from another



Cost-Effectiveness: Summary Points

- **2. Challenges of CEA for TB Diagnostics**
- TB treatment is so effective that even bad diagnostics can look very cost-effective.
- Assumptions that more sensitive diagnosis = more people treated and more lives saved may not be accurate.
- Difficult to incorporate transmission effects and impacts on the health system
 - Though we are improving in this regard



Final Summary Point

Integrating Epidemic-Economic Models into Frameworks for Targeted, Data-Driven Decision Making

- Users want to be able to adapt results to their settings but may not have the expertise to use models appropriately.
- Modeling expertise in TB diagnostics is limited (and largely confined to academia) – must be realistic about how best to use that expertise in practice.
- Decision makers must first understand both the power and limitations of models in order to advance this discussion.

