

1 **Semi-artificial datasets as a resource for validation of bioinformatics** 2 **pipelines for plant virus detection**

3 Lucie Tamisier^{1*}, Annelies Haegeman², Yoika Foucart², Nicolas Fouillien¹, Maher Al Rwahnih³,
4 Nihal Buzkan⁴, Thierry Candresse⁵, Michela Chiumenti⁶, Kris De Jonghe², Marie Lefebvre⁵,
5 Paolo Margaria⁷, Jean Sébastien Reynard⁸, Kristian Stevens^{3,9}, Denis Kutnjak¹⁰, Sébastien
6 Massart^{1*}

7
8 ¹ Université de Liège, Terra-Gembloux Agro-Bio Tech, Plant Pathology Laboratory, Passage
9 des Déportés, 2, 5030 Gembloux, Belgium

10 ² Plant Sciences Unit, Flanders Research Institute for Agriculture, Fisheries and Food (ILVO),
11 Burg. Van Gansberghelaan 96, 9820 Merelbeke, Belgium

12 ³ Department of Plant Pathology, University of California, Davis, 95616

13 ⁴ Department of Plant Protection, Faculty of Agriculture, University of Sütçü Imam,
14 Kahramanmaraş 46060, Turkey

15 ⁵ Univ. Bordeaux, INRAE, UMR BFP, CS20032, 33882 Villenave d'Ornon cedex, France

16 ⁶ Institute for Sustainable Plant Protection, CNR, Via Amendola 122/D, Bari 70126, Italy

17 ⁷ Leibniz Institute - DSMZ, German Collection of Microorganisms and Cell Cultures GmbH,
18 38124 Braunschweig, Germany

19 ⁸ Virology, Agroscope, Nyon, Switzerland

20 ⁹ Department of Evolution and Ecology, University of California, Davis, California 95616, USA

21 ¹⁰ Department of Biotechnology and Systems Biology, National Institute of Biology, Ljubljana,
22 Slovenia

23

24 *Corresponding authors: Lucie Tamisier; E-mail: lucie.tamisier@uliege.be, Sébastien Massart;
25 E-mail: sebastien.massart@uliege.be

26

27 **Keywords**

28 High-Throughput Sequencing, Reference data, Semi-artificial dataset, Plant virus detection,
29 Bioinformatics pipelines, Haplotype reconstruction

30 **Abstract**

31 The widespread use of High-Throughput Sequencing (HTS) for detection of plant viruses and
32 sequencing of plant virus genomes has led to the generation of large amounts of data and of
33 bioinformatics challenges to process them. Many bioinformatics pipelines for virus detection
34 are available, making the choice of a suitable one difficult. A robust benchmarking is needed
35 for the unbiased comparison of the pipelines, but there is currently a lack of reference datasets
36 that could be used for this purpose. We present 7 semi-artificial datasets composed of real
37 RNA-seq datasets from virus-infected plants spiked with artificial virus reads. Each dataset
38 addresses challenges that could prevent virus detection. We also present 3 real datasets

39 showing a challenging virus composition as well as 8 completely artificial datasets to test
40 haplotype reconstruction software.

41

42 In the last decade, High-Throughput Sequencing (HTS) has revolutionized plant virus
43 discovery and diagnosis (Maree *et al.*, 2018; Massart *et al.*, 2014). The main advantage of this
44 technology is that it allows a complete characterization of the virus populations infecting a
45 plant, without any *a priori* knowledge of the infecting viruses. Current HTS platforms can
46 ascertain the molecular sequences of large quantities of nucleic acid fragments at a very low
47 base pair price, allowing the simultaneous sequencing of many samples. The increased use
48 of HTS in the diagnostic field has led to the generation of massive amounts of data and resulted
49 in computational and bioinformatics challenges to process them (*i.e.* storage, processing
50 speed, bioinformatics competence) (Olmos *et al.*, 2018). Many bioinformatics pipelines for
51 plant virus detection have been developed, from easy-to-use commercial software to
52 command line tools (Blawid *et al.*, 2017; Jones *et al.*, 2017). Most of them aim to improve virus
53 detection and/or reduce processing time, but the high number of pipelines available complicate
54 the choice of the most appropriate for a given goal or environment. Moreover, the sequence
55 analysis strategy can have a significant influence on the ability to detect viruses from identical
56 datasets, as shown by a large-scale performance testing involving 21 plant virology
57 laboratories (Massart *et al.*, 2019). Performing a robust benchmarking is therefore essential
58 for the unbiased comparison of the pipelines (Escalona *et al.*, 2016; Jones *et al.*, 2017). In
59 plant disease diagnostics, validation of the bioinformatics pipelines used for the detection of
60 viruses in HTS datasets is at its infancy and there is currently a lack of reference datasets
61 generated for benchmarking purposes. The development of such datasets is a key step in the
62 standardization of bioinformatics protocols, since it allows objective comparison between
63 pipelines. These observations have led to the creation of the Plant Health Bioinformatics
64 Network (PHBN), an Euphresco network project aiming to build a community network of
65 bioinformaticians/computational biologists working on plant health. One of the objectives of
66 this project is to help researchers to compare and validate their virus detection pipelines by
67 creating open access reference datasets.

68 **Creation of the datasets**

69 Two main kinds of reference datasets can be used: real and artificial ones. Working with real
70 datasets offers the benefit of providing real life scenarios which are close to those encountered
71 by plant pathologists and diagnosticians. However, the use of such purely empirical data has
72 limitations since it is impossible to know with an absolute certainty the “true” value that should
73 be used to benchmark the performance of the pipelines (Escalona *et al.*, 2016). Artificial
74 datasets do not have this drawback since their composition is totally controlled and known.

75 However, completely artificial datasets are often unrealistic and too simple, and may thus fail
76 to represent accurately the complexity of real HTS datasets. In order to overcome the
77 drawbacks of these two approaches, we have chosen to create semi-artificial datasets
78 composed each of a real HTS dataset from virus-infected plants spiked with additional *in-silico*
79 generated viral reads. The artificial component of these semi-artificial datasets is totally known,
80 but the datasets are still complex and close to real-life situations. We also developed and
81 propose some real and some completely artificial datasets, which can be used for specific
82 purposes as explained bellow.

83 A total of 8 real RNA-seq datasets from virus/viroid-infected plants obtained using Illumina
84 technology have been chosen in order to cover as much as possible host plant diversity (fruit
85 trees, vegetables and biological indicator plants), pathogen diversity (RNA and DNA viruses,
86 viroids) and sequencing options (reads length from 50 to 301 bp, number of reads per dataset
87 from 65,177 to 49,052,832 reads, and single-end or paired-end reads). For each real dataset,
88 the presence of the viruses/viroids identified has been confirmed by PCR and/or ELISA. Five
89 of these real datasets have been used to create 7 semi-artificial datasets (Datasets 1, 2, 3, 4,
90 5, 6 and 10) (Table 1), either by adding artificial reads of a virus/viroid (already present or not
91 in the dataset) or by removing part of the real viral reads. The artificial viral reads were
92 synthesized using the ART software (Huang *et al.*, 2012) which allows the generation of
93 artificial next-generation sequencing reads showing the same quality score as the reads from
94 a real datasets. For each semi-artificial dataset, similar headers have been assigned to the
95 artificial and real reads, and both types of reads have been mixed in each FASTA file. The
96 three other real datasets (Datasets 7, 8 and 9) were already showing a challenging viral
97 composition (presence of a defective variant, presence of a cryptic virus and presence of
98 several genomic segments showing different concentrations) and have not been modified.

99 Each dataset has been developed or selected to address one or several challenges that could
100 prevent virus detection or a correct virus identification from HTS data (*i.e.* low viral
101 concentration, new viral species, non-complete genome, etc). In addition, eight fully artificial
102 datasets (Datasets 11-18), composed only of viral reads have also been created. These
103 datasets can be used to test haplotype reconstruction software, the goal being to evaluate the
104 ability to reconstruct all the strains present in a dataset. Each artificial dataset consists of a mix
105 of several stains from the same viral species showing different frequencies. The virus species
106 have been selected to be as divergent as possible. Therefore, the selected viruses have (i) a
107 DNA or RNA genome, (ii) a single or double-stranded genome, (iii) a linear, circular and/or
108 segmented genome, and (iv) show a genome length ranging from 2.8 to 17.1 kb. For each
109 strain, artificial viral reads of 150 bp have been synthesized using the ART software (Huang *et*

110 *al.*, 2012) from NCBI reference genomes and no single nucleotide polymorphisms (SNPs) have
111 been added.

112 **Availability and description of the datasets**

113 A GitLab repository (<https://gitlab.com/ilvo/VIROMOCKchallenge>) is available and provides a
114 complete description of the composition of each dataset, the methods used to create them, a
115 link to download them and their goals. The datasets themselves are stored in Dryad
116 (datadryad.org). We provide here a quick summary of the composition of the datasets and the
117 challenges they address (Table 1).

118 - Dataset 1: The challenge addressed is the detection of several virus strains showing different
119 concentrations, some being very low. In this case, one or more strains can be missed,
120 especially if the sample has not been enriched in viral sequences (Barzon *et al.*, 2013; Knierim
121 *et al.*, 2019). The real dataset is composed of mixed infections of citrus tristeza virus (CTV),
122 citrus vein enation virus (CVEV), citrus exocortis viroid (CEVd), citrus viroid III (CVd-III) and
123 hop stunt viroid (HSVd) on citrus. Artificial reads for three CTV strains (JQ911663 – strain T68,
124 KU883267 – strain S1 and MH323442 – strain T36) have been added to the dataset at different
125 read depth.

126 - Dataset 2: The challenge addressed is the identification of different types of mutations at
127 different frequencies. The viral populations infecting a plant are usually composed of closely
128 related virus genotypes, differing by a few SNPs (substitution) or indels (insertion or deletion)
129 and at differing relative concentrations. Some variants can be missed depending on their
130 frequencies, the bioinformatics strategy or the presence of sequencing errors (Lefterova *et al.*,
131 2015). The same real data set from a naturally infected citrus as in dataset 1 has been used
132 with the addition of artificial reads for the CTV MH323442 isolate, using 5 nearly identical
133 sequences of this isolate, each differing by 1 substitution, 1 base deletion and 1 base insertion.
134 Artificial reads for the unmutated MH323442 isolate have also been added to the dataset 2.
135 The reads for the various MH323442 variants have been added at different frequencies.

136 - Dataset 3: The challenge addressed is the detection of several viral/viroid species showing
137 different frequencies and incomplete genome coverage. The assembly process can result in
138 incomplete genome sequences, making virus identification challenging (Boonham *et al.*, 2014),
139 in particular when the whole genome is not completely covered, or when a genomic segment
140 is absent or is covered by a low number of reads in the case of a multipartite virus. The real
141 dataset corresponds to a mixed infection of grapevine rupestris vein feathering virus (GRVfV),
142 grapevine rupestris stem pitting-associated virus (GRSPaV), grapevine leafroll-associated
143 virus 2 (GLRaV2), hop stunt viroid (HSVd) and grapevine yellow speckle viroid 1 (GYSVd1) on

144 grapevine. Reads assigned to GRSPaV, GRVfV and GLRaV2 have been randomly removed
145 in order to obtain incomplete genome coverage for these 3 viruses.

146 - Dataset 4: The challenge addressed is the detection of closely related viroids. Closely related
147 virus/viroid species within a genus can share high nucleotide identities, leading to taxonomic
148 assignment problems and complicating the identification of the virus/viroid (Thekke-Veetil *et*
149 *al.*, 2018). The real dataset is composed of mixed infections of grapevine red blotch virus
150 (GRBV), grapevine rupestris stem pitting-associated virus (GRSPaV), hop stunt viroid (HSVd)
151 and grapevine yellow speckle viroid 1 (GSYVd1) on grapevine (Reynard *et al.*, 2018). Artificial
152 reads of grapevine yellow speckle viroid 2 (GYSVd2) isolate DQ377131 have been added to
153 the dataset. This reference shows a pairwise nucleotide identity of 73.9% with the consensus
154 sequence of the naturally present GYSVd1, a portion of the two genomes being very similar
155 while the other part show more variability.

156 - Dataset 5: The challenge addressed is the detection of a recombinant strain and one of its
157 parents in mixed infection. HTS samples can be infected by genetically close parental and
158 recombinant strains. During the assembly process, it can sometimes be challenging to
159 assemble and detect recombinant genomes while avoiding to create artefactual ones, in
160 particular when using short-sequence reads (Martin *et al.*, 2011). The real dataset contains
161 reads of two potato virus Y (PVY) isolates belonging to different strains (an isolate belonging
162 to the NTN recombinant strain and the N605 isolate belonging to the N strain). Artificial reads
163 to a further two isolates have been added, the parental isolate AY884983 (N strain), and isolate
164 EF026076, a recombinant between isolates belonging to the N and O strains (Hu *et al.*, 2009).
165 Both isolates show an overall pairwise nucleotide identity of 88.2% but the 5' part of their
166 genomes (first ~2,000 nucleotides) are almost identical.

167 - Dataset 6: The challenge addressed is the detection of a new PVY strain that does not exist
168 in the database, within a dataset already involving other PVY strains. Novel viruses can be
169 detected by homology searches with databases. Nevertheless, viral sequences that are too
170 divergent from known viruses might not be detected by this such searches. Other approaches
171 like homology-independent algorithms may be needed to fully characterize such new viruses
172 (Wu *et al.*, 2015). The real dataset is the same as dataset 5. It has been spiked with artificial
173 reads from the FJ214726 PVY isolate, which was selected because it is among the most
174 divergent PVY isolates available in GenBank (maximum 84% nucleotide identity with any other
175 available PVY isolate). The amino acid sequence of the polyprotein of FJ214726 was obtained
176 and then reverse translated into a nucleotide sequence using the online EMBOSS Backtranseq
177 tool (Madeira *et al.*, 2019). Thanks to the degeneracy of the genetic code, the nucleotide
178 sequence thus obtained was different from the original FJ214726 sequence. Non-synonymous

179 substitutions were further manually added to the new artificial sequence, increasing divergence
180 from any known PVY isolate. The final artificial sequence shows only 71.8% nucleotide identity
181 and 98.9% amino acid identity with FJ214726 and was used to generate the artificial reads
182 finally added to the dataset. The artificial genomic sequence is available in the GitLab
183 repository for comparison purposes.

184 - Dataset 7: The challenge addressed is the detection of both a defective and a normal length
185 variant from the same sample. Related viral variants infecting a sample and showing similar
186 genome portions can be particularly difficult to distinguish. The real dataset is composed of
187 two variants of tomato spotted wilt virus (TSWV) from tobacco. The genome of TSWV consists
188 of 3 negative single-stranded RNA segments named S, M and L. The variants diverge only for
189 the L genomic segment, one being full length (8,913 bp) and the other being a shorter defective
190 form (2,612 bp) missing the genomic region from genome position 760 to 7,060 bp. The real
191 dataset shows already a challenging composition, and has therefore not been spiked with
192 artificial viruses.

193 - Dataset 8: The challenge addressed is the detection of a low concentration persistent virus.
194 The real dataset is composed of *Pelargonium* flower break virus (PFBV) and *Chenopodium*
195 quinoa mitovirus 1 (CqMV1), a virus from *Chenopodium* which is localized in mitochondria and
196 presents only one ORF that encodes the RNA-dependent RNA polymerase (Nerva *et al.*,
197 2019). The cryptic virus CqMV1 represents a low proportion of reads (around 0.5%). The real
198 dataset shows already a challenging composition, and has therefore not been spiked with
199 artificial viruses.

200 - Dataset 9: The challenge addressed is the detection of all the genomic segments of a virus
201 with each segment having a different concentration. The real dataset is composed of *Pistacia*
202 emaravirus B (PiVB), a newly discovered Emaravirus from the pistachio tree (Buzkan *et al.*,
203 2019). The viral genome is composed of seven distinct negative-sense, single-stranded RNAs,
204 showing different frequencies in the dataset. The real dataset shows already a challenging
205 composition, and has therefore not been spiked with artificial viruses.

206 - Dataset 10: The challenge addressed is the detection of a new viral strain that does not exist
207 in the database, thus adding a 'virus' that is not already present in the dataset (in contrast to
208 the challenge addressed in dataset 6). The real dataset is composed of plum bark necrosis
209 stem pitting-associated virus (PBNSPaV) from *Prunus*. A new artificial isolate of plum pox virus
210 (PPV) has been created as described above for the creation of the artificial PVY isolate in
211 dataset 6. The new artificial PPV strain has finally been added to the dataset, and its sequence
212 has been made available as well to be able to compare resulting assemblies with it.

213 - Datasets 11 to 18 can be used to test the ability to reconstruct haplotypes from mixed
214 infections of virus isolates belonging to the same virus species. They are completely artificial
215 datasets and their composition is summarized in Table 1.

216 **The VIROMOCK challenge**

217 The goal of all these reference datasets is to allow to perform an objective comparison of
218 bioinformatics pipelines used to detect and analyse viruses. At first, researchers can use these
219 datasets to check whether their current pipelines are behaving as expected, and how modifying
220 some parameters can affect their pipeline performance depending on the challenge
221 investigated. Second, it can be interesting for researchers to compare their results with those
222 of other labs/pipelines. For this purpose, we propose to organize a “VIROMOCK challenge”.
223 In the frame of this challenge, researchers are encouraged to provide feedback on the results
224 they obtained for each dataset they analyse and on the difficulties they may have encountered.
225 This can simply be done by completing a Google spreadsheet added to each dataset page of
226 the GitLab repository. Then, the results will be compiled for each dataset, helping to identify
227 which pipelines perform best in approximating the real composition of the datasets and
228 providing an idea about the robustness of the parameters used. If researchers agree, the
229 compiled results will be open access on the GitLab repository for each dataset, allowing an
230 easy and objective comparison of the results.

231 **Conclusion**

232 The two main bottlenecks slowing down the adoption of HTS in plant health diagnostics are (i)
233 the lack of consensus on the standardization of the data analysis and (ii) the lack of expertise
234 of some laboratories. Within the frame of PHBN project, we have generated semi-artificial, real
235 and artificial reference datasets in order to help to overcome these bottlenecks. Firstly, the
236 diversity of the challenges addressed by these datasets will allow to benchmark the
237 bioinformatics pipelines used by different laboratories. Secondly, these datasets can also be
238 viewed as open source training materials. They could be extremely valuable for laboratories
239 with little experience, allowing them to improve their skills. Currently, there are many pipelines
240 available, but many laboratories do not know where to start when it comes to the analysis of
241 their HTS data in the context of virus detection. This represents a big challenge, especially in
242 situations where HTS and data analysis are newly established or not part of the routine
243 activities. These datasets will help them to either validate their pipelines or choose the most
244 suitable one for their analyses.

Table 1: Characteristics of each dataset

Dataset	Dataset type	Plant species	Virus/Viroids already present ¹	Modification	Reads (bp)	Total number of reads ²	Challenge	Dryad DOI
1	Semi-artificial	Citrus	CTV, CVEV, CEVd, CVd-III, HSVd	Addition of CTV	2 x 150	21,703,434 (R1) 21,703,434 (R2)	Viral concentration (at the strain level)	10.5061/dryad.crjdfn32c
2	Semi-artificial	Citrus	CTV, CVEV, CEVd, CVd-III, HSVd	Addition of CTV	2 x 150	21,756,961 (R1) 21,756,961 (R2)	Mutation	10.5061/dryad.ns1rn8pq9
3	Semi-artificial	Grapevine	GRSPaV, GLRaV2, GRVfV, HSVd, GYSVd1	Removing of real viral reads	2 x 150	24,526,416 (R1) 24,526,416 (R2)	Viral concentration (at the species level) + Non complete genome	10.5061/dryad.zs7h44j6d
4	Semi-artificial	Grapevine	GRBV, GRSPaV, HSVd, GYSVd1	Addition of GYSVd2	2 x 75	10,054,658 (R1) 10,054,658 (R2)	Viroids with very similar sequence	10.5061/dryad.jsxksn06w
5	Semi-artificial	Potato	PVY	Addition of PVY	1 x 50	31,277,475	Mix of recombinant and parental viral strains	10.5061/dryad.xgxd254dw
6	Semi-artificial	Potato	PVY	Addition of PVY	1 x 50	31,327,327	New strain	10.5061/dryad.tx95x69vw
7	Real	Tobacco	TSWV	-	2 x 301	1,904,369 (R1) 1,904,369 (R2)	Complete genome + defective form	10.5061/dryad.c2fqz615w
8	Real	Chenopodium	PFBV + mitovirus	-	2 x 301	65,177 (R1) 65,177 (R2)	Cryptic virus + low concentration	10.5061/dryad.wpzgmsbjj
9	Real	Pistachio	PIVB	-	2 x 151 (R1) 2 x 84 (R2)	5,259,903 (R1) 5,259,903 (R2)	Concentration of different genomic segments	10.5061/dryad.p5hqbzkmx
10	Semi-artificial	Prunus	PBNPaV	Addition of PPV	1 x 75	24,573,681	New strain	10.5061/dryad.rr4xgd6n
11	Artificial	-	PepMV	-	2 x 150	48,578 (R1) 48,578 (R2)	Haplotype reconstruction of 6 strains	10.5061/dryad.866t1g1nx
12	Artificial	-	<i>Cassava mosaic virus</i>	-	2 x 150	48,222 (R1) 48,222 (R2)	Haplotype reconstruction of 4 strains	10.5061/dryad.ns1rn8pqb
13	Artificial	-	BSV	-	2 x 150	47,240 (R1) 47,240 (R2)	Haplotype reconstruction of 6 strains	10.5061/dryad.573n5tb59
14	Artificial	-	PVY	-	2 x 150	52,333 (R1) 52,333 (R2)	Haplotype reconstruction of 5 strains	10.5061/dryad.pc866t1m5

15	Artificial	-	EMDV	-	2 x 150	48,504 (R1) 48,504 (R2)	Haplotype reconstruction of 3 strains	10.5061/dr yad.p2ngf 1vnq
16	Artificial	-	BPEV	-	2 x 150	49,980 (R1) 49,980 (R2)	Haplotype reconstruction of 4 strains	10.5061/dr yad.xpnvx 0kcn
17	Artificial	-	LChV1	-	2 x 150	49,513 (R1) 49,513 (R2)	Haplotype reconstruction of 5 strains	10.5061/dr yad.9p8cz 8wdh
18	Artificial	-	BYDV	-	2 x 150	46,917 (R1) 46,917 (R2)	Haplotype reconstruction of 6 strains	10.5061/dr yad.zkh18 937t

246

247 ¹ R1: Forward read, R2: Reverse read.

248 ² CTV: citrus tristeza virus, CVEV: citrus vein enation virus, CEVd: citrus exocortis viroid, CVd-III: citrus viroid III, HSVd:
249 hop stunt viroid, GRSPaV: grapevine rupestris stem pitting-associated virus, GLRaV2: grapevine leafroll-associated
250 virus 2, GRVfV: grapevine rupestris vein feathering virus, GYSVd1: grapevine yellow speckle viroid 1, GRBV: grapevine
251 red blotch virus, PVY: potato virus Y, TSWV: tomato spotted wilt virus, PFBV: *Pelargonium* flower break virus, PiVB:
252 *Pistacia* emaravirus B, PBNSPaV: plum bark necrosis stem pitting-associated virus, PepMV: pepino mosaic virus, BSV:
253 banana streak virus, EMDV: eggplant mottled dwarf virus, BPE: bell pepper endornavirus, LChV1: little cherry virus 1,
254 BYDV: barley yellow dwarf virus

255

256 Funding

257 This work reports the results of the Plant Health Bioinformatics Network (PHBN) Euphresco
258 project (European Phytosanitary Research Coordination), funded by Special Research Funds
259 (FSR) of Liège University (byPOP project), and the Belgian Federal Government (FPS Health
260 project RI 18/A-289 PHBN).

261

262 References

263 **Barzon, L., Lavezzo, E., Costanzi, G., Franchin, E., Toppo, S. and Palù, G.** (2013) Next-generation
264 sequencing technologies in diagnostic virology. *J. Clin. Virol.* **58**, 346–350.

265 **Blawid, R., Silva, J. and Nagata, T.** (2017) Discovering and sequencing new plant viral genomes by next-
266 generation sequencing: description of a practical pipeline. *Ann. Appl. Biol.* **170**, 301–314.

267 **Boonham, N., Kreuze, J., Winter, S., Vlugt, R. van der, Bergervoet, J., Tomlinson, J. and Mumford, R.**
268 (2014) Methods in virus diagnostics: from ELISA to next generation sequencing. *Virus Res.* **186**, 20–31.

269 **Buzkan, N., Chiumenti, M., Massart, S., Sarpkaya, K., Karadağ, S. and Minafra, A.** (2019) A new
270 emaravirus discovered in *Pistacia* from Turkey. *Virus Res.* **263**, 159–163.

271 **Escalona, M., Rocha, S. and Posada, D.** (2016) A comparison of tools for the simulation of genomic
272 next-generation sequencing data. *Nat. Rev. Genet.* **17**, 459.

273 **Hu, X., Karasev, A.V., Brown, C.J. and Lorenzen, J.H.** (2009) Sequence characteristics of potato virus Y
274 recombinants. *J. Gen. Virol.* **90**, 3033–3041.

275 **Huang, W., Li, L., Myers, J.R. and Marth, G.T.** (2012) ART: a next-generation sequencing read
276 simulator. *Bioinformatics* **28**, 593–594.

277 **Jones, S., Baizan-Edge, A., MacFarlane, S. and Torrance, L.** (2017) Viral diagnostics in plants using next
278 generation sequencing: computational analysis in practice. *Front. Plant Sci.* **8**, 1770.

279 **Knierim, D., Menzel, W. and Winter, S.** (2019) Immunocapture of virions with virus-specific antibodies
280 prior to high-throughput sequencing effectively enriches for virus-specific sequences. *PLoS One* **14**,
281 e0216713.

282 **Lefterova, M.I., Suarez, C.J., Banaei, N. and Pinsky, B.A.** (2015) Next-generation sequencing for
283 infectious disease diagnosis and management: a report of the Association for Molecular Pathology. *J.*
284 *Mol. Diagn.* **17**, 623–634.

285 **Madeira, F., Park, Y.M., Lee, J., et al.** (2019) The EMBL-EBI search and sequence analysis tools APIs in
286 2019. *Nucleic Acids Res.* **47**, W636–W641.

287 **Maree, H.J., Fox, A., Al Rwahnih, M., Boonham, N. and Candresse, T.** (2018) Application of HTS for
288 routine plant virus diagnostics: state of the art and challenges. *Front. Plant Sci.* **9**, 1082.

289 **Martin, D.P., Lemey, P. and Posada, D.** (2011) Analysing recombination in nucleotide sequences. *Mol.*
290 *Ecol. Resour.* **11**, 943–955.

291 **Massart, S., Chiumenti, M., De Jonghe, K., et al.** (2019) Virus detection by high-throughput sequencing
292 of small RNAs: Large-scale performance testing of sequence analysis strategies. *Phytopathology* **109**,
293 488–497.

294 **Massart, S., Olmos, A., Jijakli, H. and Candresse, T.** (2014) Current impact and future directions of high
295 throughput sequencing in plant virus diagnostics. *Virus Res.* **188**, 90–96.

296 **Nerva, L., Vigani, G., Di Silvestre, D., Ciuffo, M., Forgia, M., Chitarra, W. and Turina, M.** (2019)
297 Biological and molecular characterization of Chenopodium quinoa mitovirus 1 reveals a distinct small
298 RNA response compared to those of cytoplasmic RNA viruses. *J. Virol.* **93**.

299 **Olmos, A., Boonham, N., Candresse, T., et al.** (2018) High-throughput sequencing technologies for
300 plant pest diagnosis: challenges and opportunities. *EPPO Bull.* **48**, 219–224.

301 **Reynard, J.-S., Brodard, J., Dubuis, N., Zufferey, V., Schumpp, O., Schaerer, S. and Gugerli, P.** (2018)
302 Grapevine red blotch virus: Absence in Swiss vineyards and analysis of potential detrimental effect on
303 viticultural performance. *Plant Dis.* **102**, 651–655.

304 **Thekke-Veetil, T., Ho, T., Postman, J., Martin, R. and Tzanetakis, I.** (2018) A Virus in American
305 Blackcurrant (*Ribes americanum*) with Distinct Genome Features Reshapes Classification in the
306 Tymovirales. *Viruses* **10**, 406.

307 **Wu, Q., Ding, S.-W., Zhang, Y. and Zhu, S.** (2015) Identification of viruses and viroids by next-
308 generation sequencing and homology-dependent and homology-independent algorithms. *Annu. Rev.*
309 *Phytopathol.* **53**, 425–444.