African Medicinal Plants: Natural Product Database Development, Lead Discovery and Toxicity Assessment

Dr. Fidele Ntie-Kang^{1,2}

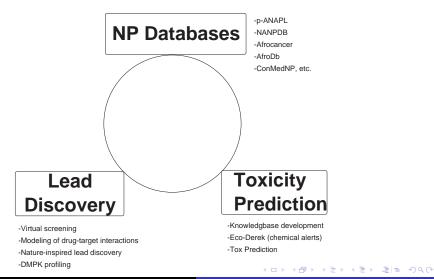
¹Department of Informatics and Chemistry, University of Chemistry and Technology, Prague, Czech Republic

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12 June 2018

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Concept



Outline



- 2 Lead Compound Discovery
 - Lead Compounds Discovery by Virtual Screening and Biological Testing
- 3 Toxicity Prediction
 - Develoment of Toxicity Prediction Knowledgbase

Lead Compound Discovery Toxicity Prediction Summary

African flora and other sources

Outline



2 Lead Compound Discovery

• Lead Compounds Discovery by Virtual Screening and Biological Testing

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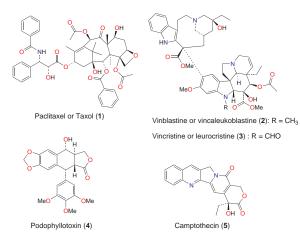
• Develoment of Toxicity Prediction Knowledgbase

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Lead Compound Discovery Toxicity Prediction Summary

African flora and other sources

Natural Products Preamble



2D structures of selected naturally occurring NP anticancer drug leads.

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Natural Products Some statistics

Table: Natural products versus synthetic drugs

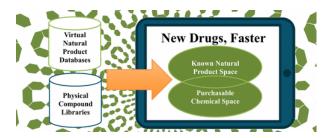
Newman and Cragg. J. Nat. Prod. 2016, 79:629-661

| Property | NPs | SDs |
|----------------|--|-------------------------|
| Samples | Limited quantities (time consuming | Readily available |
| | extraction processes) | |
| Drug-likeness | Weaker bioavailability (poor DMPK) | More bioavailable |
| Chemistry | Complex scaffolds, more stereogenic | Less O atoms, |
| | centres | less aromatics, etc. |
| Marketed drugs | - 6% (unaltered), | |
| | -26% (NP derivatives), | |
| | -32% (NP mimics) or from NP ph4s | |
| | -73% of small molecule antibacterials | |
| | -50% of anticancer drugs (e.g. taxol) $_{<}$ | ▼ ▲ 별 ▶ ▲ 별 ▶ ▲ 별 ⊨ ♥ 9 |

Lead Compound Discovery Toxicity Prediction Summary

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Natural Products



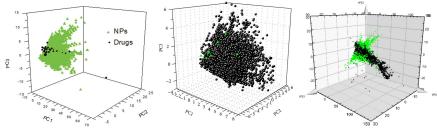
- ~10% of known NP chemical space is purchasable
- Much more on demand (outsourcing services, collaborations, etc.)
- Chen *et al.*, Data resources for the computer-guided discovery of bioactive natural products. *J. Chem. Inf. Model.* **2017**, 57(9):2099-2111

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Lead Compound Discovery Toxicity Prediction Summary

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Natural Products Chemical space of natural products



(left) NPs (green) in the UNPD and FDA-approved drugs (black): Lachance et al., J. Med. Chem., **2012**, 55:5989-6001. (middle) NPs in MPs (black) and 25 FDA-approved drugs against T2DM (green): Rosén et al., J. Med. Chem., **2009**, 52:1953-1962.

(right) Predicted score (tPS) plots of NPs (green) and bioactive med chem cpds from the WOMBAT database (black):

Feher & Schmidt. J. Chem. Inf. Comput. Sci., 2003, 43:218-227.

315

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Assessment Criteria Drug-likeness versus natural product-likeness assessment

'Drug-likeness': Lipinski *et al.* (2001)

• Likely OA if: $MW \le 500 \text{ Da}$; $\log P \le 5$; $HBA \le 10$; $HBD \le 5$

'Lead-likeness': Teague et al. (1999)

• Likely LC if: $150 \le MW \le 350$ Da; log $P \le 4$; $HBA \le 6$; $HBD \le 3$

'NP-likeness': Ertl *et al.* (2008)

• Likely an NP if:

 $f_i = \log\left(\frac{A_i}{B_i} \cdot \frac{B_{tot}}{A_{tot}}\right)$

African flora and other sources

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Ntie-Kang, F Databases, Lead Discovery, Toxicity Prediction

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Databases, Lead Discovery, Toxicity Prediction

Natural Products from African Medicinal Plants II General objectives

- Generate electronically accessible 3D models for molcular modeling research.
- Valorise the use of medicinal plants in Africa in traditional medicine.
- Identify lead compounds from medicinal plants by using computer modeling (e.g. *via in silico* docking and ph4 modeling).
- Assess the toxicity profiles of metabolites from African sources.

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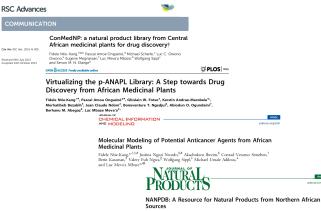
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Lead Compound Discovery Toxicity Prediction Summary

African flora and other sources

Natural Products from African Medicinal Plants IV Our contributions I.



Fidele Ntie-Kang.^{10,1,4,0} Kiran K. Telukunta,^{4,4} Kersten Döring,⁴ Conrad V. Simoben,[†] Aurélien F. A. Moumbock,[†] Yvette I. Malange,[‡] Leonel E. Njume,¹¹ Joseph N. Yong,[‡] Wolfgang Sippl,[†] and Stefan Günther^{10,1}

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http://african-compounds.org/about/

African flora and other sources

Natural Products from African Medicinal Plants VI Our contributions III.

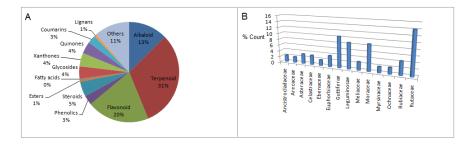
Summary of electronic databases developed within this work.

| Library name | Library size | Source organisms | Families |
|---------------|--------------|------------------|----------|
| CamMedNP | 1,859 | 224 | 55 |
| ConMedNP | 3,177 | 376 | 79 |
| AfroDb | 986 | - | - |
| AfroCancer | 390 | - | - |
| AfroMalariaDb | 511 | 131 | 45 |
| Afrotryp | 321 | - | 22 |
| p-ANAPL | 534 | ND | ND |
| NANPDB | 4,928 | 751 | 155 |

Lead Compound Discovery Toxicity Prediction Summary

African flora and other sources

Natural Products from African Medicinal Plants IV Modeling AfroCancer compounds.



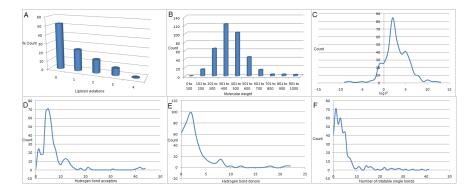
Ntie-Kang et al. J. Chem. Inf. Model., 2014, 54(9):2433-2450

Ntie-Kang, F Databases, Lead Discovery, Toxicity Prediction

Lead Compound Discovery Toxicity Prediction Summary

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Ntie-Kang et al. J. Chem. Inf. Model., 2014, 54(9):2433-2450

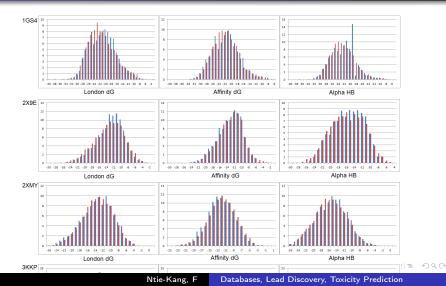
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Lead Compound Discovery Toxicity Prediction Summary

African flora and other sources

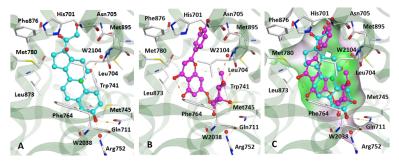
Natural Products from African Medicinal Plants IV Modeling AfroCancer compounds.



Lead Compound Discovery Toxicity Prediction Summary

African flora and other sources

Natural Products from African Medicinal Plants IV Modeling AfroCancer compounds.



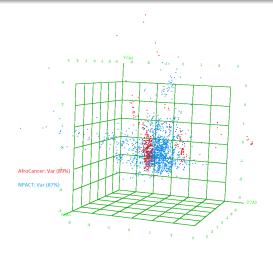
Top scoring pose for Glide docking of AfroCancer for modeling of the androgen receptor: (A) crystal structure the drug target (1GS4) in complex with cocrystallized 9α -fluorocortisol. (B) in complex with docked luteolin-7-O- β -glucopyranoside (from the Egyptian medicinal plant, *Livistona australis*). (C) Comparison of binding modes

of docking pose of the luteolin-7-O- β -glucopyranoside with co-crystallized 9α -fluorocortisol. Polar regions are shown in magenta, hydrophobic regions in green.

Lead Compound Discovery Toxicity Prediction Summary

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Natural Products from African Medicinal Plants IV Modeling AfroCancer compounds.

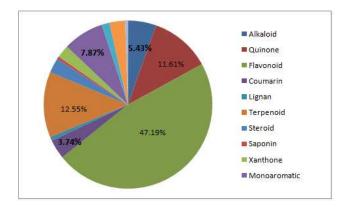


Ntie-Kang et al. Drug Design Dev Therapy., 2016, 10:2137-2154 B A C A C

Lead Compound Discovery Toxicity Prediction Summary

African flora and other sources

Natural Products from African Medicinal Plants V The p-ANAPL project.



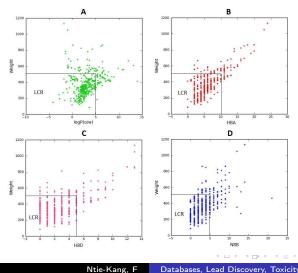
Ntie-Kang et al. PLoS ONE, 2014, 9(3): e90655.

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Lead Compound Discovery Toxicity Prediction Summary

African flora and other sources

Natural Products from African Medicinal Plants V The p-ANAPL project.

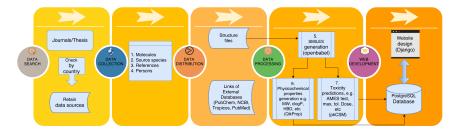


Databases, Lead Discovery, Toxicity Prediction

Lead Compound Discovery Toxicity Prediction Summary

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Natural Products from African Medicinal Plants V The NANPDB project.



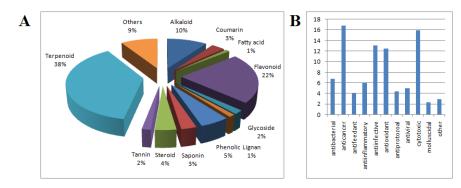
Ntie-Kang et al. J. Nat. Prod., 2017, 80(7):2067-2076.

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Lead Compound Discovery Toxicity Prediction Summary

African flora and other sources

Natural Products from African Medicinal Plants V The NANPDB project.



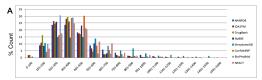
Ntie-Kang et al. J. Nat. Prod., 2017, 80(7):2067-2076.

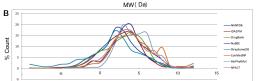
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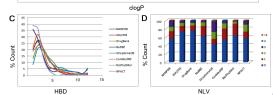
Lead Compound Discovery Toxicity Prediction Summary

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Natural Products from African Medicinal Plants V The NANPDB project.







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Databases, Lead Discovery, Toxicity Prediction

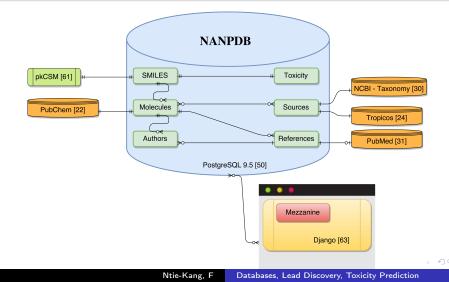
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Lead Compound Discovery Toxicity Prediction Summary

African flora and other sources

Natural Products from African Medicinal Plants V The NANPDB project.



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Outline



2 Lead Compound Discovery

• Lead Compounds Discovery by Virtual Screening and Biological Testing

3 Toxicity Prediction

• Develoment of Toxicity Prediction Knowledgbase

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Pharmacophore-based Virtual Screening Background and motivation

- Currently, no licensed ARVs target the accessory proteins of HIV-1.
- Vpu is an 81–82 amino acid transmembrane protein that is found in HIV-1.
- Vpu enhances viral replication through multiple functions, e.g. by downregulating CD4 and the host restriction factor BST2/CD317/tetherin. Vpu is also reported by some to have ion channel activity
- HIV-1 viruses with defective Vpu generally display reduced spread, defects in viral budding, and accumulation at the surface of infected cells.
- Thus, effective replication of HIV *in vivo* requires a functional Vpu protein, which makes it a promising drug target.

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Pharmacophore-based Virtual Screening Literature

Anal Bioanal Chem (2010) 396:2559–2563 DOI 10.1007/s00216-010-3498-x

SHORT COMMUNICATION

Ligand-protein docking studies of potential HIV-1 drug compounds using the algorithm FlexX

George Patargias • Gary Ewart • Carolyn Luscombe • Wolfgang B. Fischer





Biochimica et Biophysica Acta 1512 (2001) 291-298

www.bba-direct.com

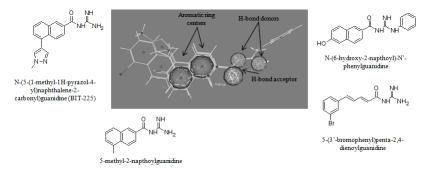
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The structure of the HIV-1 Vpu ion channel: modelling and simulation studies

F.S. Cordes ^a, A. Kukol ^{1,b}, L.R. Forrest ^a, I.T. Arkin ^{2,b}, M.S.P. Sansom ^a, W.B. Fischer ^{a,*}

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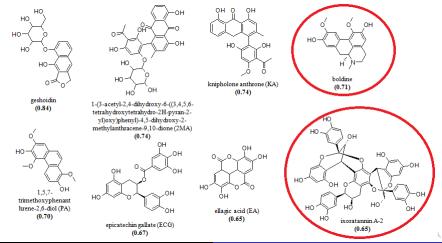
Pharmacophore-based Virtual Screening Our contribution



Tietjen I, Ntie-Kang F, et al., PLos ONE, 2015, 10(4): e0121099.

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Pharmacophore-based Virtual Screening Virtual hits



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Databases, Lead Discovery, Toxicity Prediction

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Pharmacophore-based Virtual Screening Virtual hits

Table 1. Cell toxicity and inhibition of HIV-1_{NL4-3} in CEM-GXR cells by p-ANAPL compounds.

| Compound | Cell toxicity (CC50, µM) | HIV-1 _{NL4-3} inhibition (EC50, μ M) | |
|-----------------|--------------------------|---|--|
| BIT-225 | 10.7 | n/d | |
| geshoidin | >10 | >100 | |
| 2MA | 50.9 | >100 | |
| KA | 0.9 | n/d | |
| boldine | >100 | 50.2 | |
| PA | 26.8 | n/d | |
| ECG | >100 | >100 | |
| EA | 52.3 | >100 | |
| ixoratannin A-2 | 57.5 | 34.4 | |

n/d, not determined.

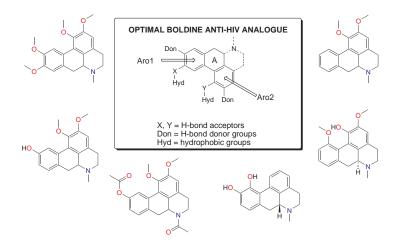
doi:10.1371/journal.pone.0121099.t001

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Pharmacophore-based Virtual Screening

Ideas for Boldine analogues



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Structure-based Virtual Screening Background on sirtuins

- Sirt = silent information regulator, belonging to a highly conserved family of drug targets.
- In the category of epigenetic drug targets, they are referred to as "erasers".
- Sirts are nicotinamide adenine dinucleotide (NAD⁺)-dependent class III histone deacetylases.
- Sirts are linked to the pathogenesis of numerous diseases, e.g. HIV, metabolic disorders, neurodegeneration (including Alzheimer's disease and Parkinson's disease), aging and cancer.

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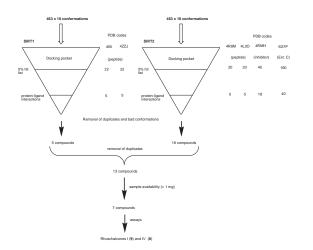
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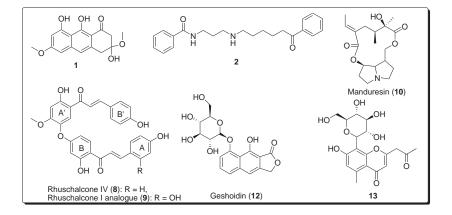
Structure-based Virtual Screening Discovery of sirtuin inhibitors



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LBVS/SBVS

Structure-based Virtual Screening Discovery of sirtuin inhibitors



Ntie-Kang, F Databases, Lead Discovery, Toxicity Prediction

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Table 1. IC_{50} or percentage inhibitions at 50% of tested pan-African Natural Products Library (p-ANAPL) compounds against sirt1, 2 and 3.

| Compound Number | Sirt 1 (µM) | Sirt 2 (µM) | Sirt 3 (µM or % Inhibition) |
|-----------------|-------------------|-------------------|-----------------------------|
| 1 ^b | n.d. ^c | n.d. ^c | n.d. ^c |
| 2 | n.i. ^a | n.i. ^a | n.i. ^a |
| 8 | 46.7 ± 6.0 | 48.5 ± 39.5 | 38% |
| 9 | 40.8 ± 8.5 | 44.8 ± 5.1 | 23% |
| 10 | n.i. ^a | n.i. ^a | n.i. ^a |
| 12 ^b | n.d. | n.d. | n.d. |
| 13 | n.i. ^a | n.i. ^a | n.i. ^a |
| NA | 142.4 ± 9.1 | 49.8 ± 4.6 | 67.9 ± 3.3 |
| EX-527 | 1.4 ± 0.1 | 10.6 ± 1.1 | 19% |

^a n.i. = no inhibition (<10%). ^b autofluorescence. ^c n.d. = not detectable. Note that activity was not detectable due to the autofluorescence. NA = nicotinamide, EX-527 = sirt inhibitor in clinical trials.

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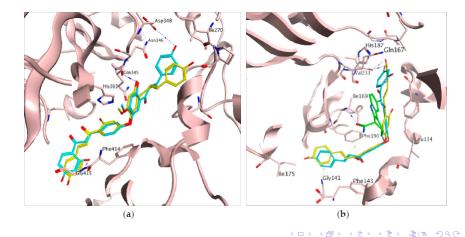
-*Rhus pyroides* (Anacardiaceae) -Tree from Eastern Botswana -Antifeedant properties

-Rich source of O-linked and C-C -Coupled bischalcones and biflavonoids

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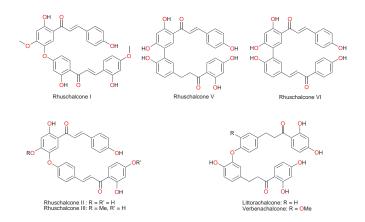
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Ntie-Kang, F Databases, Lead Discovery, Toxicity Prediction

LBVS/SBVS

Structure-based Virtual Screening Some suggestions



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Outline



- 2 Lead Compound Discovery
 - Lead Compounds Discovery by Virtual Screening and Biological Testing
- 3 Toxicity Prediction
 - Develoment of Toxicity Prediction Knowledgbase

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Knowledgbase for Toxicity Prediction Eco-Derek Background

- Toxicity model: 40 hour static flow growth inhibition assay (log(1/IGC₅₀) values) for the ciliated protozoan *Tetrahymena pyriformis*, from Schultz *et al.* Toxicol. Methods 1997, 7: 289-309.
- Published data on over 1200 chemicals, from Xue *et al.* Chem. Res. Toxicol. 2006, 19:1030-1039.
- log(1/IGC₅₀) was predicted as a function of log P, e.g. log (1/IGC₅₀50 NPN) = 0.78 log P - 2.01 (n = 87, r² = 0.96).

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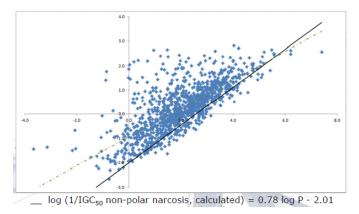
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Knowledgbase for Toxicity Prediction Eco-Derek Background



- Computer modeling was used to valorise of the medicinal potential of African medicinal plants (databases, lead compounds, etc.).
- New databases were developed and published in the web.
- Identification NP lead molecules via LBVS and SBVS were carried out.
- NP mimics with potent activities were synthesized and tested.
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Thanks for your kind attention I





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